5. TARGET CAPACITY AND CAPACITY OUTPUT

5.1 Output and input target capacity

Capacity output or input levels, established by output- or input-oriented measurement respectively, must be compared to some base level in order to establish the existence and extent of capacity utilization. This comparison point may be either observed output or input levels, or some other reference point that represents a “better”, or more interpretable, comparative reference. In particular, capacity output may be compared to a target level of output or catch determined by biological or regulatory goals. It is important, however, to recognize that the appropriate comparison point depends on whether the focus of analysis occurs in the context of the short term, or represents a more long-term situation during which stock levels have been regenerated, or adjustment costs have been mitigated in some fashion.

That is, target capacity output is some form of desired level of output from the fishery. In a given, short-term scenario, it may be defined in terms of regulatory goals designed to regenerate biomass stocks. This may translate to observed output levels if a TAC is in place and a binding constraint. Over the long term, however, it is expressed as a long-term yield curve and evaluated at long-term target stock levels.

Target capacity output has been defined as the maximum amount of fish over a period of time (i.e. year or season) that can be produced by a fishing fleet if fully utilized while satisfying fishery management objectives designed to ensure sustainable fisheries (FAO, 2000). Although this definition expresses the target in terms of catch, since it focuses on the long run and full utilization it also implies corresponding input measures. Associated with each target output level is a target capital, and corresponding variable input, level. Thus, the question of target levels for comparison of capacity measures is relevant for both input- and output-oriented concepts of capacity.

In particular, the notion of target capacity output suggests that measured current capacity output levels might best be compared to these output levels, rather than to existing harvest conditions, to identify excess capacity levels relative to fishery objectives. On the input side, this suggests that imputing K_C (“potential” or capacity input) levels associated with the target output level be the focus of input-contraction measures. It must be emphasized, however, that such long-term target levels are primarily relevant comparison points for capacity output and input measures corresponding to long-term stock levels, rather than to existing stock levels. A number of typical target capacity reference points are presented in Table 2.

Table 2 – Typical capacity targets

Acronym	Description
Output-based capacity targets	
MSY	Maximum sustainable yield
MCY	Maximum constant yield
MEY	Maximum economic yield
LTAY	Long-term average yield
MOOY	Multi-objective optimal yield
Input-based capacity targets	
K_{MSY}	K (capital – fixed inputs, or capacity base) at MSY
K_{MCSY}	K at MCY
K_{MESY}	K at MEY
K_{LTAY}	K at LTAY
K_{MOOY}	K at MOOY
$K_{0.1}$	K at which the slope of the yield per recruit curve is 10 percent of the slope near the origin (i.e. equivalent to $F_{0.1}$)
K_{AY}	K at the average yield
K_{MAX}	K at the maximum yield per recruit

Source: Derived from Caddy and Mahon (1995), FAO (1999b).

Target output refers to some long run optimal sustainable yield defined by the objectives of the management plan. As shown in the first panel of Table 2, this may be the maximum sustainable yield (the maximum level of harvest that can be taken on a continuous basis), the maximum economic yield (the level of harvest that produces the maximum level of economic profit on a continuous basis), or some other measure that takes into account economic and social factors. These latter measures are referred to as the Alternative Sustainable Yield (ASY) and take into account precautionary, economic and social objectives, as well as conservation objectives of fisheries management.

These target levels are typically associated with some notion of the path that should be taken to move to this point, allowing for stock regeneration. In a short-term situation where the stock is in an overfished state, the catch must be reduced below that corresponding to the long run yield curve, for the given stock level, in order to allow for regeneration of the stock to a target level in the long run. The desired target *path* of catch according to stock regeneration may, at any point in time, therefore be thought of as a short-term target level.

Catch-based target *levels* as defined in the table are fundamentally based on some notion of a long run state, with implied optimal levels of catch and fishing effort. That is, associated with each level of sustainable yield in terms of catch is a long-term level of overall fishing effort, *E*, or capital (vessel) stock, *K*, combined with (variable) input effort, *V*. This notion is founded on the level of fixed inputs, or the capacity base, *K*, to which the variable inputs are applied. The target input level associated with input-oriented capacity utilization measures is thus based on *K*, so input-based targets are represented in the table in terms of *K*.

The distinction between *K* and *V* inputs is important. However, in many countries target levels of inputs defined either in terms of *K*, *V*, or a combination of these inputs (i.e. boat numbers, days at sea, or different combinations of inputs such as kW*days), are set as management objectives. A key issue for constructing and using capacity and capacity utilization measures is distinguishing input targets based on moving toward full capacity utilization, such as boat numbers, from those that focus on limiting the use of the capacity, such as days at sea, that may exacerbate excess capacity. For the purposes of analyzing capacity, it is necessary to differentiate between the two separable components of the "effective" or standardized unit of effort, kW*days, that disallows this distinction. Also, note that for effective capacity management, input capacity targets might best be set at the fleet segment level. However, separate targets for each sub-fleet of (relatively) homogeneous boats in terms of fishing activities, which control for heterogeneous capital stocks, or fishing power of different types of vessels, also may be relevant.

It should be recognized also that defining long-term, input-based target capacity may be complicated by technological change that could alter the relationship between the level of catch and the nominal (or observed) measure of input capacity over time. That is, over the long term, investment in new technology will increase the power of any given vessel. Generally, technological change results in the target input capacity in terms of boat numbers decreasing over time, even though output-based target capacity may remain constant. Similarly, where economic target levels of capacity are to be established, in terms of determining the most efficient or cost-minimizing fleet for catching target output levels, changes in costs (or prices if profit maximization is the goal) also can affect the optimal fleet configuration and size. Hence, input capacity targets require continual revision to account for technological developments or technical change, and changes in prices and costs. No single long-run measure may therefore be relevant when addressing long-term issues, since technological and economic changes occur continuously over time.

For purposes of deriving measures of excess capacity in fisheries, the use of sustainable yields as target output capacity measures also must be adapted to take short-term fluctuations into account. Sustainable yields are essentially long-term concepts (i.e. achieved when the fishery is in equilibrium). The output capacity measures defined in the previous sections are, by contrast, essentially short-term measures, which are influenced by the prevailing stock conditions in the years in which they were measured, to the extent that these fluctuations cannot be taken into account or controlled for. This exacerbates the issue of short- versus long-term evaluation of excess capacity alluded to in previous sections.

For example, in Figure 12, we assume that excess capacity is defined in terms of a capacity level of output that coincides with that on the short term yield curve for time 1, although this does not explicitly build in the underlying production function relationship. If the associated catch for E, given the prevailing stock level, C_1, is compared to C_{MSY} to generate a capacity utilization measure, it appears that no excess capacity is evident. This raises the issue of the short- (path) versus the long-term (level) target mentioned above. In terms of the growth associated with the given stock level, excess capacity already prevails, since the capacity output is higher than that on the long run yield curve.

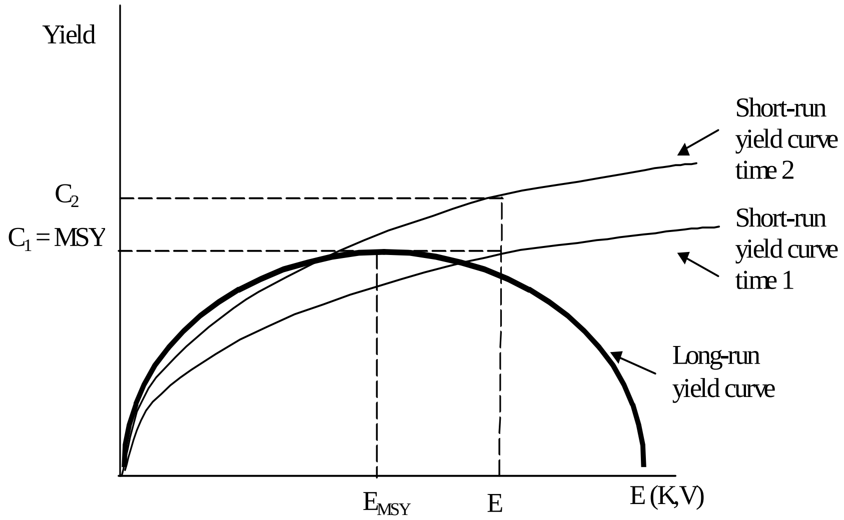

Figure 12 – Changes in capacity output over time

In year two, this problem is further worsened due to short run fluctuations; C_2 (assumed to be equivalent to the capacity output, given E) is not only greater than the associated long run yield for that stock, but also is greater than MSY. If an input utilization measure was calculated, however, it would likely indicate a surplus of effort and fleet size could be reduced to achieve E_{MSY}.

This issue underscores two points: short- and long-term capacity output and input measures should be compared to the associated relevant target; and short-term fluctuations in yield due only to short-term stock fluctuations should not drive the resulting capacity output measure. The former issue requires consideration of how a long-term capacity output measure that could relevantly be compared to long-term targets might be constructed. The latter suggests that capacity output levels should be measured over time to purge the impacts of such fluctuations.

These issues also suggest that measures of input capacity may be more reliable in measuring the extent of excess capacity than output measures. Like the issue of returns to inputs or scale, which motivated our discussion of the relationship between input- and output-oriented measures, this is at least partly driven by the point at which the measures are evaluated. Again in Figure 12, the level of combined effort (E) producing both of the estimated capacity yields (C_1 and C_2) is constant and greater than that which would be required to produce MSY (E_{MSY}).

Two alternatives may be developed to address the issues related to short- versus long-term measures. The short-term capacity output measures developed in the preceding sections may be compared to current target output measures, based on a path toward the long run level. Or, a longer term capacity output measure evaluated in terms of long-term stock levels may be constructed to compare to long-term target output measures. Both of these measures require imputation from the more standard measurement processes that rely on observed (short-term) data. The former requires adapting the target catch goal into a current target, but this is already the focus of most stock regeneration plans and resulting TACs. The latter requires imputing capacity output for stock levels outside the range of those observed which is somewhat more problematic, and thus less definitive, than measures based on observed relationships.

In the short term, in fisheries managed using output controls, the total allowable catch (TAC) imposed on the fishery may be assumed to represent the target output level most consistent with the current stock size and objectives of management. As a result, this is an appropriate short-term target output measure for the assessment of excess capacity and thus to be used instead of observed levels (if they differ) to construct capacity utilization measures. For fisheries managed using input controls, an estimate of the appropriate target output level will need to be undertaken using either expert opinion, or biological, bio-economic or multi-objective models of the fishery (see Section 5.4) to use as a comparison point for short-term, input-oriented capacity measures.

For imputation of long-term measures, both the numerator and denominator of the capacity utilization ratios developed in Section 3 need to be adapted. In particular, for the CU measure defined as Current Catch/Potential Catch, the numerator should instead reflect a target catch level and the denominator should be evaluated at target stock levels corresponding to this catch level. This may be accomplished for either the DEA or SPF measures discussed in Section 4, as overviewed by Kirkley, Morrison and Squires (2001).

In practice, this is not as significant an issue for input-oriented measures, since such measures are defined according to existing catch and stock levels, and thus do not impute beyond the observed data. It is still the case, however, that if long-term output and stock levels are the focal points, the long-term level of capacity consistent with the target output and stock level should be imputed for comparison purposes. If the stock is currently overfished, this may imply a higher capacity base than that associated with the given levels of catch and stock, since C_{msy} will exceed the current output level (or TAC). But this is likely to be more than counteracted by the greater catch per unit of K possible at higher stock levels.

5.2 Excess capacity, overcapacity and absolute capacity

The difference between excess capacity and overcapacity is not well specified in the fisheries capacity and capacity utilization literature. A useful distinction, however, is that employed by the National Marine Fisheries Service (2001). Overcapacity occurs when the potential output that could be produced, conditional on desired resource levels and full utilization of variable inputs, exceeds the level desired by management (i.e. a target level). Return to Figure 11 and assume that the desired resource condition corresponds to the resource condition producing the short-run yield curve in time two. This stock level is higher than the stock level supporting MSY. In this case, we would have overcapacity because our potential output is higher than the level needed to support our target stock level. If we further applied our weak concept of capacity output, catch or output would become bounded or limited at some point of fishing effort. That point would coincide with our potential capacity output, and the difference between output levels corresponding to that point and the point corresponding to the intersection of the short- and long-run yield curves would represent overcapacity. In contrast, excess capacity implies that, likely due to regulatory constraints, existing catch levels could potentially be taken more efficiently at existing biomass stock levels.

Since management is typically concerned about the capacity of a fishing fleet, it is important to make the distinction between excess and overcapacity. Excess capacity is essentially a short-run concept; in fact, the concept of capacity is a short-run concept. Excess capacity equals the difference between the potential output that could be produced given existing technology, resource conditions, and full variable input utilization and either the observed output or technically efficient output level (Färe, Grosskopf and Kokkelenberg, 1989).

In contrast, overcapacity has been characterized relative to desired resource conditions. As such, it is an intermediate to long-run notion, although this is somewhat inconsistent with the concept of capacity output. Overcapacity is the difference between the potential output that could be produced given existing technology, desired resource conditions (i.e. target level), and full variable input utilization, and the output level desired to support target resource conditions. Whether or not overcapacity is always a problem depends, in part, on the flexibility of the fleet to change to other fisheries. If an existing fleet of vessels operating in a particular fishery poses serious overcapacity concerns and the vessel operators have no flexibility to change to other fisheries, overcapacity will continue to pose a long-term problem. Excess capacity poses problems if it is chronic, and again, vessel operators have no flexibility to change to other fisheries. It is often the case that existing vessels cannot easily change to other fisheries, because of management and regulatory strategies.

Overcapacity also has been identified as the difference between current capacity and target capacity. That is, overcapacity (OC) might be expressed as the ratio:

$$OC = \frac{current\ capacity}{target\ capacity} \quad .$$

So if the target output in a fishery was 125 tonnes (based on biological and/or economic objectives), while the current capacity output was 200 tonnes, the fishery has the potential to harvest 60 percent more than the target capacity. Alternatively, such a ratio could be expressed directly in terms of capacity input levels.

This defines OC essentially as an inverse capacity utilization measure, where current capacity is expressed in terms of potential output given the current capacity base, and the comparison or reference point is target output (or, analogously, for an input measure). However, as noted prior, this comparison may be somewhat misleading since it may contain both short and long run measures, which are not necessarily comparable, and it finesses the issue of current stock dependence (i.e. comparisons of current capacity should be made in terms of current targets rather than long-run target levels). Alternatively, "current capacity" should be evaluated at long run stock levels to generate a more appropriate long-term measure of capacity (i.e. current capacity should be estimated conditional upon resource conditions necessary to support the target capacity level; for example, the population needed to yield MSY or some other objective).

The relative capacity measure specified above (OC), and implicitly (in inverse form) in the earlier discussion of CU, is also sometimes expressed in absolute terms, or levels, as:

$$Overcapacity = Current\ Capacity - Target\ Capacity$$

Overcapacity of 75 tonnes is implied for the above example.

Relative measures are usually more desirable for measuring overcapacity or excess capacity, since they are in proportional terms and measurement units are not an issue. Thus, they better facilitate identifying which fisheries (or species) are in most need of capacity management intervention. A large fishery may have a large, absolute overcapacity measure, while a small fishery may have a substantially smaller absolute overcapacity measure. However, in relative terms, the smaller fishery may have a greater overcapacity "problem" than the larger fishery. Similarly, a species with a relatively small catch in a multispecies fishery may have a small, absolute overcapacity problem but a large, relative overcapacity problem.

Finally, note that the term "overcapitalization" is often used interchangeably with overcapacity. The concept of overcapitalization directly refers to input capacity and to the level of capital stock in particular. A fishery is considered to be overcapitalized if the capital stock is greater than that required to efficiently achieve the target level of output. The existence of excess capacity generally implies overcapitalization, but it is possible to have excess capacity without having overcapitalization (e.g. too many variable inputs applied to the capital stock). In addition, a fishery can be overcapitalized even if excess capacity is not apparent, if reallocation or a different fleet configuration could take the same catch at lower cost. This is partly an issue of boat level as compared to aggregate measures of capacity and capacity utilization. Indicators of overcapitalization also often implicitly involve a cost component, which has not been factored into our technical or physical definitions of capacity and CU. These issues are elaborated further here.

5.3 Estimation of target capacity

The concepts of target output capacity and target input capacity are inextricably linked. With the exception of the long-term average yield, which can be observed directly from catch data, all other output targets require some model (explicit or implicit) of stock dynamics that make assumptions about the level and/or form (i.e. mesh size) of effort applied to the fishery. Hence, for every target output is associated a potential equivalent target input. Similarly, where fisheries are managed by controls on inputs, input targets are set on the basis of the expected output that those inputs will produce.

As just noted, the models used to determine target capacity may be either explicit or implicit. Explicit models may be either biological (e.g. MSY is the preferred target), bio-economic (e.g. MEY is the preferred target), or multi-objective (if some alternative output level is the preferred target). These models have a formal mathematical structure and are generally estimated from data. An advantage of such models is that their robustness can be tested by comparing the estimates with known events, and the structure and underlying assumptions are readily apparent and hence can be debated, agreed or disagreed. In some nations, explicit biological, bio-economic and multi-objective models have been developed that can be used for estimation of long term target output and input levels for many fisheries. On a global scale, however, neither bio-economic models nor multi-objective models have been widely used to estimate the long-term output or input levels of fisheries. Where such models do not exist, expert opinion may be sought to provide estimates of target capacity.

