Assessing Efficiency and Capacity in Fisheries

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1. Introduction

1.1 Introduction and Overview

The concepts of excess capacity, overfishing, and overcapitalization are symptoms of the same underlying problem and, as such, are closely related. Without property rights for fish in the sea, fishermen have a market incentive to over invest in capital (overcapitalization) and other productive inputs used to harvest fish. As a consequence, excess capacity and biological overfishing typically occur. While the concept of capacity has been used effectively in other economic sectors and has been discussed in the fisheries literature, the application of this concept to fisheries has not been clearly delineated or explained. This has not prevented recent attempts to estimate excess capacity on a world wide basis. Fitzpatrick (1995) calculated a 270 percent increase in an average fishing technology coefficient between 1965 and 1995; a 9 percent annual growth rate. This increase in technological efficiency has been coupled with an increase in total vessels from 0.6 million in 1970 to 1.2 million in 1992; a 2.2 percent annual growth rate. Garcia and Newton (1996) estimated that world fishing capacity should be reduced by 25 percent for revenues to cover operating costs and by 53 percent for revenues to cover total costs. Mace (1996) identified excess "capacity as the single most important factor threatening the long-term viability of exploited fish stocks and the fisheries that depend on them" requiring a 50 percent reduction in existing global fishing capacity for levels to become commensurate with sustainable resource productivity.

This renewed interest in global fishing capacity is the result of the Environmental Agenda for the 21st Century (Agenda 21) arising from the 1992 Green Summit in Rio de Janeiro. Agenda 21 included a call for governments to cooperate in addressing crises in global fisheries. As a result of a series of negotiations beginning in 1993, three international agreements were completed: (1) the FAO Code of Conduct for Responsible Fisheries, (2) The FAO Agreement on Compliance, and (3) the UN Agreement on Highly Migratory and Straddling Fish Stocks.

With this increased interest in global fisheries, the NOAA Deputy Assistant Secretary for International Affairs, Will Martin, in conjunction with Mary Beth West and Larry Snead of the U.S. Department of State, tabled a proposal at the 1997 Committee on Fisheries (COFI) meeting that resulted in three international plans of action (IPOA) concerning sharks, sea birds, and fishing fleet capacity. The fishing capacity IPOA directs FAO member nations to assess their domestic fishing capacity. This resulted in a FAO technical working group meeting in La Jolla, California in 1998 to develop definitions of fishing capacity and a second technical working group meeting in Mexico planned for late 1999 to discuss measurement of fishing capacity in world fishing fleets.

As a result of these international agreements and plans of action, and a NOAA Fisheries Strategic Plan objective to eliminate overcapitalization in 15 percent of federally managed fisheries by 2004, NMFS established a national capacity task force. Under a partnership developed by William Fox, Director of the Office of Science and Technology (F/ST), and Gary Matlock, Director of the Office of Sustainable Fisheries (F/SF), tasks to be undertaken by each office were clearly defined. Initially, the F/ST task force developed technical and economic definitions of capacity and metrics to measure domestic capacity that resulted in a technical report on domestic capacity. The Science Board endorsed the technical report recommendations at its August 1999 meeting. Subsequently, the F/SF began the process of implementing the recommendations of the task force report. This includes generating measures of fishing capacity for domestic, federally managed fisheries, conducting a capacity measurement workshop for regional NMFS economists, and developing an outreach program to explain the capacity measurement program to industry and the Fishery Management Councils.

The capacity measurement workshop focused on three quantitative techniques identified in the NMFS capacity report to estimate fishery capacity levels and the official U.S. government approach used by the U.S. Census Bureau and the Federal Reserve to determine capacity and capacity utilization. The "peak-to-peak" method of Klein (1960) and the data envelopment analysis (DEA) model developed by Fare et al. (1989) are two quantitative approaches that have been used to estimate technical capacity in fisheries. The stochastic production frontier (SPF) is an alternative method that has been used to estimate efficient (frontier) production in fisheries (Kirkley and DuPaul 1994; Kirkley et al. 1995, 1998) and may be a useful method for developing a measure of capacity under certain circumstances. A fourth method that has not been rigorously examined by the National Marine Fisheries Service, but was discussed at the NMFS workshop, is the survey approach used by the United States Census Bureau and Federal Reserve; the Census Bureau conducts an annual survey of manufacturing firms and asks specific questions about full production value and capacity utilization. Each method has strengths and weaknesses, and the choice of the appropriate method will vary depending on the nature of the fishery, the data available, and the intended use of the capacity measure. In this report, the four basic techniques that might be used to calculate capacity and capacity utilization are discussed. It is anticipated that the discussion of the various methods will offer analysts with sufficient information and knowledge to estimate capacity for different fisheries.

This report introduces the concepts of efficiency (TE), capacity (CAP), capacity utilization (CU), and input utilization (IU). Technical, allocative, and scale efficiency are also explained along with overall economic efficiency. Concepts of congestion are also discussed and examined with respect to measuring capacity in fisheries. Discretionary versus non-discretionary inputs and outputs and weak versus strong disposability concerns are also discussed relative to assessing capacity. The four basic methods of estimating capacity are presented. Building upon the concepts of efficiency, capacity and capacity utilization are presented, and methods to estimate capacity are explained in terms of single and multiple inputs and outputs. In order to provide a practical understanding of the various techniques, empirical examples and tutorials are included in the report. A careful review of the theory and techniques contained in this report should provide the necessary skills to develop estimates of both efficiency and capacity utilization based on the best scientific information presently available.

This report is organized as follows. Section 2 of the report provides numerous definitions of capacity and capacity utilization consistent with definitions used by various government agencies, the National Marine Fisheries Service, the Food and Agriculture Organization, and the academic literature. Section 3 provides theoretical and practical concepts for defining and measuring efficiency, capacity, and capacity utilization. Section 4 provides an overview of various approaches or methods for estimating and calculating technical efficiency, which is requisite information for estimating and understanding capacity and capacity utilization. Section 5 introduces various methods and empirical illustrations of the more typically used approaches for estimating and calculating technical efficiency, capacity, capacity utilization, and optimum input utilization; section 4 also provides tutorials for using GAMS, DEAP, and OnFront for non-parametric assessments and LIMDEP and Frontier 4.1 for parametric or stochastic assessments. Section 6 provides conclusions and recommendations for assessing capacity in fisheries.

2. Technical Efficiency, Capacity, and Capacity Utilization Defined

2.1 Definitions and Concepts: The Basics

In order for various nations to reduce fishing capacity, individuals determining the necessary levels of capacity reduction must have a clear understanding of efficiency, capacity, and capacity utilization. That is, there must be a clear understanding of what is meant by capacity and capacity utilization. It is also essential to know, however, whether or not production is technically efficient. Alternatively, if producers are not operating at capacity output or fully utilizing their fixed inputs, how much of the deviation from full capacity utilization is because of inefficient production. In this section, basic definitions and concepts related to efficiency, capacity, capacity utilization (CU), and input utilization are introduced and discussed

2.2 Technical Efficiency

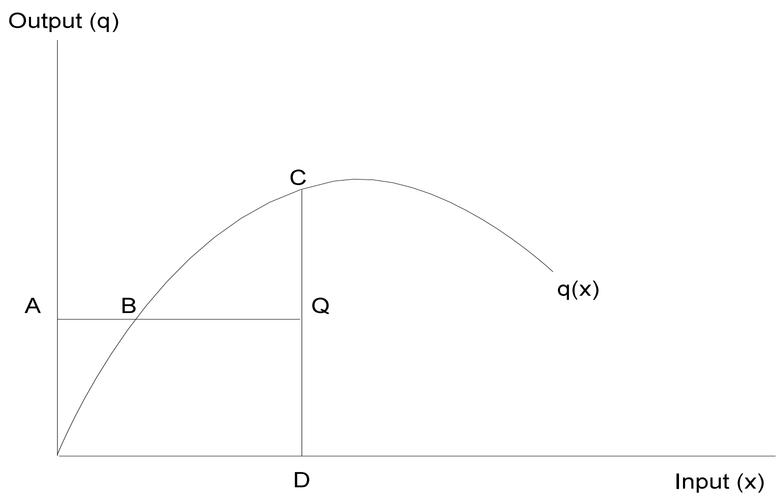
In the simplest of terms, technical efficiency (TE) is an indicator of how close actual production is to the maximal production that could be produced given the available fixed and variable factors of production. Technical efficiency also, however, may be an indicator of the minimum levels of inputs or factors of production necessary to produce a given level of output relative to the levels of inputs actually used to produce that same level of output. In the case of fisheries, TE is a measure of the ability of a producing unit (e.g., vessel) to either produce the maximum output given input levels and the technology, or to utilize as few inputs as is possible to produce a given output level, subject to the technology.

Rarely is it possible to obtain an absolute measure of technical efficiency, and thus, technical efficiency is usually defined relative to some benchmark level. The benchmark is referred to as the "best practice frontier" and represents actual observed achievements in similar operations (Färe and Grosskopf 1998). Technical efficiency is thus a relative measure and indicates how close observed production is to production corresponding to the "best practice frontier" level of output.

To gain a better understanding of technical efficiency, consider Figure 2.1 which depicts a simple production process in which a single input (x) is used to produce a single output (q). The figure depicts the frontier or maximum level of output which could be produced given input levels and the technology. The explanation of efficiency is based on the Farrell (1957) static and deterministic concept of TE; an explanation based on a stochastic framework is discussed in section 4. All points on the frontier depict technically efficient production; all combinations of inputs and outputs lying below or inside the frontier depict inefficient production. Point B and C represent efficient production. At point C, the efficient production requires D units of input x. In contrast, production at point Q is inefficient; the producer is using D units of input x to produce q units of output (y). Production could be expanded from point Q to point C with no change in input levels. Point

B is also efficient and production requires only AB units of input x. Output level B could be produced by simply reducing input x by BQ units. Technical efficiency relative to reducing inputs is measured by the ratio of AB to AQ, and relative to expanding output by the ratio of DQ to DC. When technical efficiency is defined relative to input contraction, $0 \leq TE \leq 1.0$. When TE is assessed relative to potential output expansion, however, two limits may be used. For the ratio of DQ to DC, $0 \leq TE \leq 1.0$. Alternatively, some researchers,

Figure 2.1. Technical Efficiency: Input and Output Measures



when assessing the potential expansion of outputs, define and measure TE in terms of the ratio of DC to DQ–$1.0 \leq TE \leq \infty$. A score of 1.0 relative to potential input reduction or output expansion indicates that production is technically efficient.

Information on technically efficiency, from either an input reduction or output expansion perspective, is useful for determining the level by which inputs could be reduced or outputs could be increased. For example, consider a TE score of 0.5 relative to reducing inputs and producing a given output. All inputs could be reduced by 50% (1.0 - TE) while producing a given output level. Now consider a TE score of 1.5 relative to expanding outputs. Production could be increased by 50% (TE-1.0) by efficiently utilizing the given inputs and technology.

2.3 Capacity

Given the level of national and international attention devoted to defining, measuring, and assessing capacity, it is surprising that there is no universally accepted definition of capacity. Yet, a more precise and widely acceptable definition is required to monitor and measure excess harvesting capacity and to develop capacity reduction programs. A simple and widely accepted definition of capacity is that level of output produced in accordance with obtaining some underlying behavioral objective (e.g., the level of output determined to maximize profits or revenues) and operating under customary and normal operating procedures..

Presently, the Federal Reserve and the U.S. Bureau of Census define capacity in terms of "full production capability." The full production capability is the maximum level of production that a producing unit could reasonably expect to attain under normal operating conditions. Normal operating conditions include the following considerations: (1) only the machinery and equipment in place and ready to operate will be utilized; (2) maximum potential production must be adjusted to reflect normal downtime, maintenance, repair, cleanup, and other shifts; (3) consider only the number of shifts, hours of operations, and overtime pay that can be sustained under normal conditions and a realistic work schedule; and (4) assume availability of labor, materials, utilities, etc., are not limiting factors. The capacity measures of the Federal Reserve and U.S. Bureau of Census "attempt to capture the concept of sustainable practical capacity, which is the greatest level of output that a plant can maintain within the framework of a realistic work schedule, taking account of normal downtime, and assuming sufficient availability of inputs to operate machinery and equipment in place" (Federal Reserve Board, 1999, Capacity Utilization Explanatory Notes).

There are also many other definitions of capacity. Morrison (1985) and Nelson (1989) offer three definitions of capacity that specifically relate to an economic foundation and have been widely used (Cassel 1937, Chenery 1952, Klein 1960, Friedman 1963, and Hickman 1964): (1) capacity is the output corresponding to the tangency of the short- and long-run average cost curves; (2) capacity is the output corresponding to the minimum point on the short-run average cost curve; and (3) capacity is the output corresponding to the tangency between the long-run average cost curve and the minimum short-run average total cost curve; this latter point represents the long-run competitive equilibrium point.

Relative to the case of fisheries, Johansen (1968) offers a definition similar to that presently used by the Federal Reserve Board and the U.S. Bureau of Census. "Capacity is the maximum amount that can be produced per unit of time with existing plant and equipment, provided the availability of variable factors of production is not restricted" (Johansen 1968, p. 52).

The Technical Working Group of the FAO meeting on the Management of Fishing Capacity proposed the following definitions of fishing capacity: (1) The ability of a stock of inputs (capital) to produce output (measured as either effort or catch); fishing capacity is the ability of a vessel or fleet of vessels to catch fish; (2) optimum capacity is the desired stock of inputs that will produce a desired level of outputs (e.g., a set of target fishing mortality rates for the species being harvested) and will best achieve the objectives of a fishery management plan (e.g., minimize costs); current optimal capacity may differ from long run optimal capacity, particularly if the fishery resource is currently depleted and the management strategy is to rebuild this depleted resource; and (3) fishing capacity is the maximum amount of fish over a period of time (year season) that can be produced by a fishing fleet if full-utilized, given the biomass and age structure of the fish stock and the present state of the technology.

Although there are many possible definitions of capacity, fishery managers and administrators tend to prefer the physical or technological-engineering concept of capacity. Moreover, the data necessary for calculating the economic concepts of capacity are seldom available for fisheries (i.e., costs and earnings data). A physical-based definition also most closely conforms to fishing mortality in that the input levels (standardized fishing effort) corresponding to capacity output can be related to fishing mortality.

At the same time, fishery managers and administrators and industry and community leaders are often concerned with other economic, social, and cultural aspects (e.g., full-employment, educational attainment, crime, and social infrastructure). It is therefore appropriate to consider a modified definition of capacity that explicitly allows the introduction or consideration of other economic, social, and cultural constraints. A potential definition of capacity is the output level that satisfies the socio-economic goals and objectives of management but is less than or equal to a specified biological limit (e.g., total allowable catch).

There is a growing concern among fishery administrators and researchers, however, that the conventional economic definitions and measures of capacity may pose problems for realizing biological goals and objectives, particularly sustainable fisheries. They, thus, suggest that capacity might be better defined and measured in terms of fishing mortality (F). Since F is a multi-valued function and there is not necessarily a unique one-to-one mapping between F, catch, and resource abundance, a measure of capacity in terms of fishing mortality would have to be based on a sustainable production or catch and resource concept. That is, given a sustainable yield function, it would be possible to measure a level of fishing mortality for each combination of catch, capital, and sustainable resource abundance.

2.4 Capacity Utilization

There are also numerous definitions of capacity utilization. The most generalized and publically accepted definition is that of the Federal Reserve Board and U.S. Census Bureau: "capacity utilization (CU) measures the extent to which the nation's capital is being used in the production of goods." A more formal definition is offered by the U.S. Census Bureau in FAQs about the Survey of Plant Capacity (1999, p. 1) "The capacity utilization rate is the ratio of actual value of production to the level of production at full production capability." Under the Federal Reserve Board and U.S. Census Bureau's definition of capacity utilization, CU must be less than or equal to 1.0.

In general, the concept of capacity utilization may be defined from a primal or physical based measure or an economic-based measure. From a technological basis, CU is the ratio of observed output to capacity output. From an economic basis, CU is the ratio of observed output to the output determined by the tangency between the long and short-run average cost curves. Numerous other economic-based definitions have been offered in the literature (e.g., Morrison 1985, Nelson 1989, and Berndt and Fuss 1986). An alternative definition of capacity utilization and one which allows for a technological or economic-based orientation is the ratio of observed production (Y) to optimum production (Y*) or Y/Y*.

There are, however, some important distinctions between an economic-based definition and a primal-based definition of capacity utilization. The economic measure of CU is limited to the range $0.0 < CU_E < \infty$, where CU_E denotes an economic concept of capacity. If $CU_E = 1.0$, the production entity is operating at the optimum utilization of capacity. A value of $CU_E > 1.0$ implies that there is a shortage of capacity relative to demand. A value of $CU_E < 1.0$ indicates a surplus (excess capacity) of capacity relative to demand. In comparison, the technological-engineering definition of capacity is limit to being less than or equal to $1.0–CU_{TE} \leq 1.0$, where CU_{TE} indicates the technological-engineering measure of capacity. If $CU_{TE} = 1.0$, the optimum utilization of capacity is occurring relative to maximum physical output conditional on the fixed factors limiting production. If $CU_{TE} < 1.0$, there is excess capacity.

Färe et al. (1989), however, introduce the notion that measures of CU based on the numerator being observed output might yield biased estimates of CU. Färe et al. demonstrated that the use of observed output in the numerator of the CU measure could represent inefficient production, which would result in a downward bias to the utilization rate. For that reason, Färe et al. suggest that CU should be defined as the ratio of technically efficient production to capacity or maximum output. Moreover, the definition by Färe et al. allows the determination of whether or not plant and equipment inputs are not being fully utilized because of inefficient production.

2.5 Variable Input Utilization Rate

Färe et al. (1989) and Färe et al. (1994) introduced the concept of variable input utilization rate. The variable input utilization rate is simply the ratio of observed input usage to the optimal input usage, which is defined as the level of variable input usage required to operate at full capacity utilization. The definition of variable input utilization offered by Färe et al. (1989) is based on the technological-engineering concept of capacity as proposed by Johansen (1968). It could, however, be derived for economic-based measures of capacity. The calculation or derivation of the variable input utilization rate is further discussed in section 4.

3. Theoretical Concepts of Technical Efficiency and Capacity

3.1 Theoretical and Practical Concepts

Section 2 provided an introduction to the basic concepts required to understand and assess efficiency, capacity, capacity utilization, and variable input utilization. Unfortunately, the world of fisheries is not as simple as suggested in section 2. Fishing vessels or operations often harvest more than one product or species of fish. Inputs are often not well defined. Economic data necessary for assessing efficiency and economic measures of capacity and capacity utilization are usually not available. Fisheries are typically exploited by heterogeneous operating units or vessels; these operating units typically vary in size, hull construction, gear design and size, operating characteristics and configuration, and vintage. More important, most of the traditional concepts of efficiency, capacity, and CU were developed without consideration of natural resource-based industries such as fisheries; the lack of concern about natural resource levels generates a series of questions of whether or not resource levels should be included in the assessment of efficiency, capacity, and capacity utilization. Fisheries and other natural resource industries often have the problem of joint production of undesirable outputs or utilization of undesirable inputs (e.g., in the tuna purse seine fishery, dolphins may be captured with yellowfin tuna; alternatively, there may be large catches of non-marketable juveniles of certain species). Should efficiency and capacity estimates be adjusted to reflect the fact that some outputs or inputs may be undesirable (e.g., should purse seine vessels landing less yellowfin and less dolphin have a higher efficiency score than vessels landing more yellowfin and more dolphin using the same level of inputs)? Last, all definitions and concepts, except the modified definition of capacity, presented in the last section are relatively void of social and community concerns and practices. If the definitions presented in section 2 are used as a basis for determining the necessary levels of capacity that should be reduced in a fishery, they could yield social and community outcomes that are inconsistent with the desires of fishing communities (e.g., a highly efficient fleet but with reduced labor employment opportunities in a community).

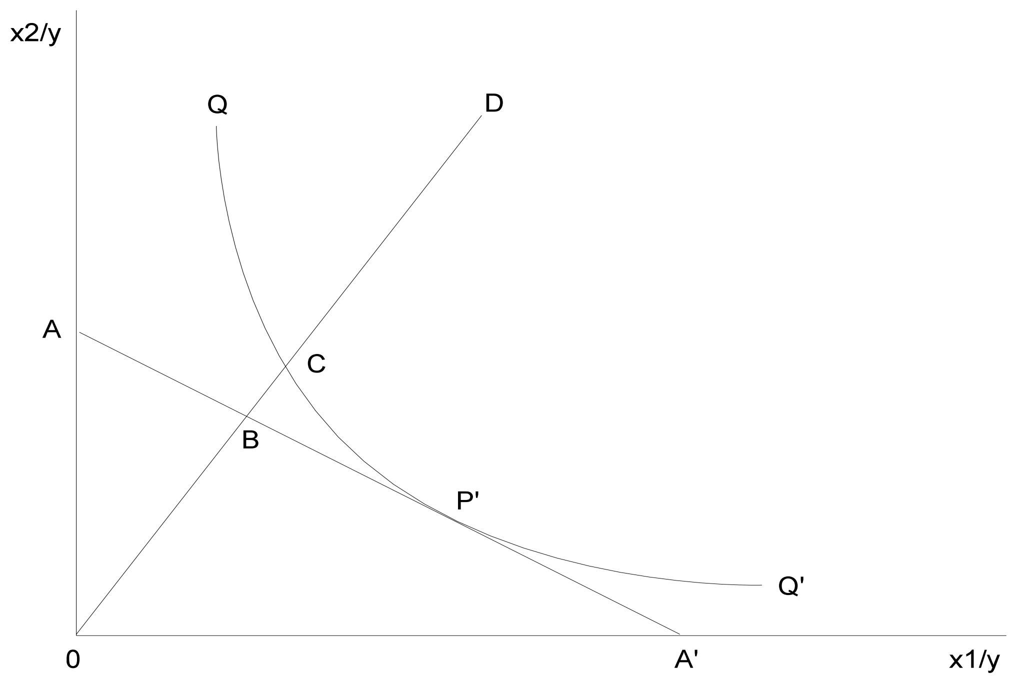
Section 3 expands upon the definitions and concepts offered in section 2. It provides a discussion about the theoretical and practical aspects of defining and measuring efficiency, capacity, and capacity utilization, particularly for fisheries. Initially, Farrell's (1957) concept of efficiency is introduced. The next discussion focuses on various aspects of definitions and measures of capacity and efficiency. Next, economic efficiency and capacity are introduced and discussed relative to the case of fisheries. Last, Practical aspects of measuring and assessing efficiency and capacity are discussed relative to various social and management concerns.

3.2 Farrell's Concepts of Technical and Economic Efficiency

3.2.1 Input-Oriented Measures of Technical and Allocative Efficiency

Debreu (1951) and Farrell (1957) are credited with introducing modern efficiency measurement (Coelli et al. 1998; Färe et al. 1994), with Farrell empirically assessing technical efficiency of agricultural production. Farrell's original concept of technical efficiency (TE) focused on determining the amount that inputs could be reduced without reducing output (i.e., holding output constant). The original concept of Farrell is referred to as a radial input-oriented measure of technical efficiency. Farrell considered firms that used two inputs (x_1 and x_2) to produce a single output (Q), given constant returns to scale (CRS). Then, by constructing the unit isoquant for technically efficient firms, measures of technical efficiency and inefficiency could be developed (Figure 3.1).

Figure 3.1 Farrell's Concepts of Technical and Allocative Efficiencies



Adopted from Coelli et al. (1998), "An Introduction to Efficiency and Productivity Analysis."