Implicit models are informal models that may have no foundation in existing data (possibly because such data do not exist) but may be based on observation and experience. These models have no explicit structure that can be debated and agreed upon. Such models often exist in the minds of experts, who may form opinions about how the fisheries may respond to certain changes based on their own experiences. Midway between these models are theoretical models that are based on established theory and opinion. Such models may have a formal mathematical structure but may not have sufficient data to derive the appropriate modelling parameters and conduct tests on their robustness.

5.3.1 Expert knowledge

A panel of experts may provide "educated guesses" about the level of capacity utilization and the potential harvesting ability of particular fleets, as well as estimates of target capacity (defined by the objectives of the fisheries policy or management plan) and, consequently, relative capacity. A formal technique (the Delphi Technique) has been developed that facilitates consensus between a group of individuals with expert knowledge on the issues to be examined. Tone (1999), however, offers an alternative to the traditional Delphi Technique to obtain both consensus and empirical estimates of economic parameters.

The Delphi Technique was pioneered by the RAND Corporation to gather opinions from a group of experts (Patton, 1986). A key feature of the technique is the anonymity of the participants. The experts neither meet nor know each other's identity.

The first step of the technique is to form a panel of experts and involved parties in the area of research. For the purposes of capacity estimation, this might include industry representatives as well as scientists. Information about who is on the team is not disclosed to others in the team. The basis of the anonymity requirement is that in any group of experts, it is likely that some individuals will be perceived to have had more experience than others. As a result, the opinions of these individuals may be perceived to have greater credibility than those of the others in the group. Consequently, less experienced team members might be reluctant to challenge the opinions of better known experts. Therefore, the opinion of the team would often reflect the opinion of the dominant team member and would not constitute a true, unbiased consensus. To overcome this problem, the Delphi Technique involves using a team of experts who do not know who the other team members are.

The second step is to have individuals within the team provide initial estimates (in this case, capacity, capacity utilization and target capacity) and the reasoning behind their estimates. Ideally, the participants will have some information available on current catch and activity levels, such as might be collected in a Rapid Appraisal (RA) or survey of the fishery. Participants document their opinions and supporting reasons, and return these to the group moderator. The moderator is independent of the team, and does not participate directly in the estimation of capacity (i.e. does not provide an opinion).

The moderator synthesizes the information provided by each expert into a single document outlining the estimates and reasoning of each expert. Care is taken that no comment or opinion is traceable to its originator.

The fourth step is to send a summary document to all experts for their responses. At this stage, the experts are asked to re-evaluate their estimates on the basis of the arguments proposed by other experts. The experts also are requested to propose reasons why they do not support other estimates. These responses are then sent to the moderator, who again compiles all responses into an updated summary document.

The process continues until either the experts' opinions converge or the moderator concludes that the comments have ceased to change substantively during successive rounds. In the latter case, if consensus is not achieved, the moderator must make a subjective assessment about which values to accept. At this point, greater weight may be given to the estimates of more experienced panel members, or the members who present the more convincing arguments for their estimates.

An advantage of the Delphi technique is that it works as an informal, subjective model when decisions are based on opinion, and can be directly converted to a formal model when the data are more knowledge based (e.g. based on information on catch and effort levels). However, the technique has a number of problems that need to be considered. Employing a team of experts may be expensive, and the iterative process may be time consuming. There also exists the potential for bias to be introduced (intentionally or unintentionally) by the person administering the technique (the moderator) through the summary reports presented to the group. While the group of experts does not know the members of the group, the moderator would be aware of the members and may inadvertently bias the summary towards the opinions of individuals who are perceived to be more authoritative.

An alternative process involves the use of face-to-face meetings, in which the moderator compiles the answers and presents them immediately while ensuring confidentiality. There are several computer programmes designed to assist in this process. While some anonymity and time for reflection are lost, a face-to-face meeting can provide quicker results.

Expert knowledge also can be obtained through surveys or RA. This might be useful for producing initial estimates of potential output and target capacities. However, without the potential for feedback and revision, the resulting survey-based estimates may be less reliable than those achieved through the more formal Delphi approach.

5.3.2 Biological, bio-economic and multi-objective modelling

Biological models have been developed for many fisheries around the world and underpin many fisheries management decisions. In most cases, the models are developed from commercial catch and effort data and, in some cases, supplemented with fishery independent data. The use of commercial catch and effort data requires an assumption about the relationship between catch and effort. Furthermore, such models often are used to assess the effects of different levels of fishing effort on fish stocks as an aid to fisheries management decision-making. As a result, most biological models can be used to assess both target output levels and input levels.

Bio-economic models are less common than biological models and have to date played a lesser role in fisheries management decision-making. Nevertheless, a substantial number of bio-economic models have been developed for a wide range of species in many countries, and such models provide the type of information discussed in Chapter 2. Bio-economic models provide a means to combine what is known about the biology and the fleet into a single framework for policy analysis. Generally, a bio-economic model will have a biological component that is used to estimate how the stocks may change under different levels of exploitation and an economic component that estimates how fishers may react to changing stock, price and cost conditions. The combination of these activities upon the underlying stock structure can provide an estimate of the expected level of catch and profits within the fishery. Management regulations can be inserted into the model to estimate their effects on the level of output, stock and profitability. An example of the use of a bio-economic model for the estimation of target capacity is presented in Appendix E).

Bio-economic models may have a number of applications in assessing target output and input levels. Where MSY is considered the most appropriate target output level, a bio-economic model can be used to estimate the fleet composition and size that produces the greatest economic benefits. Conversely, a bio-economic model can be used to estimate the fleet size and structure that maximizes economic benefits for the fishery as a whole, and the associated target level of output. This is particularly useful in multispecies fisheries where harvesting the MSY of individual species may lead to incompatible targets, because one “optimally” managed fishery may result in some other species being harvested above and others, below MSY.

One form of model that is particularly relevant for estimating target capacity is a bio-economic, multiobjective optimization model. Such a model is generally developed as an extension to standard bio-economic models, and includes a range of other factors associated with the fishery and fishing activity (e.g. employment level, pollution levels). Such optimization models can be used to estimate the level of output and fleet configuration that best achieves the objectives of fisheries management. This, then, can provide managers with an indication of both output-based and input-based target levels of capacity either in the long run or short run (or both in some cases). Further, optimization models also can be used to estimate the most economically efficient fleet structure to achieve the target output. Hence, they also provide information on the level of overcapitalization in the fishery. Multiple objectives of management can thus be combined into a single optimization framework to provide estimates of optimal sustainable yield that are consistent with the range of objectives usually inherent in fisheries management plans. Multiple-objective models have not been widely used to determine management and regulatory strategies for fisheries. They are often quite complex to solve, and their results are often quite difficult to apply. They do offer, nevertheless, a comprehensive framework for determining capacity output in fisheries. A recent review of the use of multiobjective programming in fisheries is given by Mardle and Pascoe (1999). A simple example of this work is presented in Appendix F.

Development of bio-economic multiobjective optimization models is a multidisciplinary task involving input from biologists, economists, fishery managers and commercial operators. Further, development of such models requires detailed biological and economic data, and constructing and validating the model can take a considerable amount of time. As a result, it is unreasonable to expect that models be developed solely for the purposes of estimating target capacity. However, because bio-economic models can be useful tools for the management of fisheries in general, States are encouraged to develop bio-economic and multiobjective models to do so. Once developed, the models also can be used to provide estimates of target capacity.

6. ADDITIONAL CONSIDERATIONS

6.1 Distinction between technical and economic measures

The methods of output-based capacity measurement outlined in Section 4 were developed from a technological perspective. Although based on production theory, the measures have little direct economic content. Formally, technological-engineering measures are defined according to the maximum possible output that could be produced per unit of time (a year or season), with existing plant (the vessel and its characteristics) and equipment (gear or nets), and under customary and usual practices, provided the availability of variable factors of production (e.g. labour and fuel) are not restricted. Such measures thus represent maximum physical output levels that a vessel or operating unit could produce, regardless of input and output prices. Some economic content is implicitly accommodated in what have been called technological-economic measures that do not impute capacity output measures beyond the scope of the observed data, and thus are restricted by observed behaviour. To some extent, the technological-economic measures implicitly reflect economic responses (i.e. landings were actually determined by fishers in accordance with underlying behavioural objectives). However, technological measures are only rough approximations of an economic measure of capacity, since they are not explicitly linked to any behaviour from economic incentives.

Different cost structures within a fishery could result in measured potential (technical) output levels for some vessels being inconsistent with an operator's objective of profit maximization. Whether this is a problem, however, depends on whether profit maximization may be considered a relevant goal for the operator. For many fisheries it may not be reasonable to think that such a goal is the main driving factor behind behaviour. It remains true, however, that some measured potential levels of output might not be economically feasible, as the added cost of harvesting the catch would exceed the additional revenue gained. This may not be well reflected by the technological-economic approach. Alternatively, cost minimization may not be the behavioural objective that best characterizes decision-making behaviour, and approaches for determining capacity based on cost minimization may be inappropriate to use estimating capacity output. Also, even if cost minimization or profit maximization may not be perceived as a relevant goal, in a multiple species setting with possible choice among species, revenue maximization may be a relevant economic goal to build into the analysis. Färe, Grosskopf and Kirkley (2000) demonstrate how a cost- or revenue-based approach may be used to estimate capacity when production involves multiple outputs.

Economic indicators, or at least imputation of the implied costs of production decisions, are even more important to represent at the fleet level, since generation of rents from reduced capacity is one of the goals of fishery management. Therefore, even if individual fishers do not have explicit economic incentives, such goals may be relevant to managers. Also, if regulatory schemes in place may impose upon property rights, thus causing fishers to operate more clearly in response to economic motivations, such behaviour is important to impute for appropriate measurement of capacity and capacity utilization.

The economic concept of capacity output is the output level (nominal catch or landings) determined in accordance with a given behavioural objective (e.g. profit maximization, cost minimization, or revenue maximization) by a fishing unit operating under customary and normal operating conditions. The economic measure is distinguished from the technological-economic measure in that it explicitly determines the economically optimal output or input levels consistent with optimizing behaviour of fishing units or operators. Provided adequate data on costs and earnings are available, such economic capacity measures may be calculated in several ways. For example, one very crude measure sometimes suggested is to determine the output level corresponding to minimum average cost. This would require a sufficiently long-time series of costs and landings data to compare unit costs across boats and time.

Although such a measure could provide useful information for fisheries managers, it does not directly address the issue of associated capacity utilization. One type of cost-oriented approach, however, may be drawn from the technological economic framework. If an input-oriented approach is used, the implied reduction of capital from existing K levels that would still support production of observed catch levels is the focus of the analysis. If the associated capital costs associated with this contraction in the fleet can be estimated, the implied reduction in costs for a given output (and thus revenue) level may be imputed. This is not directly related to economic optimization but allows implicit consideration of potentially reduced costs associated with contractions of the fleet. With heterogeneous capital stocks, however, and thus potential ambiguities associated with what form a capacity reduction programme would take, construction of such measures is difficult. This suggests, in turn, that an appropriate “price” of capital to use for cost-based economic models might be similarly difficult to compute.

A more direct approach involves the use of economic optimization models based on cost or profit functions, using DEA or SPF methods. With information on input and output prices, an economic measurement consistent with cost minimization, revenue maximization, or profit maximization may be calculated by imputing the least cost, fixed input level for production of observed output levels. A capacity utilization measurement then can be constructed in terms of the additional costs that are unnecessarily incurred in the fishery by non-optimal fixed input levels. And the deviation of the fixed input levels may in turn be imputed from this cost gap. Although this method has rarely been applied to DEA or SPF methods, such models in a standard economic framework have been specified and implemented in studies such as Morrison (1985) and Färe, Grosskopf and Kirkley (2000). It should again be emphasized, however, that using this type of modelling framework requires one to assume that the relevant behavioural objective of boat operators is the economic one of, say, cost minimization.

An advantage of using an economic-based approach to capacity measurement is that potential economic waste in fisheries may be identified. Excess capacity can be measured not just in terms of changes in the quantity of catch, or more relevantly in the level of inputs, but also in terms of foregone economic profits. Difficulties that persist, however, involve the existence (and appropriateness) of cost and price data; the relevance of economic behavioural assumptions in fisheries that remain subject to common property motivations; and the nature of existing management and regulation.

Also, estimation of economic measures of capacity and capacity utilization requires significant economic data, and these data are generally not available.[43] It is therefore

[43]Several European Union Nations and the United States have begun collecting detailed economic data on costs and earnings. The eventual availability of detailed economic data, thus, warrants that various economic concepts of capacity be estimated. Methods and procedures for these approaches are available in Morrison (1985a, b), Fousekis and Stefanou (1996), Keeler and Ying (1996), Fagnart, Licandro and Portier (1999), Färe, Grosslopf

unrealistic to require states to produce such estimates for the purpose of international comparisons. Ultimately, it will be important for states to develop such measures for managing their fishing capacity, if the economic ramifications of excess capacity are driving management decisions.

6.2 Aggregation across species and fleet segments

Estimation of capacity output or catch for fisheries is best carried out at low levels of aggregation – for example, the boat level – for a particularly fishery. Once capacity utilization indicators have been estimated for the boats and species in individual fisheries, however, this information must be aggregated by various dimensions – such as boats, gear, species, fisheries and regions – to provide useful information about excess capacity over entire fisheries, or even countries. Such aggregation does not, however, have a strong theoretical basis unless production is fully and linearly additive (Daal and Markies, 1984). That is to say, the individual components of the overall aggregate are essentially independent from one another, and thus can simply be added together.

The basic problem is this: How does one use estimates at the firm or operating unit level to obtain estimates of the fleet, fishery, or industry. Daal and Merkies (1984) suggest that realistic and consistent aggregation is nearly impossible. Moreover, in the presence of technological externalities, consistent aggregation is not possible. This is likely to be the case for many fisheries. Kirkley *et al.* (2001), Färe and Zelenyuk (2001) and Färe, Grosskopf and Zelenyuk (2001) provide a comprehensive theoretical framework and discuss aggregation over firms to obtain a measure of industry efficiency or capacity. They demonstrate that industry capacity is greater than or equal to the sum of firm level capacity. In contrast, Blackorby and Russell (1999, p. 7-8) state "…there does not exist a technology set such that the widely used Debreu (1951)/Farrell (1957) measure of technical efficiency can be aggregated." The three previously cited works, however, adopt Koopmans (1957) concept of efficiency and propose the use of directional distance functions to examine technical efficiency and capacity.

Aggregation of output-based measures of capacity becomes increasingly less definitive at higher levels, since comparability is lost. For example, it is less problematic across fisheries and between countries that harvest a shared stock for a given species, such as the cod stock in the North Sea. In this scenario, capacity output can be derived from the addition of such output of cod from each country participating in the common-pool fishery. This, however, provides only a rough approximation, which would underestimate total capacity. The sum of individual capacity estimates would be underestimated, because it does not allow for allocation of inputs among different operating units (e.g. allocating labour or days from one vessel in a given fishery to another vessel in a different fishery). This will be even more true when adding across species, particularly if capacity output measures impute the potential output from latent capacity, and thus, possibly double-count boats that are currently operating in different fisheries. Also, with diminishing returns, increased exploitation of a shared stock by all participants would result in a less than proportional increase in output because the stock is limited. However, since output measures are typically used indirectly to impute required capacity or capital contraction to produce desired catch levels, rather than as an

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and Kirkley (2000), and Coelli, Grifell-Tatje and Perelman (2001). There are also several problems with estimating a stochastic cost or profit function (see Kumbhakar and Lovell (2000) for a comprehensive discussion on estimating stochastic cost, revenue and profit functions).

indicator of what would happen if capacity were actually unleashed on the fishery, this is unlikely to be a binding constraint in practice.

With several fleet segments catching different combinations of species, the problem of aggregation becomes even more complex. One possibility is to use techniques such as DEA or SPF to estimate the capacity output of each species per fleet segment separately in a multiple species fishery. These can be aggregated across fleet segments for individual species as indicated in Table 3, where the X's represent the capacity output of a given species of a given fleet segment. An example of aggregation of species across fleet segments is also provided in Appendix C. It is preferable, however, to recognize multispecies issues more directly, at least within a particular fishery, by using DEA or SPF models that recognize technical and economic interactions among the various outputs produced (e.g. how the catch of one species increases or decreases as the catch of another species increases or decreases). That is, the estimation may be performed for a multi-output, or multispecies, production technology that accommodates at least some forms of jointness (more than one species or product is produced for a given level of fishing effort) that are ignored when potential output from separate estimations are simply added together. Also, if revenue rather than quantity is the focus of the analysis, and estimation of multispecies fishery capacity output is carried out directly rather than simply added, it also may be useful to recognize the economic motivations underlying different catch compositions. This can be accomplished by postulating revenue rather than output maximization as a basis for capacity output measure.

Table 3 – Interactions between fleet segments and species in multispecies/fleet fisheries

Fleet segment	Species			
	1	2	3	4
A	X	X		
B		X	X	
C	X		X	
D				X
Total fishery	A1+C1	A2+B2	B3+C3	D4

Deriving overall output-based measures of capacity utilization and excess capacity at higher aggregation levels, such as for a country will inevitably require some form of aggregation across species, gear and region, since estimation cannot justifiably be carried out at such an aggregated level. The simplest approach is to add up the quantities of different fish stocks. However, for most purposes it will be more informative to weight this sum in some manner, such as weighing the output of each species by its price to produce a total value of output (Gross Value of Production). Note also that in order to impute capacity utilization measures from such an aggregation process, target output measures of capacity used as comparison points for CU measures also must be aggregated using price weights.