In Figure 3.1, any production along the unit isoquant, QQ', is technically efficient. If a producer uses input levels corresponding to point D to produce a unit of output along the isoquant, production is inefficient and the level of inefficiency may be represented by the distance CD. The distance CD is the amount by which all inputs may be proportionally reduced without affecting output. The ratio CD/OD is the percentage by which all inputs should be reduced to obtain technically efficient production. If the ratio OC/OD is formed, that is a measure of technical efficiency and equals 1.0 minus the level of inefficiency (CD/OD). The input oriented measure is restricted to values between 0.0 and 1.0; a value of 1.0 implies that production is technically efficient. The input-oriented measure of technical efficiency for point C would equal 1.0.

Further drawing upon the ideas of Farrell, allocative efficiency (AE), an economic-based measure, may be developed. Given input prices for x_1 and x_2, the isocost line, AA', may be constructed. Allocative efficiency is determined by the ratio of OB to OC. The distance BC is the reduction in costs if production occurred at the allocatively efficiency point P'.

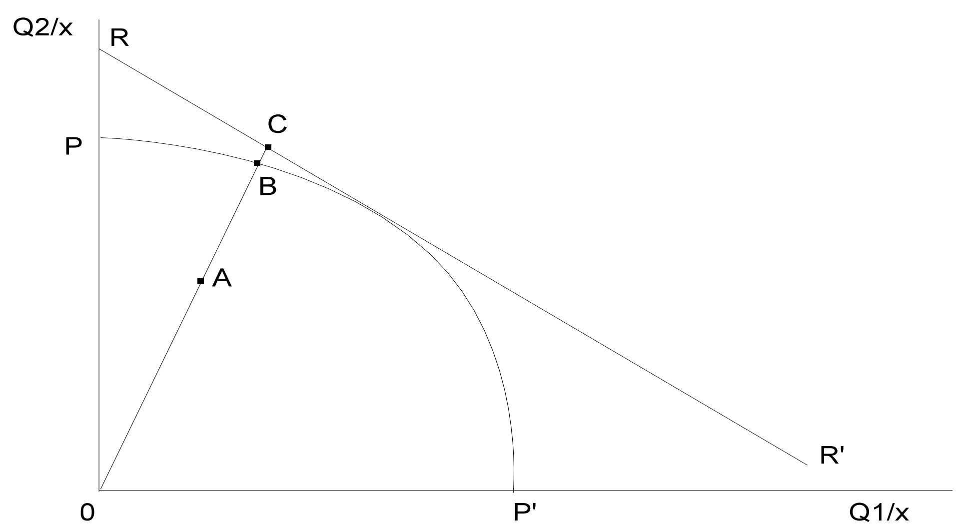
There also is a concept of overall or total economic efficiency (Coelli et al. 1998). An overall measure of economic efficiency may be defined by the ratio OB/OD or by the product of technical and allocative efficiency–TE*AE. All three efficiency measures are limited to values between 0.0 and 1.0.

3.2.2 Output-Oriented Measures of Technical and Allocative Efficiency

The work of Farrell and Debreu focused primarily on radial input-oriented measures of technical efficiency. Farrell did, however, recognize a symmetry between the input-based measure of TE and an output-based measure of TE. Boles (1966), Aigner and Chu (1968), Arifat (1972), and Fare et al. (1985, 1994) substantially advanced the concept and literature on output-oriented measures of technical efficiency.

In contrast to the input-oriented measure of TE which assesses TE relative to a radial input reduction given a constant output level, the radial output-oriented measure of TE provides a measure of the amount by which outputs may be proportionally expanded given inputs held constant. The output-oriented measure is illustrated in Figure 2.2 which depicts the production possibilities curve for a producer using one input (x_1) to produce two outputs (Q_1 and Q_2).

Figure 3.2 Technical and Allocative Efficiency: Output Orientation



Adopted from Coelli et al. (1998), "An Introduction to Efficiency and Productivity Analysis."

The curve PP' represents the production possibilities frontier. All points along the frontier are technically efficient (e.g., point B). All points on the interior of PP' represent technical inefficiency (e.g., point A). The distance defined by AB represents technical inefficiency; this is the amount by which outputs could be increased with no change in the level of x. The ratio 0A/0B is an output-oriented measure of technical efficiency. Färe et al. (1985, 1994), however, define technical efficiency in terms of OB/OA which indicates the total efficient production level for each output. Subtracting 1.0 from the Färe et al. (1985, 1994) output-oriented measure indicates the proportional by which outputs may be expanded relative to their observed levels.

Not surprising, there is also an allocative measure of efficiency which corresponds to the mix of outputs that maximize revenue. The ratio 0B/0C is a measure of allocative efficiency which indicates the percent by which revenue may be increased without changing the input level. There also is an overall economic efficiency measure which equals the product of the output oriented technical efficiency measure and the allocative efficiency measure; it equals the ratio OA/OC. Färe and Grosskopf (1998) discuss additional concepts of efficiency and other important decompositions (e.g., Färe and Grosskopf illustrate how the overall revenue-based measure of efficiency can be decomposed into the product of allocative efficiency, output scale efficiency, an output congestion efficiency, and the output-oriented measure of technical efficiency). The additional concepts and decompositions will be further discussed in section 3.

3.3 Technical and Economic Concepts of Capacity:

Capacity is a short-run concept in that firms face numerous short-run constraints such as capital, plant size, regulations, and the state of technology (Kirkley and Squires 1999). Capacity may be defined and characterized with respect to physical aspects or economic aspects. That is, capacity may be defined as the maximum output the fixed inputs are capable of supporting. Capacity could also be defined as the output level that satisfies the goals and objectives of producers (e.g, profit maximization). A key feature that distinguishes capacity from the technically efficient output is that capacity is the output when only the fixed factors limit production. The technically efficient output is the maximum output given fixed and variable factors of production.

The most common measures of capacity–technological engineering or economic–are primal measures (i.e., output). The primal measure was proposed in 1937 by Cassels and further developed by Klein (1960) and Hickman (1964). The basic concept behind primal measures is that firms are confronted with short-run constraints (e.g., stocks of fixed inputs), and the optimal short-run or temporary equilibrium output may be different than that for a steady-state, long-run equilibrium. Berndt and Morrison (1981) and Morrison (1985) demonstrate that if firms minimize costs; input prices and the fixed input stocks are given; and production is characterized by long-run constant returns to scale; capacity output, Y*, may be defined as the output level that minimizes the short-run average costs. Morrison also defines capacity output when the long-run production is consistent with nonconstant returns to scale; the capacity output level is that level of output determined by the tangency between the short-run average cost and long-run average cost curves.

3.4 Management and Social Concerns: Practical Aspects

Estimating and assessing technical efficiency, capacity, and capacity utilization in fisheries poses many problems; Kirkley and Squires (1998, 1999) provide an extensive discussion on various problems of assessing efficiency, capacity, and capacity utilization in fisheries. First and perhaps foremost is the absence of appropriate data. Cost data are not available for many fisheries. Inputs are seldom well defined, or the traditional economic concepts of inputs are inconsistent with the needs of resource managers (e.g., an traditional economic input is energy or fuel, but managers typically desire production analyses in terms of fishing effort). Captains and skilled crew certainly account or contribute to efficiency and capacity, but it is difficult to adequately incorporate managerial skills into the technical measures. It is highly likely that many economic analyses of production in fisheries suffer from omitted variable bias. Most fisheries produce multiple products; there are few methods for dealing with multiple products without imposing restrictive assumptions on the underlying technology (e.g., separability between inputs and outputs; fixed proportions in outputs; and radial expansion/contraction possibilities). Then, there are potential problems with developing the technical measures without regard to management and social concerns. For example, an assessment of capacity of a fleet comprised of 200 vessels in a community leads to the recommendation that the number of vessels should be reduced to 50. Operating at 50 vessels provides maximum flexibility for operators, maximum efficiency, and maximum net returns. At the same time, however, a reduction of 150 vessels from the fishery would have substantial impacts of the social and economic structures of the community; management may want to consider trade-offs between efficiency, capacity, and community concerns.

In essence, the problems associated with defining and measuring efficiency, capacity, and capacity utilization in fisheries are driven by the need to determine excess capacity. And excess capacity must be defined relative to underlying goals and objectives of fisheries management. A simple definition of excess capacity is the level of actual capacity in excess of the level desired by management–$C_A - C_D = EC$, where C_A is actual capacity, C_D is the capacity level desired or established by management, and EC is the level of excess capacity. A starting point for determining excess capacity is the determination of potential capacity output of a fleet relative to the maximum sustainable yield (MSY); presently, the U.S. Sustainable Fisheries Act (1996) requires that resources be rebuilt to at least maximum sustainable yield levels within a ten year period. The determination of excess capacity relative to MSY, however, raises several important issues. First, if an optimum fleet size and configuration were based strictly on the technical and economic definitions and measures of efficiency and capacity, that optimum might be considerably less than was socially desired by individuals and communities. Second, MSY is a physical concept and void of economic and social content; a fleet size and configuration consistent with MSY would not likely provide maximum net returns or maximum net social surplus. Third, MSY, like capacity and efficiency, must be estimated, and thus, there is the potential for errors.

Another problem with determining capacity and excess capacity is how to treat the resource stocks. Should an assessment of harvesting capacity or capability of an existing fleet be based on existing resource conditions; if so, estimates of harvesting capacity may be highly variable. In contrast, the determination of excess capacity must be made conditional on desired resource levels and possibly various social and economic constraints. Thus far, the issue of whether or not to include resources levels in an assessment of harvesting capacity has not been fully addressed (Kirkley and Squires 1998, 1999). The issue which needs to be address is whether or not NMFS and management agencies desire to know the maximum potential harvest when resource levels do not constrain production or nominal catch or the maximum potential harvest conditional on prevailing resource conditions. The Technical Working Group for the FAO Consultation on Fishing Capacity (1998, para 66) and the U.S. National Marine Fisheries Service Capacity Management Team explicitly require that actual capacity be defined and measured relative to biomass and age structure of the fish stock. In contrast, the U.S. Congressional Task Force Report (1999) on "Subsidies and Investment in Fisheries" recommended that capacity and capacity utilization be defined and measured without respect to resource conditions.

Defining and measuring capacity relative to existing biomass and age structure conditions, however, may pose several problems for management. If capacity was determined during periods when resource abundance was low, the potential capacity output may be substantially underestimated. As a consequence, capacity reduction initiatives may permit more capacity to remain in a fleet than is appropriate to harvest a desired level. Alternatively, the determination of capacity during periods when resource abundance is high may yield estimates which are not at all indicative of normal operating conditions. Capacity reduction initiatives based on estimates of capacity reflecting high resource abundance levels would require a larger reduction in fleet size than suggested by estimates based on relatively low resource levels. A consequence of assessing capacity during periods of high resource abundance, however, is that the allowable level of capacity would be somewhat consistent with the precautionary approach of fisheries management.

Another aspect related to including resource conditions is how to treat the resource in the assessment of efficiency and capacity. Resource abundance may be treated as a discretionary or nondiscretionary input. If it is discretionary, it is assumed that abundance is under the control of the captain. In actuality, the only control a captain may have over abundance is in the selection of areas. If resource conditions are treated as nondiscretionary, they are viewed as being beyond the control of the captain or vessel operator. The issue of how to treat resource conditions remain unresolved.

An issue for assessing efficiency and capacity is how to deal with multiple product technologies and undesirable outputs or bycatch. Numerous techniques are available for assessing efficiency and capacity of firms or industries producing multiple outputs (Kirkley and Squires 1998, 1999). Most methods or measures require some type of aggregation over outputs. Other methods or measures restrict the measures along a ray such that efficiency and capacity is measured relative to proportional changes. Two recent methods that have been used to assess technical efficiency of multiple product firms involve using polar coordinates and distance functions (Lundgren 1998, Coelli and Perleman 1996a, 1996b). Both approaches involve specification of stochastic production frontier models, which will be discussed in section 4, and the assumption that errors associated with each output cancel out since output ratios are used as right hand side variables of the models.

Undesirable outputs or bycatch pose a variety of problems for assessing efficiency and capacity. Should the estimation of efficiency and capacity ignore undesirable outputs? If eliminating or reducing bycatch is not costless, capacity reduction programs based on estimates ignoring the reduction of bycatch well lead to a fleet size smaller than necessary to harvest target levels. This is because if reducing bycatch has a cost, production levels of desired or marketable products will be lower than if disposing of undesirable products had no costs.

4. Estimating Technical Efficiency

4.1 Technical Efficiency Measures: Concepts and Methods of Estimating TE

Understanding technical efficiency is a prerequisite for estimating and assessing capacity and capacity utilization. It is particularly important for determining appropriate capacity reduction initiatives. Not only is it necessary to have information on the maximum potential output, it is also necessary to have information on the maximum potential output given different levels of the variable and fixed factors of production. In this section, various approaches for estimating and assessing technical efficiency are discussed. The approaches range from the very simple calculation of reference ratios–output divided by a single input–to complex stochastic production frontiers. Section 4 is limited to mostly primal-based methods. This is done to offer researchers the broadest and most applicable possible approaches for estimating capacity; that is, those approaches which can be used when only quantity data on inputs and outputs are available.

4.2 Simple Approaches:

Prior to the introduction of deterministic, statistical, and stochastic frontiers, two approaches frequently used in the past to estimate technical efficiency are presented. A third approach has been to estimate the production relationship and obtain fitted values using the same level of variable inputs while holding all fixed inputs constant, and then examine the ratio of fitted values of output.

4.2.1 Ratio of Average Products

One simple approach for estimating technical efficiency has been to calculate the ratio of output to input (Dyson et al.). Recognizing that it is usually not possible to actually calculate technical efficiency, a relative efficiency measure is often constructed by dividing the observed output by input of one operating unit to that of a known efficient unit (Dyson et al., Beasley):

$$RE = \frac{\dfrac{output_j}{input_j}}{\dfrac{output_{te}}{input_{te}}}$$

where j indicates the jth producing unit, te indicates the technically efficiency unit, and RE indicates relative technical efficiency. Alternatively, efficiency has often been calculated by constructing simple output to single input ratios over time and then comparing those ratios over time to determine maximum efficiency. Coelli (1996) and Coelli et al. (1998) show that such ratios are clearly productivity or partial productivity measures. A measure of technical efficiency should indicate whether or not a firm is operating along the frontier.

In the case of fisheries, the RE measure has been widely used to assess the relative technical efficiency of different types and configurations of gear. This is done when assessing existing and proposed commercial fishing gear. For example, two vessels tow a given piece of gear a fixed length of time (e.g. 50 minutes) and make several tows (e.g., 20 tows). Indices of relative catch per tow from one vessel and gear type are compared to indices of catch per tow from the other vessel and gear type; the ratios of the indices provide estimates of relative technical efficiency. These measures indicate relative productivity and provide no information about how far or close production is from the efficient frontier.

4.2.2 Intercepts and Fitted Value Ratios

In addition to estimating or calculating TE using simple ratios, TE has also been calculated by constructing ratios of fitted output levels conditional on input levels and by estimating intercepts of different operating units. In the first case, ordinary least squares is typically used to estimate the production correspondence using either fixed or random effects type models. Alternatively, dummy variables are included to account for differences among operating units. Output is estimated for each operating unit conditional on holding all input levels constant but adjusting for the different operating characteristics (e.g., gross registered tonnage and engine horsepower). That is, the expected value of output is obtained conditional on all variable factors being equal and the fixed factors or operating characteristics being different. The ratio of one fitted value of output to that of another fitted value of output is then used as an estimate of technical efficiency. The second relatively simple approach is similar to that of the first in that ordinary least squares is used to estimate the production correspondence for different categories of operating units. The specification must be multiplicative. Estimates of the intercept have been shown by Chiang (1967) to equal average technical efficiency of the group of firms comprising the data set. By estimating such functions for different groups of operating units, it is possible to obtain relative efficiency measures by simply dividing the estimate of the intercept of one group by the estimate of the intercept of another group.

A major problem with both approaches, however, is that neither indicates whether or not the operating unit is on the frontier. As a consequence, it is possible to obtain biased estimates of relative technical efficiency. Both approaches, however, have been widely used to compare technical efficiency of different types or configurations of fishing gear. For example, an experiment is conducted using 5 inch mesh on the port side and 6.5 inch mesh on the starboard side of a vessel. Catch and effort data are collected. Catch is regressed against effort for each mesh size (i.e., two separate regressions). The regression has the highest intercept is recognized as being indicative of the fact that one gear size is more technically efficient than the other gear size. Alternatively, two regressions are run and fitted values of output are obtained conditional on effort being equal for each gear size; the gear size having the highest estimated output is termed to be more technically efficient than the other gear size. Neither of these approaches, however, explicitly attempts to assess TE relative to a frontier level of output.

4.3 Statistical and Deterministic Approaches for Estimating Technical Efficiency:

4.3.1 Deterministic Full Frontier:

There are four basic methods for estimating technical efficiency: (1) a nonparametric linear programming approach which yields what is termed a full frontier; (2) a parametric approach which provides estimates of technical efficiency from a deterministic full frontier; (3) a statistical frontier which is based on assumed error distributions for technical efficiency and corrected ordinary least squares or maximum likelihood; and (4) the stochastic production frontier which introduces a conventional error term assumed$\rightarrow N(0,\sigma^2)$ and an error term following one of three distributions–half normal, exponential, or truncated normal. The first approach will be later discussed under the heading of data envelopment analysis. Attention is now directed to introducing the deterministic full frontier.

A deterministic full frontier involves the specification of a normal error term to estimate parameters for a given functional form specification of the technology (i.e., the form of the production function such as a Cobb-Douglas). The approach requires mathematical programming to obtain estimates of output based on estimates of parameters, and technical efficiency (TE) is calculated as the ratio of observed y to the exponential value raised to the power of the fitted value of natural log of y (i.e., ln y). The deterministic full frontier model is given by

$$y = f(x)\ \exp^{-u},\ u \geq 0$$

where f(x) is some underlying multiplicative function with n factors of production and y is the level of output. The measure of inefficiency is given by u; technical efficiency is given by the value of the exponential raised to the negative power of u. Natural logarithms are used to transform all observations such that we have the natural log specification of the deterministic full frontier:

$$\ln f(x) = \beta_0 + \sum_i \beta_i X_{ij}$$

where $X_{ij} = \ln x_{ij}$ where x_i is the ith input. To obtain estimates of each β, it is necessary to minimize the absolute value of the sum of u, an error term, or solve the following mathematical programming problem:

$$\text{Minimize} \sum_{J=1}^{m} |\hat{u}_j|$$

$$\begin{aligned} \text{subject to: } & \hat{\beta}_0 + \hat{\beta}_1 X_{11} + \ldots + \hat{\beta}_n X_{nl} \geq Y_1 \\ & \hat{\beta}_0 + \hat{\beta}_1 X_{1m} + \ldots + \hat{\beta}_n X_{nm} \geq Y_m \\ & \hat{\beta}_0 \ . \ . \ . \ \hat{\beta} n \geq 0 \end{aligned}$$

$$\textit{and where } \hat{u}_j = \hat{\beta}_0 + \hat{\beta}_1 X_{1j} + \ldots + \hat{\beta}_n X_{nj} - Y_j.$$

Corbo and de Melo (1986) and Coelli et al. (1998) provide a detailed discussion on estimating the deterministic frontier.

Once the parameters have been estimated by mathematical programming methods (i.e., linear programming), technical efficiency for the jth observation is calculated as follows:

$$Technical\ \ Efficiency = \frac{y_j}{\exp^{\hat{Y}_j}}$$

$$where\ \hat{Y}_j = \hat{\beta}_0 + \sum_{i=1}^{n} \hat{\beta}_i X_{ij}$$

where Y and X are natural logarithms of output and input and n is the number of inputs.

4.3.2 Statistical Frontier

Alternatively, technical efficiency (TE) may be estimated by what is called a statistical frontier. This is also called a parametric full frontier for which a functional form is specified for the production function and there is a separate specification for the inefficiency term. In this section, we present a framework for estimating a statistical frontier based on Corbo and de Melo (1986). The parameters may be estimated either by mathematical programming as in Aigner and Chu (1968) or by statistical techniques as in Richmond (1974) and Greene (1980) (Corbo and de Melo (1986). Two distributions have typically been used to specify technical inefficiency: (1) a one-parameter gamma distribution, and (2) the exponential distribution.

Consider the following model:

$$y = f(x)\ e^{-u},\ u \geq 0.$$

The model is made linear in parameters by taking logarithms:

$$Y = \beta_0 + b_1 X_1 + \ldots + \beta_n X_n - u,$$

where Y equals the natural logarithm of output and X_n equals the natural logarithm of the nth input. X is assumed to be independent of u. The inefficiency distribution for the one parameter gamma distribution is as follows:

$$g(u,\phi) = \frac{1}{\Gamma(\phi)}\ u^{(\phi-1)}\ \exp^{-u}$$

for which E(u) = ϕ and the variance of u equals ϕ. The distribution of u from the exponential is

$$g(u,\phi) = \frac{1}{\phi}\exp\left(-\frac{u}{\phi}\right),$$

and E(u) = ϕ and the variance of u equals ϕ^2.

Estimates of efficiency may be obtained by estimating the production specification using corrected ordinary least squares (COLS) or maximum likelihood; COLS estimation is detailed in Greene (1980, 1998) and Coelli (1995). The efficiency scores for each observation are calculated as follows:

$$E_j = \frac{y_j}{\exp^{\hat{Y}_j}} = \exp^{(-\hat{u}_j)}$$

where $\hat{u}$ is the residual from the COLS estimator. A consistent estimate of the expected value of u may be derived from the choice of the distribution selected for u. Two other efficiency indexes may also be calculated: (1) the average efficiency index, and (2) the expected efficiency of the industry or sector being analyzed.

In estimating technical efficiency for the firm or relative to an observation, it is necessary to impose the condition that all observations are below the frontier. This requires imposing the condition of Greene (1980):

$$\hat{\beta}_{\hat{0}} = \hat{\beta}_0 + \max|\hat{u}_i|.$$

$\hat{\beta}_{\hat{0}}$ is the COLS estimator of β_0 and $\hat{\beta}_0$ is the ordinary least squares estimator of β_0.

4.4 The Stochastic Production Frontier (SPF)

4.4.1 The Basics of the SPF

Of all the parametric approaches for estimating technical efficiency, the SPF approach has probably become the most widely used approach. The literature on the SPF approach is too immense to adequately discuss in the present report; therefore, only the necessary basics are presented. A more complete discussion on the SPF approach is available in Bauer (1990), Battese (1992), Coelli et al. (1998), Førsund et al. (1980),Greene (1993), Lovell (1993), and Schmidt (1986). Issues currently under debate relative to the SPF with no definitive answers include the following: (1) selection of functional form; (2) selection or distribution for inefficiency term; (3) use of panel data; (4) testing for the existence of a frontier function; (5) sensitivity to outliers or extreme observations (either dependent or independent variables); (6) testing hypothesis; (7) modeling inefficiency effects; and (8) treatment of multiple outputs.

A major disadvantage of previous approaches for estimating TE is that all random noise is attributed to inefficiency. Alternatively, all deviations from the frontier are attributed to inefficiency. To deal with this criticism, Aigner et al. (1977) and Meeusen and van den Broeck (1977) proposed the stochastic production frontier in which there are two random variables: (1) a random error term (v), and (2) a non-negative random variable–typically denoted by u. The random variable u, as in the deterministic and statistical full frontiers, specifies technical inefficiency. The random error v is the conventional error term in regressions and is assumed to be normally distributed with a mean of zero and a constant variance.

Considering the statistical frontier, the SPF may be specified as

$$\ln(y_i) = \beta_0 + \sum_i \beta_i \ln x_i + v_i - u_i,\ i = 1,2,..,N.$$

where y and x represent the inputs and outputs, respective; v is a random error term assumed to be normally distributed with a mean of zero and a constant variance, and u, which is the technical inefficiency term, and assumed to have a nonnegative distribution. The random error, v, serves to account for measurement error and other random factors, such as the effects of weather or unexpected factors on production. The random error term, v, is assumed to be independent of the non-negative random variable, u. A Cobb-Douglas specification is assumed; other specifications such as the translog and transcendental, however, may also be used.

What exactly is going on with the stochastic production frontier? The SPF imposes the condition that output values are bounded above by the stochastic or random variable,

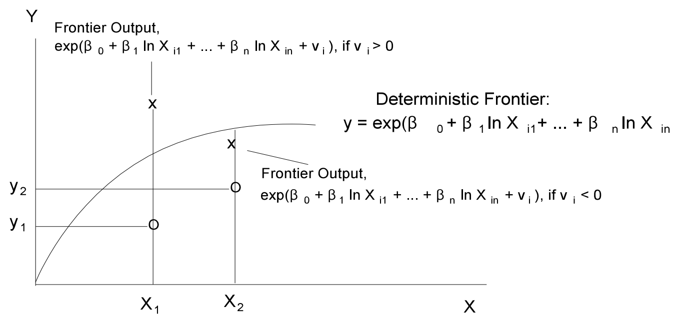
$$\exp^{(\beta_0 + \sum_{i=1} \beta_i \ln x_i + v_i)}$$

The stochastic error, which accounts for noise, has values between - infinity and positive infinity (i.e., its value may be positive or negative). Therefore, the SPF output levels vary about the deterministic part of the frontier model, which is

$$\exp^{(\beta_0 + \sum_{i=1} \beta_i \ln x_i)} .$$

To gain a better understanding of the SPF, consider Figure 4.1. The deterministic frontier is defined by the curved line relating output to input. We find that our stochastic frontier is defined by deviations from the deterministic frontier. Output levels are bounded from above by the stochastic

Figure 4.1. Stochastic Production Frontier



random variable $\exp(\beta_0 + \beta_1 \ln X_{i1} + \ldots + \beta_n \ln X_{in} + v_i)$. With the SPF, observed output levels may be greater than the deterministic part of the frontier ($v_i > u_i$). If v_i is less than 0, the frontier output will be less than the deterministic frontier output level.

One aspect of the SPF that is often overlooked by many researchers is that the SPF is similar to Farrell's (1957) specification in that it is output oriented. That is, the SPF, as specified above, provides an estimate of the amount by which outputs could be increased given input levels. Although there does not appear to have been any empirical studies on an input orientation, there is no reason why a factor requirements function could not be specified with a stochastic frontier framework. Coelli et al. (1998) provide an in-depth introduction and review of the stochastic production frontier specification and method.

There is general recognition that the stochastic production frontier provides a useful framework for assessing technical efficiency for production subject to randomness (e.g., crop production and weather; catching fish and storms; timber production and parasitic infestation; and aircraft manufacturing and labor strikes). The SPF, however, does have its share of problems.

One major problem, of course, is that estimation of the SPF requires specification of some underlying functional form. Moreover, the specification must be multiplicative in inputs, the random error term, and the non-negative random variable for inefficiency. Given flexible functional form (FFF) specifications, however, there should be few problems associated with specification of the underlying functional form.

Another major problem, and one that has not been resolved, is the selection of the distribution of the random variable for inefficiency, u. Three specifications are widely used: (1) half-normal; (2) exponential; and (3) the truncated-normal. More recently, Greene (1990) offered a two-parameter gamma distribution. Schmidt and Lin (1984) demonstrate that there are no completely acceptable tests for determining the appropriate inefficiency distribution. Coelli et al. (1998) suggest that estimated efficiency values may be very sensitive to the assumed distribution of the inefficiency term.

Bhattacharyya et al. (1995) have offered a possible empirical approach for evaluating which inefficiency distribution might be preferred. They use what is called a data generating process (DGP) validation. The process of Bhattacharyya et al. requires estimating the SPF conditional on all four distributions (i.e., half normal, truncated normal, exponential, and the gamma). Then, to select the model and distribution which most closely follows the DGP based on non-nested model selection tests (Vuong 1989).

Two basic tests are used to select the preferred distribution. First, the likelihood dominance criterion (LDC) is used to select between models with inefficiency specified with the four candidate distributions. This test is simply a comparison of the values of the log-likelihoods (L) of two competing models. For example, let Model A be the half normal model and Model B be the truncated normal model. Both models are to be estimated with maximum likelihood procedures. The LDC prefers Model A over Model B if

$$L_B - L_A < \frac{\left[C\,(N_B + 1) - C\,(N_A + 1)\right]}{2}$$

where N_A and N_B are the number of respective independent parameters in Models A and B; and C(N) is the critical value of the chi-squared distribution with N degrees of freedom. In the event of two competing models or uncertainty about the preferred model, the Vuong test is conducted. The Vuong test is a likelihood ratio test for selecting between two competing models and rquires the following test statistics:

$$ST = \sqrt{\left[(F - 1)/F\right]}\ x\ t_s$$

In ST, t_s is the t-statistic of the regression of a series of one on m_t, and m is the difference between the log-likelihood values of two models (evaluated at eeach data point for both models being tested) (Bhattacharyya et al.). F is the total number of observations. If ST > C, where C is the critical value from the standard normal distribution, the null hypothesis that the two models are equivalent is rejected. If the absolute value of ST is less than or equal to C, it is not possible to discriminate between two competing models given the data. To date, only Bhattacharyya et al. and Vuong have used these tests; other examples do not appear in the published literature.

4.4.2 The Stochastic Frontier and Potential Models

4.4.2.1 General Model and Background

Perhaps the easiest way to begin to understand the concept of the SPF is to examine the various candidate models. We start with the original specification of Aigner et al. (1977):

$$\ln (y_i) = \beta_0 + \sum_i \beta_i \ln x_i + v_i - u_i,\ i = 1,2,..,N.$$

The variables are as follows: (1) y is the production of the ith firm; (2) x is a vector of the input quantities of the ith firm; (3) β is a vector of unknown parameters; (4) v are random variables assumed to be iid. $N(0,\sigma_v^2)$, and independent of u; and (5) u is a non-negative random variable which accounts for technical inefficiency and is assumed to be iid. $|N(0,\sigma_u^2)|$. The preceding specification, of course, is the familiar Cobb-Douglas specification. Although the Cobb-Douglas function is still widely used, most stochastic production frontier studies specify the translog, or more formally, the translogarithmic function:

$$\ln y_i = \beta_0 + \sum_j \beta_j \ln x_{ji} + \sum_j \sum_k \beta_{jk} \ln x_{ji} \ln x_{ki} + \varepsilon_i$$

$$where\ \varepsilon = v_i - u_i.$$

In most previous empirical studies, u was specified to follow a half-normal distribution. Presently, there is a tendency to use the truncated normal distribution (i.e., $N(\mu,\sigma_u^2)$, which is truncated at zero). Most empirical studies have found no differences in estimates of technical efficiency when using the half-normal or the exponential. Attention is restricted to the truncated normal and the half-nomal in this work book; estimates using the exponential distribution, however, are included for comparative purposes.

An important aspect of the stochastic production frontier is whether or not one needs to estimate a stochastic frontier to obtain estimates of technical efficiency. That is, could estimates of technical efficiency be obtained using the deterministic full frontier or the statistical frontier in which there are no random errors in production. Alternatively is the average response function the appropriate characterization of the technology (i.e., are all firms operating efficiently?). This may be assessed by testing whether or not the parameter

$$\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)}$$

equals one in value. The initial test for determining whether or not there are technical inefficiency effects in the model or that the traditional average response function, without the technical inefficient effect, is an appropriate specification is a test of the null vs. the alternative: $H_0\colon \gamma = 0,\ or\ H_1\colon \gamma > 0$. If H_0 is true, the conventional average response function, without technical inefficiency effects, is the appropriate specification. If the alternative is true, then, the SPF is the appropriate specification. If γ greater than 0 but less than 1.0, the SPF specification is the appropriate specification for technical inefficiency. If $\gamma = 1.0$, however, the deterministic or statistical frontier model is the appropriate specification.

$$\textit{OLS Model} \rightarrow 0.0 \le \gamma \le 1.0 \leftarrow \textit{DeterministicStatistical Full Frontier}$$
$$0.0 < \gamma < 1.0$$
$$\uparrow$$
$$\textit{StochasticProductionFrontier}$$

The test or determining whether or not the stochastic production frontier is the appropriate specification is actually a one-sided likelihood ratio test (Coelli 1995). The likelihood ratio test simply requires estimating the production model under both the null and alternative hypothesis and obtaining the corresponding values of the likelihood function (Battese and Corra 1977; Coelli et al. 1998).

$$\mathrm{LR} = -2\{\ln[L(H_0)/L(H_1)]\} = -2\{\ln[L(H_0)-\mathrm{Ln}[L(H_1)]\}$$

where L is the value of the likelihood function under each hypothesis. Coelli demonstrates that the generalized likelihood-ratio statistic has an asymptotic distribution which is a mixture of chi-square distributions. Coelli then demonstrates that the critical value for a test of size α (e.g., 0.05)is equal to the chi-squared valued corresponding to 2α . The critical values for the one-sided likelihood ratio test are also available in Table 1 of Kodde and Palm (1986).

4.4.2.2 Panel Data, Potential Models, and Specifications

Following Battese and Coelli (1992), a relatively straightforward specification is considered. The SPF of Battese and Coelli is for unbalanced panel data and allows for firm effects; the firm effects are assumed to be distributed as truncated normal random variable, but also are permitted to vary systematically with time. The general model is as follows: $y_{it} = x_{it}\,\beta + (v_{it} - u_{it})$ where y and x are in natural logarithms. The u_{it} are assumed to account for technical inefficiency in production and are assumed to be iid as truncations at zero of the truncated normal distribution. For the case of firm effects and systematic variation with time, $u_{it} = (U_i \exp^{(\eta(t - T))})$, where η is a parameter that must be estimated.

There are some special cases of the Battese and Coelli model. If η is set to zero, the model becomes the time-invariant model of Battese et al. (1989). Other models include the Battese and Coelli (1988) model for a full balanced panel of data; the Pitt and Lee model if μ is set to zero. Adding the restriction that T=1 to the other restrictions reduces the model to the half-normal distribution model of Aigner et al. (1977). Coelli (1994) provides an extensive listing of different models given different restrictions. One additional important model, however, is that of Stevenson (1980) which is the initial specification of Aigner et al. with the inefficiency distributed as a truncated normal rather than a half-normal. The Stevenson model requires the following restrictions: (1) $\eta = 0$, and (2) T = 1. A balanced panel data set is not required for the truncated normal distribution.

A second, and highly interesting and useful specification, is the Battese and Coelli (1993) specification involving the use of a one-stage routine to model inefficiency effects. In this model, inefficiency is specified to be a function of explanatory variables which might help to better predict or explain the inefficiency effects (e.g., firm size, age and education of manager, and rainfall or weather variables): $\mu_{it} = z_{it}\ \delta_{it}$, where z is a vector of observable explanatory variables, and δ is a vector of unknown parameters to be estimated. If there is only one z and it consists of all ones and T equals 1.0, we have the truncated normal specification of Stevenson (1980).

A remaining issue is whether or not to specify the SPF with a random effects model. The two major programs–LIMDEP and Frontier 4.1–that have routines for estimating the SPF allow for balanced and unbalanced panel data. With the random effects model, it is important to understand that estimation requires the computation of more than one value for the same u_i where i is the ith firm. In general, if there are T observations for the ith firm, the random effects model will compute T estimates of u. The Battese and Coelli (1992) specification provides a good example of the random effects model when inefficiency is permitted to vary systematically with time and there are differences among firms. With the random effects model, each error is an individual specific disturbance. LIMDEP and Frontier permit both balanced and unbalanced panel data. The Battese and Coelli model, however, is not a true random effects model. It is actually an error components model and is not the same as the random effects model available in LIMDEP or as discussed in the panel data literature.

The SPF model is usually estimated via maximum likelihood. Both programs, LIMDEP and Frontier 4.1, have extensive options for considering different specifications of technical inefficiency (e.g., half normal (LIMDEP and Frontier 4.1), exponential (LIMDEP), and truncated normal (LIMDEP and Frontier 4.1). The likelihood functions corresponding to each inefficiency distribution are described in Greene (1998) and Coelli et al. (1998).

4.4.2.3 Predicting Technical Efficiency Scores

There is actually little difference in the basic aspect of predicting technical efficiency from the various efficiency type models. In general, TE equals the ratio of the observed output to the frontier output. With the deterministic and statistical frontiers, TE is equal to the value exp(-u) where u is the inefficiency distribution. Predicting or actually estimating efficiency scores from the SPF, however, is methodologically complicated. For the most part, the Jondrow et al. (1982) approach has been widely used. With the Jondrow approach, technically inefficiency is estimated in terms of the expected value of u_i conditional on ϵ_i where $\epsilon_i = v_i - u_i$; formally, Jondrow et al. suggest that the technical efficiency of the ith observation or firm can be predicted using $1 - E[u_i | \epsilon_i]$. Battese and Coelli (1988), however, offer an alternative approach which is more consistent with directly estimating technical efficiency. They show that technical efficiency can be estimated by calculating the expected value of the exponential function raised to the negative power of the inefficiency term conditional on $\epsilon_i = v_i - u_i$ (i.e., $E[\exp^{-u_i} | \epsilon_i]$; Coelli et al. (1998) provide a detailed discussion on predicting technical efficiency.

The Jondrow et al. (1982) and Battese and Coelli (1988) derivations, respectively, are as follows:

$$E[u_i|\epsilon_i] = -\gamma\ \epsilon_i + \sigma_A\left(\frac{\phi(\gamma\ \epsilon_i\ /\sigma_A)}{1\ -\ \Phi(\gamma\ \epsilon_i/\sigma_A)}\right)$$

$$E[\exp^{-u_i}|\epsilon_i] = \frac{1-\Phi(\sigma_A\ +\ \gamma\ \epsilon_i\ /\sigma_A)}{1\ -\ \Phi(\gamma\ \epsilon_i/\sigma_A)}\ \exp^{(\gamma\ e_i\ +\ \sigma_A^2/2)}$$

where $\phi(.)$ and $\Phi(.)$ are the density and distribution functions for the standard normal and

$$\sigma_A = \sqrt{\gamma(1-\gamma)\sigma_S^2}$$

4.5 Estimating Technical Efficiency: An Illustrative Example:

In this section, we present a discussion on estimating technical efficiency using a panel data set on trip-level production for nine vessels operating in the U.S. Northwest Atlantic sea scallop fishery in 1990. The panel data are unbalanced and fail to satisfy the data requirements for using either LIMDEP or Frontier 4.1 to estimate a random effects model. LIMDEP and Frontier 4.1 require that there be at least the same beginning and ending time period for all observations. Technically inefficiency is assumed to initially follow the half normal distribution. Subsequently, technically inefficiency is assumed to follow the truncated normal. Last, the estimation is modified to partially reflect firm level and temporal effects through the use of the one-stage routine of Battese and Coelli (1993). The major focus of this section is to provide an introduction to empirically estimating efficiency using the SPF.

Although the subsequent estimation and analysis are based on Frontier 4.1 (Coelli 1994) and LIMDEP (Greene 1998), this report does not endorse any of the available software packages. For purposes of illustrating LIMDEP, the initial simple model ignoring random effects is estimated. The production function is specified with a conventional translog specification. The simple model is also estimated imposing the truncated normal distribution on the inefficiency term. Later the one-stage routine of Battese and Coelli (1995) is used to examine inefficiency as a function of month and individual vessel under the assumption that the inefficiency term follows the truncated normal distribution. A subset of the data, statistical results, and conclusions are presented in Tables 4.1-4.10.

The technical effects model estimated includes 19 dummy variables in the technical effects specification. There are 11 dummies for months and 8 dummies for individual vessels. The data were not consistent with the panel data approaches available in either LIMDEP or Frontier 4.1. The inclusion of the dummies in the technical effects specification was done in an effort to better capture the possible influences of vessel and seasonal differences on technical efficiency.

The data in Table 4.1 were obtained from vessel owners. The variables are as follows: (1) days is days at sea; (2) crew is the number of crew; (3) stock is a measure of resource abundance; (4) hp is engine horsepower; (5) dredge is the size of the dredge; (6) length is vessel length in feet; and (7) catch is catch in pounds of meats. The fixed factors were not included in the specification.

Overall, we find no substantial differences between the conclusions derived from

LIMDEP and those based on results from Frontier 4.1. Both sets of estimates indicate that a deterministic frontier is an appropriate specification. Results from the technical effects model of Frontier 4.1, however, suggest the SPF is an appropriate specification. That is, there are technical inefficiency effects that explain technical efficiency.

Table 4.1 Twenty-five of 132 Observations.

	days	crew	stock	grt	hp	dredge	length	catch
1	13	9	2.27985	181	620	15	90	5595
2	18	9	2.15278	181	620	15	90	5878
3	18	9	1.63343	181	620	15	90	8495
4	18	10	2.36067	181	620	15	90	15897
5	18	12	4.4176	181	620	15	90	20268
6	17	11	5.63225	181	620	15	90	18306
7	19	12	5.38627	181	620	15	90	23692
8	11	12	6.23723	181	620	15	90	11268
9	17	12	5.12387	181	620	15	90	19826
10	17	11	5.83351	181	620	15	90	17200
11	18	11	5.06085	181	620	15	90	15818
12	20	11	4.39565	181	620	15	90	15100
13	19	10	3.77651	181	620	15	90	11497
14	14	9	3.02674	181	620	15	90	6412
15	12	9	2.29092	181	620	15	90	5523
16	5	9	2.30217	181	620	15	90	2263
17	13	9	2.26391	181	620	15	90	9440
18	9	9	3.63222	181	620	15	90	5975
19	4	9	3.32077	181	620	15	90	1768
20	19	9	2.21088	181	620	15	90	13228
21	20	10	3.48245	181	620	15	90	17043
22	19	10	4.26245	181	620	15	90	14790
23	17	10	3.89366	181	620	15	90	12954
24	20	9	3.81152	181	620	15	90	13783
25	19	9	3.44713	181	620	15	90	14570

Table 4.2 LIMDEP OUTPUT

Ordinary Least Squares:
Limited Dependent Variable Model - FRONTIER Regression
Ordinary least squares regression Weighting variable = ONE
Dependent variable is LNCAT Mean = 9.00657, S.D. = 0.7942
Model size: Observations = 132, Parameters = 10, Deg.Fr. = 122
Residuals: Sum of squares= 17.6062 Std.Dev. = 0.37989
Fit: R-squared = 0.78691, Adjusted R-squared = 0.77119
Model test: F[9, 122] = 50.06, Prob value = 0.00000
Diagnostic: Log-L = -54.3394, Restricted(ß=0) Log-L = -156.3772
Amemiya Pr. Crt.= 0.155, Akaike Info. Crt.= 0.975

Variable	Coefficient	Standard Error	z=b/s.e.	P[│Z│≥z]	Mean of X
Constant	-11.547	7.2817	-1.586	0.11280	
LNEFF	3.6423	1.4151	2.574	0.01006	2.804
LNCREW	12.417	6.2093	2.000	0.04552	2.180
LNSTOCK	-2.8495	1.5974	-1.784	0.07445	0.8769
LNEFF2	-0.20544	0.14551	-1.412	0.15799	8.035
LNCREW2	-2.4527	1.4292	-1.716	0.08613	4.771
LNSTOCK2	0.16864	0.98471E-01	1.713	0.08679	1.068
LNEFFCRE	-0.60154	0.79464	-0.757	0.44905	6.121
LNEFFST	0.50402E-01	0.19569	0.258	0.79675	2.479
LNCREST	1.2886	0.77862	1.655	0.09793	1.937

Table 4.3. Half-normal

Limited Dependent Variable Model - FRONTIER
Maximum Likelihood Estimates
Dependent variable LNCAT
Number of observations 132
Iterations completed 51
Log likelihood function -25.62101
Variance components: $\sigma^2(v)=$ 0.00000
$\sigma^2(u)=$ 0.34338

Variable	Coefficient	Standard Error	z=b/s.e.	P[|Z| ≥z]	Mean of X
Constant	-18.377	10.152	-1.810	0.07026	
LNEFF	4.0667	1.4578	2.790	0.00528	2.804
LNCREW	17.981	9.5351	1.886	0.05933	2.180
LNSTOCK	-1.5190	1.4613	-1.039	0.29858	0.8769
LNEFF2	-0.27495	0.13325	-2.063	0.03908	8.035
LNCREW2	-3.7123	2.2108	-1.679	0.09312	4.771
LNSTOCK2	-0.19107E-01	0.77560E-01	-0.246	0.80541	1.068
LNEFFCRE	-0.49133	0.46409	-1.059	0.28974	6.121
LNEFFST	-0.29215	0.29952	-0.975	0.32936	2.479
LNCREST	1.1478	0.89869	1.277	0.20154	1.937
$\sigma u/\sigma v$	337.53	7118.2	0.047	0.96218	
$\sqrt{\sigma^2 v+\sigma^2 u}$	0.58599	0.39872E-01	14.697	0.00000	

Note: The likelihood ratio test value equals 57.44, and for one degree of freedom exceeds the critical value of 2.71. The null hypothesis that the traditional average response function is the appropriate model is rejected. However, we also find that $\sigma^2(v) = 0$ and $\sigma^2(u) \neq 0$; we thus conclude that the deterministic or statistical frontier could be used to estimate technical efficiency.

Table 4.4 Truncated Normal

Limited Dependent Variable Model - FRONTIER
Maximum Likelihood Estimates
Dependent variable LNCAT
Number of observations 132
Iterations completed 23
Log likelihood function -20.49123
Variance components: $\sigma^2(v)=$ 0.00863
$\sigma^2(u)=$ 1.58096

Variable	Coefficient	Standard Error	z=b/s.e.	P[| Z | ≥z]	Mean of X
Constant	-11.862	5.9535	-1.992	0.04632	
LNEFF	3.9748	1.6888	2.354	0.01859	2.804
LNCREW	11.845	4.5607	2.597	0.00940	2.180
LNSTOCK	0.42155E-01	1.2166	0.035	0.97236	0.8769
LNEFF2	-0.41482	0.13224	-3.137	0.00171	8.035
LNCREW2	-2.3348	0.99809	-2.339	0.01932	4.771
LNSTOCK2	0.83000E-01	0.69141E-01	1.200	0.22996	1.068
LNEFFCRE	-0.22650	0.72119	-0.314	0.75348	6.121
LNEFFST	-0.27840	0.22388	-1.244	0.21367	2.479
LNCREST	0.34123	0.50022	0.682	0.49514	1.937
$\mu/\sigma u$	3.1090	5.9642	0.521	0.60217	
$\sigma u/\sigma v$	13.533	9.2298	1.466	0.14257	
$\sqrt{\sigma^2 v+\sigma^2 u}$	1.2608	0.96355	1.308	0.19071	

Note: The likelihood ratio test value equals 67.70, and for one degree of freedom exceeds the critical value of 2.71. The null hypothesis that the traditional average response function is the appropriate model is rejected. The ratio

$$\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)}$$

equals 0.99455 which is approximately 1.0. We thus conclude that the deterministic or statistic frontier could be used to estimate technical efficiency.

Table 4.5 Exponential

Limited Dependent Variable Model - FRONTIER
Maximum Likelihood Estimates
Dependent variable LNCAT
Number of observations 132
Iterations completed 15
Log likelihood function -18.56456
Exponential frontier model
Variance components: $\sigma^2(v)=$ 0.00979
$\sigma^2(u)=$ 0.10783

Variable	Coefficient	Standard Error	z=b/s.e.	P[│Z│≥z]	Mean of X
Constant	-12.105	4.9922	-2.425	0.01532	
LNEFF	4.0069	1.1306	3.544	0.00039	2.804
LNCREW	12.034	4.2592	2.825	0.00472	2.180
LNSTOCK	0.27960	1.2256	0.228	0.81954	0.8769
LNEFF2	-0.46170	0.11448	-4.033	0.00006	8.035
LNCREW2	-2.4107	0.96476	-2.499	0.01246	4.771
LNSTOCK2	0.97783E-01	0.70251E-01	1.392	0.16395	1.068
LNEFFCRE	-0.14926	0.59924	-0.249	0.80330	6.121
LNEFFST	-0.28379	0.22414	-1.266	0.20547	2.479
LNCREST	0.23009	0.49202	0.468	0.64003	1.937
Θ	3.0453	0.28758	10.590	0.00000	
σv	0.98956E-01	0.23282E-01	4.250	0.00002	

Θ (theta) is a parameter of the exponential distribution of inefficiency, u.

$$f(u) = \theta \exp^{-\theta u}$$

We also note that technical inefficiency dominates inefficiency associated with randomness; the ratio of

$\frac{\sigma_u}{\sigma_v} = 3.31$ which is considerably larger than 1.0 in value.