A potential interpretation difficulty for measures added according to their value is that excess capacity measures can vary with a change in relative prices, all other things being equal. This is particularly problematic when examining trends in capacity and comparing capacity measures between years. For example, an apparent decline in total excess capacity over time may be a result of a decrease in price for a species that is subject to equivalent or even greater levels of excess capacity than in the previous year. To limit this, a constant set of prices could be applied to a given time series of output values for purposes of international comparisons. However, this raises questions about how market mechanisms and true capacity output are linked and how to distinguish their effects. This, in turn, suggests that evaluation of capacity output in such terms is questionable. In summary, aggregation or even comparison of capacity output measures across fisheries is difficult to accomplish effectively and should be undertaken with care.

Aggregation of many input-based measures of capacity also can be undertaken, although it again raises difficulties of interpretation. For example, total gross tonnage or total kW days fished can be aggregated across all fleet segments, as can their target levels. However, the more variation there is across boats, the more this measure is questionable, since it implies that a "representative" boat can be defined and the relationship between inputs and output harvesting capacity is linear. Similarly, inaccuracies in the aggregate measure may increase at higher levels of aggregation due to incompatibility of effort units. For example, the importance of kW days is greater for fleet segments using mobile gear (e.g. trawl gear) than for fleet segments using static gear (e.g. pots). It also precludes the incorporation of activity in fisheries that are not based on readily measurable physical inputs (e.g. labour rather than capital intensive fisheries). And when only measures such as boat numbers are available, a mixture of large and small boats in the population will create a bias in the estimate of total capacity (most likely an overestimate, because one large boat may be equivalent to several small boats in harvesting capacity). Consequently, any aggregation of input-based capacity measures should be viewed with substantial caution.

Despite the problems associated with aggregation, such information is important for providing a general indication of the order of magnitude of capacity utilization in a fisheries sector. Computing an indicator of total capacity utilization for all fleet segments that are harvesting a given species or stock provides a useful, albeit approximate, indication of the magnitude of balance or imbalance that exists between fishing capacity and the overall resource.

At the international level, aggregation could potentially be undertaken between those countries harvesting shared international, transboundary, highly migratory and straddling fish stocks, although again the aggregation is problematic and should be undertaken with care. The purpose of this exercise would be to provide information to the appropriate, regional fisheries management organization (RFMO) about the potential risks that a combined national fleet capacity prosecuting these shared fish resources may present for the short- and long-term conservation of such stocks. In this context, RFMO officials would have an opportunity to consider the implications of the mobility of certain countries and/or fleet segments across species and/or national lines and to discuss any policies or measures that may eventually be considered to manage such fleet mobility (FAO, 2000). For such aggregation to work, the countries involved will need to coordinate their data collection and capacity estimation approaches to ensure that compatible measures are developed.

6.3 Artisanal fleets

In many countries, the artisanal sector is often not adequately incorporated into fisheries management plans and measures, despite its importance. In many developing countries, attention is focused on the development of mechanized and/or commercial fisheries, with traditional and subsistence fisheries often incorrectly regarded as being insignificant. Even in countries that have relatively advanced fisheries management systems, such as the

United Kingdom, the level of information collected on the small boat sector (under ten s in length) is negligible, even though these boats comprise almost two thirds of the entire fleet.

Three main types of artisanal fleets/fishers can be defined as: pure subsistence fishers, part-time commercial fishers, and full-time commercial fishers. The capital used by these fishers may not involve a vessel but, instead, may take the form of fishing gear or even labour. In such cases, the most appropriate inputs should be used to define fishing units in subsequent analyses.

For pure subsistence fisheries, the concepts of capacity utilization and excess capacity as defined in previous sections of the guidelines are not necessarily meaningful. This sector catches only what is needed and, while they could catch more, by definition they do not catch more than is required for food or subsistence purposes. As a result, it is not clear that they behave in the same optimizing manner as commercial fishers (e.g. who maximize their outputs given fixed inputs, or minimize their costs to achieve a desired catch). They may, of course, have other optimizing behaviour), and hence, the analytical methods such as SPF and DEA may not be appropriate. For this user group, rather than operating according to a strict, firm level objective, individuals may be more concerned about satisfying or maximizing utility subject to various constraints. Similar problems are likely to exist when attempting to assess capacity in recreational fisheries.

For purposes of defining and measuring capacity in subsistence fisheries, the current catch levels can be considered to be the current output capacity, because, by definition, this is the maximum catch that will be taken under normal operating conditions. Furthermore, because most subsistence fisheries interact with commercial or industrial fisheries to some extent, the ability of their fishing activity to expand is limited.

Small-scale fishing in many countries is also associated with part-time farming (or other activities). Hence, when conditions are not favourable for farming, fishing activity may increase. In such cases, the potential capacity of this group should be considered in the same manner as full-time fishing units. This will result in these fleet segments demonstrating substantial latent effort and capacity underutilization. This needs to be considered when assessing the overall level of overcapacity in the fishery.

Small-scale commercial fishing units operating on a full-time basis need to be assessed in the same manner as their larger counterparts in the measurement of fishing capacity. However, data related to this sector are often poor or non-existent. As a result, the available approaches may be limited and resulting estimates, subject to some uncertainty. This may present problems when aggregating capacity measures at the national or regional level, particularly if output-based measures of capacity by species are not available.

6.4 Pelagic and highly variable fisheries

Many pelagic fisheries are subject to large inter-annual variations in catch, because stock size is highly dependent upon spawning success and subsequent recruitment, both of which are highly susceptible to variations in environmental conditions (e.g. food availability and water temperature). This represents an extreme example of the general issue of short run fluctuations in stocks that generate output changes that should not be attributed to capacity changes.

Without some measure of stock that can be used to control for these fluctuations, estimates of capacity output derived through peak-to-peak, SPF, or DEA analysis with a single series of fleet level data will be largely influenced by the years in which the fish stocks were either highly abundant or very dense.[44] Where panel data (time series of individual vessel level data) are available, dummy variables can be used in the SPF approach to try to capture the effects of such stock fluctuations on output. Similarly, treating time (and, implicitly, stock size) as a categorical variable and estimating capacity output in each separate time period will reduce potential distortions when using DEA.

Ideally, some measure of stock or resource density can be directly incorporated into the analysis as a fixed input into the production process. In such a case, the resulting estimates of capacity output would be more representative of the real value. When using DEA, the stock needs to be treated as a non-discretionary input. (See Cooper, Seiford and Tone, 2000.) In actuality, however, stock or resource conditions represent disembodied technical change (i.e. technical progress that is generally beyond the control of the vessel operator).

The issue of short-run fluctuations is particularly a problem when imputing long-run measures from short run evidence; for example, when comparing current capacity output measures with target catch estimates such as MSY. As noted above, target measures are based on long run equilibrium values of output, and implicitly a stable (or average) stock size, whereas usual capacity output estimates are based on current stock size. If comparison is carried out using these types of measures, it is particularly likely that a fishery may be perceived as not having overcapacity in a “poor” recruitment year, because capacity output is less than (average) target capacity. However, the level of inputs employed may be greater than that which would be expected to produce the target capacity under “normal” or average conditions. Conversely, a fishery may be perceived as having substantial overcapacity in a “good” year when capacity output exceeds target capacity, but the level of inputs may be less than or equal to the level associated with target capacity under average conditions.

In such highly fluctuating fisheries, controlling for stock levels and for long-run comparisons that impute capacity output levels at target rather than current biomass stock levels is key to constructing interpretable and useful measures. For short run comparisons, if a bio-economic model of the fishery is available, optimal yields given current stock conditions can be estimated to provide a short run measure of target capacity for comparative purposes. Also, directly constructing input-oriented measures of capacity could bypass some of these issues if an estimate of optimal input use at (average) target capacity output can be derived.

6.5 Processing and hold capacity

Both onshore and onboard processing can affect the measurement of fishing capacity. Onboard processing can act as a constraint to vessel production. That is, some of the input

[44] In addition, some pelagic species, such as tuna, are often prosecuted by complex fishing gear and technology. For example, purse vessels are typically deployed from a mother ship in response to aerial-based descriptions of stocks. In other cases, vessels use dolphin feeding behavior to identify schools of tuna, speedboats to help herd the dolphin, and divers to free the dolphin. In addition, the inputs typically considered for many fisheries may not be appropriate indicators of capacity. For such fisheries, it will be a challenge to estimate capacity output. Squires (pers. comm.) is presently estimating capacity for several Pacific tuna fisheries. The problem may become more complicated because of the need to treat undesirable outputs (e.g. dolphin).

base is used for processing purposes rather than catch, so if variations in output composition are not taken into account, the link between measured input and output is misrepresented. Also, processing facilities are only able to process a given quantity of catch-per-unit of time, and thus, onboard processing activities may actually determine harvesting capacity levels. While boats could potentially catch more, they are unable to process this catch, so there is no economic incentive to continue fishing beyond the ability of the boat to process the catch. This can be incorporated into DEA analysis directly as a technical constraint, provided information is available. Alternatively, vessel capacity could be estimated by examining onboard processing capacity. Where information on output composition or the processing constraint is not available, measures of capacity output are likely to be over-estimated.

Similarly, constraints in onboard freezer and storage capacity also will restrict the level of potential catch. Once full, the boat must return to port to unload, even though higher catches could be achieved by continuing to fish. In most cases, these constraints will be implicitly incorporated in the analysis as boats of similar sizes would be expected to have similar hold or freezer constraints, and hence, returning to port would be part of the normal working practice reflected in their effort data (e.g. days at sea). This issue can be accommodated if data on this capital characteristic are available and used as part of the measure of K.

In addition, in some cases, onshore processing may impose limits on the quantity of catch that can be utilized upon landing. In such cases, processing acts as a constraint to the total capacity of the fleet. The maximum output for all boats may be negatively impacted, and hence, the resulting estimate of capacity reflects the processing rather than the harvesting capacity. Given that an objective of capacity management is to ensure that harvesting capacity is commensurate with reproductive capacity of the resource, an unconstrained estimate of output capacity is required. Where such a constraint can be identified and the carrying capacity measured, it can be incorporated into the analysis, much like onboard processing capacity. The constraint can then be relaxed to provide a more appropriate measure of fleet capacity.

It is also the case that when fishing vessels and processors are vertically integrated, production decisions are made on the basis of the value of the final product. As a result, cross-subsidization may occur between the processing activity and the harvesting activity in order to maximize overall profits. Consequently, fleet activity may not be consistent with the assumptions underlying the main techniques used to assess capacity. In such a case, estimated capacity output may not reflect the potential output of the fishery, unless output compositional and values are taken into account. This requires both the separate measurement of different types of product, and the assumption of maximum revenue rather than output as the retained assumption about behavioural motivations. If this is not possible, the bias in the measure cannot readily be identified; the measures may be either over- or under-estimated depending on the extent of cross-subsidization in the fishery.

6.6 Other factors that may affect the measure of capacity

Other factors that also may distort the measurement of capacity include quality and discards. Haul reduction may increase the quality of the landed fish and result in higher market prices. Where a fishery consists of a mix of fishers, some of whom aim to land a lesser quantity of high-quality catch and others, to land a higher quantity catch, the capacity output will be defined by the latter rather than the former. As a result, boats landing the higher quality catch will be perceived as operating at less than full capacity. One way to deal with this issue, as alluded to above for other types of output compositional issues, is to weight the measure of the catch by their prices and construct the estimating framework according to revenue instead of output maximization. Alternatively, if boats that aim to land higher quality but small quantity catches can be identified, constraints on their capacity output can be incorporated directly into the analysis, or the boats can be analyzed separately (so the quality aspect is treated as a categorical variable). This may only be accomplished, however, if individual vessel level data are available, and the harvesting strategies of the individual vessels can be identified. The latter concern, in particular, requires information on individual boats that is not likely to be readily available.

Estimates of output capacity are generally based on estimates of the landed catch rather than the total catch, as often only the former is recorded. In many fisheries, particularly those subject to quota controls, part of the catch of some species is discarded. The effect of this is that both actual and capacity outputs are under-estimated.

Where discard data are available, they can be incorporated into the analysis (i.e. added to the landed catch to provide an estimate of total catch). It may also be possible in this case to take discards or by-catch into account as a negative output, particularly if discards stem from restrictions on catch for controlled species. However, it is unlikely that such information is available at the individual boat level for all boats in the fishery. If estimates of discards are available at the fleet level (e.g. derived from a discard sampling programme), some adaptation to estimated capacity output levels may be possible. For example, if it is assumed that discards are proportional to catch, then discarding at the capacity output level can be estimated by dividing the current discard estimate by the measure of capacity utilization.

7. INTERPRETATION AND USE OF EXCESS CAPACITY MEASURES

Measures of capacity, capacity utilization and overcapacity outlined in previous sections provide indications of potential problems in particular fleet segments, species and fisheries. Such information is essential to the effective management of capacity. Generation of such indicators, however, is not sufficient to ensure effective capacity management. In many cases, researchers who are not directly involved in the management process will be estimating the measures. The information generated needs to be distributed to fisheries managers, industry representatives and other groups with an interest in providing management advice (e.g. economists, biologists, technicians). Consequently, the assessment of overcapacity or under capacity in each fishery requires a general reporting framework that allows the information generated to be readily accessible to those who are likely to use it.

The objective of this section is to provide a possible reporting framework that states may wish to adopt for the purposes of reporting an assessment of capacity, and excess and overcapacity in their respective fisheries. An advantage of adopting such a reporting framework is that it facilitates the presentation of key measures and explicit recognition of underlying assumptions (underlying both the measurement of capacity output and input levels, and of target input and output levels to be used as a basis for comparison). Examples of tables that might be completed by each State when reporting their capacity measures are provided in Appendix F.

The reporting framework is based on the assumption that states have Level 3 data (see Appendix A). This was considered by the Mexico City consultation to be the desired data level for estimating fishing capacity. Where only Level 0 or 1 data are available, it will not be possible to report at the level of detail suggested for the individual fishery level reports. However, it is expected that most information could be constructed to complete the general and national level tables. When Level 2 data are available, it is likely that input-based indicators of capacity could be estimated at the individual fishery level.

Although the Mexico City consultation established data levels and the feasibility of estimating capacity using that data, resource managers would probably have to assign priorities initially to the fisheries to be examined. They may want to consider prioritizing according to the type of existing management, nature of overfishing, value of the fishery, or some other criteria.

The tables provide a snapshot of the current extent of overcapacity in each fishery. In developing such tables, potential problems in individual fisheries, fleet segments and species will become apparent, which will enable better targeting of capacity management measures. Subsequent aggregation of this information at the national level will provide an overview of the general extent of a country's problem, even when it may overlook specific situations.

7.1 General information

The general information suggested in Table F.1 is primarily intended to provide an indication of the relative importance of each fishery. Much of the information required for Table F.1 should be generally available, and is generally reported currently by most countries. For artisanal and subsistence fisheries, estimates of production value and activity levels (e.g. boat numbers and employment) may be necessary. These estimates can be derived largely from the information collected for estimating capacity in these fisheries.

7.2 Fishery level information

A separate analysis of capacity, capacity utilization and relative capacity is recommended (Tables F.2 to F.5) for each fishery identified in Table F.1. Analyses are to be estimated for each fleet segment that participates in the fishery and for each key species. Input-based indicators are presented in Tables F.2 to F.5, and output based indicators, in Tables F.6 to F.10.

Key input-based capacity indicators for each fleet segment in each fishery are presented in Table F.2. For purposes of international comparisons and aggregation across fisheries, it is recommended that gross tonnage, engine power (in kW) and standardized days fished (days times kW) be used, because these measures should be readily available in each country. For non-mechanized fisheries, only days fished should be reported (assuming that all days fished are homogeneous). Latent effort and (input-based) capacity utilization estimates should also be presented for each fleet segment. It will be necessary, however, to develop allocation rules to determine potential capacity output when latent effort exists. One possible method involves allocating according to historical participation, if there has been actual participation in more than one fishery.

Alternatively, capacity output could be calculated conditional on the assumption that all effort by vessels having latent effort in a fishery could be allocated to the same fishery. This places an upper limit on capacity output. There are other optimization or DEA options that also could be considered, which determine the allocation of variable and fixed factors, such that the allocation maximizes technical efficiency over a group of fisheries. (See, for example, Färe, Grosskopf and Li, 1992; Färe *et al.*, 2000.) Changes in input-based indicators of capacity and capacity utilization over the last five years (Table F.3) also should be reported where possible to provide an indication of trends in the fishery. Where possible, target levels of inputs associated with MSY[45] and ASY also should be identified for each fleet segment (Tables F.4 and F.5). Given these target levels, estimates of overcapacity at the fleet segment and total fishery can be derived.

Output measures of capacity and capacity utilization (Tables F.6 to F.8) ideally should be made at the species level. The number of key species examined in each fishery will vary. However, species that are nationally important should be reported for each fishery in which it is caught, even if it is relatively unimportant to some. This enables aggregation of species across all fisheries for the purpose of producing a national assessment. Less nationally important species can be aggregated into an “other” category.

For each species in a particular fishery, a target capacity should be specified where possible (Table F.9). Ideally, to allow for international comparisons, two target capacity measures should be provided, which are consistent with the target levels of inputs detailed in Tables F.4 and F.5 and prevailing stock conditions. Where a fishery is managed by output controls, the TAC can be assumed to represent the target output equivalent to the ASY for the purpose of estimating overcapacity.

The information in Tables F.6 to F.9 provides only a snapshot of current capacity utilization and relative capacity. Where possible, a summary table of the key information for each species over the last five years should be presented to demonstrate trends in capacity utilization and relative capacity (Table F.10).