θ is highly significant, however, and we conclude that the stochastic production frontier is an appropriate specification. We also note that by the likelihood dominance objective, the exponential distribution provides the best fit (highest positive value). Last, we find that the ratio

$\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)}$ equals 0.916 which is less than one in value.

Table 4.6 Frontier 4.1 Estimation Procedures:

In contrast to LIMDEP which now has both a Windows and DOS version, Frontier 4.1 runs only with DOS.
Steps:

1. Data are in ascii file format
2. Frontier 4.1 requires all variables to be in ln format
3. Construct a Frontier file using any program that allows you to write an ascii file
4. Data file requires that the first column be a firm number or observation number (e.g., firm 1, firm 2, ..., etc.). The next column should be a year or time period number (1,...,N and not 90, 91, etc.). The next column is the log of output. After the log of output, the log of each input should be in the next columns. If there are technical inefficiency effects, those variables should fill the remaining columns; these may or may not be logs depending upon the specification being examined.
5. For frontier 4.1, you can use either an instruction file or you can specify the model and parameters interactively.
6. Instruction file: scalp.ins
7.

```
           2                 1=ERROR COMPONENTS MODEL, 2=TE EFFECTS MODEL
scalptef.dta                                               DATA FILE NAME
 scaltef.out                                             OUTPUT FILE NAME
           1                  1=PRODUCTION FUNCTION, 2=COST FUNCTION
           y                            LOGGED DEPENDENT VARIABLE (Y/N)
         132                                 NUMBER OF CROSS-SECTIONS
           1                                   NUMBER OF TIME PERIODS
         132                            NUMBER OF OBSERVATIONS IN TOTAL
           9                          NUMBER OF REGRESSOR VARIABLES (Xs)
           y            MU (Y/N) [OR DELTA0 (Y/N) IF USING TE EFFECTS MODEL]
          19           ETA (Y/N) [OR NUMBER OF TE EFFECTS REGRESSORS (Zs)]
           n                                       STARTING VALUES (Y/N)
                                                  IF YES THEN     BETA0
                                                                BETA1 TO
                                                                   BETAK
                                                           SIGMA SQUARED
                                                                   GAMMA
                                                 MU           [OR DELTA0
                                                 ETA         DELTA1 TO
                                                                 DELTAP]

                                  NOTE: IF YOU ARE SUPPLYING STARTING VALUES
                                AND YOU HAVE RESTRICTED MU [OR DELTA0] TO BE
                                 ZERO THEN YOU SHOULD NOT SUPPLY A STARTING
                                                VALUE FOR THIS PARAMETER.
```

Table 4.7 Output from the program FRONTIER (Version 4.1)

Half Normal:
Error Components Frontier (see B&C 1992)
The model is a production function
The dependent variable is logged
Note: we impose mu or the truncated normal equals 0.0
the ols estimates are :

	coefficient	standard-error	t-ratio
beta 0	-0.11547093E+02	0.72817441E+01	-0.15857592E+01
beta 1	0.36423260E+01	0.14151025E+01	0.25738956E+01
beta 2	0.12417291E+02	0.62092916E+01	0.19997919E+01
beta 3	-0.28494595E+01	0.15973731E+01	-0.17838409E+01
beta 4	-0.20544363E+00	0.14551079E+00	-0.14118790E+01
beta 5	-0.24526699E+01	0.14291687E+01	-0.17161515E+01
beta 6	0.16863807E+00	0.98471241E-01	0.17125617E+01
beta 7	-0.60155324E+00	0.79463935E+00	-0.75701415E+00
beta 8	0.50403024E-01	0.19569385E+00	0.25756060E+00
beta 9	0.12886014E+01	0.77862336E+00	0.16549740E+01
sigma-squared	0.14431281E+00		

the final mle estimates are :

	coefficient	standard-error	t-ratio
beta 0	-0.14342498E+02	0.97837848E+00	-0.14659458E+02
beta 1	0.38108449E+01	0.29360434E+00	0.12979525E+02
beta 2	0.14600000E+02	0.89032345E+00	0.16398534E+02
beta 3	-0.93392078E+00	0.50564435E+00	-0.18469914E+01
beta 4	-0.29747358E+00	0.14220994E-01	-0.20917918E+02
beta 5	-0.30352705E+01	0.23873695E+00	-0.12713870E+02
beta 6	-0.13306477E-01	0.37951717E-01	-0.35061593E+00
beta 7	-0.32289639E+00	0.14028813E+00	-0.23016658E+01
beta 8	-0.33513584E+00	0.64157327E-01	-0.52236566E+01
beta 9	0.92123470E+00	0.26435283E+00	0.34848680E+01
sigma-squared	0.33722392E+00	0.35592443E-01	0.94745932E+01
gamma	0.99999999E+00	0.14300949E-07	0.69925431E+08

LR test of the one-sided error = 0.56734882E+02
with number of restrictions = 1
[note that this statistic has a mixed chi-square distribution]
Since gamma = nearly 1.0 in value, we may conclude that the SPF is not necessary and we can use a deterministic specification (full or statistical), the random part or average response function with the non-negative term is inappropriate.

Table 4.8 Output from the program FRONTIER (Version 4.1)

Truncated Normal
the ols estimates are :

	coefficient	standard-error	t-ratio
beta 0	-0.11547093E+02	0.72817441E+01	-0.15857592E+01
beta 1	0.36423260E+01	0.14151025E+01	0.25738956E+01
beta 2	0.12417291E+02	0.62092916E+01	0.19997919E+01
beta 3	-0.28494595E+01	0.15973731E+01	-0.17838409E+01
beta 4	-0.20544363E+00	0.14551079E+00	-0.14118790E+01
beta 5	-0.24526699E+01	0.14291687E+01	-0.17161515E+01
beta 6	0.16863807E+00	0.98471241E-01	0.17125617E+01
beta 7	-0.60155324E+00	0.79463935E+00	-0.75701415E+00
beta 8	0.50403024E-01	0.19569385E+00	0.25756060E+00
beta 9	0.12886014E+01	0.77862336E+00	0.16549740E+01
sigma-squared	0.14431281E+00		

the final mle estimates are :

	coefficient	standard-error	t-ratio
beta 0	-0.12244730E+02	0.85085077E+00	-0.14391161E+02
beta 1	0.41056924E+01	0.59054969E+00	0.69523234E+01
beta 2	0.12021703E+02	0.78084572E+00	0.15395747E+02
beta 3	0.22306220E+00	0.69529341E+00	0.32081736E+00
beta 4	-0.42217888E+00	0.96888846E-01	-0.43573527E+01
beta 5	-0.23315254E+01	0.37013593E+00	-0.62991058E+01
beta 6	0.84618381E-01	0.69846490E-01	0.12114908E+01
beta 7	-0.27757769E+00	0.37193793E+00	-0.74630112E+00
beta 8	-0.26786898E+00	0.11046078E+00	-0.24250144E+01
beta 9	0.24545885E+00	0.34789455E+00	0.70555531E+00
sigma-squared	0.99338380E+00	0.26043080E+00	0.38143868E+01
gamma	0.99152487E+00	0.52499413E-02	0.18886399E+03
mu	-0.19849078E+01	0.58092280E+00	-0.34168186E+01

Gamma is still close to 1.0 in value and we conclude that SPF is inappropriate.
We can examine inefficiency using the deterministic full frontier or statistical frontier.
log likelihood function = -0.21818081E+02
LR test of the one-sided error = 0.65042616E+02
with number of restrictions = 2
Since gamma = nearly 1.0 in value, we may conclude that the SPF is not necessary and we can use a deterministic specification (full or statistical), the random part or average response function with the non-negative term is inappropriate.

Table 4.9 Output from the program FRONTIER (Version 4.1)

Technical inefficiency effects model with truncated normal distribution:
Tech. Eff. Effects Frontier (see B&C 1993)
the ols estimates are :

	coefficient	standard-error	t-ratio
beta 0	-0.11547093E+02	0.72817441E+01	-0.15857592E+01
beta 1	0.36423260E+01	0.14151025E+01	0.25738956E+01
beta 2	0.12417291E+02	0.62092916E+01	0.19997919E+01
beta 3	-0.28494595E+01	0.15973731E+01	-0.17838409E+01
beta 4	-0.20544363E+00	0.14551079E+00	-0.14118790E+01
beta 5	-0.24526699E+01	0.14291687E+01	-0.17161515E+01
beta 6	0.16863807E+00	0.98471241E-01	0.17125617E+01
beta 7	-0.60155324E+00	0.79463935E+00	-0.75701415E+00
beta 8	0.50403024E-01	0.19569385E+00	0.25756060E+00
beta 9	0.12886014E+01	0.77862336E+00	0.16549740E+01
sigma-squared	0.14431281E+00		

the final mle estimates are :

	coefficient	standard-error	t-ratio
beta 0	-0.11077356E+02	0.10267593E+01	-0.10788659E+02
beta 1	0.37702961E+01	0.77548732E+00	0.48618410E+01
beta 2	0.11611503E+02	0.82933091E+00	0.14001050E+02
beta 3	0.29443225E+00	0.97953157E+00	0.30058474E+00
beta 4	-0.36059963E+00	0.10035676E+00	-0.35931772E+01
beta 5	-0.23297858E+01	0.39642066E+00	-0.58770543E+01
beta 6	0.94748546E-01	0.74233220E-01	0.12763631E+01
beta 7	-0.25108754E+00	0.44878583E+00	-0.55948188E+00
beta 8	-0.21875047E+00	0.15448314E+00	-0.14160152E+01
beta 9	0.11684445E+00	0.50585821E+00	0.23098261E+00
sigma-squared	0.24523991E+00	0.65166553E-01	0.37632789E+01
gamma	0.94111373E+00	0.18452196E-01	0.51002804E+02
delta 0	-0.15882836E+01	0.89481092E+00	-0.17749935E+01
delta 1	0.10813027E+01	0.43954885E+00	0.24600284E+01
delta 2	0.53503714E+00	0.43433948E+00	0.12318409E+01
delta 3	0.11633028E+01	0.44706003E+00	0.26021177E+01
delta 4	0.52501025E+00	0.41973736E+00	0.12508066E+01
delta 5	0.66017110E+00	0.42681512E+00	0.15467379E+01
delta 6	-0.34838645E-01	0.38836340E+00	-0.89706303E-01
delta 7	0.18030839E+00	0.42327923E+00	0.42597977E+00
delta 8	-0.14050076E+00	0.46870207E+00	-0.29976560E+00
delta 9	-0.14750217E+00	0.59123720E+00	-0.24948053E+00
delta10	-0.22212078E+01	0.12935894E+01	-0.17170887E+01

delta11	-0.17761951E+01	0.12115043E+01	-0.14661072E+01
delta12	0.39808690E+00	0.51422043E+00	0.77415614E+00
delta13	0.23786085E-01	0.69085501E+00	0.34429923E-01
delta14	-0.38249587E+00	0.84223136E+00	-0.45414584E+00
delta15	0.46819670E+00	0.55313677E+00	0.84643930E+00
delta16	0.57795562E+00	0.54334046E+00	0.10637081E+01
delta17	0.14129891E+01	0.60633953E+00	0.23303595E+01
delta18	0.18600791E+01	0.63633208E+00	0.29231265E+01
delta19	0.13872971E+01	0.58165062E+00	0.23851038E+01

log likelihood function = 0.16050853E+02

LR test of the one-sided error = 0.14078048E+03
with number of restrictions = *
[note that this statistic has a mixed chi-square distribution]

number of iterations = 38

For this model, the delta variables are dummy variables for 8 vessels and 11 months (i.e., 19 delta variables); we have nine vessels and 12 months of data.

We conclude that the technical inefficiency effects model is an appropriate specification (i.e., use the SPF with a truncated normal). Gamma is < 1.0 in value.
(maximum number of iterations set at : 250)

Table 4-10. Comparison of TE scores for different inefficiency distributions

Technical Efficiency: TE Model-Truncated Normal	Technical Efficiency: Truncated Normal Model	Technical Efficiency: Half-Normal Model
0.742	0.657	0.5721
0.941	0.921	0.8399
0.941	0.796	0.6986
0.959	0.907	0.8275
0.933	0.909	0.8523
0.918	0.875	0.7992
0.931	0.904	0.8041
0.843	0.729	0.6208
0.910	0.852	0.7181
0.851	0.773	0.6750
0.761	0.694	0.6221
0.580	0.594	0.4845
0.633	0.600	0.4967
0.883	0.878	0.8023
0.901	0.703	0.6164
0.884	0.675	0.5911
0.950	0.937	0.9457
0.935	0.866	0.9107
0.843	0.760	0.6830
0.205	0.163	0.1603
0.588	0.590	0.7460
0.865	0.821	0.6954
0.517	0.478	0.4034
0.643	0.636	0.4955
0.606	0.631	0.5363

Technical effects model

4.6 Data Envelopment Analysis, Stochastic Frontiers, and Technical Efficiency:

As illustrated in the previous example, a deterministic frontier or a statistical Frontier would be appropriate. The stochastic frontier may not be the preferred specification, even though the technical effects specification was not rejected. In recent years, there has been a growing interest in using data envelopment analysis (DEA) to assess technical efficiency. DEA is a deterministic mathematical programming approach that permits technical efficiency to be calculated. It has been offered by numerous researchers as an alternative approach to the SPF for calculating technical efficiency (Charnes et al. 1995; Fare et al. 1985,1994). Although DEA has its own set of problems, it does not suffer from any of problems that characterize the SPF model.

There are some general, but well known, limitations of the SPF. First, if the half normal or exponential distributions are used, inefficiency effects are in the neighborhood of zero (i.e., there is relatively high efficiency, especially when compared to deterministic assessment methods. Second, the SPF approach is quite sensitive to selection of error distribution and data outliers (ys or xs). Third, the SPF does require selection of the functional form of the technology. Fourth, the SPF approach does not easily handle multiple outputs. Fifth, and possibly most important for assessing capacity, is that the SPF approach does not really focus on assessing capacity, capacity utilization, or input utilization.

4.6.1 What Exactly is Data Envelopment Analysis or DEA?

Several definitions have been offered by researchers [Pick a definition]:

(1) “DEA is a nonparametric and extremal method for determining production frontiers” (Olesen and Peterson 1996); (2) “DEA is a performance measurement technique which can be used for evaluating relative efficiency of decision-making units (DMUs).” (Beasley 1997); (3) “DEA (Data Envelopment Analysis) is the optimisation method of mathematical programming to generalise the Farrell (1957) single-input/single-output technical efficiency measure to the multiple-input/multiple-output case by constructing a relative efficiency score as the ratio of a single virtual output to a single virtual input." (Dyson et al. 1990); (4) A non-parametric approach which envelops the data with a quasi-convex hull and permits Farrell Measures of efficiency to be calculated (Cornwell and Schmidt. 1996 in Matyas, L. and P. Sevestre 1996); (5) “DEA is a linear programming approach to construct a non-parametric piecewise surface (or frontier) over data, so as to be able to calculate efficiencies relative to this surface.” (Coelli 1996); (6) “DEA determines which of n decision-making units (DMUs) determine an envelopment surface when considering m inputs and s outputs.” (1 Consulting, Inc. 1995); (7) In essence, DEA is an approach which allows us to calculate the efficiency of a technology having minimal structure imposed. (Färe and Grosskopf 1996); and (8) DEA is an empirically oriented approach to the envelopment of production data that integrates the construction of production frontiers with the measurement and interpretation of efficiency relative to the constructed frontiers (Fare et al.1994).

4.6.2 What Do We Know about DEA?

It is a non-parametric, mathematical programming method which allows us to calculate various types of efficiency (technical, scale, and allocative) in terms of the difference between an observed output and a reference hypothetical frontier level of output. The DEA specification used in this study is actually a fractional linear program. In practice, we have converted the fractional linear program into a linear form, which in turn, allows methods of linear programming to be used to calculate the envelop or frontier.

Three individuals are usually credited as the developers of DEA: (1) A. Charnes, (2) W.W. Cooper, and (3) E. Rhodes (Charnes et al. 1994). Charnes et al. (1978) actually had one of the earliest publications dealing with DEA, multiple outputs, and prices. Charnes et al. generalized the Farrell (1957) single output/input TE measure to multiple output/input case. The activity analysis framework, upon which DEA is based, may actually date back to von Neuman (1938).

Initially, DEA was primarily concerned with evaluating the technical efficiency of decision-making units (typically referred to as DMUs). Since the original publication by Charnes et al, DEA has been used to assess a wide variety of economic performance measures under a wide array of circumstances: (1) scale and allocative efficiency; (2) efficiency of economies or diseconomies of scope;(3) single and multiple product capacity and capacity utilization; (4) optimal input utilization; (5) productivity; (6) identification of strategic groups; (7) benchmarks and total quality management programs (TQM); (8) social and private costs of regulating undesirable outputs; (9) technical change; and (10) discretionary, non-discretionary, and undesirable inputs and outputs. (See the following references for a comprehensive listing of articles and types of research: (1) Anderson, T. (1998). DEA WWW Bibliography (http://www.emp.pds.edu/dea/deabib.html). Listing of articles sorted by year, application, theory and methodology, and recent dissertations. Portland State University, Portland, OR.; (2) Charnes, A., W. Cooper, A. Lewin, and L. Seiford. (1994). Data Envelopment Analysis: Theory, Methodology, and Applications. Kluwer Academic Publishers, Boston/Dordrecht/London; (3) Färe, R., S. Grosskopf, and C.A.K. Lovell. (1985). The Measurement of Efficiency In Production. Kluwer-Nijhoff Publishing, Boston/Dordrecht/Lancaster; (4) Färe, R., S. Grosskopf, and C.A.K. Lovell. (1994). Production Frontiers. Cambridge University Press, Cambridge; and (5) Seiford, L. M. (1996). A Bibliography of Data Envelopment Analysis (1978-1996). Department of Mechanical and Industrial Engineering, University of Massachusetts, Amherst, MA.

4.6.3 DEA and the Estimation and Assessment of Efficiency

In contrast to the conventional stochastic production frontier (SPF) approach which optimizes a single regression plane through the data, DEA optimizes on each individual observation with an objective of calculating a discrete piecewise frontier determined by the set of Pareto-efficient DMUs (Charnes et al., 1994, p. 4). Results from the regression are assumed to apply to all DMUs. One purported advantage of DEA is that no a priori assumptions about the underlying production function are required; it is a non-parametric calculation. Moreover, DEA, unlike the SPF, does not necessarily impose the same production frontier on each individual observation. It can easily handle multiple input-multiple output technologies. DEA avoids the problems caused by selection of functional forms (e.g., the Cobb-Douglas may not allow for a factor combination to be plant capacity limiting) (Färe 1984). DEA is non-stochastic, and therefore, the properties of the inefficiency calculations cannot be determined; in recent years, however, there has been considerable work on stochastic DEA. Work has been done to demonstrate that DEA is a maximum likelihood estimator with a very slow rate of convergence. Moreover, bootstrapping of DEA estimates has been done to assess the underlying statistical inferences. DEA cannot, however, disentangle inefficiency from random noise; all deviations from the frontier are regarded an inefficiency; estimates of efficiency may therefore be very sensitive to outliers.

A common criticism of DEA has been than it considers only radial expansions of outputs or radial contractions of inputs; DEA can be formulated to deal with nonradial changes (e.g., Russell's (1990) input and output measures). There also has been considerable work using the LP approach to look at the usual cost minimization, revenue maximization, and profit maximization (i.e., optimization with prices). The concept of radial change, however, is based strictly on Farrell and the ease of computation. That is, how could output be efficiently increased if output is restricted to only radial expansions. We can, however, introduce the concept of Koopmans (1951) efficiency measure which considers changes in slack inputs or outputs. With slacks, gains in outputs or decreases in inputs are not restricted to radial changes. Last, DEA can accommodate dummy variables, discretionary and nondiscretionary inputs and outputs, time series, undesirable outputs and inputs, and multiplier constraints. In the next section, the basic concepts of efficiency measurements are presented. We then follow that discussion with a brief DEA tutorial based on Dyson et al., Beasley; Charnes et al., Färe et al., and Färe and Grosskopf 1998) The brief tutorial is offered to provide a better understanding of the theory underlying DEA. Next, a tutorial for assessing TE using existing commercial DEA software is presented. Last, we provide a discussion of using GAMS to calculate TE; GAMS is a widely used commercial software package that permits a wide array of optimization programs which can be easily tailored for different DEA models.

4.6.4 DEA and Measuring Concepts of Efficiency

Farrell's (1957) original work provides the original ideas behind the use of DEA to assess technical efficiency. Farrell demonstrated that knowledge of the unit isoquant of fully efficient firms would allow the measurement of technical efficiency (TE) (Coelli et al. 1998). Consider the isoquant in Figure 4.2. It depicts the input combinations that could be used to produce output Y. Production levels not on the unit isoquant are inefficient. The unit isoquant provides an assessment of TE from an input orientation. That is, we obtain a measure of TE that indicates the proportion by which inputs may be reduced holding output levels constant. There also is an output orientation. A measure of TE from an output orientation indicates the proportion by which outputs may be expanded given the vector of inputs or with no change in the input levels (Figure 4.2). The lower section of Figure 4.2

depicts a production possibility frontier for two outputs and a single input. With the unit isoquant or from the input orientation, TE equals the ratio of OB/OC. Given an output orientation, TE equals the ratio of OA/OB.

Figure 4.2 Technical and Allocative Efficiency

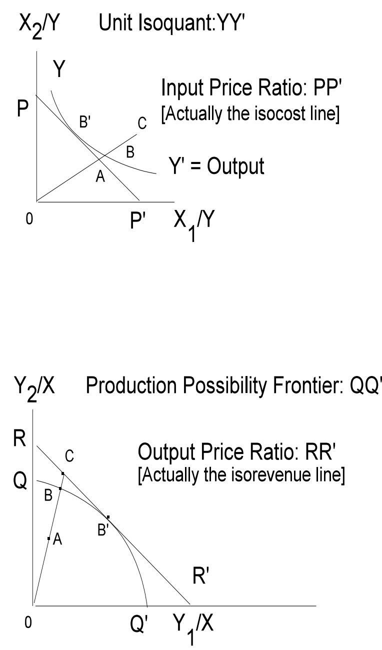


Figure 4.2 also depicts the notion of allocative efficiency from either an input or output orientation. Allowing PP' and RR' to be isocost and isorevenue lines, respectively, allocative efficiency can be determined. With an input orientation, production is allocative efficient at point B'; given the firm is operating at point B, which is technical efficient, a measure of allocative efficiency equals the ratio of OA/OB. The distance AB indicates the reduction in production costs that would occur if production was allocatively and technically efficient (Coelli et al. 1998). A similar measure of allocative efficiency is derivable from the output orientation. In this case, however, allocative efficiency indicates the potential increase in revenue that would occur if production was allocative and technically efficient. Allocative efficiency for the output orientation equals OB/OC.

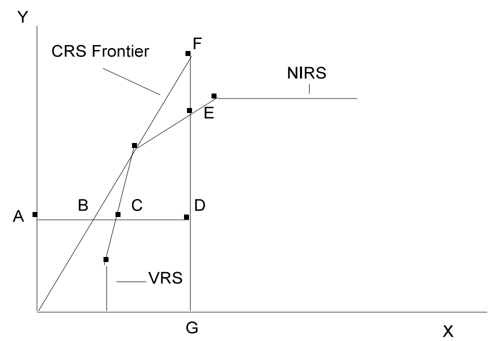
In addition to offering measures of TE and allocative efficiency (AE), there are several useful decompositions of efficiency which are possible with DEA. There is a measure of total efficiency for both orientations. In general, total efficiency equals the product of technical efficiency and allocative efficiency–TE*AE. It also is possible to decompose total efficiency into a product of allocative efficiency, scale efficiency, congestion, and technical efficiency; additional decompositions are discussed in Färe et al. (1994) and Coelli et al. (1998).

Scale efficiency is simply the ratio of technical efficiency for constant returns to scale to technical efficiency for variable returns to scale (Figure 4.3). With information on scale efficiency, we can determine whether or not DMUs are operating at too small or too large a scale of operation. This can be done for an input or output orientation. A measure of congestion can be constructed as the ratio of technical efficiency associated with strong disposability to technical efficiency associated with weak disposability (strong disposability implies that outputs or inputs are strongly disposable—depending upon orientation). With an output congestion measure, we can determine the loss of potential output associated with the weak disposability of outputs). With an input congestion measure, we can assess the loss or gains in output associated with increasing or decreasing some input(s). A comprehensive listing of different types of efficiency measures, decomposition issues, and alternative uses of DEA is found in Charnes et al. (1994) and Färe et al. (1994).

Scale efficiency (SE) is a measure of efficiency relative to operating at the optimum constant returns to scale (CRS). The assumption of CRS is only correct when all firms are operating at an optimum scale (Coelli et al. 1998). Imperfect competition and various constraints may cause firms to operate at other than CRS. Technical efficiency may be decomposed into scale efficiency and pure technical efficiency; the difference between the CRS and VRS measures of TE indicates the amount of inefficiency by operating at the wrong scale. The measure of scale efficiency, while applicable to conventional statistical models of production, is more amenable to DEA. Scale efficiency may be calculated for either an input or output orientation. Scale efficiency (SE) equals the ratio of TE_{CRS}/TE_{VRS} or the value of technical efficiency corresponding to constant returns to scale divided by the value of technical efficiency corresponding to variable returns to scale. From an input orientation, production is scale efficient if SE = 1.0 and inefficiency if SE < 1.0. Production is scale efficient, from an output orientation, if SE = 1.0 and inefficient if SE > 1.0. In Figure 4.3, TE_{CRS} from an input orientation equals AB/AD and TE_{VRS} = AC/AD, and thus, SE = AB/AC. Similarly, TE_{CRS} from an output orientation equals GD/GF and TE_{VRS} = GD/GE; SE thus equals E/GF.

Two potentially useful measures related to technical efficiency and to capacity utilization are input and output congestion. Input congestion allows for a backward bending portion of an isoquant or the range for which the marginal product of an input becomes negative. Output congestion is typically defined in terms of undesirable outputs or byproducts produced with desirable outputs (e.g., pollution and electricity generation; dolphin and tuna; undersize and market-size fish). Reinhard et al. (1999) and Färe et al. (1993) provide a more thorough introduction to input and output congestion and undesirable products and inputs.

Figure 4.3 Scale Efficiency



4.6.5 A Brief DEA Tutorial

The subsequent tutorial was adapted from Dyson et al.; Beasley; Charnes et al.; Färe et al; and Färe and Grosskopf (1998). In our brief tutorial, we have seven decision making units or DMUs. Their input and output levels are given in Table 4.11. We desire to assess technical efficiency:

$$efficiency = \frac{output}{input}$$

Table 4.11 Example Input and Output Levels

DMU	Input	Output
1	2	2
2	3	5
3	6	7
4	9	8
5	5	3
6	4	1
7	10	7

In the case of multiple inputs and/or outputs, this above simplistic concept of efficiency is inadequate. We consider the Farrell and Fieldhouse (1962) measure of relative efficiency which allows for multiple inputs and multiple outputs:

$$efficiency = \frac{weight \sum\ of\ outputs}{weight \sum\ of\ inputs}$$

Unfortunately, there are problems of assuming a common set of weights: (1) it may be difficult to value the inputs or outputs; and (2) different DMUs may organize their operations differently so that the relative values of the different outputs may actually be different. Charnes et al. (1978) proposed that each DMU should have a set of weights which depicts that DMU in the most favorable position relative to the other DMUs. The efficiency of a target unit can be obtained as a solution to the problem:

Maximize the efficiency of unit j subject to the efficiency of all units being ≤ 1.0. Algebraically, the problem is

Maximize $h_0 = \dfrac{\sum_r u_r\, y_{rj0}}{\sum_i v_i\, x_{ij0}}$
subject to

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leq 1\ for\ each\ unit\ j$$

and u_r and $v_i \geq \epsilon$. The u's and v's are variables of the problem and are constrained to be greater than or equal to some small positive quantity, ϵ, in order to avoid any input or output being totally ignored in determining the efficiency. Solution to the problem provides a measure of efficiency for DMU j. The problem is solved for all DMUs. If the value of the solution is 1.0, DMU_j is technically efficient.

The problem is actually a fractional linear program and can be transformed into a linear form so that linear programming can be used to calculate efficiency:

$$Max\ h_0 = \sum_r u_r\, y_{rj0}$$
$$s.t. \sum_i v_i\, x_{ij0} = constant\ (1.0)$$
$$\sum_r u_r\, y_{rj} - \sum_i v_i\, x_{ij} \leq 1.0,\ j = 1,2,...,n$$
$$and\ u_r\ and\ v_i \geq \epsilon.$$

The preceding problem is a DEA problem which permits the calculation of efficiency from an "input orientation." That is, output is held constant and efficiency is calculated relative to decreasing input levels. For example, an efficiency score of 0.70 means that the same level of output could have been produced using 30% less of the input levels actually used. There also is an output orientation. The output orientation permits the calculation of efficiency relative to holding input levels constant and allowing the level of output to increase.

We now consider our seven DMUs and calculate their efficiency from both the input and output orientation and both constant and variable returns to scale. In DEA, constant returns to scale is viewed as the most unconstrained because variable returns requires the imposition of another constraint

$$(\sum_n \lambda_n = 1, \textit{ n equals number of DMUs}).$$

There are numerous ways to specify the DEQ problem. Different DEA researchers often specify different formulations of the DEA problem. We consider the more typical specifications that appear in the literature (Coelli et al. 1998 and Färe et al. 1994). We initially specify the problem from an input orientation; subsequently, we present the problem from the output orientation.

From an input orientation:

We use the duality in linear programming. We want to

$$\begin{aligned}
&\textit{Minimize}_{\lambda z}\ \lambda \\
&s.t.\ -y_i + Y z \geq 0 \\
&\lambda\ x_i - X z \geq 0 \\
&\textit{and } z \geq 0.
\end{aligned}$$

where y and Y represent the output of the ith firm and the output levels of all firms, x and X represent the input of the ith firm and the inputs of all firms, λ is a scalar, and z is a Nx1 vector of constraints or intensity variables. If there is more than one output or input, additional constraints would be added. The value of λ is the efficiency score for the ith DMU. The value $1 - \lambda$ indicates the percentage by which inputs could be reduced without reducing output.

From the output orientation, we have the following problem:

$$\begin{aligned}
&\textit{Maximize}_{\theta z}\theta \\
&s.t.\ -\theta y_i + Y z \geq 0 \\
&x_i - X z \geq 0 \\
&\textit{and } z \geq 0.
\end{aligned}$$

In the output orientation, θ is a scalar. The value of $1/\theta$ is the measure of technical efficiency such that $0 \leq \text{TE} \leq 1.0$. The value θ - 1.0 is the proportional increase in outputs that could be achieved by the ith DMU with input quantities held constant and the firm operating efficiently.

We also consider the long algebriac version of the two DEA problems. We have M outputs and N inputs and consider variable returns to scale (the variable returns to scale requires adding the constraint $\sum_{j=1}^{J} z_j = 1.0$). From the input orientation, we have the following problem:

minimize λ

subject to the following constraints:

$u_{11}z_1 + u_{21}z_2 + \ldots + u_{J1}z_J \geq u_{j1}$
$u_{12}z_1 + u_{22}z_2 + \ldots + u_{J2}z_J \geq u_{j2}$

$u_{1M}z_1 + u_{2M}z_2 + \ldots + u_{JM}z_J \geq u_{jM}$

and

$x_{11}z_1 + x_{21}z_2 + \ldots + x_{J1}z_J - x_{j1}\lambda \leq 0$

$x_{12}z_1 + x_{22}z_2 + \ldots + x_{J2}z_J - x_{j2}\lambda \leq 0$

$x_{1N}z_1 + x_{2N}z_2 + \ldots + x_{JN}z_J - x_{Jn}\lambda \leq 0$

$$\sum_{j=1}^{J} z_j = 1.0.$$

The preceding problem is slightly different than that presented in matrix algebra form. The signs of the inequalities and the input constraints were changed by multiplying both sides of the input constraints by negative one.

From the output orientation, we have the long algebraic version as follows:

Maximize θ

subject to

$u_{11}z_1 + u_{21}z_2 + \ldots + u_{J1}z_J \geq \theta u_{j1}$
$u_{12}z_1 + u_{22}z_2 + \ldots + u_{J2}z_J \geq \theta u_{j2}$

$u_{1M}z_1 + u_{2M}z_2 + \ldots + u_{JM}z_J \geq \theta u_{jM}$

and

$x_{11}z_1 + x_{21}z_2 + \ldots + x_{J1}z_J - x_{j1} \leq 0$
$x_{12}z_1 + x_{22}z_2 + \ldots + x_{J2}z_J - x_{j2} \leq 0$

$x_{1N}z_1 + x_{2N}z_2 + \ldots + x_{JN}z_J - x_{Jn} \leq 0$

$$\sum_{j=1}^{J} z_j = 1.0.$$

Returning to our simple tutorial example of seven firms producing one output using one input, we solve the DEA input and output oriented problems with constant and variable returns to scale imposed. We could solve our example problem using a wide variety of software (e.g., OnFront, GAMS, EXCEL, Quatro, Gauss, Minos, SAS LP, DEAP, IDEAS, Frontier Analyst, and several others). We use OnFront to solve.

Table 4.12 presents the data and efficiency scores given constant and variable returns to scale. As is evident in the table, different units are judged to be efficient when constant vs. variable returns to scale were imposed. Under constant returns to scale, only the second unit was determined to be efficient. Under variable returns to scale, however, DMUs one to four were determined to be technically efficient. The TE scores for the output orientation are restricted one or greater in value. The inverse of these scores equal the conventional TE scores presented in the literature. Relative to the proportionate contraction of inputs to achieve efficiency, production of seven units of output by DMU 7 could be achieved with a reduction of 40% in the input usage in variable returns to scale characterize the technology. DMU #7 could alternatively increase production by 14% using the same level of inputs and given variable returns to scale. A remaining point is that under constant returns to scale, the inverse of TE from the input orientation equals TE for the output orientation.

Table 4.12 DEA Results for the Input and Output Oriented Example Problem

DMU	Input	Output	Constant Returns		Variable Returns		Technical Efficiency	
			Input	Output	Input	Output	CRS	VRS
1	2	2	0.60	1.67	1.00	1.00	0.60	1.00
2	3	5	1.00	1.00	1.00	1.00	1.00	1.00
3	6	7	0.70	1.43	1.00	1.00	0.70	1.00
4	9	8	0.53	1.88	1.00	1.00	0.53	1.00
5	5	3	0.36	2.78	0.47	2.11	0.36	0.47
6	4	1	0.15	6.67	0.50	5.67	0.15	0.18
7	10	7	0.42	2.37	0.60	1.14	0.42	0.88

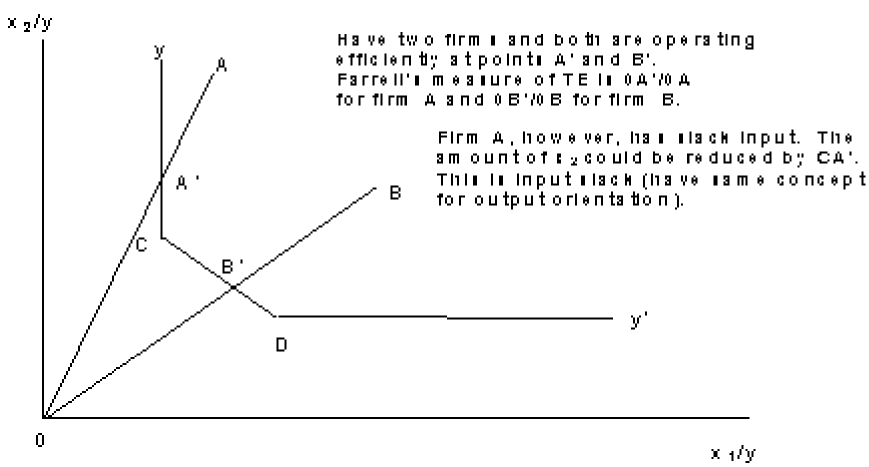
4.6.6 Additional DEA Issues and Topics

Thus far, we have considered efficiency and DEA relative to radial contractions in inputs or expansions in outputs. These radial changes are not truly necessary. We can consider Koopmans concept of efficiency which is a total measure of efficiency (Koopmans, T.C. (1951). Koopmans and other individuals (e.g., Coelli et al. (1998)) have argued that efficient production should be assessed not only with respect to the radial changes but also with respect to slack (inputs or outputs) being zero. For example, consider Figure 4.4 which depicts TE and the concept of slack input from an input orientation.

4.6.7 Expanded Tutorial on DEA-based Assessments of TE

This section presents an expanded tutorial on using DEA to assess technical efficiency. Initially, technical efficiency is calculated or estimated using two commercial DEA software packages–OnFront and DEAP. The program DEAP, however, is no longer a commercial package; T. Coelli now permits users to freely download DEAP. The example is based on 581 observations depicting trip-level activity for nine northwest Atlantic sea

Figure 4.4 Input Orientation: TE and Input Slacks



Adopted from Coelli et al. (1998), An Introduction to Efficiency And Productivity Analysis.

scallop vessels operating between 1987 and 1990. The vessels are relatively homogeneous in size, gear, and other characteristics. Data, by trip, are available on catch or nominal landings, days at sea, crew size, dredge size, engine horsepower, gross registered tonnage and length of the vessel, and stock abundance (Table 4.13). We initially assess TE using OnFront and an input orientation. We next estimate TE using DEAP (Coelli 1994). Other commercial DEA programs include IDEAS, Frontier Analyst, and Decision Pro (Charnes et al. (1994) provide a more extensive listing of commercial DEA software packages).

OnFront is a Windows based program. Data may be entered in ascii format, directly onto an OnFront spreadsheet, or by copying and pasting using popular spreadsheet programs such as EXCEL and Quatro Pro. In OnFront, the data are loaded in accordance with inputs first and then outputs; a more recent release, however, allows any order of entry of inputs and outputs. The first data column, however, must contain an identification number for each DMU or observation (a simple numerical count will suffice).

OnFront then permits the user to specify whether or not they desire an input or output orientation; constant, variable, or non-increasing returns to scale; and whether or not there are strongly or weakly disposable inputs or outputs. OnFront also permits allocative efficiency to be determined by allowing the user to specify whether or not they desire efficiency scores from a cost or revenue orientation. The user also has the option of obtaining technical and scale efficiency measures, dual values, and intensity scores.

DEAP is strictly a DOS based program. Data are entered via an ascii format. DEAP, like OnFront, permits the usual options of constant vs. variable returns to scale, input vs. output orientation, scale efficiency, and allocative efficiency based on cost or revenue optimizing behavior. DEAP also, however, allows the direct calculation of slack inputs or outputs, depending upon the orientation, using a multi-stage optimization algorithm. DEAP therefore does not restrict the analysis of TE to strictly radial changes in inputs or outputs. Using DEAP to estimate efficiency scores requires the user to prepare a short instruction file that specifies the nature of the problem (e.g., input or output orientation and returns to scale). There must be a separate data file and that file is identified in the instruction file. Upon execution, DEAP writes the estimate scores and associated results to an output file which then may be examined using the DOS editor.

Table 4.13 Data for Assessing TE of Northwest Atlantic Sea Scallop Fishing Vessels (first 25 observations)

	days	crew	stock	grt	hp	dredge	length	catch
1	13	9	2.27985	181	620	15	90	5595
2	18	9	2.15278	181	620	15	90	5878
3	18	9	1.63343	181	620	15	90	8495
4	18	10	2.36067	181	620	15	90	15897
5	18	12	4.4176	181	620	15	90	20268
6	17	11	5.63225	181	620	15	90	18306
7	19	12	5.38627	181	620	15	90	23692
8	11	12	6.23723	181	620	15	90	11268
9	17	12	5.12387	181	620	15	90	19826
10	17	11	5.83351	181	620	15	90	17200
11	18	11	5.06085	181	620	15	90	15818
12	20	11	4.39565	181	620	15	90	15100
13	19	10	3.77651	181	620	15	90	11497
14	14	9	3.02674	181	620	15	90	6412
15	12	9	2.29092	181	620	15	90	5523
16	5	9	2.30217	181	620	15	90	2263
17	13	9	2.26391	181	620	15	90	9440
18	9	9	3.63222	181	620	15	90	5975
19	4	9	3.32077	181	620	15	90	1768
20	19	9	2.21088	181	620	15	90	13228
21	20	10	3.48245	181	620	15	90	17043
22	19	10	4.26245	181	620	15	90	14790
23	17	10	3.89366	181	620	15	90	12954
24	20	9	3.81152	181	620	15	90	13783
25	19	9	3.44713	181	620	15	90	14570

Table 4.14 Results from OnFront

Obs	Fi(y,x | V,S)	x1 (S,Yes) days	x2 (S,Yes) crew	x3 (S,Yes) stock	x4 (S,Yes) grt	x5 (S,Yes) hp	x6 (S,Yes) dredge	x7 (S,Yes) length	y1 catch
1	0.90	13.00	9.00	2.28	181.00	620.00	15.00	90.00	5595.00
2	0.90	18.00	9.00	2.15	181.00	620.00	15.00	90.00	5878.00
3	0.91	18.00	9.00	1.63	181.00	620.00	15.00	90.00	8495.00
4	0.94	18.00	10.00	2.36	181.00	620.00	15.00	90.00	15897.00
5	0.94	18.00	12.00	4.42	181.00	620.00	15.00	90.00	20268.00
6	0.94	17.00	11.00	5.63	181.00	620.00	15.00	90.00	18306.00
7	1.00	19.00	12.00	5.39	181.00	620.00	15.00	90.00	23692.00
8	0.90	11.00	12.00	6.24	181.00	620.00	15.00	90.00	11268.00
9	0.93	17.00	12.00	5.12	181.00	620.00	15.00	90.00	19826.00
10	0.93	17.00	11.00	5.83	181.00	620.00	15.00	90.00	17200.00
11	0.91	18.00	11.00	5.06	181.00	620.00	15.00	90.00	15818.00
12	0.90	20.00	11.00	4.40	181.00	620.00	15.00	90.00	15100.00
13	0.90	19.00	10.00	3.78	181.00	620.00	15.00	90.00	11497.00
14	0.90	14.00	9.00	3.03	181.00	620.00	15.00	90.00	6412.00
15	0.90	12.00	9.00	2.29	181.00	620.00	15.00	90.00	5523.00
16	0.90	5.00	9.00	2.30	181.00	620.00	15.00	90.00	2263.00
17	0.92	13.00	9.00	2.26	181.00	620.00	15.00	90.00	9440.00
18	0.91	9.00	9.00	3.63	181.00	620.00	15.00	90.00	5975.00
19	0.90	4.00	9.00	3.32	181.00	620.00	15.00	90.00	1768.00
20	0.93	19.00	9.00	2.21	181.00	620.00	15.00	90.00	13228.00
21	0.93	20.00	10.00	3.48	181.00	620.00	15.00	90.00	17043.00
22	0.92	19.00	10.00	4.26	181.00	620.00	15.00	90.00	14790.00
23	0.91	17.00	10.00	3.89	181.00	620.00	15.00	90.00	12954.00
24	0.93	20.00	9.00	3.81	181.00	620.00	15.00	90.00	13783.00
25	0.93	19.00	9.00	3.45	181.00	620.00	15.00	90.00	14570.00

F_i is the efficiency score; S is indicates strong disposability, and V indicates variable returns to scale.

The program file required for estimating TE using DEAP are presented in Table 4.15. The results for a subsample of the observations are presented in Table 4.16. The one-stage slacks were considered because there was only one output. In contrast to OnFront, DEAP specifically calculates whether the level of operation or scale in increasing, decreasing, or constant returns to scale.

Table 4.15 Instruction File for DEAP

scalp.dta	DATA FILE NAME
scalp.out	OUTPUT FILE NAME
581	NUMBER OF FIRMS
1	NUMBER OF TIME PERIODS
1	NUMBER OF OUTPUTS
6	NUMBER OF INPUTS
0	0=INPUT AND 1=OUTPUT ORIENTATED
1	0=CRS AND 1=VRS
3	0=DEA(MULTI-STAGE), 1=COST-DEA, 2=MALMQUIST-DEA, 3=DEA(1-STAGE), 4=DEA(2-STAGE)

Table 4.16 Results from Deap 2.1

Results from DEAP Version 2.1
Instruction file = egscalp.ins
Data file = scalp.dta
Input orientated DEA
Scale assumption: VRS
Single-stage DEA – residual slacks presented
EFFICIENCY SUMMARY:

firm	crste	vrste	scale	
1	0.369	0.867	0.425	irs
2	0.343	0.867	0.396	irs
3	0.510	0.867	0.588	irs
4	0.853	0.928	0.919	irs
5	0.903	0.934	0.967	irs
6	0.823	0.937	0.879	irs
7	1.000	1.000	1.000	-
8	0.677	0.895	0.756	irs
9	0.880	0.938	0.938	irs
10	0.774	0.921	0.840	irs
11	0.716	0.891	0.804	irs
12	0.692	0.867	0.799	irs
13	0.576	0.867	0.665	irs
14	0.374	0.867	0.431	irs
15	0.387	0.867	0.446	irs
16	0.295	0.890	0.331	irs
17	0.623	0.901	0.692	irs
18	0.451	0.891	0.506	irs
19	0.227	0.901	0.252	irs
20	0.763	0.899	0.849	irs
21	0.858	0.910	0.943	irs
22	0.729	0.886	0.823	irs
23	0.655	0.881	0.743	irs
24	0.746	0.898	0.831	irs
25	0.799	0.919	0.870	irs

Results for firm: 15
Technical efficiency = 0.867
Scale efficiency = 0.446 (irs)

Table 4.16–Continued
Projection Summary:

variable		original value	radial movement	slack movement	projected value
output	1	5523.000	0.000	0.000	5523.000
input	1	12.000	-1.600	0.000	10.400
input	2	9.000	-1.200	0.000	7.800
input	3	181.000	-24.133	-34.558	122.308
input	4	620.000	-82.667	-25.298	512.036
input	5	15.000	-2.000	0.000	13.000
input	6	2.291	-0.305	0.000	1.985

For comparative purposes, estimates of TE based on DEA and the stochastic frontier are presented in Table 4.17. The scores are presented in terms of averages per boat for the year and averages per month. Technical efficiency scores corresponding to the vessels are neither close in value nor comparable. The scores corresponding to the monthly averages are relatively similar in general trend and seasonality. DEA did not, however, pick up the usual large efficiency values that characterize operations during the spring when there are extremely high densities of scallops due to recruitment.

The next section presents a more rigorous tutorial for estimating technical efficiency and capacity. The tutorial is based on the program GAMS, which stands for the General Algebraic Modeling System. GAMS is a mathematical programming package that permits a wide array of mathematical optimization problems to be solved. Its advantage over the commercial DEA programs is that it offers greater flexibility for estimating efficiency. That is, nearly any orientation or type of constraint can be introduced. With the commercial DEA packages, only those TE scores corresponding the structures permitted by the software can be obtained.