7.3 National level information

Information from individual fisheries can be aggregated into national indicators of capacity and capacity utilization. Input-based indicators for each fishery could be summarized and aggregated to provide an estimate of the total level of physical inputs utilized in the fisheries (Table F.11).[46] For measures such as total tonnage and engine power, this may provide an overestimate of total capacity, because some boats may operate in more than one fishery and hence may be double counted. A note outlining the potential overestimate should be made in the accompanying text. Measures of capital utilization (i.e. standardized days fished) should not be distorted, because fishing activity is only counted once for each fishery.

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[45]The Mexico Conference concluded that maximum sustainable yield (MSY) should be considered as an upper bound limit to target output and should be used as the basis for international comparisons. MSY also has been adopted as the limit reference point by the Code of Conduct for Responsible Fishing.

[46]It is stressed that in addition to obtaining and summarizing information on the physical aspects of production (i.e. input and output levels), there should be a broad emphasis placed on collecting and summarizing detailed economic information (e.g. costs, input and output prices, revenues, capital values and returns to factors of production).

Target levels of input capacity for each fishery (provided separately for each fleet segment in Tables F.4 and F5) could be aggregated to provide an overview of input-based overcapacity at the national level (Tables F.12 and F.13). Similarly, information on catch, capacity output, capacity utilization and relative capacity could be aggregated across the fisheries for each species to provide an overall indicator of species exploitation (Table F.14).

Summary estimates of the total level of capacity output for each fishery could be estimated by aggregating across species in each fishery (Table F.15). Target capacity measures also could be aggregated in a similar way. It may be useful to the aggregation to use prices as weights, to provide an estimate of capacity in terms of revenue and thus provide an indication of the economic significance of any observed overcapacity. Aggregation of commodities does, however, pose particularly vexing problems, and therefore, should be done in a manner consistent with aggregation theory. (See, for example, Cornes, 1992) For international comparisons, these could be converted to United States dollars at the prevailing exchange rate for each country. Tables may also be presented in local currency in addition to the table in US$. Countries with Level 1 data could also attempt to provide estimates in terms of US$. If information on species composition is not available to derive a reliable estimate of the output value, then information could be presented in terms of aggregated catch weight. This is less desirable, because it does not provide any indication of the extent of economic overcapacity, because high volume low value species often dominate the catch weight. It does, however, preclude confusion arising from market differences that affect relative prices (across species or time) but not actual quantities that may be produced with existing capacity.

The different estimates of aggregate national capacity utilization and relative capacity should be summarized to provide an overall picture of capacity in the state (Table F.16). Because measures are derived on the basis of different assumptions, there are no *a priori* reasons why consistent measures should be achieved. That is, there are no reasons why relative output capacity should be the same as relative input capacity. Also, aggregation across non-homogeneous units can add distortions to the final measure (e.g. same sized boats in different fisheries will have different levels of catch). For example, potting boats will have lower catch of higher valued species while pelagic trawlers will have higher catches of lower valued species. The different measures are presented in the table only as indicators of the possible extent of overcapacity in each state.

Although aggregation of capacity estimates at the state or national level poses several problems, there is, nevertheless, a need to secure such estimates. A primary need, of course, is to develop national policies on capacity reduction. Moreover, vessels in some fisheries may actually change their geographical home port or fishery (e.g. a vessel moves from the east coast of a nation to the west coast and enters a similar gear fishery involving different species). One potential way to deal with aggregation across different species and fisheries is to develop meaningful price weighted aggregates. This is regularly done to measure gross and net national products or the output of a diverse industry (e.g. agriculture, which produces pork, poultry, beef, lamb and various crops). A simple Divisia or Tornqvist aggregate could be constructed, provided output price information was available.[47]

[47]Numerous other forms of aggregate outputs are possible. Detailed discussions on aggregation over commodities or inputs are available in Johnson, Hassan and Gren (1984), Deaton and Muellbauer (1980), and Cornes (1992). All three references, as well as Daal and Merkies (1984), provide discussions on aggregating over firms or individuals.

7.4 Additional information (qualitative review)

Presentation of tables also will need accompanying text highlighting the potential distortions that may have been introduced into the analysis through necessary assumptions. For example, the text could indicate which, if any, fisheries are subsistence-based, such that capacity output is assumed to be equivalent to current catch. Similarly, fisheries with a high proportion of part-time fishers will exhibit relatively low capacity utilization. These also will need to be noted in accompanying text.

The management objectives of each fishery also should be presented, and the effect of these on the estimation of Alternative Sustainable Yield (ASY) outlined (i.e. information on the relative weights assigned to each objective should be provided). Related to this are short-term and long-term targets. If target capacity is primarily short run, it needs to be explained and an indication of long-term targets needs to be provided.

As noted above, some fishers will operate in more than one fishery. As a result, a simple aggregation of the physical inputs in each fishery will lead to an overestimate of the total level of inputs employed. An estimate of the potential overestimate of these inputs could be provided in the text.

Attention could be drawn to likely distortions caused by incompatible units, particularly in relation to measures of input capacity. Aggregation of these units across fisheries is likely to cause distortions, and a qualitative assessment of the extent of these distortions would be useful in interpreting these figures.

A description of the methodology used to estimate the individual capacity measurements should also be provided, particularly as different methods may result in different measures (a consequence of the underlying assumptions). For example, the text should explain which techniques were used to estimate capacity output for each fishery and how the estimates of target capacity were derived (e.g. bio-economic or stock dynamic models, or average of previous years).

For states exploiting shared resources (e.g. straddling stocks), coordination of the methodology for estimating capacity and target capacity is essential. Details about which stocks are shared and the coordination process for their assessments also should be provided.

Finally, an assessment of the situation in each fishery based on the data in the tables should be undertaken, taking into account the estimation problems encountered in each fishery (e.g. aggregation problems, or stock fluctuations in pelagic fisheries). In particular, consideration should be given to what might be considered an “acceptable” level of capacity underutilization in each fishery. For relatively stable fisheries, this might be small, whereas greater capacity underutilization may be acceptable in more variable fisheries, particularly if conditions in the assessment year are relatively “poor”.

8. CONCLUDING REMARKS

The process of estimating capacity and capacity utilization is not just an academic exercise. The measures derived will provide valuable information relevant to the future management of capacity in the fisheries under consideration. The Code of Conduct for Responsible Fishing identified overcapacity as a major constraint to sustainability in world fisheries and consequently places significant emphasis on the need to manage capacity. Management of capacity is not possible unless some indication is available of the species affected and the extent to which overcapacity may exist in the different fisheries.

As noted in Section 2, the input and output based measures presented in the guidelines are not equivalent, although they are complementary. Equivalent measures only can be produced under restrictive conditions, which rarely hold, or with explicit information about returns to inputs (including biomass stocks) or to scale. As a result, the measures provide different information to managers and need to be interpreted according to their different perspectives. However, as most fisheries are managed through some form of input control, both approaches are useful for providing sufficient information on the fisheries for the effective management of capacity. When possible, therefore, countries should attempt to undertake computation of all measures outlined above.

The ability of the states to develop reliable indicators of capacity is largely predicated on the existence of reliable data. The Mexico City consultation concluded that Level 3 data (see Appendix A) should be regarded as the desired standard for estimating fishing capacity. Countries with data collection programmes that do not meet these data requirements should develop institutions capable of collecting such data. Although measures exist to estimate capacity with less data, these measures are relatively crude, and hence may provide incorrect measures of capacity. While data collection may be perceived as expensive, efficient data collection systems are likely to be less expensive than the economic losses that could occur as a result of fishery mismanagement.

The Mexico City consultation also concluded that obtaining Level 4 data (see Appendix A) was a desirable long-term objective. The addition of economic information about fisheries allows an estimate of the most cost-effective means of harvesting the resource, and hence provides information on the potential economic losses arising from excess capacity. States that currently collect Level 3 data should therefore consider developing systems to collect Level 4 data.

APPENDIX A: LEVELS OF DATA AVAILABILITY AND PREFERRED CAPACITY ESTIMATION METHODS

The Mexico City consultation identified four levels of data availability (Table A.1). Level 1 is the minimum level of data necessary for estimating fishing capacity. Countries with Level 0 data (i.e. essentially no quantitative data) should give high priority to the collection of sufficient data to reach at least Level 1 as soon as possible.

Table A.1 – Levels of data availability

Level	Data available
0	Little or no quantitative data.
1	An estimate of total landings; in vessel-based fisheries, an estimate of total vessels; in non-vessel-based fisheries, number of participants or a measure of the total gear units in use (e.g. total number of beach nets).
2	As for Level 1, plus an index of vessel size and/or power; gear type; a “rough” index of trends in fishing success; “rough” measures of total time spent fishing and maximum time that could be spent fishing under normal operating procedures per year or season; basic relevant characteristics of fishing operations (e.g. seasonality, number and types of other fisheries in which vessels operate, use of fish aggregating and fish finding devices such as FADs, sonar, satellite tracking, other examples of changes in technology, autonomy of vessels, trans-shipment practices).
3	As for Level 2, plus total catch (including discards) split by fleet segment and by species; basic biological information (e.g. resource distribution, catch by species, size structure, “rough” estimates of potential maximum sustainable yield); comprehensive primary characteristics determining fishing power (e.g. gross tonnage or other volume measures, engine power, fish hold capacity, vessel age – see Table 1); comprehensive information on gear type and dimensions; prices or revenues by major species; detailed effort and catch per unit effort (CPUE) data, including time spent fishing.
4	As for Level 3, plus detailed biological information on fish stocks (e.g. estimated biomass, fishing mortality rates, age/size structure, uncertainty in stock assessments); comprehensive data on other important features of the fishery such as detailed information on fish aggregating and finding devices (e.g. sonar, FADs, satellite tracking), skipper and crew skill levels, fuel consumption, autonomy of vessels, processing capacity, cost and earnings information, value of capital stock, employment, subsidies and economic incentives, and fishing operations relative to fish distributions.

Source: FAO (2000)

Level 3 is the desired standard for the estimation of fishing capacity. Countries with Levels 1 and 2 data should aim to collect data to move to Level 3 as soon as possible. The benefits of moving to Level 3 include improved accuracy and precision of capacity measures.

Level 4 is the long-term desired level of data for estimating capacity. This allows not just the measurement of capacity and capacity utilization, but also estimation of economically optimal levels of capacity.

The method adopted for measuring capacity will largely depend on the quantity and quality of available data. A summary of the methods available to estimate capacity given the data available is presented in Table A.2.

Table A.2 – Available and preferred methods for capacity estimation depending on data quality

Data Level	Methods available	Preferred method(s)
0	Rapid rural appraisal, survey, expert opinion	Combination of methods
1	Output-based measures: peak-to-peak, SPF, DEA, survey, expert opinion Input-based measures: based on available input information (e.g. ether boat numbers or gear use), survey, expert opinion	No preference, best to try all three output-based measurement approaches and compare results. All available input-based measures. Expert opinion may be necessary to determine input and output-based target capacity
2	Output-based measures: peak-to-peak, SPF, DEA, survey, expert opinion Input-based measures: aggregate potential effort and latent effort; aggregate size/power based measure of inputs (e.g. total kW), survey, expert opinion	SPF or DEA as only single output, but can utilize effort data to produce unbiased estimates All available input-based measures Expert opinion may be necessary to determine input and output-based target capacity
3	Output-based measures: SPF, DEA, survey, expert opinion Input-based measures: aggregate and fleet segment estimates of potential effort and latent effort; aggregate and fleet segment estimates of size/power based measure of inputs, survey, expert opinion Crude bio-economic models can be developed to estimate target capacity	DEA or SPF can provide species specific measures of capacity output Best available input-based measures Bio-economic model estimates of both input- and output-based target capacity
4	Output-based measures: SPF, DEA, survey, expert opinion Input-based measures: aggregate and fleet segment estimates of potential effort and latent effort; aggregate and fleet segment estimates of size/power based measure of inputs, survey, expert opinion Bio-economic models can be developed to estimate target capacity	DEA or SPF can provide species-specific measures of capacity output and economic measures using cost data Best available input-based measures Bio-economic model estimates of both input- and output-based target capacity

APPENDIX B: PEAK-TO-PEAK ANALYSIS

Peak-to-peak analysis is a relatively simple method to assess the capacity utilization of an industry over time. An advantage of peak-to-peak analysis is that it requires information on only one output measure and one input measure, and hence is suited to estimating capacity utilization with only Level 1 data (see Table A.1). Peak-to-peak analysis has been applied in fisheries by Ballard and Roberts (1977), Ballard and Blomo (1978) and Hsu (2003).

The underlying theory

Peak-to-peak analysis is based on an underlying assumption that output is a function of the level of inputs and a technology trend, such that

$$Y_t = \alpha_o V_t T_t \tag{1}$$

where Y_t is the output in time, t; α_0 is a proportionality constant; V_t is a composite or aggregate index of inputs; and T_t is the technology trend that represents productivity change. An implicit assumption in the use of a composite index of inputs is that the technology displays constant returns to scale. That is, increasing all inputs will result in a proportional increase in output.

The level of technology is determined by the average rate of change in productivity between peak years, where productivity is given by Y_t/V_t (i.e. average output per unit of input). The technology in any one year is thus

$$T_t = T_{t-m} + \left\{ \frac{\dfrac{Y_{t+n}}{V_{t+n}} - \dfrac{Y_{t-m}}{V_{t-m}}}{\dfrac{m+n}{m}} \right\} \tag{2}$$

where m is the length of time from the previous peak year, and n is the length of time to the following peak year, and T_{t-m} is the level of technology at the previous peak (i.e. year m) equivalent to the average productivity (e.g. catch per unit of effort) in that period. The other term on the right hand side (i.e. the term inside the brackets) represents the cumulative change in productivity between the two peaks. This is added to the average productivity in the previous peak year (i.e. year m) to give an estimate of the average productivity of capacity in subsequent years.

An alternative way of estimating the level of technology between peaks is given by

$$T_t = T_{t-1} + \left\{ \frac{\dfrac{Y_n}{V_n} - \dfrac{Y_m}{V_m}}{n-m} \right\} \tag{3}$$

where Y_n/V_n is the average productivity in the upper peak and Y_m/V_m is the average productivity in the lower peak. The term in the brackets represents the average change in productivity between the two peaks. Both approaches produce identical results.

Assuming the proportionality constant has a value of 1, the estimate of the level of technology is equivalent to the capacity level of productivity (i.e. $T_t = Y_t^*/V_t$, where Y_t^* is the capacity level of output). From this, the capacity level of production can be estimated from the product of the inputs and the capacity level of productivity, such that

$$Y_t^* = V_t T_t \tag{4}$$

and capacity utilization can be estimated by

$$CU_t = Y_t^*/Y_t. \tag{5}$$

A particular difficulty in interpreting the results of a peak-to-peak analysis in fisheries is that no consideration is given to changes in the stock level. Apparent changes in productivity may be due to either changes in technology (the underlying assumption of the technique) or changes in the stock level.

This problem may be particularly pertinent in developing fisheries, where catch rates may increase rapidly initially, with the main peak occurring in the middle of the time series. Subsequent declines in catch rates may reflect falling stock levels. However, if the main peak is used as the last peak in the series (all other years showing a steady decline), it is likely that the technique will over-estimate capacity output and under-estimate capacity utilization.

The problem can be minimized by including lower peaks rather than successively higher peaks as is generally used in other industries that do not rely upon a biological resource base.

Example of use: Nigerian artisanal fishing sector

Data on the artisanal fishing sector in Nigeria were used as an example of how peak-to-peak analysis can be used to estimate capacity. The data were derived from Amire (2003), and are presented in Table B.1.

Table B.1 – Nigerian artisanal fisheries productivity, 1976-1994

				Average catch per:	
Year	Canoes	Fishers	Production	Canoe	Fisher
1976	134 337	413 832	327 561	2 438	0.792
1977	137 447	424 838	331 280	2 410	0.780
1978	138 447	425 298	336 138	2 431	0.790
1979	133 728	446 152	356 888	2 669	0.800
1980	133 723	459 065	274 158	2 050	0.597
1981	120 142	440 592	323 916	2 696	0.735
1982	105 239	416 959	377 683	3 589	0.906
1983	129 555	472 122	376 984	2 910	0.798
1984	109 638	342 219	246 784	2 251	0.721
1985	80 688	302 234	140 873	1 746	0.466
1986	77 134	408 927	160 169	2 077	0.392
1987	76 644	437 465	145 755	1 902	0.333
1988	77 144	447 850	185 181	2 400	0.413
1989	77 155	470 250	171 332	2 221	0.364
1990	76 981	452 187	170 459	2 214	0.377
1991	77 093	457 102	168 211	2.182	0.368
1992	77 076	459 847	184 407	2 393	0.401
1993	77 050	456 381	106 276	1 379	0.233
1994	77 073	457 775	124 117	1 610	0.271

Source: Amire (2003).

The choice of input may have an impact on the measure of capacity output and, consequently, capacity utilization. In the Nigerian artisanal fleet, the number of canoes active in the fishery had declined over time while the number of fishers remained relatively constant (a result of more fishers operating per canoe). Over the same period, motorization increased in the fishery from 8.7 percent in 1996 to 20.8 percent in 1994 (Amire, 2003). As a result, it would be expected that there was substantial technological change in the fishery. Developing a composite index of inputs in such a case is difficult without first estimating a production function and imposing constant returns to scale.

For purposes of illustration, capacity was assessed using both canoes and fishers (separately) for the input measure. From Table B.1, it can be seen that the peak productivity periods for both inputs were 1976, 1979, 1982, 1988 and 1992. These peaks also are apparent by graphing the catch per unit input series (Figure B.1).

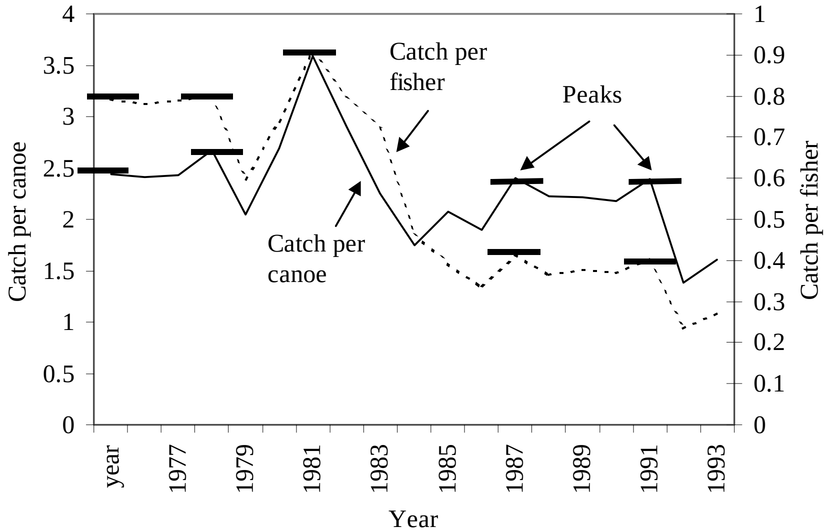

Figure B.1 – Catch-per-unit input, Nigerian artisanal fleet

Table B.2 – Peak-to-peak analysis using canoes as input measure

Year (t)	Canoes (V_t)	Production (Y_t)	CPUE (Y_t/V_t)	Average technological change[a]	Capacity CPUE (T_t)	Capacity output (Y_t*)	Utilization rate (Y_t/Y_t*)
1976	134 337	327 561	2 438	-	2 438	327 561	100%
1977	137 447	331 280	2 410	0.0768	2 515	345 701	96%
1978	138 247	336 138	2 431	0.0768	2 592	358 330	94%
1979	133 728	356 888	2 669	0.0768	2 669	356 888	100%
1980	133 723	274 158	2 050	0.3067	2 975	397 885	69%
1981	120 142	323 916	2 696	0.3067	3 282	394 321	82%
1982	105 239	377 683	3 589	0.3067	3 589	377 683	100%
1983	129 555	376 984	2 910	-0.1981	3 391	439 289	86%
1984	109 638	246 784	2 251	-0.1981	3 193	350 041	71%
1985	80 688	140 873	1 746	-0.1981	2 995	241 631	58%
1986	77 134	160 169	2 077	-0.1981	2 797	215 711	15%
1987	76 644	145 755	1 902	-0.1981	2 599	199 161	73%
1988	77 144	185 181	2 400	-0.1981	2 400	185 181	100%
1989	77 155	171 332	2 221	-0.0020	2 398	185 055	93%
1990	76 981	170 459	2 214	-0.0020	2 396	184 485	92%
1991	77 093	168 211	2 182	-0.0020	2 395	184 600	91%
1992	77 076	184 407	2 393	-0.0020	2 393	184 407	100%
1993	77 050	106 276	1 379	-0.0020	2 391	184 192	58%
1994	77 073	124 117	1 610	-0.0020	2 389	184 094	67%

Note: Peak years in bold, a) estimated by $[(Y_n/V_n)-(Y_m/V_m)]/(n-m)$

The analyses, undertaken in an Excel spreadsheet, are given in Tables B.2 and B.3 using canoes and fisher numbers respectively. Average technological change was estimated between the peak years (indicated in bold). For example, between 1976 and 1979, average productivity change was (2.669-2.438)/(4-1) = 0.0768.

Capacity CPUE is estimated by adding the average technological change to the preceding year's value. Capacity output is estimated by multiplying the capacity CPUE by the input level. The utilization rate is estimated by dividing actual output by capacity output.

Table B.3 – Peak-to-peak analysis using number of fishers as input measure

Year (t)	Fishers (V_t)	Production (Y_t)	CPUE (Y_t/V_t)	Average technological change[a]	Capacity CPUE (T_t)	Capacity output (Y_t*)	Utilization rate (Y_t/Y_t*)
1976	413 832	327 561	0.792		0.792	327 561	100%
1977	424 838	33 1280	0.780	0.003	0.794	337 461	98%
1978	425 298	336 138	0.790	0.003	0.797	339 016	99%
1979	446 152	356 888	0.800	0.003	0.800	356 888	100%
1980	459 065	274 158	0.597	0.035	0.835	383 419	72%
1981	440 592	323 916	0.735	0.035	0.871	383 540	84%
1982	416 959	377 683	0.906	0.035	0.906	377 683	100%
1983	472 122	376 984	0.798	-0.082	0.824	388 911	97%
1984	342 219	246 784	0.721	-0.082	0.742	253 823	97%
1985	302 234	140 873	0.466	-0.082	0.660	199 368	71%
1986	408 927	160 169	0.392	-0.082	0.578	236 194	68%
1987	437 465	145 755	0.333	-0.082	0.496	216 782	67%
1988	447 850	185 181	0.413	-0.082	0.413	185 181	100%
1989	470 250	171 332	0.364	-0.003	0.410	192 977	89%
1990	452 187	170 459	0.377	-0.003	0.407	184 155	93%
1991	457 102	168 211	0.368	-0.003	0.404	184 731	91%
1992	459 847	184 407	0.401	-0.003	0.401	184 407	100%
1993	456 381	106 276	0.233	-0.003	0.398	181 594	59%
1994	457 775	124 117	0.271	-0.003	0.395	180 722	69%

Note: Peak years in bold, a) estimated by $[(Y_n/V_n)-(Y_m/V_m)]/(n-m)$

Despite differences in the input measure used, the estimated capacity output was fairly similar in both instances (Figure B.2a). The estimated capacity utilization in each year was also relatively similar (Figure B.2b).

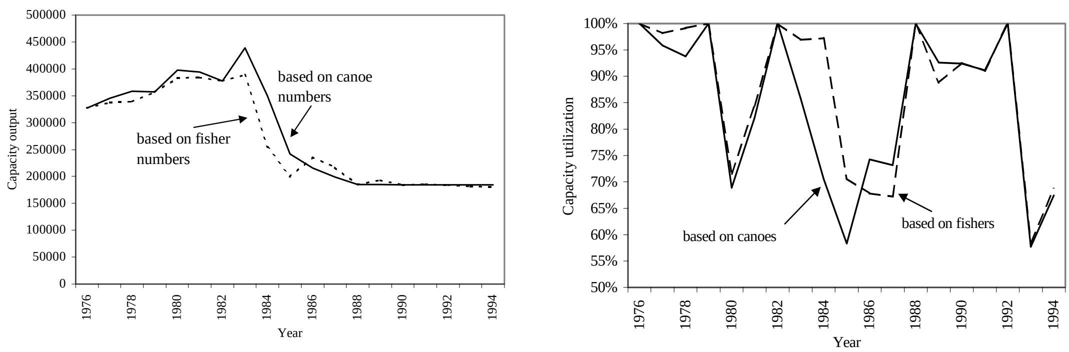

Figure B.2 – a) estimated capacity and b) estimated capacity utilization

APPENDIX C: STOCHASTIC PRODUCTION FRONTIERS

Stochastic production frontiers were initially developed for estimating technical efficiency rather than capacity and capacity utilization. However, the technique also can be applied to capacity estimation through modification of the inputs incorporated in the production (or distance) function. A potential advantage of the stochastic production frontier approach over DEA is that random variations in catch can be accommodated, so that the measure is more consistent with the potential harvest under “normal” working conditions. A disadvantage of the technique is that, although it can model multiple output technologies, doing so is somewhat more complicated, requires stochastic multiple output distance functions, and raises problems for outputs that take zero values (Paul, Johnson and Frengley, 2000).

The underlying theory

A production function defines the technological relationship between the level of inputs and the resulting level of outputs. If estimated econometrically from data on observed outputs and input usage, it indicates the average level of outputs that can be produced from a given level of inputs (Schmidt, 1986). A number of studies have estimated the relative contributions of the factors of production through estimating production functions at either the individual boat level or total fishery level. These include Cobb-Douglas production functions (Hannesson, 1983), CES production functions (Campbell and Lindner, 1990) and translog production functions (Squires, 1987; Pascoe and Robinson, 1998).

An implicit assumption of production functions is that all firms are producing in a technically efficient manner, and the representative (average) firm therefore defines the frontier. Variations from the frontier are thus assumed to be random, and are likely to be associated with mis- or un-measured production factors. In contrast, estimation of the production frontier assumes that the boundary of the production function is defined by “best practice” firms. It therefore indicates the maximum potential output for a given set of inputs along a ray from the origin point. Some white noise is accommodated, since the estimation procedures are stochastic, but an additional one-sided error represents any other reason firms would be away from (within) the boundary. Observations within the frontier are deemed “inefficient”, so from an estimated production frontier it is possible to measure the relative efficiency of certain groups or a set of practices from the relationship between observed production and some ideal or potential production (Greene, 1993).

A general stochastic production frontier model can be given by:

$$\ln q_j = f(\ln \mathbf{x}) + v_j - u_j \tag{1}$$

where q_j is the output produced by firm j, x is a vector of factor inputs, v_j is the stochastic (white noise) error term and u_j is a one-sided error representing the technical inefficiency of firm j. Both v_j and u_j are assumed to be independently and identically distributed (iid) with variance σ_v^2 and σ_u^2 respectively.

Given that the production of each firm j can be estimated as:

$$\ln \hat{q}_j = f(\ln \mathbf{x}) - u_j \tag{2}$$

while the efficient level of production (i.e. no inefficiency) is defined as:

$$\ln q^* = f(\ln \mathbf{x}) \tag{3}$$

then technical efficiency (TE) can be given by:

$$\ln TE_j = \ln \hat{q}_j - \ln q^* = -u_j \tag{4}$$

Hence, $TE_j = e^{-u_j}$, and is constrained to be between zero and one in value. If u_j equals zero, then TE equals one, and production is said to be technically efficient. Technical efficiency of the *j*th firm is therefore a relative measure of its output as a proportion of the corresponding frontier output. A firm is technically efficient if its output level is on the frontier, which implies that q/q* equals one in value.

While the techniques have been developed primarily to estimate efficiency, they can be readily modified to represent capacity utilization. In estimating the full utilization production frontier, a distinction must be made between inputs comprising the capacity base (usually capital inputs), and variable inputs (usually days, or variable "effort"). If capacity is defined only in terms of capital inputs, the implied variation in output, and thus variable effort, from its full utilization level is sometimes termed an indicator of capital utilization.

If variable inputs are assumed to be approximated by the number of hours or days fished (i.e. nominal units of effort), estimating the potential output producible from the capacity base with variable inputs "unconstrained" implies removing this variable from the estimation of the frontier. The resulting production frontier is thus defined only in terms of the fixed factors of production, or *K*. In particular, it will be supported by observations for the boats that have the greatest catch per unit of fixed input (which generally corresponds to the boats that employ the greatest level of nominal effort for a particular level of *K*). The resulting measure of technical efficiency is equivalent to the technically efficient capacity utilization (TECU); accommodating both the impacts of technical inefficiency and deviations from full utilization of the capacity base. That is, it represents the ratio of the potential capacity output that could be achieved if all fixed inputs were being utilized efficiently and fully to observed output.

Only limited attempts to estimate stochastic production frontiers for fisheries have been undertaken (Kirkley, Squires and Strand, 1995, 1998, Coglan, Pascoe and Harris, 1999, Sharma and Leung, 1999, Squires and Kirkley, 1999; Pascoe, Andersen and de Wilde, 2001; Pascoe and Coglan, 2002). These have focused upon an estimation of efficiency rather than capacity, although the capacity problem has recently been addressed by Kirkley, Morrison and Squires (2001) and Tingley and Pascoe (2003) using SPF procedures.[48] The techniques used and problems encountered are similar, and distinction between the utilization and efficiency components – thus providing an unbiased estimate of capacity utilization – requires first computing the more standard inefficiency measure.

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[48] Pascoe and Coglan (2000) estimated the effects of variations in efficiency upon physical capacity measures used in the UK and demonstrated the problems associated with assuming homogeneity in physical inputs.

Functional forms for the production function

Estimation of the SPF requires a particular functional form of the production function to be imposed. A range of functional forms for the production function frontier are available, with the most frequently used being a translog function, which is a second order (all cross-terms included) log-linear form. This is a relatively flexible functional form, as it does not impose assumptions about constant elasticities of production[49] nor elasticities of substitution[50] between inputs. It thus allows the data to indicate the actual curvature of the function, rather than imposing *a priori* assumptions. In general terms, this can be expressed as:

$$\ln Q_{j,t} = \beta_0 + \sum_i \beta_i \ln X_{j,i,t} + \frac{1}{2}\sum_i \sum_k \beta_{i,k} \ln X_{j,i,t} \ln X_{j,k,t} - u_{j,t} + v_{j,t} \qquad (5)$$

where $Q_{j,t}$ is the output of the vessel j in period t and $X_{j,i,t}$ and $X_{j,k,t}$ are the variable and fixed vessel inputs (i, k) to the production process. As noted above, the error term is separated into two components, where $v_{j,t}$ is the stochastic error term and $u_{j,t}$ is an estimate of technical inefficiency.

Alternative production functions include the Cobb-Douglas and CES (Constant Elasticity of Substitution) production functions. The Cobb-Douglas production function is given by:

$$\ln Q_{j,t} = \beta_0 + \sum_i \beta_i \ln X_{j,i,t} - u_{j,t} + v_{j,t} \qquad (6)$$

As can be seen, the Cobb-Douglas is a special case of the translog production function where all $\beta_{i,k} = 0$. The production function imposes more stringent assumptions on the data than the translog, because the elasticity of substitution has a constant value of 1 (i.e. the functional form assumption imposes a fixed degree of substitutability on all inputs). And the elasticity of production is constant for all inputs (i.e. a 1 percent change in input level will produce the same percentage change in output, irrespective of any other arguments of the function).

The CES production function is given by:

$$Q_{j,t} = \gamma\left[\delta X_{i,j,t} + (1-\delta) X_{2,j,t}\right]^{-1/\theta} - u_{j,t} + v_{j,t} \qquad (7)$$

where θ is the substitution parameter related to the elasticity of substitution (i.e. θ = (1/σ)-1 where σ is the elasticity of substitution) and δ is the distribution parameter. The CES production function is limited to two variables, and is not possible to estimate in the form given in (7) in maximum likelihood estimation (MLE) (making it unsuitable for use as the basis of a production frontier). However, a Taylor series expansion of the function yields a functional form of the model that can be estimated, given as:

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[49] This represents the percentage change in output from a 1 percent change in the input level.

[50] This represents the degree to which one input is able to substitute for another as a result of relative input price changes while still holding output constant. The values range from 0 (which indicates the inputs are used in fixed proportions and are not substitutable) to infinity (in which case the inputs are perfectly substitutable and their use is highly responsive to relative price changes).

$$\ln(\frac{Q_{j,t}}{X_{2,j,t}}) = \ln\gamma + (\upsilon - 1)\ln X_{2,j,t} + \upsilon\delta\ln(\frac{X_{1,j,t}}{X_{2,j,t}}) - \frac{1}{2}\upsilon\theta\delta(1-\delta)\left[\ln(\frac{X_{1,j,t}}{X_{2,j,t}})\right]^2 - u_{j,t} + v_{j,t} \quad (8)$$

The model can be estimated as a standard or frontier production function, and the parameter values derived through manipulation of the regression coefficients. The functional form in (8) can be shown to be a special case of the translog function where $\beta_{i,i} = \beta_{k,k} = -0.5\beta_{i,k}$.

Given that both the Cobb-Douglas and CES production functions are special cases of the translog, ideally the translog should be estimated first and the restrictions outlined above, tested. However, the large number of variables required in the process of estimating the translog may cause problems if a sufficient data series is not available, resulting in degree of freedom problems. In such a case, more restrictive assumptions must be imposed.

Separating capacity utilization from random variations in catch

To estimate the stochastic production frontier, an appropriate functional form is assumed (i.e. Cobb-Douglas, CES or Translog production function) and the parameters of the model (including σ^2_v and σ^2_u) are estimated by MLE. Estimation of the maximum value of the logged likelihood function is based on a joint density function for the split error term $\varepsilon_j = v_j - u_j$ (Stevenson, 1980). From this, technical efficient capacity utilization (TECU) can be calculated for the individual firm, given by:

$$E\left[\exp(-u_j)\middle|\varepsilon_j\right] = \frac{1-\Phi(\sigma_A + \gamma\,\varepsilon_j/\sigma_A)}{1-\Phi(\gamma\,\varepsilon_j/\sigma_A)}\exp(\gamma\,\varepsilon_j + \sigma_A^2/2) \quad (9)$$

where $\sigma_A = \sqrt{\gamma(1-\gamma)\sigma_s^2}$, $\sigma_s^2 \equiv \sigma_u^2 + \sigma_v^2$, $\gamma \equiv \sigma_u^2/\sigma_s^2$ and $\Phi(.)$ is the density function of a standard normal random variable (Battese and Coelli, 1988). From this, if $\gamma = 0$, then the expected value of the TECU score is one. That is, there are no deviations due to technical inefficiency or capacity underutilization (i.e. $\sigma_u^2 = 0$). If $\gamma = 1$, then all deviations are due to technical inefficiency and capacity underutilization (i.e. $\sigma_v^2 = 0$). Hence if $0<\gamma<1$, deviations are characterized by both TECU and a random or stochastic component (Battese and Corra, 1977). Standard estimation programmes such as FRONTIER, discussed below, may be used to compute these estimates.