4.7 GAMS and Technical Efficiency

The General Algebraic Modeling System (GAMS) is a language for modeling large scale mathematical programming problems. Examples of the types of problems GAMS can solve are linear and non-linear programming models, mixed integer programming models, mixed complementarity models, computable general equilibrium models, network models and mixed integer non-linear programming models.

Although there are many DEA specific programs available to estimate efficiency, programs developed using GAMS are presented below. The specific approach shown is based on work done by Olesen and Petersen (1996) where they showed the flexibility GAMS offered for modeling DEA problems, and recommended a standard solver such as GAMS. Because GAMS is a highly flexible language, it can easily handle non-standard models such as those involving weak sub-vector disposability. Additionally, having GAMS available to model DEA problems also allows the analyst to model other types of problems found in fisheries, such as non-linear programming problems.

Table 4.17 A Cursory Comparison of SPF and DEA:

Boat	Technical Effects	Truncated Normal	DEA: Output/VRS	Month	Technical Effects	Truncated Normal	DEA: Output/VRS
1	84	79	75	1	88	86	88
2	69	66	65	2	87	82	76
3	77	73	73	3	94	83	80
4	66	62	62	4	93	83	79
5	79	71	69	5	84	77	73
6	79	78	79	6	85	81	80
7	83	81	80	7	88	80	75
8	83	76	71	8	81	76	74
9	86	82	75	9	77	72	68
				10	67	68	65
				11	48	50	52
				12	58	61	69

This section will present an overview of how to model DEA problems using GAMS. Programs will model the output technical efficiency measure, and capacity output; programs for estimating TE from an input orientation may be obtained from the authors. The output technical efficiency problem will be shown first with just minimal GAMS code. This program will then be modified to measure capacity output, and added programming features will be included to show the flexibility that GAMS offers. These programs could be easily modified to estimate capacity for any fishery in the world given that data are available to allow DEA methods to be employed.

4.7.1 Modeling Technical Efficiency in GAMS

Färe, Grosskopf and Lovell (1994) presented the following model to estimate an output oriented technical efficiency measure:

$$\begin{aligned}
&\max_{\theta, z} \theta \\
&\text{subject} \sim \text{to} \\
&\theta u_{jm} \leq \sum_{j=1}^{J} z_j u_{jm}, m = 1,2,\ldots, M, \\
&\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}, n = 1,2,\ldots, N, \\
&z_j \geq 0, j = 1,2,\ldots, J.
\end{aligned}$$

where:

θ = measure to be estimated
u_{jm} = output by firm j of product m
x_{jn} = amount of input n used by firm j.
z_j = intensity variable for firm j

Theta is measured on an observation (or firm) level basis (i.e., the model is estimated once for each observation or DMU in the dataset). This is easily done in GAMS because it allows the user the ability to solve an LP problem multiple times in a single program. For the purpose of learning how to use GAMS to estimate TE, we present a simple example with 10 firms, 2 outputs and four inputs using randomly generated data. The GAMS syntax is then explained further in the next section. While the program found in this section give the basics for modeling an output oriented technical efficiency measure and capacity output using GAMS, further details about the GAMS language can be found in the GAMS manual[1]. We initially start by presenting the various instruction files. Each line is discussed and explained following the instruction file.

```
1   Sets Inout /spec1, spec2,  fix1, fix2, var1, var2/
2        Output(Inout) /spec1, spec2/
3        Input(Inout) /fix1, fix2, var1, var2/
4        Obs /1*10/
5        Subobs(obs) /1*10/
6        Actobs(obs);

7   alias (subobs, subobs1);

8   Table Act(Obs,Inout) input output table

              spec1     spec2      fix1      fix2      var1      var2

         1    13295     27065        55        60         4        94
         2    13255     10090        63        70         8       127
         3      614      3427        59        59         6        35
         4   106461     58705        63        69         5       185
         5     3540      9130        53        60         5        46
         6      602      6900        62        74         5        37
         7    12920     18128        69        78         6       133
         8     8312      5145        65        63         8       162
         9     3276      4430        70        62         3        24
        10     4143      8486        63        61         5        81
9   ;

10  VARIABLES
11          theta efficiency score
12          weight(obs) intensity variable;

13  POSITIVE Variable weight;

14  Equations
15     CONSTR1(OUTPUT,OBS) DEA constraint for each output
16     CONSTR2(INPUT,OBS) DEA constraint for each input;

17  CONSTR1(OUTPUT,ACTOBS)..  SUM(SUBOBS, WEIGHT(SUBOBS)*ACT(SUBOBS,OUTPUT)) =G=
                                   THETA*ACT(ACTOBS,OUTPUT);
18  CONSTR2(INPUT,ACTOBS)..   SUM(SUBOBS, WEIGHT(SUBOBS)*ACT(SUBOBS,INPUT)) =L=
                                   ACT(ACTOBS,INPUT);
19  PARAMETER
20  score1(obs) efficiency scores;
```

[1]Information on GAMS can be found at www.gams.com.

```
21      MODEL TEDEA /CONSTR1, CONSTR2/;

22      LOOP(SUBOBS1,
23              ACTOBS(OBS)=NO;
24              ACTOBS(SUBOBS1)=YES;
25              OPTION LP=OSL;
26              SOLVE TEDEA maximizing THETA USING LP;
27              Score1(SUBOBS1)=THETA.L;
28      );

29      display score1;
```

Lines 1-6 define sets, which are the basic building blocks in most GAMS programs, and in this case, conform to the indices n (input), m(output) and j (firm or observations). Line 1 defines a set which containing all inputs and outputs. Lines 2 and 3 define two subsets of set INOUT, named OUTPUT and INPUT. Subset OUTPUT contains the outputs spec1 and spec2 while subset INPUT contains the elements which are inputs, fix1, fix2, var1 and var2. Elements contained in either subset must be members of set INOUT and declared in the set statement on line 1. Lines 4-6 define sets which correspond to index j in the DEA model. The set OBS contains the number of observations in the dataset, where observations are numbered consecutively between 1 and 10. Line 5 declares a subset of OBS named SUBOBS which in this case is defined as containing all members of set OBS, but it also could contain only selected observations such as observations 5-10. Line 6 defines another subset of OBS, called ACTOBS, which is initially empty. This is an example of a dynamic set, which is a set whose membership can change. Line 7 declares an alias for set SUBOBS, called SUBOBS1, which allows a set to be referred to by more than one name.

Line 8 shows the table which actually contains the data. Table ACT is a two dimensional table containing members of set OBS and INOUT. Each column label corresponds to one element of set INOUT , and the column heading should be right justified. Most realistic problems in fisheries will probably have a very large dataset, and it's usually easier to store these in external files and read them into the program. It's recommended that MS-Excel files saved as a CSV file type (comma separated values) be used. An example of this will be given in the next program which models capacity output.

Lines 10-13 define variables which will be used in the program. Variables are equivalent to endogenous variables in standard econometric models, and can be declared to be of a certain type, as is shown in line 13, where weight is defined as being a positive variable. The decision variable which is being optimized, must be of type free. Other variable types include negative, binary (0 or 1) or integer.

Lines 14-18 define the equations used in the model. Equations need to be declared first (lines 14-16) and then defined (lines 17-18). Both equations which are declared have two dimensions, output or input, and observation number. In lines 17 and 18, the set ACTOBS, which is a subset of OBS is substituted in place of OBS. Notice that in line 17, the constraint is reversed from the first constraint shown in the mathematical model above in order to put the constraint set in standard LP format.

Lines 19-20 declare a parameter SCORE1 which holds the model results. Parameters are a useful way to store results which can later provide output to different files. Line 21 defines the model named TEDEA and consists of two equations CONSTR1 and CONSTR2.

Lines 22-28 contain statements which solve the model. This is accomplished through the use of a loop statement, which is executed over all elements contained in the subset SUBOBS1. Line 23 removes all elements from the subset ACTOBS, which is necessary for each pass through the loop. Line 24 then puts one element back into the subset ACTOBS, which is the current observation in the loop. Since the equations in lines 17 and 18 are defined over elements in the subsets INPUT or OUTPUT and ACTOBS, the equation is effectively indexed over only the inputs or outputs because the set ACTOBS contains only one element. Line 25 tells GAMS that the solver to use for this model is OSL, one of several solvers available from GAMS Development Corporation. The OSL solver handles both LP problems and Mixed Integer Programming problems. It was found that the OSL solver could solve most DEA problems, while the BDMLP solver which is the standard GAMS solver did not solve all DEA problems. Olesen and Petersen (1996) used the Minos5 solver, which solves both linear and non-linear programming problems. The model TEDEA, which consists of equations CONSTR1 and CONSTR2, is solved in line 26. The Solve statement tells GAMS to solve model TEDEA by maximizing the variable THETA using linear programming. Results from the model are then stored in the parameter SCORE1 (line 27). The values of theta which are returned are accessed by putting the suffix .L on the variable THETA (THETA.L). The loop command is then closed on line 28 with a);. Line 29 shows the values of THETA which have been stored in parameter SCORE1 through the use of the display statement.

4.7.2 Capacity Output and GAMS

Färe, Grosskopf and Lovell (1994) proposed the following model to estimate capacity output:

$$
\begin{aligned}
&\max_{q,z} q \\
&\text{subject} \sim \text{to} \\
&q u_{jm} \leq \sum_{j=1}^{J} z_j u_{jm}, m = 1,2,\ldots,M, \\
&\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}, n \in a, \\
&\sum_{j=1}^{J} z_j x_{jn} = 1_{jn} x_{jn}, n \in \hat{a}, \\
&z_j \geq 0, j = 1,2,\ldots,J, \\
&1_{jn} \geq 0, n \in \hat{a}
\end{aligned}
$$

where

θ = measure to be estimated
u_{jm} = output by firm j of product m
x_{jn} = amount of input n used by firm j.
z_j = intensity variable for firm j
λ_{jn}= variable input utilization rate by firm j of variable input n
$\hat{\alpha}$ = variable inputs.
α = fixed inputs.

Below is the GAMS program used to estimate the model. This is essentially the same program as the output oriented efficiency program previously shown, but with different constraints for the variable and fixed factors of production. This program has a few more features added to demonstrate different ways to output model results, and also utilizes Excel tables to read in the data. The capacity model could also be estimated in GAMS, or with specific DEA solvers, by dropping the constraint on variable input usage. The optimum variable input utilization rate would then need to be calculated separately using the following formula (Färe et al. 1994):

$$\lambda^*_{jn} = \frac{\sum_{j=1}^{J} z_j^* x_{jv_i}}{x_{jv_i}}, n \in \hat{\alpha}$$

where * defines the optimal level of the variable in question. The advantage of using GAMS instead of specific DEA solvers is that the variable λ is directly estimated in GAMS.

```
$oninline
 /*GAMS program used to estimate capacity output and
variable input utilization*/

 SET INOUT /spec1, spec2, fix1, fix2, var1, var2/

OUTPUT(INOUT) /spec1, spec2/
FIXED(INOUT) /fix1, fix2/
VAR(INOUT) /var1, var2/
OBS /1*10/
SUBOBS(OBS) /1*10/
ACTOBS(OBS);

alias (subobs, subobs1)

$OFFLISTING

TABLE ACT(OBS,INOUT)  INPUT OUTPUT TABLE
$ondelim
$INCLUDE "data1.csv"
```

```
$offdelim
$ONLISTING

VARIABLES

theta      efficiency score
weight(obs)  weights
lambda(obs, VAR );

POSITIVE Variable weight, lambda;


 EQUATIONS

CONSTR1(OUTPUT, OBS)  DEA constraint for each output
CONSTR2(FIXED, OBS)  DEA Constraint for FIXED Inputs
CONSTR3(VAR, OBS)  DEA Constraint for Variable Inputs
CONSTR4  DEA Constraint for Variable returns to scale ;

CONSTR1(OUTPUT, ACTOBS)..
   SUM(SUBOBS,WEIGHT(SUBOBS)*ACT(SUBOBS,OUTPUT))    =G=
theta*ACT(ACTOBS,
 OUTPUT);

CONSTR2(FIXED, ACTOBS)..
SUM(SUBOBS,WEIGHT(SUBOBS)*ACT(SUBOBS,FIXED))
                    =L= ACT(ACTOBS, FIXED);

CONSTR3(VAR, ACTOBS).. SUM(SUBOBS,
WEIGHT(SUBOBS)*ACT(SUBOBS,VAR))
                    =E= LAMBDA(ACTOBS,VAR)*ACT(ACTOBS,VAR);

CONSTR4.. SUM(SUBOBS, WEIGHT(SUBOBS)) =E= 1;

PARAMETER

score1(obs)  theta estimates
score2(obs,VAR) hold variable input levels;

file capdea /grcapres.txt/;

MODEL CAP  /CONSTR1, CONSTR2, CONSTR3, CONSTR4/

LOOP(SUBOBS1,
         ACTOBS(OBS) = NO;
         ACTOBS(SUBOBS1) = YES;
```

```
40        Option Lp=OSl;
41        SOLVE CAP  maximizing THETA USING LP;
42        score1(SUBOBS1) = theta.l;
43        score2(subobs1,var)=lambda.l(subobs1,var);

44        put capdea;
45
46        if ((cap.modelstat eq 1 and cap.solvestat eq 1),
47         put @1, subobs1.tl, @10, "optimal", @20, "normal completion"/
48               else
49         put @1, subobs1.tl, @10, cap.modelstat:>2:0, @20,
50          cap.solvestat:>2:0/
51          )
52  );


53  file res /cap_inp.csv/ ;
54  res.pc=5;
55  res.pw=160;
56  put res;
57  put "Obs", "THETA",

58  loop(output,
59        put output.tl);
60        loop(var,
61              put var.tl);
62             put "LVAR1", "LVAR2"

63              loop (subobs1,
64                     put /
65                     put subobs1.tl, score1(subobs1),
66                     loop(output,
67                           put act(subobs1,output));
68                           loop (var,
69                                  put act(subobs1, var));
70                           loop (var,
71                                  put score2(subobs1,var));
72  );

73  putclose;
```

Line 1 shows an example of a dollar control operator in GAMS, which allows comments to be written using a "/*" to start the comment and "*/" to end the comment (lines 2 and 3) Line 4 is identical to the technical efficiency program, and defines the set which holds the output and input labels. Line 5 declares a subset of outputs from the set INOUT, called OUTPUT. Lines 6 and 7 declare two subsets of inputs, one called FIXED, which holds the fixed inputs, while VAR holds the variable inputs. Line 8 declares a set called OBS, which holds the observation labels, and lines 9 and 10 declare subsets of obs. Line 11 defines an alias for set SUBOBS, which is called SUBOBS1.

Data are read in through an external file in lines 12-17. The dollar control operator $OFFLISTING shown on line 12 means that any lines following the operator won't be included in the listing file, which is often useful when reading in large datasets. The table statement in line 13 declares a table ACT, having dimension defined by the sets OBS and INOUT. Line 14 uses the dollar control operator $ondelim which tells GAMS that a file using comma separated values (CSV) will be read into the program. Line 15 reads in the file data1.csv , which is an excel spreadsheet saved in CSV format, using the dollar control operator $Include. Line 16 uses the dollar control operator $offdelim to tell GAMS there are no more CSV file types to be included, while line 17 turns back on the listing of output to the log file. The format of the spreadsheet file used to store data in csv format are shown below. Note that column 1 needs to be labeled "dummy" in the spreadsheet file.

dummy	spec1	spec2	fix1	fix2	var1	var2
1	13295	27065	55	60	4	94
2	13255	10090	63	70	8	127
3	614	3427	59	59	6	35
4	106461	58705	63	69	5	185
5	3540	9130	53	60	5	46
6	602	6900	62	74	5	37
7	12920	18128	69	78	6	133
8	8312	5145	65	63	8	162
9	3276	4430	70	62	3	24
10	4143	8486	63	61	5	81

Variables are declared in lines 18-22. This model has an additional variable called LAMBDA, which is the optimum variable input utilization rate. Note that the dimensions of LAMBDA are the sets OBS and VAR. Both WEIGHT and LAMBDA are declared to be positive variables in line 22.

Four equations are declared in lines 23-27, and then defined in lines 28-31. This model differs from the technical efficiency model because there are separate constraints for the fixed and variable inputs (CONSTR2 and CONSTR3), which corresponds to the model found in Färe et al. (1994). CONSTR4 (line 27) is an equation which imposes variable returns to scale on the model (non-increasing returns to scale would be imposed with a <= constraint). The previous technical efficiency model implicitly assumed constant returns to scale because CONSTR4 was not included.

Parameters are declared in lines 32-34 to hold results from the model each time it's solved. Line 35 declares a file grcapres.txt, which is referred to using the name CAPDEA. This file will be used to hold results which show whether or not the model solved at each iteration. This is particularly important when constructing a model with several hundred observations. Line 36 names the model CAP, and declares it to contain four equations, CONSTR1, CONSTR2, CONSTR3 and CONSTR4.

The model is solved in lines 37-41, and the basic looping structure is unchanged from the technical efficiency program shown previously. Lines 42 and 43 store results from the model in parameters SCORE1 and SCORE2. Lines 44-50 are included to output results showing whether there was an optimal solution during each pass through the loop, using an if-else construct. Lines 45 and 46 test for the condition that the solution is optimal and the model finished running normally, and if these two conditions both exist, two phrases are written out to the file CAPDEA. Lines 48 and 49 write out to the file CAPDEA any other modelstat or solvestat codes which are returned by the solver. This allows the user to quickly look through a file and determine if there was a problem solving the model at any iteration. If there was, data for that particular observation can be examined and corrected, if necessary, and the program can be rapidly run again.

Line 52-71 are used to output model results to a comma separated file using the put command. A file named cap_inp.csv is declared and referred to using the filename RES (line 52). Line 53 tells gams that the file will be a comma separated file through the use of the suffix .pc, and line 54 says the page width of the file will be 160 characters (the default is 132). Lines 56-61 put a header line in the file consisting of "OBS", "THETA", the outputs in the model, the variable inputs, and two labels called "LVAR1" and "LVAR2". The outputs and input labels are put in the header line with the loop command (lines 57-60). The ".tl" suffix attached to both OUTPUT and VAR tells GAMS to print out the element labels found in the two respective sets. Lines 62-70 print out the actual model results to the file with the use of the loop command. Line 63, forces a carriage return so that each pass through the loop will begin on a new line. The first two columns written to the file consist of the observation number, and the estimate of theta which is stored in the parameter SCORE1. Lines 65 and 66 write the data contained in table ACT, whose members belong to subset OUTPUT, to the file using the loop command. Lines 67 and 68 write out the variable input data contained in table ACT. Lines 69 and 70 write the parameter SCORE2 (variable input utilization rates) to the file. Line 72 uses the putclose command to close the output file.

The estimate of capacity for each observation can be calculated in the GAMS program before outputting the results to a spreadsheet by multiplying the value of THETA obtained for each observation by the quantity of each output produced by the firm (radial expansion). Alternatively, it could be calculated in a spreadsheet which holds the model results in the same manner.

The programs shown have demonstrated how a general solver such as GAMS can be used to model DEA problems for measuring technical efficiency and capacity output. These programs can be extended or modified to handle different types of models for which specific DEA solvers might not be suited. An additional advantage of GAMS is that it can easily be transferred between different operating systems. GAMS code written for one operating environment, such as Unix, can also be run in another environment, such as a PC.

5. Capacity and Capacity Utilization in Fisheries

5.1 The Basics of Capacity, Capacity Utilization, and Input Utilization

In order to reduce fishing capacity, individuals determining the necessary levels of capacity reduction must have a clear understanding of capacity and capacity utilization. That is, there must be a clear understanding of what is meant by capacity and capacity utilization. It is also essential to know, however, whether or not production is technically efficient. Alternatively, if producers are not operating at capacity output or fully utilizing their fixed inputs, how much of the deviation from full capacity utilization is because of inefficient production. In this section, basic definitions and concepts related to capacity, capacity utilization (CU), and input utilization are introduced and discussed. This section concludes with an empirical assessment of capacity.

5.2 Definitions and Concepts

5.2.1 Capacity

Presently, the Federal Reserve and the U.S. Bureau of Census define capacity in terms of "full production capability." The full production capability is the maximum level of production that a producing unit could reasonably expect to attain under normal operating conditions. Normal operating conditions include the following considerations: (1) only the machinery and equipment in place and ready to operate will be utilized; (2) maximum potential production must be adjusted to reflect normal downtime, maintenance, repair, cleanup, and other shifts; (3) consider only the number of shifts, hours of operations, and overtime pay that can be sustained under normal conditions and a realistic work schedule; and (4) assume availability of labor, materials, utilities, etc., are not limiting factors.

The capacity measures of the Federal Reserve and U.S. Bureau of Census "attempt to capture the concept of sustainable practical capacity, which is the greatest level of output that a plant can maintain within the framework of a realistic work schedule, taking account of normal downtime, and assuming sufficient availability of inputs to operate machinery and equipment in place" (Federal Reserve Board, 1999, Capacity Utilization Explanatory Notes).

5.2.2 An Economic Concept

There are also many other definitions of capacity. Morrison (1985) and Nelson (1989) offer three definitions of capacity that specifically relate to an economic foundation and have been widely used (Cassel 1937, Chenery 1952, Klein 1960, Friedman 1963, and Hickman 1964): (1) capacity is the output corresponding to the tangency of the short- and long-run average cost curves; (2) capacity is the output corresponding to the tangency between the long-run average cost curve and the minimum short-run average total cost curve–this gets at a long-run competitive equilibrium; and (3) capacity is the output corresponding to the output obtained when the short-run average total cost is minimum.

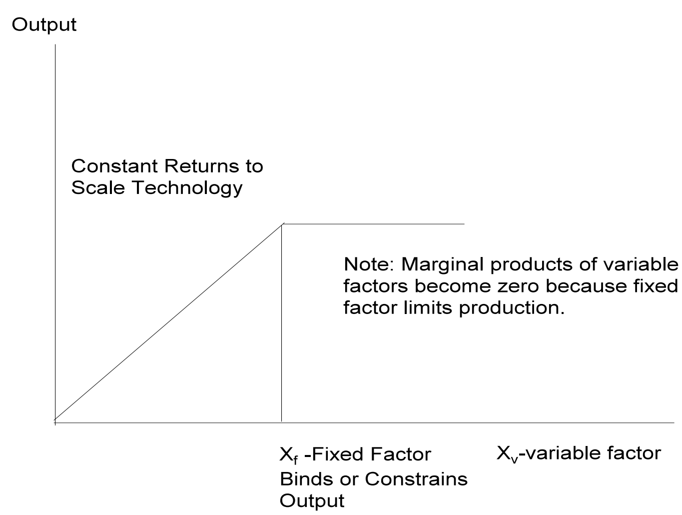
A simple and widely accepted economic definition of capacity is that level of output produced in accordance with obtaining some underlying behavioral objective (e.g., the level of output determined to maximize profits or revenues) and operating under normal operating conditions. With this definition, capacity reflects important economic factors such as input and output prices and behavioral objectives of firms.

Unfortunately, it will not often be possible to estimate or assess the widely accepted economic definition of capacity. The necessary economic data are typically not available. For many fisheries, estimates of capacity and capacity utilization will have to be based on either data on the quantities of inputs and outputs or on direct interviews of operators. Alternatively, estimates of capacity and capacity utilization may have to be restricted to a technological engineering concept. That is, the maximum potential output that may be produced given no restrictions on the variable factors and only the fixed factors are allowed to limit production.

5.2.3 A Practical Concept for Fisheries: Technological-Engineering and Johansen

Relative to the case of fisheries, Johansen (1968) offers a definition similar to that presently used by the Federal Reserve Board and the U.S. Bureau of Census and one that could be calculated for many fisheries . "Capacity is the maximum amount that can be produced per unit of time with existing plant and equipment, provided the availability of variable factors of production is not restricted" (Johansen 1968, p. 52). Under the Johansen concept, it is the fixed factors that bind or constrain production (Figure 5.1).