In order to separate the stochastic and TECU effects in the model, a distributional assumption has to be made for u_j (Bauer, 1990). From the literature on technical efficiency estimation, four distributional assumptions have been proposed: an exponential distribution i.e. $u_j \approx \exp(\theta)$ (Meeusen and van der Broeck, 1977); a normal distribution truncated at zero, for example, $u_j \approx \left|N(\mu_j, \sigma_u^2)\right|$ (Aigner, Lovell and Schmidt, 1977); a half-normal distribution truncated at zero i.e. $u_j \approx \left|N(0, \sigma_u^2)\right|$ (Jondrow *et al.*, 1982); and a two-parameter Gamma/ normal distribution (Greene, 1990).

There are no *a priori* reasons for choosing one distributional form over the other, and all have advantages and disadvantages (Coelli, Rao and Battese, 1998). For example, the exponential and half-normal distributions have a mode at zero, implying that a high proportion of the firms being examined are perfectly efficient. The truncated normal and two-parameter gamma distribution both allow for a wider range of distributional shapes, including non-zero modes. However, these are computationally more complex (Coelli, Rao and Battese, 1998). Empirical analyses suggest that the use of the gamma distribution may be impractical and undesirable in most cases. Ritter and Simar (1997) found that the requirement for the estimation of two parameters in the distribution may result in identification problems, and several hundreds of observations would be required before such parameters could be determined. Further, a maximum of the log-likelihood function may not exist under some circumstances. Bhattacharyya *et al.* (1995), however, offer one approach for selecting the distribution to reflect technical inefficiency; they suggest the use of a data generating process.

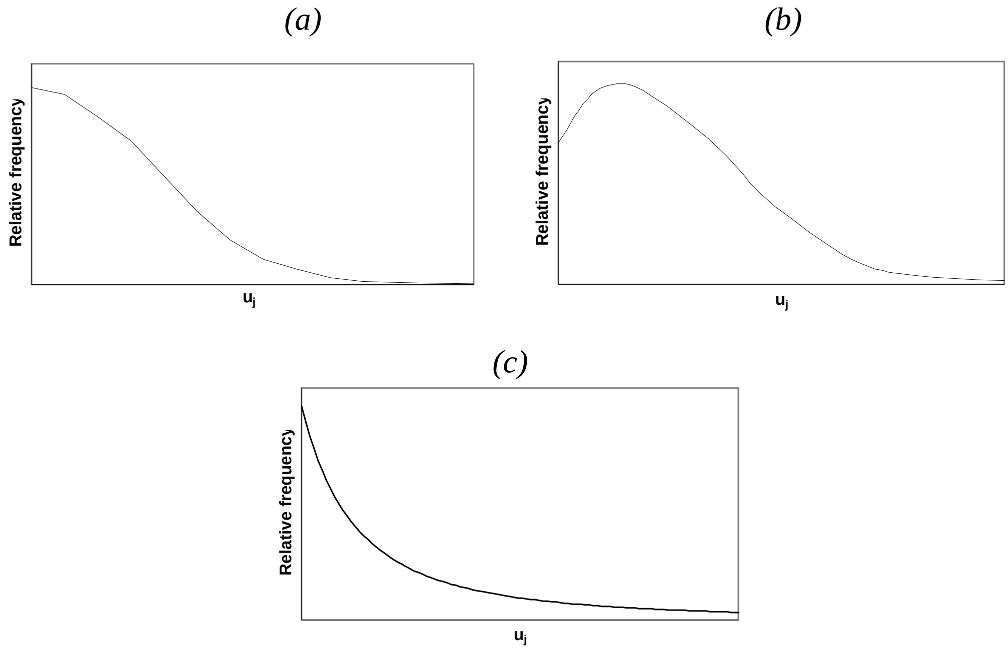

Figure C.1 – Capacity utilization distributional assumptions:
(a) half-normal; (b) truncated normal; (c) exponential (Note: TECU= e^{-u_j} **)**

The half-normal, truncated normal and exponential distributions of the inefficiency term are illustrated in Figure C.1. The half normal distribution assumes that the mode in the distribution is zero. This produces the greatest number of boats operating at full capacity in the estimated capacity utilization distribution (i.e. u_j = 0 and hence TECU = 1 as $e^{-0}=1$). In contrast, with the truncated normal, the mode of the distribution (the greatest number of observations with any particular u_j score) is greater than zero. With such a distribution, the proportion of boats operating at full capacity in the sample can vary. The half-normal distribution is a special case of the truncated normal distribution, with the estimated mode being zero. Hence, the truncated normal distribution is a more general specification (out of the two), and the regression output can be tested to see if the mode (equivalent to the mean value in a non-truncated distribution) is equal to zero. The average capacity utilization in the sample is lower if a truncated normal distribution is assumed than if a half-normal distribution is assumed (unless the estimated mode of the truncated distribution is zero, in which case they are identical).

The exponential distribution also allows for a high number of boats to be operating at full capacity. While the range of TECU scores may be as great (if not greater) than under the assumption of a half-normal or truncated normal distribution, the frequency of low TECU scores is less than under the other two distributional assumptions. As a result, the average capacity utilization is likely to be higher under the assumption of an exponential distribution than under either of the other two distributional assumptions.

Time variant TECU

An implicit assumption in estimating efficiency using the above specification is that efficiency is time invariant. A number of studies have attempted to estimate time varying efficiency, allowing for technological change to affect the efficiency measurement over time. For the estimation of TECU, it would be expected that technology would change over time, and that a time variant measure would be more relevant. Note also, however, that technical change may instead be assumed to shift the frontier, and thus appear in the production function specification instead of the stochastic specification underlying the inefficiency measurement.

Cornwell, Schmidt and Sickles (1990) replace the firm effect by a squared function of time with parameters that vary over firms (i.e. $U_{i,t} = U_i \left[1 + bt + ct^2\right]$). Kumbhakar (1990) also allowed a time-varying inefficiency measure assuming that it was the product of the specific firm inefficiency effect and an exponential function of time, such that:

$$U_{i,t} = U_i \left[1 + e^{bt+ct^2}\right]^{-1} \qquad (10)$$

where U_i are assumed to be iid as truncations at zero of the N(0, σ_u^2) (half-normal case). This allows flexibility in inefficiency changes over time, although no empirical applications have been developed using this approach (Coelli, Rao and Battese, 1998).

Battese and Coelli (1992) proposed a time-varying inefficiency measure given as:

$$TE_{j,t} = u_j e^{\eta(T-t)},\ t = 1,2,\ldots T \qquad (11)$$

where u_j are assumed to be iid truncations at zero of the normal distribution N(μ_j, σ_u^2) and η is the rate of change in efficiency over time. If $\eta>0$, the TECU term, $u_{j,t}$, is always increasing over time (i.e. as (T-t) increases), whereas $\eta<0$ implies that $u_{j,t}$ is always decreasing with time. Hence, one of the main problems of this model is that TECU is forced to be a monotonic function of time. This not desirable, as it might be expected that capacity utilization would fluctuate from year to year, and that changes in technology would be discrete events rather than continuous. Again, this may be accommodated to some extent by including t instead in the production function specification, which for a translog model allows for cross-effects with all other arguments of the function, including potential measures of the resource stock.

Inefficiency models

In many studies of technical efficiency, the results are used to estimate the effects of various factors on inefficiency. These may be estimated using either a one-step or two-step process.

In the two-step procedure, the production frontier is first estimated and the technical efficiency of each firm, derived. These are subsequently regressed against a set of variables, Z_{it}, which are hypothesized to influence the firm's efficiency. This approach has been adopted in a range of studies (e.g. Kalijaran, 1981; Pitt and Lee, 1981).

A problem with the two-stage procedure is a lack of consistency in assumptions about the distribution of the inefficiencies. In the first stage, inefficiencies are assumed to be independently and identically distributed (iid) in order to estimate their values. However, in the second stage, estimated inefficiencies are assumed to be a function of a number of firm-specific factors, and hence are not identically distributed (Coelli, Rao and Battese, 1998).

Kumbhakar, Ghosh and McGuckin (1991) and Reifschneider and Stevenson (1991) estimated all of the parameters in one step to overcome this inconsistency. The inefficiency effects were defined as a function of the firm-specific factors (as in the two-stage approach), but were incorporated directly into the MLE. Battese and Coelli (1995) also suggested a one-step procedure for using the model (now accounting for time), such that:

$$\ln q_{j,t} = f(\ln \mathbf{x}) + v_{j,t} - u_{j,t} \tag{12}$$

and the mean inefficiency is a function of firm-specific factors, such that:

$$m_{j,t} = \mathrm{Z}\delta + W_{j,t} \tag{13}$$

where Z is the vector of firm-specific variables which may influence the firm's efficiency, δ is the associated matrix of coefficients and $W_{j,t}$ is an iid random error term.

Huang and Liu (1994) proposed a non-neutral stochastic frontier model. This is estimated by regressing the inefficiency term upon two sets of variables, $\mathrm{Z_{it}}$ and $\mathrm{Z_{it}}$*, the first representing some firm-specific variables which may influence the firm's efficiency and the latter variables representing the interactions between $\mathrm{Z_{it}}$ and the input variables in the stochastic frontier, such that:

$$Y_{i,t} = \beta\, \mathbf{x_{i,t}} + (V_{i,t} - U_{i,t}) \quad \text{and} \quad \mathrm{U_{i,t}} = \mathbf{z}_{i,t}\delta + \mathbf{z}^{*}_{i,t}\delta^{*} + W_{i,t} \quad . \tag{14}$$

This allows movement of the function to be biased towards certain inputs. However, it again imposes an assumption that the inefficiency determinants are linearly related to efficiency.

The various approaches discussed thus far raise the question of whether or not these determinants of efficiency should be accommodated in the production function specification itself, or as determinants of measured inefficiency. We would think that it would be preferable to consider as many production determinants as possible in the technological specification, rather than in the stochastic specification, to represent their productive effects (marginal products) directly. This reduces the potential for calling something "inefficiency" when it may be explainable by the effective level of the productive inputs. This is particularly important if the efficiency and utilization components of overall deviations from the frontier are to be distinguished separately, which is important for unbiased estimation of capacity utilization. Appropriate representation of the characteristics of inputs, such as those comprising the "power" embodied in the capacity base, is critical for interpretable and usable capacity and utilization estimates.

"Unbiased" estimates of capacity output

As noted above, the stochastic production frontier approach was developed primarily to estimate technical efficiency. It also can be modified to produce estimates of capacity and capacity utilization by removing the constraining influence of variable inputs in the production function, usually represented for the fishery by a measure of "effort", such as days or hours fished. The resulting "efficiency" score will combine both capacity utilization and technical inefficiency. Full efficiency capacity output can be estimated by scaling up current output by the efficiency score generated from this estimation process (i.e. by dividing current output by the efficiency score). However, this may be a biased measure of capacity output, because under normal working conditions it would be expected that most of the fleet would be operating at less than full efficiency, due at least in part to mis- or un-measured factors of production.

To reduce these distortions, an unbiased measure of capacity utilization may be derived by dividing the combined measure of capacity utilization and efficiency by the efficiency scores estimated in the traditional manner (e.g. estimated with the measure of capital utilization such as days or hours fished), such that:

$$CU = \frac{TECU}{TE} \qquad (15)$$

where *TECU* is the combined measure of capacity utilization and efficiency and *TE* is the efficiency score computed for the full production function relationship with the contribution of variable inputs incorporated rather than removed. This will result in a higher estimate of capacity utilization (i.e. as $TE \leq 1$, $CU \geq TECU$).

Capacity output is estimated by dividing the actual catch by the capacity utilization measure, or multiplying by the inverse capacity utilization ratio, 1/CU, often called a measure of overcapacity, such that:

$$Capacity = \frac{actual\ output}{CU} \quad . \qquad (16)$$

This can be estimated for every observation for every boat, and aggregated across the fleet to provide estimates of total capacity in each time period examined.

Data requirements – panel, cross sectional and time series data

In order to separate out the effects of random fluctuations in output from systematic differences due to inefficiency and capacity utilization, the estimation of TECU ideally requires repeated observations for the same boat. This requires a time series of information for a cross-section of boats in the population. This is generally referred to as panel data. Panel data may be balanced or unbalanced. Balanced panel data exist where there are an equal number of observations for all boats in the sample and every boat operates in every time period of the data. Unbalanced panel data occur when there are not an equal number of observations for each boat, and/or the boats do not operate in every time period of the data.

A difficulty with unbalanced panel data is that different sets of boats may be compared in different time periods, and there may be instances where some boats are not directly compared. Estimation is readily carried out for unbalanced panel data using programmes such as FRONTIER. But since efficiency and capacity utilization are relative (rather than absolute) measures, estimation may be problematic if there are only a few boats in the sample for given time periods, so that the boats are only compared to a small number of other boats in the same period. Ideally, the data set should be broad enough for this not to occur, and ideally every boat should operate in the same period with every other boat (not all at the same time necessarily) at least once (and preferably more times). Time periods when only a few boats are operating should be excluded from the data set. Similarly, boats that have only a few observations should be excluded from the sample, as their efficiency score will be measured relative to only a few other boats in only a few time periods. This requires a subjective assessment about which observations to exclude. For example, Pascoe and Coglan (2002) included boats that had observations for at least four months a year in at least three of the four years of the data. This resulted in only 63 boats out of a possible 457 being included in the analysis. In contrast, Kirkley, Squires and Strand (1995, 1998) limited their analysis to only 10 boats for which a long and consistent time series was available.

When cross-sectional data only are available (i.e. only one observation per boat), a strict assumption about the distribution of the inefficiency term is required. Resulting estimates of TECU will conform to the imposed distribution, and it is not possible to statistically distinguish between the nested distributions (i.e. half-normal and truncated normal). Similarly, if an inefficiency model is imposed, the TECU measures will conform to the model. Statistical measures of the parameters in the inefficiency model are not reliable. Consequently, there is little benefit in imposing such a distribution onto the data, and it is preferable to use the standard distributions (i.e. half- or truncated normal).

Despite these concerns, Sharma and Leung (1999) developed their model using cross-sectional data only and imposed an inefficiency model onto the data. As would be expected, most of the parameters were non-significant, with only one variable defining the inefficiency distribution at the 5 percent level of significance.

When only aggregated time series data are available, the estimation encounters similar problems to that of only cross-sectional data. While TECU can be estimated for each year for the fleet as a whole, it is highly sensitive to underlying assumptions about the TECU distribution.

Output measures

Although the SPF approach can be used to estimate efficiency and capacity of a multispecies fisher or a multiple product technology, it is computationally complex to undertake. As a consequence, researchers often aggregate over different outputs to construct a composite output (e.g. cod plus haddock equal groundfish). The resulting capacity and capacity utilization estimates will, however, reflect the aggregated output, and may therefore yield inadequate estimates of capacity relative to individual species or products.

When data are limited, only aggregate output catch data may be available, which precludes consideration of relevant aggregation. Estimation of capacity and capacity utilization, however, may be influenced by changes in the catch composition, particularly if some species in the catch fluctuate substantially from year to year. These factors should be taken into consideration when reviewing the results of the analysis.

When data are available on a species basis, they need to be aggregated into a composite output measure. One method is to use the prices of the species as weights to estimate the total value of output. This approach is valid if it is reasonable to assume that fishers aim to maximize the value of their catch rather than the quantity.

The use of aggregate value of the multi-product firm as the output measure has implications for analysis. First, value is a factor of prices as well as quantity, so that price changes may affect the measurement of capacity utilization. A price index may be constructed to deflate the value series to remove general inflationary price changes and relative price changes between species, leaving only relevant “effective value” impacts such as quality changes. Details on the construction of such indexes are given in Coelli, Rao and Battese (1998). Further, if fishers may be assumed to be profit maximizers, changes in relative prices may result in changes in fishing strategy. As a result, the function is not truly a production function and the TECU scores may represent a combination of allocative as well as technical efficiency.

The potential biases introduced into the analysis by using value as the output measure are not likely to be large. Squires (1987) and Sharma and Leung (1999) note that fishers base their fishing strategies on expected prices, the level of technology and resource abundance. However, price expectations are not always accurate, fishing gear is not species selective (so the species mix is a function of seasonal abundance) and changing gear types is time consuming and generally needs to be done onshore before the trip rather than at sea. Hence, the ability of fishers to immediately respond to changes in relative prices is limited. Finally, the effects of changes in price on the level of outputs can be incorporated through the use of a stock index as an input in the model that is based on the value of the available resource (i.e. stock multiplied by price).

Software packages

Two packages are generally available for estimating stochastic production frontiers - FRONTIER 4.1 (Coelli, 1996a) and LIMDEP (Greene, 1995). Both packages use the MLE approach. A recent review of both packages is provided by Sena (1999).

FRONTIER 4.1 is a single purpose package specifically designed for the estimation of stochastic production frontiers and technical efficiency, while LIMDEP is a more general package designed for a range of non-standard (i.e. non-OLS) econometric estimation. An advantage of the former model (FRONTIER) is that estimates of efficiency are produced as a direct output from the package. The user is able to specify distributional assumptions for estimating the inefficiency term in a programme control file. In LIMDEP, the package estimates a one-sided distribution, but separation of the inefficiency term from the random error component requires additional programming.

Table C.1 – Distributional assumptions allowed by the software

Distribution	LIMDEP	FRONTIER
Time invariant firm specific inefficiency		
• Half-normal distribution	✓	✓
• Truncated normal distribution	✓	✓
• Exponential distribution	✓	✗
Time variant firm specific inefficiency		
• Half-normal distribution	✗	✓
• Truncated normal distribution	✗	✓
One step inefficiency model	✗	✓

Source: Sena (1999).

FRONTIER is able to accommodate a wider range of assumptions about the error distribution term than LIMDEP (Table C.1), although it is unable to model exponential distributions. Neither package can model gamma distributions. Only FRONTIER is able to estimate an inefficiency model as a one-step process. An inefficiency model can be estimated in a two-stage process using LIMDEP, although this may create biases, because distribution of the inefficiency estimates is pre-determined through underlying distributional assumptions.

In the literature, the most commonly used package for estimating stochastic production frontiers is FRONTIER 4.1. This is freely available over the Internet from the Centre for Efficiency and Productivity Analysis, University of New England, Australia (http://www.une.edu.au/econometrics/cepa.htm). User guides and examples also are provided when downloading the software.

Example of use: Nigerian artisanal fishery

The Nigerian data used in the peak-to-peak analysis also was used to estimate capacity utilization and capacity output from the stochastic production frontier approach. An advantage of the SPF approach is that more inputs can be incorporated into the analysis than in the peak-to-peak approach. In this case, both the number of canoes and average crew per canoe could be used in the production frontier estimation.

With such a limited data set, a number of assumptions were necessary. First, a simple Cobb-Douglas production function was assumed of the form $Q = \beta_0 Canoes^{\beta_1} Crew^{\beta_2}$ where Q is the actual total output, and the *β's* are parameters to be estimated. To estimate the model, the variables are logged to produce a linear version of the model (i.e. $\ln(Y) = \ln(\beta_0) + \beta_1 \ln(Canoes) + \beta_2 \ln(Crew)$, where *ln(x)* represents the natural log of the variable *x*). As there were no data representing capital utilization (e.g. hours or days fished), only estimates of technically efficient capacity utilization (TECU) are possible, and resulting estimates of capacity may be overestimated (as CU $\geq$ TECU from (15)).

As the data were aggregated, there was only one observation a year. An assumption was made that capacity utilization would vary over time, so a time-variant measure was required. In estimating the capacity utilization in each period, an assumption also had to be made about the distribution of the measures. Both the half-normal and the truncated normal were tested.

The models were estimated using FRONTIER 4.1. The results of the maximum likelihood estimation are given in Table C.2.

Table C.2 – Results from Maximum Likelihood Estimation

	Half-normal		Truncated normal	
	Coefficient	t-value	Coefficient	t-value
beta 0	-8.74	-1.96	-7.51	-7.53
beta 1	1.77	5.08	1.68	11.14
beta 2	0.52	1.44	0.35	0.36
sigma-squared	0.20	0.68	0.03	1.31
Gamma (γ)	0.89	5.17	0.07	0.09
Mu (μ)	restricted to be zero		0.10	3.66
Eta (η)	-0.53	-1.35	-0.27	-0.51
log likelihood function	8.55		7.03	
LR test of the one-sided error	4.86 (2 restrictions)		1.82 (3 restrictions)	

From Table C.2, the values beta 0, beta 1 and beta 2 refer to the coefficients of the production function outlined above. The value of gamma (γ) indicates the proportion of variation in the model that is due to capacity utilization. Since this value is relatively high in the half normal distribution model (0.88), it suggests that much of the variation not due directly to changes in the level of fixed inputs is due to changes in capacity utilization. In contrast, the value of γ in the truncated-normal model is low (0.07) and not significantly different from zero, suggesting that very little variation in output between years is due to differences in capacity utilization.

A series of tests can be conducted to test the specification of the models. These are tested through imposing restrictions on the model and using the generalized likelihood ratio statistic (λ) to determine the significance of the restriction. The generalized likelihood ratio statistic (also known as the LR test) is given by:

$$\lambda = -2\left[\ln\{L(H_0)\} - \ln\{L(H_1)\}\right] \tag{17}$$

where $\ln\{L(H_o)\}$ and $\ln\{L(H_1)\}$ are the values of the log-likelihood function under the null (H_o) and alternative (H_1) hypotheses. The restrictions form the basis of the null hypothesis, with the unrestricted model being the alternative hypothesis. The value of λ has a χ^2 distribution with the degrees of freedom given by the number of restrictions imposed.

A major test used to determine the existence of a frontier (i.e. H_o: $\gamma=0$) is the one-sided generalized likelihood ratio test of Coelli (1995). Since the alternative hypothesis is that $0 < \gamma < 1$, the test has an asymptotic distribution, the critical values of which are given by Kodde and Palm (1986). If the hypothesis is accepted, there is no evidence of underutilization of capacity in the data and the production frontier is identical to a standard production function.

FRONTIER 4.1 produces the results from the one-sided generalized likelihood ratio-test automatically. From the model results, the values of the LR test can be seen to be 4.86 and 1.82 for the half normal and the truncated normal models respectively. These can be compared with the critical value table published in Kodde and Palm (1986) for two restrictions and three restrictions (representing the ‘degrees of freedom’ in the model) respectively. Standard statistical practice is to compare the results at the five percent level of significance, which allows for less than a five percent probability that the results are spurious (i.e. a 95 percent probability that the relationship is valid). The critical value at the five percent level of significance is 5 138 with two degrees of freedom and 7 045 for three degrees of freedom.

In this case, both models do not satisfy the requirements of the test (because the values are less than the critical values), which suggests that in both cases estimates of capacity utilization may be spurious. However, the half-normal model satisfies the requirements at the ten percent level of significance (critical value of 3 808). This suggests that there is a ten percent probability that the results are spurious. While this is generally not considered sufficient to accept the results, for the purposes of this example the results will be assumed to be valid.

The models also can be compared using the LR test. The half-normal is a restricted form of the truncated normal with the restriction that *μ (mu) = 0*. The value of the generalized likelihood ratio statistic in this case is $\lambda = -2[8.55 - 7.03] = -3.04$. Since the value is negative (and hence will be less than the critical χ^2 value, which is always positive), we cannot reject the hypothesis that *Ho: μ = 0* and accept the model which assumes the half-normal distribution.

The estimated capacity utilization derived from the analysis, and consequently the estimated capacity output based on the results, are given in Table C.3. The gradual decline in capacity utilization is partly an artefact of estimating the time variant model, which only allows for a constant rate of change over time. From Table C.2, the value of eta (η) was negative, suggesting technological change had decreased efficiency over time. More likely, this decline represents a decline in stock size over the period examined.

Table C.3 – Capacity utilization and output estimated using SPF

Year	Production	Capacity Utilization	Capacity output
1976	327 561	1 000	327 571
1977	331 280	1 000	331 297
1978	336 138	1 000	336 167
1979	356 888	1.000	356 941
1980	274 158	1 000	274 226
1981	323 916	1 000	324 053
1982	377 683	0.999	377 954
1983	376 984	0.999	377 442
1984	246 784	0.998	247 292
1985	140 873	0.997	141 365
1986	160 169	0.994	161 118
1987	145 755	0.990	147 221
1988	185 181	0.983	188 347
1989	171 332	0.972	176 322
1990	170 459	0.953	178 948
1991	168 211	0.921	182 627
1992	184 407	0.870	211 902
1993	106 276	0.791	134 365
1994	124 117	0.674	184 164

A comparison of the estimates of capacity from the SPF and the Peak-to-Peak methods is illustrated in Figure C.2. For purposes of illustration, only the results from using canoes as the key input for the peak-to-peak analysis are presented. From this, it can be seen that both techniques produce estimates with fairly similar trends, and the estimates of capacity in the last few years (1989-94) of the data are fairly similar.

The analysis presented here demonstrates that the SPF technique can be used to provide estimates of capacity and capacity utilization with minimal data requirements. More detailed data at the boat level disaggregated over time (e.g. monthly data) would result in more detailed estimates of capacity and capacity utilization. Further, information on time fished (e.g. hours or days) would allow estimates of technical efficiency also to be made, enabling correction for the potential biases that may be introduced into the analysis.

The example analysis also excludes a measure of the biomass stock. Ideally, some stock abundance measure might be incorporated into the analysis so the effects of changes in stocks on potential output can be estimated, providing more reliable estimates of capacity utilization.

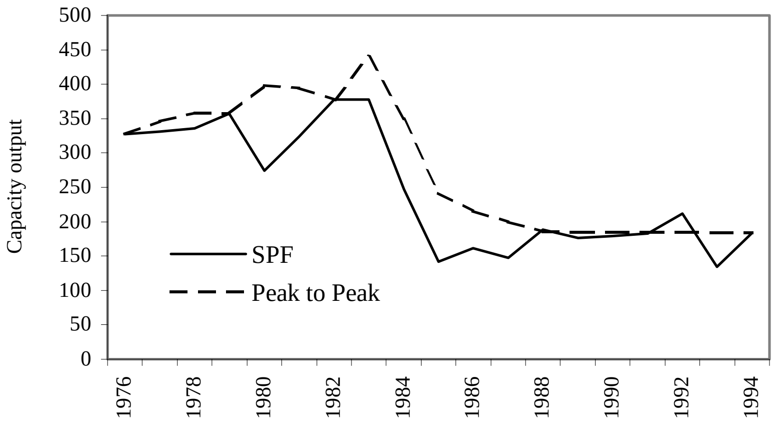

Figure C.2 – Comparison of SPF and peak-to-peak estimates of capacity output

APPENDIX D: DATA ENVELOPMENT ANALYSIS (DEA)

Data envelopment analysis or DEA is a linear programming technique developed in the work of Charnes, Cooper and Rhodes (1978). It is a non-parametric technique used in the estimation of production functions and has been used extensively to estimate measures of technical efficiency in a range of industries (Cooper, Seiford and Tone, 2000). Like the stochastic production frontiers, DEA estimates the maximum potential output for a given set of inputs, and has primarily been used in the estimation of efficiency. However, again like the SPF approach, DEA also can be used to estimate capacity utilization (Färe, Grosskopf and Lovell, 1994). The Färe, Grosskpof and Lovell approach, however, seeks to determine capacity output, conditional on the fixed input binding production. This is the weak concept of capacity output offered by Coelli, Grifell-Tatje and Perelman (2001). The strong concept includes the weak concept, while the weak concept does not include the strong concept of capacity output. In addition, the weak concept avoids problems caused by particular functional forms and decreasing returns to scale (e.g. the Cobb-Douglas production function, which does not have an absolute mathematical maximum).

Seiford and Thrall (1990) describe DEA in terms of floating a piece-wise linear surface to rest on top of the observations (i.e. envelop the data). More specifically, the key constructs of a DEA model are the envelopment surface and the efficient projection path to the envelopment surface (Charnes *et al.*, 1995). The projection path to the envelope surface is determined by whether the model is output-oriented or input-oriented. The choice of input- or output-oriented models depends upon the production process characterizing the firm (i.e. minimize the use of inputs to produce a given level of output or maximize the level of output given levels of the inputs). For the purpose of estimating capacity in fisheries, only the output-oriented DEA measures have been empirically estimated.

A key advantage of DEA over other approaches previously examined is that it more easily accommodates both multiple inputs and multiple outputs. As a result, it is particularly useful for analysis of multispecies fisheries, because prior aggregation of the outputs is not necessary. Further, as will be outlined below, a specific functional form for the production process does not need to be imposed on the model (as is required in the use of the SPF approach).

In fisheries, the technique has been applied to the Malaysian purse seine fishery (Kirkley *et al.*, 2003), United States Northwest Atlantic sea scallop fishery (Kirkley *et al.* 2001), Atlantic inshore groundfish fishery (Hsu, 2003), Pacific salmon fishery (Hsu, 2003), the Danish gillnet fleet (Vestergaard, Squires and Kirkley, 2003), English Channel multispecies multigear fisheries (Pascoe, Coglan and Mardle, 2000; Tingley, Pascoe and Mardle, 2003), the Scottish fleet (Tingley and Pascoe, 2003) and the total world capture fisheries (Hsu, 2003).

CRS and VRS frontiers

The envelopment surface will differ depending on the scale assumptions that underpin the model. Two scale assumptions are generally employed: constant returns to scale (CRS), and variable returns to scale (VRS). The latter encompasses both increasing and decreasing returns to scale. CRS reflects the fact that output will change by the same proportion as inputs are changed (e.g. a doubling of all inputs will double output); VRS reflects the fact that production technology may exhibit increasing, constant and decreasing returns to scale. As demonstrated in Section 2.6, input- and output-based capacity measures are only equivalent under the assumption of constant returns to scale. However, there are generally *a priori* reasons to assume that fishing would be subject to variable returns and, in particular, decreasing returns to scale (see Section 2.6). Cooper, Seiford and Tone (2000) provide a discussion of methods for determining returns to scale. In essence, the researcher examines the technical efficiency given different returns to scale, and determines whether or not the observed levels are along the frontier corresponding to a particular returns to scale.

The effect of the scale assumption on the measure of capacity utilization is demonstrated in Figure D.1. Four data points (A, B, C, and D) are used to estimate the efficient frontier and the level of capacity utilization under both scale assumptions. Note that only fixed inputs are considered in Figure D.1. The frontier defines the full capacity output given the level of fixed inputs. With constant returns to scale, the frontier is defined by point C for all points along the frontier, with all other points falling below the frontier (hence indicating capacity underutilization). With variable returns to scale, the frontier is defined by points A, C and D, and only point B lies below the frontier i.e. exhibits capacity underutilization. The capacity output corresponding to variable returns to scale is lower than the capacity output corresponding to constant returns to scale.

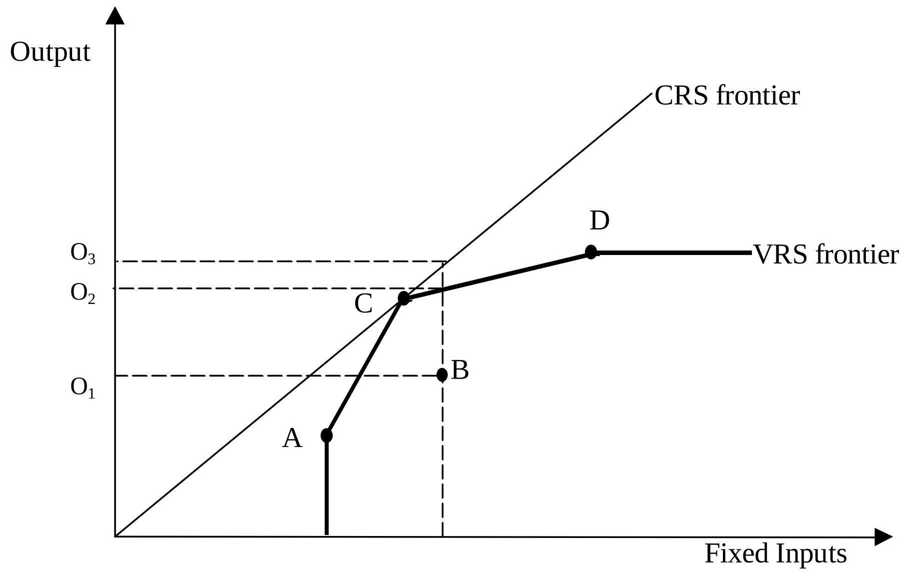

Figure D.1 – CRS and VRS frontiers

As with the SPF analysis, the measure of capacity utilization is estimated as the ratio of the actual output to the frontier level of output. With the exception of point C (which has a capacity utilization of 100 percent under both assumptions), the measure of capacity utilization is lower (i.e. more underutilization) for each point when assuming constant returns to scale than when assuming variable returns to scale. Even for point B, $O_1/O_3 < O_1/O_2$.

Hence, assuming a CRS frontier is likely to result in a greater estimate of capacity output and a lower estimate of capacity utilization than assuming a VRS frontier. As there are *a priori* reasons for assuming variable returns to scale in fisheries it is recommended that the latter be used, and the results treated as lower bounds for capacity output and upper bounds for capacity utilization.

Input and output orientations

A range of DEA models have been developed that measure efficiency and capacity in different ways. These largely fall into the categories of being either input-oriented or output-oriented models.

With input-oriented DEA, the linear programming model is configured so as to determine how much the input use of a firm could contract if used efficiently in order to achieve the same output level. For the measurement of capacity, the only variables used in the analysis are the fixed factors of production. As these cannot be reduced, the input-oriented DEA approach is less relevant in the estimation of capacity utilization. Modifications to the traditional input-oriented DEA model, however, could be done such that it would be possible to determine the reduction in the levels of the variable inputs conditional on fixed outputs and a desired output level.

In contrast, with output-oriented DEA, the linear programme is configured to determine a firm's potential output given its inputs if it operated efficiently as firms along the best practice frontier. This is more analogous to the SPF approach, which estimated the potential output for a given set of inputs and measured capacity utilization as the ratio of the actual to potential output, and is consistent with the illustration of the method in Figure D.1. Output-oriented models are "…very much in the spirit of neo-classical production functions defined as the maximum achievable output given input quantities" (Färe, Grosskopf and Lowell, 1994, p. 95).

Mathematical specification of the DEA approach

Technically speaking, DEA is an approach rather than a model. Unlike the SPF model where the parameter estimates represent the production elasticities, the resultant weights associated with the input variables have no economic interpretation.[51] They simply define the relative contribution of reference points on the frontier to the estimation of efficient or capacity output for the point under examination. As a result, it is a method for estimating efficiency and capacity utilization, but does not impart any useful information on the production processes involved in the fishery. Models can be developed, however, to assess allocative and scale efficiencies, congestion, and overall economic efficiency (Färe, Grosskopf and Kirkley, 2000). Linear programming (LP) models are developed to undertake the DEA, and for the purposes of simplicity, these can be referred to as DEA LP models.