Figure 5.1 Johansen and a Primal-based Definition



5.2.4 The FAO Definition

The Technical Working Group of the FAO meeting on the Management of Fishing Capacity proposed the following definitions of fishing capacity: (1) The ability of a stock of inputs (capital) to produce output (measured as either effort or catch); fishing capacity is the ability of a vessel or fleet of vessels to catch fish; (2) optimum capacity is the desired stock of inputs that will produce a desired level of outputs (e.g., a set of target fishing mortality rates for the species being harvested) and will best achieve the objectives of a fishery management plan (e.g., minimizing costs); current optimal capacity may differ from long run optimal capacity, particularly if the fishery resource is currently depleted and the management strategy is to rebuild this depleted resource; and (3) fishing capacity is the maximum amount of fish over a period of time (year season) that can be produced by a fishing fleet if full-utilized, given the biomass and age structure of the fish stock and the present state of the technology.

5.2.5 The Need for a Modified Definition: Social and Other Concerns

Although there are many possible definitions of capacity, fishery managers and administrators tend to prefer the physical or technological-engineering concept of capacity. Moreover, the data necessary for calculating the economic concepts of capacity are seldom available for fisheries (i.e., costs and earnings data). A physical-based definition also most closely conforms to fishing mortality in that the input levels (standardized fishing effort) corresponding to capacity output can be related to fishing mortality.

At the same time, fishery managers and administrators and industry and community leaders are often concerned with other economic, social, and cultural aspects (e.g., full-employment, educational attainment, crime, and social infrastructure). It is therefore appropriate to consider a modified definition of capacity that explicitly allows the introduction or consideration of other economic, social, and cultural constraints. A potential definition of capacity is the output level that satisfies the socio-economic goals and objectives of management but is less than or equal to a specified biological limit (e.g., total allowable catch).

5.2.6 Capacity Utilization

There are also numerous definitions of capacity utilization. The most generalized and publically accepted definition is that of the Federal Reserve Board and U.S. Census Bureau: "capacity utilization (CU) measures the extent to which the nation's capital is being used in the production of goods." A more formal definition is offered by the U.S. Census Bureau in FAQs about the Survey of Plant Capacity (1999, p. 1) "The capacity utilization rate is the ratio of actual value of production to the level of production at full production capability." Under the Federal Reserve Board and U.S. Census Bureau's definition of capacity utilization, CU must always be less than or equal to 1.0.

5.2.6.1 Two Concepts of Capacity Utilization

In general, the concept of capacity utilization may be defined from a primal or physical based measure or an economic-based measure. From a technological basis, CU is the ratio of observed output to capacity output. From an economic basis, CU is the ratio of observed output to the output determined by the tangency between the long and short-run average cost curves. Numerous other economic-based definitions have been offered in the literature (e.g., Morrison 1985, Nelson 1989, and Berndt and Fuss 1986). An alternative definition of capacity utilization and one which allows for a technological or economic-based orientation is the ratio of observed production (Y) to optimum production (Y*) or Y/Y*.

5.2.6.2 Ranges and Differences in CU

There are, however, some important distinctions between an economic-based definition and a primal-based definition of capacity utilization. The economic measure of CU is limited to the range $0.0 < CU_E < \infty$, where CU_E denotes an economic concept of capacity. If $CU_E = 1.0$, the production entity is operating at the optimum utilization of capacity. A value of $CU_E > 1.0$ implies that there is a shortage of capacity relative to demand. A value of $CU_E < 1.0$ indicates a surplus (excess capacity) of capacity relative to demand. In comparison, the technological-engineering definition of capacity is limit to being less than or equal to 1.0–$CU_{TE} \leq 1.0$, where CU_{TE} indicates the technological-engineering measure of capacity. If $CU_{TE} = 1.0$, the optimum utilization of capacity is occurring relative to maximum physical output. If $CU_{TE} < 1.0$, there is excess capacity.

5.2.7 The Unbiased CU Measure of Färe

Färe et al. (1989), however, introduce the notion that measures of CU based on the numerator being observed output might yield biased estimates of CU. Färe et al. demonstrated that the use of observed output in the numerator of the CU measure could represent inefficient production , which would result in a downward bias to the utilization rate. For that reason, Färe et al. suggest that CU should be defined as the ratio of technically efficient production to capacity or maximum output. Moreover, the definition by Färe et al. allows the determination of whether or not plant and equipment Input are not being full utilized because of inefficient production.

5.2.8 Variable Input Utilization Rate

Färe et al. (1989) and Färe et al. (1994) introduced the concept of variable input utilization rate. The variable input utilization rate is simply the ratio of observed input usage to the optimal input usage, which is defined as the level of variable input usage required to operate at full capacity utilization. The definition of variable input utilization offered by Färe et al. (1989) is based on the technological-engineering concept of capacity as proposed by Johansen (1968). It could, however, be derived for economic-based measures of capacity. The calculation or derivation of the variable input utilization rate is further discussed in section 4.

5.3 Theoretical and Practical Concepts

Section 2 provided an introduction to the basic concepts required to understand and assess efficiency, capacity, capacity utilization, and variable input utilization. Unfortunately, the world of fisheries is not as simple as suggested in section 1. Fishing vessels or operations often harvest more than one product or species of fish. Inputs are often not well defined. Economic data necessary for assessing efficiency and economic measures of capacity and capacity utilization are usually not available. Fisheries are typically exploited by heterogeneous operating units or vessels; these operating units typically vary in size, hull construction, gear design and size, operating characteristics and configuration, and vintage.

More important, most of the traditional concepts of efficiency, capacity, and CU were developed without consideration of natural resource-based industries such as fisheries; the lack of concern about natural resource levels generates a series of questions of whether or not resource levels should be included in the assessment of efficiency, capacity, and capacity utilization. Fisheries and other natural resource industries often have the problem of joint production of undesirable outputs or utilization of undesirable inputs (e.g., in the tuna purse seine fishery, dolphins may be captured with yellowfin tuna; alternatively, there may be large catches of non-marketable juveniles of certain species). Should efficiency and capacity estimates be adjusted to reflect the fact that some outputs or inputs may be undesirable (e.g., should purse seine vessels landing less yellowfin and less dolphin have a higher efficiency score than vessels landing more yellowfin and more dolphin using the same level of inputs)? Last, all definitions and concepts, except the modified definition of capacity, presented in the last section are relatively void of social and community concerns and practices.

5.3.1 Technical and Economic Concepts of Capacity

Capacity is a short-run concept in that firms face numerous short-run constraints such as capital, plant size, regulations, and the state of technology (Kirkley and Squires 1999). Capacity may be defined and characterized with respect to physical aspects or economic aspects. That is, capacity may be defined as the maximum output the fixed inputs are capable of supporting. Capacity could also be defined as the output level that satisfies the goals and objectives ofproducers (e.g, profit maximization). A key feature that distinguishes capacity from the technically efficient output is that capacity is the output when only the fixed factors limit production. The technically efficient output is the maximum output given fixed and variable factors of production.

5.3.1.1 Technical and Economic Measures

The most common measures of capacity–technological engineering or economic–use a primal measure (i.e., output). The primal measure was proposed in 1937 by Cassels and further developed by Klein (1960) and Hickman (1964). The basic concept behind primal measures is that firms are confronted with short-run constraints (e.g., stocks of fixed inputs), and the optimal short-run or temporary equilibrium output may be different than that for a steady-state, long-run equilibrium. Berndt and Morrison (1981) and Morrison (1985) demonstrate that if firms minimize costs; input prices and the fixed inputs stocks are given; and production is characterized by long-run constant returns to scale; capacity output, Y*, may be defined as the output level that minimizes the short-run average costs. Morrison also defines capacity output when the long-run production is consistent with nonconstant returns to scale; the capacity output level is that level of output determined by the tangency between the short-run average cost and long-run average cost curves.

5.3.1.2 Some Practical Problems

Estimating and assessing technical efficiency, capacity, and capacity utilization in fisheries poses many problems; Kirkley and Squires (1998, 1999) provide an extensive discussion on various problems of assessing efficiency, capacity, and capacity utilization in fisheries. First and perhaps foremost is the absence of appropriate data. Cost data are not available for many fisheries. Inputs are seldom well defined, or the traditional economic concepts of inputs are inconsistent with the needs of resource managers (e.g., an traditional economic input is energy or fuel, but managers typically desire production analyses in terms of fishing effort). Captains and skilled crew certainly account or contribute to efficiency and capacity, but it is difficult to adequately incorporate managerial skills into the technical measures. It is highly likely that many economic analyses of production in fisheries suffer from omitted variable bias.

5.3.1.3 Multiple Inputs and Outputs

Most fisheries use multiple inputs to produce multiple products. There are few methods for dealing with multiple products without imposing restrictive assumptions on the underlying technology (e.g., separability between inputs and outputs; fixed proportions in outputs; and radial expansion/contraction possibilities). Most of the empirical studies on capacity have aggregated inputs and outputs to develop economic and technical measures of capacity. Recent work, however, has begun to explore the use of stochastic distance functions which permit estimation of a multiple input-multiple output technology.

5.3.1.4 Management and Social Concerns

Then, there are potential problems with developing the technical measures without regard to management and social concerns. For example, an assessment of capacity of a fleet comprised of 200 vessels in a community leads to the recommendation that the number of vessels should be reduced to 50. Operating at 50 vessels provides maximum flexibility for operators, maximum efficiency, and maximum net returns. At the same time, however, a reduction of 150 vessels from the fishery would have substantial impacts of the social and economic structures of the community; management may want to consider trade-offs between efficiency, capacity, and community concerns.

5.3.1.5 A Need for Management Goals and Objectives

In essence, the problems associated with defining and measuring efficiency, capacity, and capacity utilization in fisheries are driven by the need to determine excess capacity. And excess capacity must be defined relative to underlying goals and objectives of fisheries management. A simple definition of excess is capacity is the level of actual capacity in excess of the level desired by management–C_A - C_D = EC, where C_A is actual capacity, C_D is the capacity level desired or established by management, and EC is the level of excess capacity.

5.4 A Starting Point for Determining Excess Capacity

A starting point for determining excess capacity is the determination of potential capacity output of a fleet relative to the maximum sustainable yield (MSY); presently, the U.S. Sustainable Fisheries Act (1996) requires that resources be rebuilt to at least maximum sustainable yield levels within a ten year period. The determination of excess capacity relative to MSY, however, raises several important issues. First, if an optimum fleet size and configuration were based strictly on the technical and economic definitions and measures of efficiency and capacity, that optimum might be considerably less than was socially desired by individuals and communities. Second, MSY is a physical concept and void of economic and social content; a fleet size and configuration consistent with MSY would not likely provide maximum net returns or maximum net social surplus. Third, MSY, like capacity and efficiency, must be estimated, and thus, there is the potential for errors.

5.4.1 Dealing with Resource Stocks

Another problem with determining capacity and excess capacity is how to treat the resource stocks. Should an assessment of harvesting capacity or capability of an existing fleet be based on existing resource conditions; if so, estimates of harvesting capacity may be highly variable. In contrast, the determination of excess capacity must be made conditional on desired resource levels and possibly various social and economic constraints. Thus far, the issue of whether or not to include resources levels in an assessment of harvesting capacity has not been fully addressed (Kirkley and Squires 1998, 1999). The issue which needs to be address is whether or not NMFS and management agencies desire to know the maximum potential harvest when resource levels do not constraint production or nominal catch or the maximum potential harvest conditional on prevailing resource conditions. The Technical Working Group for the FAO Consultation on Fishing Capacity (1998, para 66) and the U.S. National Marine Fisheries Service Capacity Management Team explicitly require that actual capacity be defined and measured relative to biomass and age structure of the fish stock.

5.4.2 Some Problems for Assessing Capacity Relative to Resource Conditions

Defining and measuring capacity relative to existing biomass and age structure conditions, however, may pose several problems for management. If capacity was determined during periods when resource abundance was low, the potential capacity output may be substantially underestimated. As a consequence, capacity reduction initiatives may permit more capacity to remain in a fleet than is appropriate to harvest a desired level. Alternatively, the determination of capacity during periods when resource abundance is high may yield estimates which are not at all indicative of normal operating conditions. Capacity reduction initiatives based on estimates of capacity reflecting high resource abundance levels would require a larger reduction in fleet size than suggested by estimates based on relatively low resource levels. A consequence of assessing capacity during periods of high resource abundance, however, is that the allowable level of capacity would be somewhat consistent with the precautionary approach of fisheries management.

5.4.3 How Can We Incorporate Resource Conditions

Another aspect related to including resource conditions is how to treat the resource in the assessment of efficiency and capacity. Resource abundance may be treated as a discretionary or nondiscretionary input. If it is discretionary, it is assumed that abundance is under the control of the captain. In actuality, the only control a captain may have over abundance is in the selection of areas. If resource conditions are treated as nondiscretionary, they are viewed as being beyond the control of the captain or vessel operator. The issue of how to treat resource conditions remain unresolved.

5.4.4 More on Multiple Products and Undesirable Outputs

5.4.4.1 Methods for Assessing Multi-product Technologies

A major issue for assessing efficiency and capacity is how to deal with multiple product technologies and undesirable outputs or bycatch. Numerous techniques are available for assessing efficiency and capacity of firms or industries producing multiple outputs (Kirkley and Squires 1998, 1999). Most methods or measures require some type of aggregation over outputs. Other methods or measures restrict the measures along a ray such that efficiency and capacity is measured relative to proportional changes. Two recent methods that have been used to assess technical efficiency of multiple product firms involve using polar coordinates and distance functions (Lundgren 1998, Coelli and Perleman 1996a, 1996b). Both of the approaches involve specification of stochastic production frontier models, which will be discussed in section 3, and the assumption that errors associated with each output cancel out since output ratios are used as right hand side variables of the models.

5.4.4.2 Undesirable Outputs

Undesirable outputs or bycatch pose a variety of problems for assessing efficiency and capacity. Should the estimation of efficiency and capacity ignore undesirable outputs? If eliminating or reducing bycatch is not costless, capacity reduction programs based on estimates ignoring the reduction of bycatch well lead to a fleet size smaller than necessary to harvest target levels. This is because if reducing bycatch has a cost, production levels of desired or marketable products will be lower than if disposing of undesirable products had no costs.

5.5 Assessing Capacity and Capacity Utilization

We have four potential methods for assessing capacity given the types of data typically available: (1) Federal Reserve Board and U.S. Bureau of Census [Just ask survey!]; (2) Peak-to-Peak; (3) Data Envelopment Analysis (DEA); and (4) Stochastic Production Frontier. A fifth and sixth approach is that of Segerson and Squires (1990, 1992, and 1995), Morrison (1985) (primal and dual), Nelson (1989), and Berndt and Fuss (1989). All require extensive economic data which are usually not available for fisheries.

5.5.1 U.S. Bureau of Census and Federal Reserve Board Method

The U.S. Census Bureau estimates capacity from information obtained from a survey of manufacturing businesses conducted during the fourth quarter of each year. The Manufacturing plants sampled are from SIC plants (Major Groups 20-39) having at least five employees. Presently, Census surveys about 17,200 plants (4 digit SIC). The sample is based on stratified probability sampling (probabilities are proportionate to size in terms of value of shipments within each industry). Also a mail survey and Dillman-type follow up survey (mail and telephone) is conducted. Data collected included actual value of production; estimated value of production at full capability; estimated value of production achievable under national emergency conditions; number of shifts; days per week; hours per week; average number of production workers; and hours under both actual and full production scenarios. Other information includes reason(s) why a plant operated at less than full production; if appropriate, why estimates of full production may have changed in past two years; and how quickly, if required, the plant could reach full production and national emergency levels of production.

The intent of the U.S. Census Bureau's survey is to obtain information sufficient for estimating a sustainable potential output that is practical. Census defines capacity output as the greatest level of output that a plant can maintain within the framework of a realistic work schedule, taking account of normal downtime, and assuming sufficient availability of inputs to operate the machinery and equipment in place. When surveying industry, Census requests that manufacturers assume the following conditions related to production activities: (1) machinery and equipment in place and ready to actually operate are included (2) normal downtime, maintenance, repair, and cleanup activities; (3) number of shifts, hours of operations, and overtime that can be sustained under normal conditions; (4) availability of labor, materials, utilities, etc., are not limiting factors; (5) a product mix that was typical or representative of production during the fourth quarter; (6) do not assume increased use of productive facilities outside the plant for services in excess of the proportion that would be normal during the fourth quarter. The survey then requests information on the full potential market value of production; there are two ways for producers to calculate the full market value: (1) full potential market value equals actual value of production divided by rate of capacity utilization (e.g., $1,200,000/0.80 = $1,500,000), or (2) market value at full production equals number of items that could have been produced at full production times sales price (25,000 x \$4.50 = \$112,500 full capacity)

The U.S. Census Bureau does not provide estimates of capacity for the commercial harvesting sector; it does, however, provided estimates of capacity for the fish processing sector (Table 5.1).

Table 5.1 Capacity Output of the Food and Kindred Products, Processed and Prepared Seafood

Product	1996	1995	1994	1993	1992	1991
Canned and cured fish and sea foods	69	81	70	72	80	78
Fresh and frozen prepared fish	62	63	63	69	73	66

Source: Current Industrial Reports, U.S. Bureau of Census, Survey of Plant Capacity.
Federal Reserve presents capacity estimates in terms of index numbers relative to 1992 = 100.

5.5.2 Peak-to-Peak Approach

The peak-to-peak (PTP) approach is another method that may be used to calculate or estimate capacity in fisheries. The approach dates back to Klein (1960). It is described in detail in Klein and Summers (1966), Klein and Long (1973), Ballard and Roberts (1977), Garcia and Newton (1997), and Kirkley and Squires (1999). The peak-to-peak approach is particularly appropriate for estimating capacity when data are extremely limited (e.g., the only data available are landings and number of vessels). Ballard and Roberts (1977) appear to be the first researchers to apply the peak-to-peak approach to estimating capacity in fisheries; Garcia and Newton (1997) also used the approach to assess capacity in various fisheries around the world. Kirkley and Gates (1978) used the peak-to-peak approach to assess capacity in the northwest Atlantic sea herring fishery for the purpose of demonstrating that the stock assessment of herring may have been inadequate. Ballard and Roberts (1977) offer that the peak-to-peak approach of Klein and Summers is very appropriate for fisheries because of problems associated with costs and revenues going to owners and crew, economic data not being available, and the erratic nature of costs and revenues in fisheries.
The peak to peak approach is a physical concept of capacity but does implicitly reflect behavioral responses over time

The U.S. Census Bureau and Federal Reserve Board estimates of capacity and capacity utilization rates are similar or nearly the same as those obtained with a peak to peak approach. The peak to peak approach was widely used in the 1960s-1980s to assess capacity utilization. It is still used by both agencies; but the estimates are now considerably more sophisticated involving numerous regressions and calculations; many of the changes are related to retrending data and estimates of capacity and capacity utilization. Emphasis is also given to adjusting estimates of capacity to better reflect short-term peak capacity rather than a sustainable level of maximum outputs; this is done mostly to improve estimates and maintain consistency with historical series. With the PTP method, periods of full utilization (peaks) are used as primary reference points for a capacity index.

There are several steps in using the PTP approach to estimating capacity: (1) identify peak years in terms of highest output per operating unit and assume operation at full capacity in those years; (2) interpret trend of potential capacity; (3) adjust catch trend to reflect changes in fleet size; (4) construct adjusted trend of historical catch rates; and (5) compare catch per operating unit in peak and nonpeak years and adjust for productivity changes to obtain historical capacity utilization rates

With the PTP approach, we define a production technology (e.g., Cobb-Douglas that is linearly homogeneous):

$$Q_t = A\, L_t^{\alpha}\, K_t^{\beta}\, T_t, \quad \alpha + \beta = 1.0$$

combine $L_t^{\alpha}\, K_t^{\beta}$ *into* V_t

divide output by the composite input such that

$$\left(\frac{Q_t}{V_t}\right) = A\, T_t$$

where V is the number of producing units, Q is total output of fishery, and T is a technology trend.

The technology trend, T is estimated by the peak-to-peak methodology:

$$T_t = T_{t-m} + \left[\frac{\left(\frac{Q_{t+n}}{V_{t+n}}\right) - \left(\frac{Q_{t-m}}{V_{t-m}}\right)}{\left(\frac{n+m}{m}\right)}\right]$$

the values of n and m correspond to the length of time from the previous and following peak years. If there are insufficient peak years, one adopts a base year comparison, and the technology trend becomes a constant (equals Q in base year divided by number of operating units in base year). The technology trend is used to adjust the capacity production between peak years to reflect changes in technology.

Total capacity output of the fleet or fishery is estimated by calculating capacity output per operating unit and multiplying by the number of operating units. Capacity utilization is estimated by dividing the observed total output by the estimated capacity output, or CU may be estimated by simply dividing observed catch per operating unit by capacity catch per operating unit.

5.5.3 DEA, Capacity, Capacity Utilization, and Input Utilization

Data envelopment analysis or DEA is another approach for estimating capacity, capacity utilization, and the input utilization corresponding to full capacity. Färe (1984) first offered DEA as a possible approach for calculating capacity, CU, and optimum input utilization; Färe also established the necessary and sufficient conditions for the existence of plant capacity as defined by Johansen. Last, Färe demonstrated that many conventional functional forms of the technology were inconsistent with calculating capacity (e.g., no upper limits of production if all factors increased). Färe et al. (1989) extended the original work via empirical illustration by estimating capacity, CU, and optimum input utilization for several Illinois power generating plants.

The DEA approach can be used to estimate either the economic or technology-engineering measures of capacity. Since the appropriate economic data for estimating the economic concept of capacity are seldom available, we restrict our attention to using DEA to estimate the technological-engineering concept of capacity. We offer Johansen's (1968) definition of plant capacity as a useful concept of capacity output: "The maximum amount that can be produced per unit of time with existing plant and equipment, provided that the availability of variable factors of production is not restricted."

5.5.3.1 The DEA Specification for Calculating Capacity, CU, and Input Utilization

In order to calculate Johansen's notion of capacity, Färe et al. (1989, 1994) proposed the following data envelopment analysis (DEA) problem:

$$\mathrm{Max}_{(\theta, z, \lambda)} \theta = \sum_{j=1}^{J} z_j u_{jm}$$

subject to the following restrictions:

$$\theta u_{jm} \le \sum_{j=1}^{J} z_j u_{jm}, \; m = 1,2,\ldots,M,$$

$$\sum_{j=1}^{J} z_j x_{jn} \le x_{jn}, \; n \in \alpha,$$

$$\sum_{j=1}^{J} z_j x_{jn} = \lambda_{jn} x_{jn}, \; n \in \bar{\alpha},$$

$$z_j \ge 0, \; j = 1,2,\ldots,J,$$

$$\lambda_{jn} \ge 0, \; n \in \bar{\alpha}.$$

The variable factors are denoted by $\bar{\alpha}$ and the fixed factors are denoted by α. Problem (1) enables full utilization of the variable inputs and constrains output with the fixed factors. Moreover, λ is a measure of the ratio of the optimal use of the variable inputs (Färe et al. 1989, 1994). Problem (1) imposes constant returns to scale, but it is a simple matter to impose variable returns to scale (i.e., variable returns to scale requires the constraint (i.e., $\sum_{j=1} z_j = 1$).

The parameter θ is the reciprocal of an output distance function and is a measure of technical efficiency relative to capacity production, $\theta \geq 1.0$. It provides a measure (θ - 1) of the possible increase in output if firms operate efficiently, and their production is not limited by the availability of the variable factors of production (e.g., a value of 1.50 indicates that the capacity output equals 1.5 times the current observed output).

If a measure of capacity utilization (CU) is desired, it is necessary to consider the possibility that the commonly used measure, observed output divided by capacity output, may be downward biased (Färe et al. 1989). The possibility for the conventional measure of CU to be downward biased is because the numerator in the traditional CU measure, observed output, may be inefficiently produced. Färe et al. (1989) demonstrate that an unbiased measure of CU may be obtained by dividing an output-oriented measure of technical efficiency corresponding to observed variable and fixed factor input usage by the technical efficiency measure corresponding to capacity output (i.e., the solution to problem (1)).

Färe et al. (1989) appears to be the only source to argue that CU must be calculated using the technically efficient output as the numerator in the CU measure. Thus far, there appears to have been no attempts, either in the literature or by government agencies, to adjust estimates of capacity utilization to remove the potential bias associated with inefficient production. A more useful consideration, however, is to calculate CU in the conventional manner (observed output divided by capacity output), and explain deviations of observed output from capacity output in terms of technical efficiency and other factors (e.g., optimum input usage).

To obtain a measure of TE corresponding to observed fixed and variable input usage, Farrell (1957), Rhodes (1978), Charnes et al. (1978), and Färe et al. (1989) suggest that TE of the jth firm, $(\theta(x^j))$, may be obtained as a solution to a linear programming problem:

$$\max_{(\theta z)} \theta$$

$$\text{s.t. } \theta u_j \leq \sum_{j=1}^{J} z_j u_j ,$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}, \; n = 1,2,...,N$$

and $z_j \geq 0$, j = 1,2,...,J. The input vector *x* includes both the fixed and variable inputs.

Problems (1) and (2) are typical DEA problems which provide measures of technical efficiency from an output orientation (i.e., inputs are held constant and outputs are allowed to vary). Problem (1) provides a measure of TE, θ_1, which corresponds to full capacity production. Problem (2) provides a measure of TE, θ_2, which corresponds to technically efficient production given the usage of the variable inputs. The ratio of the two θs, θ_2/θ_1, is a an unbiased measure of capacity utilization.

Solutions to problems (1) and (2) provide estimates of technical efficiency, capacity, capacity utilization, and information for calculating the optimal input utilization relative to a best practice frontier. The solutions are not indicative of absolute efficiency and capacity. Based on the solutions, it may only be concluded that an observation depicts more or less efficient production or capacity relative to another observation (e.g., one fishing vessel has a higher production than that of another fishing vessel but with both vessels using identical levels of inputs).

We can calculate a measure of the ith variable input utilization rate using information obtained from the DEA problem on capacity. Based on our capacity problem, we obtain a measure of observed input to optimum input or the input level corresponding to full capacity utilization or capacity output:

$$\lambda_{jk}^{*} = \frac{x_n}{\sum_{j=1}^{J} z^{*} x_{jn}},$$

n pertains to variable inputs of jth producer and z in the intensity score
This measure indicates the percentage at which the current level of input is used relative to the full capacity output level of input utilization. In the original work of Färe et al. (1989), a ratio greater than one in value indicates that the input is over utilized; a value less than one indicates that the variable input is underutilized; and a value of one indicates full utilization of the variable input relative to capacity output. In Färe et al. (1994), the input utilization ratio in inverted, and thus, conclusions about under and over utilization of the variable inputs are reversed.

5.5.3.2 A Different Perspective with DEA

The original Färe et al. (1989, 1994) approach considered only radial expansions in outputs. With the more recent multi-stage work on slacks by Coelli et al. (1998), we can expand our calculation of capacity without forcing radial expansions. The multi-stage DEA routine of Coelli (1997) permits us to determine the radial expanded output and expansions in terms of slacks. Using the framework of Koopman (1951) which allowed for non-radial changes and the work of Coelli et al. (1998), it is possible to obtain product or species specific measures of capacity output and an overall measure of capacity output and utilization.

5.5.4 Stochastic Production Frontier and Capacity

A major criticism of DEA, particularly with respect to assessing efficiency and capacity in natural resource-based industries and agriculture, is that DEA does not adequately accommodate noise. Alternatively, DEA is deterministic and fisheries production is likely to be highly stochastic. This is a fair criticism of using DEA to estimate efficiency, capacity, capacity utilization, and optimum input utilization. Work is underway, however, by numerous researchers on stochastic versions of DEA. As a consequence of concerns about the inability of DEA to deal with noise, researchers have become interested in possible ways to use estimates of the stochastic production frontier (SPF) to estimate capacity in fisheries.

The SPF has not yet been used to actually assess capacity or capacity utilization. Work has begun considering the maximum potential output given observed utilization of variable inputs. There are, however, several possible problems: (1) the SPF does not adequately deal with multiple outputs; distance functions and polar coordinates, however, may offer two possible options for estimating a multi-product SPF; (2) if using true panel data set (several years of cross-sectional observations), there may be a problem of non-stationarity in the variables, and if the data are non-stationary, it may not be possible to estimate the SPF; (3) with the SPF, it is not possible to estimate the technology subject to no restrictions on the availability of variable factors, and this leads to omitted variable bias; (4) it may not be possible to use the SPF to solve for full input utilization points because many SPF-type functional forms do not allow input limiting output levels; alternatively, many functional forms are not plant capacity limiting–that is, given a fixed factor and an unconstrained variable input, output may be increased without limit as the variable inputs are increased (Färe 1984).

If we ignore the fact that the SPF is really suitable for estimating maximum efficient output levels conditional on observed inputs, we may estimate the SPF and find the maximum efficient output conditional on observed input levels and use that estimate as an estimate of capacity output. We will thus obtain an estimate of capacity output based on observed input levels. It will not be a true estimate of capacity, but it will provide an upper bound on output conditional on observed input usage while accommodating noise.

It is often thought that the capacity output is the output corresponding to full input utilization, or the point at which the marginal products of the variable factors of production equaled zero. The specification of capacity relative to marginal products equaling zero is not completely inconsistent with the Johansen definition of capacity. Under the Johansen concept, marginal products of all the variable factors are zero, but not because variable input usage was expanded until the marginal products became zero, but instead because the fixed factors limited output and forced the marginal products of the variable factors to become zero.

Another option for using the SPF is to take SPF-derived combinations of efficient output and observed inputs and formulate a DEA problem to estimate capacity output. That is, estimate the technically efficient output levels corresponding to observed input levels using the SPF estimates. Then, use those TE output levels and observed inputs in a DEA framework to estimate capacity output.

5.6 Empirical Illustrations: Peak-to-Peak, DEA, and Stochastic Production Frontier

In this section, we present estimates of capacity and capacity utilization based on the three previously discussed quantitative methods: (1) peak to peak; (2) DEA; and (3) the stochastic production frontier. We use data on the U.S. west coast albacore fishery for the purpose of illustrating the three methods (Table 5.2). Data on landings and vessel counts or related capital measures (e.g., total gross registered tonnage of the fleet (GRT) are data that are typically available on various fisheries.

5.6.1 Peak-to-Peak

Initially, the catch rate per gross registered ton is calculated. The highest observed catch rate was 2,900 pounds per GRT. There was an inadequate number of peaks to calculate peak level production. The base peak was therefore calculated in terms of the average output per GRT between 1956 and 1957. There was no technology trend (i.e., technical change appeared to equal zero). The potential capacity output was calculated by multiplying the observed total GRT by the base period capacity output catch rate of 2.7. Capacity utilization was estimated by dividing the observed output by the estimated capacity output (Tables 5.2-5.3).

5.6.2 Data Envelopment Analysis

Using the same data available from Ballard and Roberts (1977), a DEA problem was formulated. The technically efficient output was estimated using OnFront. Capacity utilization (CU) was calculated as the average of observed output to capacity output. We did not calculate CU using the technically efficient output level in the numerator.

5.6.3 Stochastic Production Frontier

Given there was only one input–total fleet tonnage, the stochastic production frontier was specified with several options. A conventional single input Cobb-Douglas model was specified and estimated. A transcendental model was estimated. Technical change was also considered by adding a time trend to the model. Unfortunately, statistical tests rejected the existence of the SPF. Subsequently, the SPF was estimated by changing the required mathematical properties of the estimation routine (e.g., higher tolerances and convergent criteria on the estimators). Capacity output was then estimated in two ways: (1) using the technically efficient output for the fleet, and (2) using the PTP approach with the stochastic frontier output per unit input (GRT).

The latter approach of using the PTP method and estimates from the stochastic production frontier was done in several stages. Initially, the SPF was estimated and the frontier output levels were calculated. Next, the frontier output levels were divided by the total gross registered tonnage of the fleet to obtain annual maximum catch rates. The frontier catch rates for 1956 and 1957 were average to obtain a base year catch rate; the average was approximately 2,990 pounds per GRT. Capacity output was estimated by multiplying the base capacity catch rate by the total tonnage in each year. Finally, CU was calculated by dividing observed output by the SPF-derived estimates of capacity output. The PTP method could also be applied to estimates obtained from the DEA analysis.

Table 5.2 Capacity and Capacity Utilization based on PTP Method (Adopted from Ballard and Roberts 1977).

Year	Catch Million Pounds	Gross Registered Tonnage 1,000 GRT	Capacity Rate Percent	Catch Rate–1,000 pounds/GRT	
				Potential	Observed
1956	41.34	16.55	92.7	44.69	2.5
1957	46.62	16.12	107.3	43.52	2.9
1958	38.46	20.49	69.6	55.32	1.9
1959	46.29	19.24	89.3	51.95	2.4
1960	40.20	30.07	49.6	81.19	1.3
1961	32.84	25.36	48.1	68.47	1.3
1962	45.96	26.58	64.2	71.77	1.7
1963	60.80	27.90	80.8	75.33	2.2
1964	48.07	26.49	67.3	71.52	1.8
1965	37.22	29.67	46.5	80.11	1.3
1966	36.99	36.55	37.5	98.69	1
1967	48.37	37.35	48	100.85	1.3
1968	55.90	43.52	47.7	117.5	1.3
1969	48.14	49.32	36.2	133.16	1
1970	56.12	44.12	47.2	119.12	1.3
1971	49.82	47.27	39.1	127.63	1.1
1972	60.30	50.11	44.6	135.3	1.2
1973	39.46	43.53	33.6	117.53	0.9

Base peak calculated as 1956-1957 average catch rate = 2,700 pounds per GRT.

5.6.4 Comparative Assessment of Capacity and Capacity Utilization

There was surprisingly little difference in the estimates of capacity and capacity utilization obtained from the three approaches. The peak-to-peak and DEA-based assessments of capacity were the most similar in values and trends when assessed relative to projected SPF frontier output (i.e., the projected technically efficient output levels). When the PTP approach was applied to the projected frontier output catch rates (catch per GRT), however, the DEA and modified SPF approach were the closest in value. The PTP estimates of CU tended to be consistently higher than those calculated using DEA and the SPF modified approach. It is thus apparent that the SPF estimates could be used to estimate capacity output and capacity utilization if the peak-to-peak approach is applied to the SPF projected catch rates.

Table 5.3 Comparative Results of PTP, DEA, and SPF

GRT	Output	DEA TE	PTP Capacity Output	DEA/OnFront Capacity Output	SPF Capacity Output	PTP-STP Catch Rate	PTP-SPF Capacity Output	PTP CU	DEA CU	SPF CU	PTP-SPF CU
16.550	41.340	1.16	44690000	47954400	47320700	2.86	49.57	92.5	86.21	87.36%	83.40%
16.120	46.620	1	43520000	46620000	50468500	3.13	48.28	107.12	100.00	92.37%	96.56%
20.490	38.460	1.54	55320000	59228400	47442900	2.32	61.37	69.52	64.94	81.07%	62.67%
19.240	46.290	1.20	51950000	55548000	50833000	2.64	57.62	89.10	83.33	91.06%	80.33%
30.070	40.200	2.16	81190000	86832000	50582940	1.68	90.06	49.51	46.30	79.47%	44.64%
25.360	32.840	2.23	68470000	73233200	47345940	1.87	75.95	47.96	44.84	69.36%	43.24%
26.580	45.960	1.67	71770000	76753200	52057190	1.96	79.61	64.04	59.88	88.29%	57.73%
27.900	60.800	1.33	75330000	80864000	63498900	2.28	83.56	80.71	75.19	95.75%	72.76%
26.490	48.070	1.59	71520000	76431300	53252960	2.01	79.34	67.21	62.89	90.27%	60.59%
29.670	37.220	2.31	80110000	85978200	49663690	1.67	88.86	46.46	43.29	74.94%	41.88%
36.550	36.990	2.86	98690000	105791400	51146910	1.4	109.47	37.48	34.97	72.32%	33.79%
37.350	48.370	2.23	100850000	107865100	55126400	1.48	111.86	47.96	44.84	87.74%	43.24%
43.520	55.900	2.25	117500000	125775000	60528140	1.39	130.34	47.57	44.44	92.35%	42.89%
49.320	48.140	2.96	133160000	142494400	56772770	1.15	147.74	36.15	33.78	84.79%	32.59%
44.120	56.120	2.27	119120000	127392400	60738250	1.38	132.14	47.11	44.05	92.40%	42.47%
47.270	49.820	2.74	127630000	136506800	57225080	1.21	141.57	39.03	36.50	87.06%	35.19%
50.110	60.300	2.40	135300000	144720000	64361020	1.28	150.08	44.57	41.67	93.69%	40.18%
43.530	39.460	3.19	117530000	125877400	53155260	1.22	130.37	33.57	31.35	74.54%	30.27%

Stochastic Frontier was rejected by one-sided likelihood ratio test (Cobb-Douglas specification). Note SPF results did not improve when time trend for technical change included. We also have known omitted variable bias in our SPF. The PTP-SPF heading indicates that the numbers were based on or related to estimates obtained from the stochastic frontier but used within a peak to peak (PTP) framework.

6. Conclusions and Recommendations

6.1 Summary, Overview, and Conclusions

This report provided an introduction and overview on concepts and methods applicable to assessing technical and economic efficiency, capacity, and capacity utilization in fisheries. Initially, the concepts of technical, allocative, and total efficiency were introduced and discussed. The discussion of efficiency was followed by a discussion of the various methods that can be used to estimate technical efficiency. Data envelopment analysis (DEA) and the econometric estimation of a stochastic production frontier were shown to be the more common approaches for estimating technical efficiency. Tutorials on both DEA and estimation of the stochastic production frontier were provided to illustrate the two methods. Subsequently, concepts of capacity and capacity utilization were introduced. Four methods used by government agencies and researchers for estimating capacity and capacity utilization were introduced: (1) survey by the U.S. Census Bureau; (2) peak-to-peak approach; (3) DEA; and (4) the stochastic production frontier (SPF) and a peak-to-peak analysis of estimates derived from the SPF.

6.2 Summary and Overview of Methods for Calculating Capacity in Fisheries

For the purpose of calculating and assessing capacity in fisheries, the peak-to-peak method is best suited when capacity related data are especially limited (i.e., when the data are limited to catch and number of participants). The approach is called peak-to-peak because the periods of full utilization, called peaks, are used as the primary reference points for the capacity index. In practice, a peak year is often identified on the basis of having a level of output per producing unit that is significantly higher than both the preceding and following years. Capacity output is compared to actual output in different time periods to give measures of capacity utilization after adjusting catch levels for technological change. The peak-to-peak method requires data on landings and participants, such as vessel numbers, and some identification of a technological time trend.

The peak-to-peak method is quite simple to apply and can be used when little data is available. The method has been applied to fisheries and examples can be found in the literature [e.g., Kirkley and Squires (1999), Ballard and Roberts (1977) and Garcia and Newton (1995)]. However, peak-to-peak has a number of shortcomings that should be considered when evaluating the meaning of the capacity measure it provides. In most cases, peak-to-peak can be expected to provide only a rough measure of capacity since the number of vessels or other measures of physical capital are only a loose proxy for the actual catching power of the fleet. The analysis ignores economic factors that impact what the fleet will actually catch. If only the total number of participants and catch are used in the model, differences in capacity across gear types or other sectoral disaggregations cannot be identified; thus the index may not account for changes in the composition of the fleet that may have significantly changed its overall capacity. Determining the impacts of removing different groups of participants from a fishery will not be possible since the capacity of individual producing units is not identified. Also, if significant changes in fishery regulations that impact capacity have occurred, this measure of capacity may not be a reliable predictor of current capacity. Finally, while this approach provides an estimate of potential output and the potential level of capital. The measure is based on observations over time where both the resource stock and the intensity of capital input utilization have varied.

Data envelopment analysis (DEA) uses linear programming methods to determine either the maximum output that can be produced with a given set of inputs or the minimum level of inputs required to produce a given level and mix of outputs; e.g., Appendix C. DEA models were originally designed to measure technical efficiency. Färe et. al (1989) proposed a variation on the standard output oriented model that is designed to measure capacity output and capacity utilization assuming unconstrained use of variable inputs. Thus, to be on the frontier, firms must have produced the most output for a given level of fixed inputs. For the frontier to correspond with the definition of technical capacity, the firms on the frontier must be both efficient and fully utilizing variable inputs. Firms that are not on the frontier can be below it either because they are using inputs inefficiently or because they are using lower levels of the variable inputs relative to firms on the frontier.

DEA has several attributes that make it a useful tool for measuring capacity in fisheries. Capacity estimates can be calculated for multi-species fisheries if certain, fairly strong, assumptions are made about the nature of production. DEA readily accommodates multiple outputs (e.g., species and market categories) and multiple types of inputs such as capital and labor. The analysis accepts virtually all data possibilities, ranging from the most limited (e.g., catch levels, number of trips, and vessel numbers) to the most complete (i.e., a full suite of cost data), where the more complete data improve the analysis. The DEA model may also include constraints on outputs of particular species (e.g., bycatch or trip limits). Since DEA identifies the efficiency and capacity of individual firms, it can be used to identify operating units (individual vessels or vessel size classes) which can be decommissioned to meet various objectives. Capacity estimates can be made for different groups of firms (e.g., by region and vessel size class) and the number of operating units could be determined by adding the capacities of each operating unit until the total reaches a target. If data on input costs or output prices are available, DEA can be used to measure both technical and allocative efficiency of firms. That is, the model will calculate how much costs could be reduced or revenues increased by efficiently producing the optimal product mix.

As with the all capacity measurement methods, DEA has a number of potential shortcomings. DEA is a deterministic model. Random variations in measured output, which may have been caused by measurement error or simply by normal variation in catch rates, are interpreted as inefficiency and influence the position of the frontier. In effect, the model assumes that vessels should be able to duplicate the highest catch rates observed. Recent research has focused on methods to overcome this problem. However, this research is not yet conclusive and such models are not likely to be widely available or implemented in the sort-term. In addition, efficiency scores are only relative to the best firms in the sample and cannot be compared to scores from other samples. This means that DEA cannot be used to rank different fisheries based on their level of capacity. Finally, capacity output is based on observed practice and the economic and environmental conditions at the time observations were made. If fishermen were not operating at capacity in the past it may not be possible to identify the true technical capacity, and changing conditions may have altered what the fishermen can produce currently.

Stochastic production frontier analysis is an econometric approach that can be used to estimate the maximum potential output (i.e., catch) for the observed factors of production (Kirkley and Squires, 1998). The estimated frontier production function can be used to estimate the capacity of a vessel or firm by predicting output with their actual level of fixed inputs and a maximum level of variable inputs. SPF can be used to calculate both technical and allocative efficiency if data on input and output prices are available. Additional advantages of stochastic production frontier analysis relative to the other approaches are that it is designed to handle noisy data and it allows for the estimation of standard errors and confidence intervals.

SPF has the same shortcomings as DEA. In addition, the problems and assumptions associated with parametric analysis are also exist. The selection of a distribution for the inefficiency effects may be arbitrary. A particular functional form must specify the production technology. The SPF approach is only well developed for single-output technologies unless a cost-minimizing objective is assumed. To accommodate multiple outputs in a multi-species fishery, SPF requires creating an aggregate output index (e.g., total pounds caught). The accuracy of capacity estimates will decline if species are heterogeneous in price, catchability and costs of production. In addition to these problems, the SPF approach to measuring technical efficiency makes the estimation of capacity more complex. Simplistically, under SPF as a measurement of capacity, the most binding input must be identified. Capacity is then a measure of the maximum output that can be produced given this fixed input. With multiple inputs, this must be determined in an iterative process which may not result in an efficient solution. The data requirements include firm or vessel output and input quantities, but richer models can be estimated if prices are available.

6.3 Potential Concerns

There is no single preferred approach for estimating capacity and capacity utilization in fisheries. In fact, there appears to be more questions than answers. For example, should the estimate of capacity be conditional on the available resource levels and technological externalities. If resources levels did not bind production and there were no technological externalities, production would be expected to be higher than it would if resource levels did limit production. There also is the issue of technological-engineering based capacity vs. an economic-based measure of capacity. It is highly unlikely that economic measures can be easily derived for fisheries since economic data are seldom available (e.g., costs and earnings). There also is the issue of multiple products and multiple fixed factors; the literature of Berndt and Fuss (1989) demonstrated that it may not be possible to calculate an economic measure of capacity if there is more than one fixed factors and two or more outputs.

Most of the definitions and concepts pertaining to efficiency and capacity discussed in this report were purely economic based. That is, they were consistent with the concepts presented in the economic literature. In the case of fisheries, other aspects may need to be considered when determining current and desired levels of capacity. Fishery administrators and the general public have become increasingly concerned about habitat, bycatch mortality on juveniles and non-marketable species, and ecosystem interactions. Alternatively, there are important issues about undesirable outputs and inputs that might need to be addressed when developing measures of capacity for fisheries.

There are also numerous issues related to the social and cultural characteristics of commercial fishing. It does not appear that there has ever been any attempt to directly define capacity conditional on social and cultural criteria. Yet, issues such as full employment, available employment opportunities, and educational attainment within a community may be very important to a community when developing measures of capacity.

6.4 Recommendations

6.4.1 Verifying the Estimates of Capacity

Given the various methods and types of data often available on fisheries, it is expected that most estimates of capacity will be based on the peak-to-peak approach or DEA. Alternatively, a peak-to-peak analysis of estimates of outputs levels obtained from the stochastic production frontier may be quite useful to policy makers concerned with reducing capacity in fisheries; this would be one way to explicitly incorporate random noise into the estimates of capacity. In practice, the method used to estimate capacity will be driven by the available data. It is recommended, however, that once estimates of capacity have been made, an attempt should be made to obtain feedback from industry about the estimates. That is, the estimates of capacity should be verified by individuals who are knowledgeable about the particular fishery.

6.4.2 Practical Measures

If at all possible, the estimation and assessment of capacity should consider the underlying economic behavior and potential economic responses. The technological-engineering measures, regardless of the method used to calculate or estimate capacity, implicitly reflect economic behavior. Those measures do not explicitly reflect, however, possible responses by vessel captains, owners, and crew to changing economic and resource conditions. If the measure of capacity is to be practical, it must reflect customary and usual operating procedures. A measure of capacity should not be based upon data which reflect extraordinary events. For example, the opening of Georges Bank to scallop fishing resulted in vessels harvesting 9,000 to 10, 000 pounds of meats in two to four days; crew worked, however, up to 20 hours per day because there was a 10,000 trip limit and an area quota. The crew perceived very short trips and were, thus, willing to work up to 20 hours per day. Over the course of a full fishing season, crew could not continue to work the large number of hours per day.

There are several issues about the preferred level of temporal and industry aggregation. That is, should the estimation of capacity be based on trip-level or annual data? Should estimates be based on data aggregated over firms (i.e., industry level) or on data for individual firms? If the primary purpose of estimating capacity is to facilitate a capacity reduction initiative, estimates at the firm level would be most useful. Alternatively, if the primary purpose is to simply assess the total harvesting capacity relative to resource levels, an analysis done at the fishery or industry level would suffice.

One major issue left unaddressed in this report is whether or not and how capacity should be estimated at the national level. Many fishing vessels can and do exploit different species using different gear. FAO has indicated a desire to assess capacity at a national and world level. The National Marine Fisheries Service has thus far apparently limited its attention to a fishery basis.

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