An output-oriented approach is generally more appropriate for the estimation of capacity and capacity utilization. Following Färe, Grosskopf and Kokkelenberg (1989), and Färe, Grosskopf and Lowell (1994) the output-oriented DEA LP model of capacity output given current use of inputs is given as:

---

[51] Specific functional forms, however, can be estimated via DEA. For example, it is possible to specify a Cobb-Douglas specification or even a second-order translog specification and estimate the parameters by DEA (see, for example, Färe et al., (1993) and Charnes et al. (1994).

$$
\begin{aligned}
& Max\ \Phi_1 \\
& s.t \\
& \Phi_1 u_{j,m} \le \sum_j z_j u_{j,m} \quad \forall\ m \\
& \sum_j z_j x_{j,n} \le x_{j,n} \quad n \in \alpha \\
& \sum_j z_j x_{j,n} = \lambda_{j,n} x_{j,n} \quad n \in \hat{\alpha} \\
& \sum_j \ z_j = 1 \\
& \lambda_{j,n} \ge 0 \quad n \in \hat{\alpha}
\end{aligned}
\tag{1}
$$

where Φ_1 is a scalar showing by how much the production of each firm can increase output, $u_{j,m}$ is amount of output m by firm j, $x_{j,n}$ is amount of input n used by boat j and z_j are weighting factors. Inputs are divided into fixed factors, defined by the set α, and variable factors defined by the set $\hat{\alpha}$. To calculate the measure of capacity output, the bounds on the sub-vector of variable inputs, $x_{\hat{\alpha}}$, need to be relaxed. This is achieved by allowing these inputs to be unconstrained through introducing a measure of the input utilization rate ($\lambda_{j,n}$), itself estimated in the model for each boat j and variable input n (Färe, Grosskopf and Lovell, 1994). The restriction $\sum_j z_j = 1$ allows for variable returns to scale.[52]

Capacity output based on observed outputs (u^*) is defined as Φ_1 multiplied by observed output (u). Implicit in this value is the assumption that all inputs are used efficiently as well as at their optimal capacity. From this, technically efficient capacity utilization (TECU) based on observed output (u) is:

$$
TECU = \frac{u}{u^*} = \frac{u}{\Phi_1 u} = \frac{1}{\Phi_1} \quad . \tag{2}
$$

The measure of TECU ranges from zero to 1, with 1 being full capacity utilization (i.e. 100 percent of capacity). Values less than 1 indicate that the firm is operating at less than full capacity given the set of fixed inputs.

Implicit in the above is a downwards bias because observed outputs are not necessarily being produced efficiently (Färe, Grosskopf and Lovell, 1994). As with the SPF measure of capital utilization, an unbiased measure of capacity utilization is calculated as the ratio of technically efficient output to capacity output.

The technically efficient level of output requires an estimate of technical efficiency of each boat, and requires both variable and fixed inputs to be considered. The output orientated DEA model for technically efficient measure of output is given as:

[52] In contrast, excluding this constraint implicitly imposes constant returns to scale while $\Sigma z_j \le 1$ imposes non-increasing returns to scale (Färe, Grosskopf and Kokkelenberg, 1989).

$$
\begin{aligned}
&Max\ \Phi_2 \\
&s.t. \\
&\Phi_2 u_{j,m} \le \sum_j z_j u_{j,m} \quad \forall\ m \\
&\sum_j z_j x_{j,n} \le x_{j,n} \quad \forall\ n \\
&\sum_j z_j = 1
\end{aligned} \tag{3}
$$

where Φ_2 is a scalar outcome showing how much the production of each firm can increase by using inputs (both fixed and variable) in a technically efficient configuration. In this case, both variable and fixed inputs are constrained to their current level (i.e. the equality constraint on the output orientated model of capacity has been relaxed). Again, the restriction $\sum_j z_j = 1$ is imposed to allow for variable returns to scale.

In this case, Φ_2 represents the extent to which output can increase through using all inputs efficiently. From this, technical efficiency is estimated as:

$$TE = 1/\Phi_2 \quad . \tag{4}$$

The measure of technical efficiency ranges from one to infinity; Φ_2 - 1.0 is the proportion by which outputs may be expanded. Some existing software and articles, however, report the value of TE as one over Φ_2 (see for example, Coelli, Rao and Battese, 1998). Values of the ratio (Eq. 4) less than 1 indicate that, even if all current inputs (both variable and fixed) were used efficiently, output is less than potential output. That is, output could increase through efficiency gains, without changing the levels of the inputs.

The unbiased estimate of capacity utilization is consequently estimated by:

$$CU = \frac{TECU}{TE} = \frac{1}{\Phi_1} \Big/ \frac{1}{\Phi_2} = \frac{\Phi_2}{\Phi_1} \quad . \tag{5}$$

As $\Phi_1 \le 1$, the estimate of CU≥TECU. Dividing the level of output by the corrected measure of capacity utilization produces lower but unbiased estimates of capacity output.

Categorical variables

A key factor affecting the level of fishery production is the size of the stock. This is effectively an exogenous variable (also known as non-discretionary variable) as it is beyond the control of the fishers to modify their use of the stock input, other than through exploiting it harder by spending more days fished. Where information on stock is available, such as an index of stock abundance, then this can be directly incorporated into the analysis and treated the same as other fixed inputs.

A difficulty arises, however, when stock information is not available. In such a case, the analysts have two options. The first option is to ignore stock changes between time periods, as was the case in the Nigerian example using the peak-to-peak and SPF approaches. In such a case, the measure of capacity and capital utilization may be distorted, as actual output may be low due to low stock abundance rather than due to under-utilization of capacity. Where only a time series of aggregate data is available, then this may be the only option.

Where a time series of cross sectional data are available (i.e. data on individual vessels with several observations per vessel over time, also known as panel data), then it is more appropriate to treat stock (and time) as a categorical variable. Boats operating in the same time period will be subject to the same stock conditions. As a result, a direct comparison of these boats is possible. Conversely, it is not possible to compare boats across periods, as the output will be affected also by different stock conditions. In such a case, the measure of capacity in periods of low abundance will be over-estimated. In treating stock (and time) as a categorical variable, only boats that operate under the same conditions are compared. This requires undertaking several analyses, one for each time period (i.e. each period is treated as a separate category). Measures of capacity output are more reliable relative to the implicit stock abundance in that period. These measures can be consistently aggregated over time if necessary, e.g. monthly estimates of capacity can be aggregated to provide annual estimates of capacity.

Effects of random variations on estimates of capacity and capacity utilization

A shortcoming of the DEA approach is that the results may be unduly influenced by random events. Fisheries are often considered to be highly stochastic (i.e. subject to random fluctuations) because of the susceptibility to environmental fluctuations. Further, as the fishery resource is unseen and must effectively be found before it can be harvested, some fishers may be 'lucky' and find a large school of fish while others may by 'unlucky' and find few if any fish. The SPF approach filters out these random fluctuations to a large extent when estimating capacity utilization; at the same time and like all regression procedures, outliers and the central tendency of the data influence the SPF parameter estimates. Without proper examination of the data prior to estimation, estimates derived from the SPF or any regression procedure may based on a limited number of observations (e.g. the case in which it is determined that the SPF is the appropriate specification with all the data, but the SPF is rejected when one observation (outlier) is omitted).

The effects of these random fluctuations on the estimates of capacity and capacity utilization using the DEA approach are illustrated in Figure D.2. The frontier depicted in Figure D.2 is essentially the same as illustrated in Figure D.1, with the exception that an additional point E has been added. Under normal circumstances (i.e. normal operating conditions), the firm at point E would produce an output at point E*. However, due to some random event, it managed to produce at point E. The effect of this is to shift the frontier to a higher level, changing the estimated capacity and capacity utilization measures for those points not on the frontier. For example, the capacity output for firm B on the 'new' frontier is greater than the 'true' frontier, and the level of capacity utilization would therefore be lower. Similarly, firm D, which is on the original frontier (i.e. 100 percent capacity utilization), is now considered to be under-utilizing its capacity.

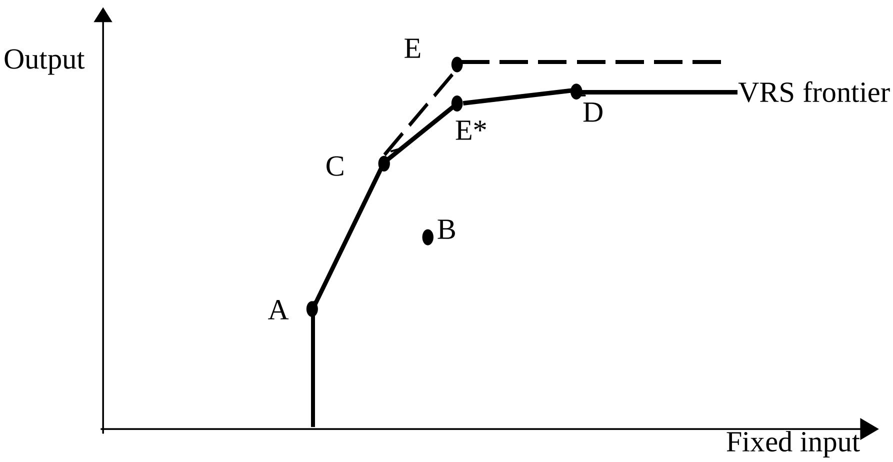

Figure D.2 – Effects of random variation on capacity utilization

Empirical testing of the DEA methodology using artificial data sets has shown that the distortion in capacity estimates is proportional to the degree of random variation in the data. However, the unbiased estimate of capacity utilization (given in (5) earlier) is not greatly affected by the amount of variation, as the estimated value of Φ_1 and Φ_2 are both (almost) equally affected, and thus the ratio of the two measures is not substantially distorted (Holland and Lee, 2002). Hence, a reliable estimate of capacity output can be derived by using the actual catch data and the unbiased estimate of capacity utilization.

Software

DEA can be undertaken using any linear programming package, including fairly basic packages such as the optimization facilities generally found in spreadsheet packages. However, as the analysis has to be repeated for each observation, using simple linear programming algorithms may be time consuming, particularly if a large number of data points are available. Mathematical programming packages such as GAMS (General Algebraic Modelling System, Brooke, Kendrick and Meerhaus, 1992) have the advantage that loops can be written into the model to repeat the analysis for every observation. However, this requires understanding of the modelling language.

A range of software has been developed specifically to undertake DEA analysis. These are generally user-friendly packages that make estimating efficiency and capacity utilization relatively straightforward. These include DEA-Solver (Cooper, Seiford and Tone, 2000), which is an add-on to Microsoft Excel, On-front (Färe and Grosskopf, 1999) and DEAP (Coelli, 1996b). The latter package is freely available over the Internet (http://www.une.edu.au/econometrics/cepa.htm) from the Centre for Efficiency and Productivity Analysis, University of New England, Australia. User guides and examples are also provided when downloading the software. Information on On-Front is also available over the internet (http://www.emq.com) from Economic Measurement and Quality.

Example of use: Nigerian artisanal fishery

The Nigerian data used in the peak-to-peak and SPF analysis were also used to estimate capacity utilization and capacity output using the DEA approach. As with the SPF analysis, both the number of canoes and average crew per canoe were used as inputs in the analysis, with one aggregated output measure.

The analysis was undertaken using the DEAP programme (Coelli, 1996b). For the purpose of the estimation of capacity utilization, each observation was assumed to occur in the same time period. As time is a categorical variable, a separate analysis of one observation in each time period would result in every observation being at full capacity (as there are no other observations against which the output can be compared). This differs from the SPF analysis, where the time element could be directly factored into the analysis.[53] As with the other two analyses (i.e. SPF and peak-to-peak), the absence of stock information results in the implicit assumption that stock has not changed, and that any change in catch rate is attributable to changes in capacity utilization.

Estimates of capacity utilization were obtained assuming both constant and variable returns to scale (Table D.1). As would be expected, the CRS analysis resulted in lower estimates of capacity utilization and greater estimates of capacity output than the VRS analysis. Further, when variable returns to scale were assumed, most years were found to reflect “operation at full capacity”.

The results of the three analyses are compared in Figure D.3. Only the VRS results are presented for the DEA analysis. From this, it can be seen that the SPF and DEA results are identical for all but the last 6 years of the data. The DEA estimates of capacity were also generally the most conservative over the period examined. In contrast, the peak-to-peak estimates of capacity were substantially greater than the other two methods over the period 1977 to 1987. This is largely an artefact of the peak in 1982, which resulted in a relatively high apparent rate of technological progress being imposed on the estimates over the period 1977 to 1982. While subsequent “technological change” was negative (most likely reflecting a decline in the stocks) the capacity catch rate did not converge with the actual catch rate until the next peak in 1988. Hence, unusually high catch rates can have longer lasting effects when using peak-to-peak analysis than with the other two techniques.

[53]Using a windows technique, which is based on the use of moving averages, different time periods can be included in the analysis (Charnes et al., 1995).

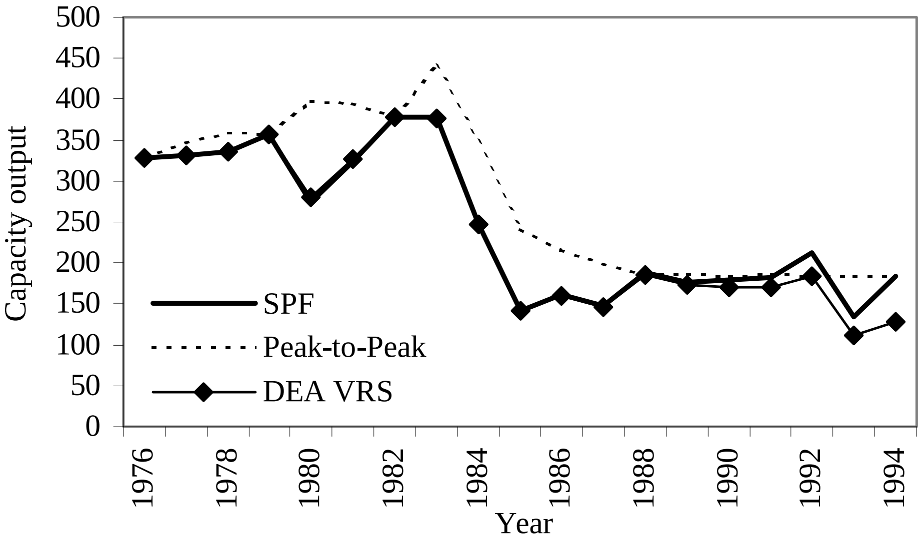

Figure D.3 – Comparison of capacity measures: peak-to-peak, SPF and DEA

Table D.1 – Capacity utilization and output, Nigerian artisanal fishery

Year	Production	Capacity utilization		Capacity output	
		CRS	VRS	CRS	VRS
1976	327 561	1	1	327 561	327 561
1977	331 280	0.999	0.999	331 612	331 612
1978	336 138	1	1	336 138	336 138
1979	356 888	0.998	1	357 603	356 888
1980	274 158	0.974	0.978	281 476	280 325
1981	323 916	0.987	0.989	328 182	327 519
1982	377 683	1	1	377 683	377 683
1983	376 984	0.994	1	379 260	376 984
1984	246 784	0.991	1	249 025	246 784
1985	140 873	0.948	1	148 600	140 873
P986	160 169	0.959	1	167 017	160 169
1987	145 755	0.952	1	153 104	145 755
1988	185 181	0.971	1	190 712	185 181
1989	171 332	0.964	0.993	177 730	172 540
1990	170 459	0.964	1	176 825	170 459
1991	168 211	0.963	0.992	174 674	169 568
1992	184 407	0.97	1	190 110	184 407
1993	106 276	0.926	0.957	114 769	111 951
1994	124 117	0.939	0.967	132 180	128 353

Example of use: multispecies fisheries in the English Channel

This example is drawn from Pascoe, Coglan and Mardle (2001). The study examined two fleet segments in the English Channel – an otter trawl fleet and a static gear fleet that used a combination of both gillnets and long lines. Both fleet segments targeted the same set of species, but their catch composition varied as a result of the different gear types. The example illustrates how capacity of two different fleet segments can be estimated and the results combined to produce an overall estimate of capacity output in a heterogeneous fishery.

A multi-output DEA analysis was undertaken with the catch of the main target species (cod, cuttlefish, hake, ling, monk, plaice, sole and whiting) included as separate outputs in the analysis. In addition, all other species were aggregated into an "other" category. While the target species formed the minority of the catch by weight, they generally formed a significant part of the value of the total catch. Further, most of the target species are subject to quota control and are of main interest to fisheries managers (e.g. cod, hake, monk, plaice, sole and whiting).

The key inputs used in the analysis were days fished, length and breadth of boat and engine power (kW) (Table D.2). Fixed inputs included length, breadth and engine power, and were assumed to represent the capital input into the fishery. Variable inputs only included days fished. While data on labour employed were available, these were only available on an annual basis. Hence, they would have effectively formed part of the fixed factors of production. They were excluded from the analysis as, in practice, labour is a variable input. Data on catch and days fished were available on a monthly basis over a 12 month period (1995).

Inputs were relatively similar between otter trawlers and netter-liners. Netter-liners fished, on average, approximately two days less a month than otter trawlers. Otter trawlers tended to have, on average, physically bigger boats (in terms of length times breath), although netter-liner boats had on average larger engines. There is no *a priori* reason why this would be the case.

Table D.2 – Key inputs for otter trawlers and netter-liners

	Variable	Fixed		
	Days fished	Length	Width	Kw
Otter Trawlers				
• Average	14.0	13.27	4.66	157.7
• Maximum	34	23.16	6.34	373
• Minimum	1	10.33	3.62	28
Netter-liners				
• Average	11.9	12.29	4.34	171.2
• Maximum	31	23.82	5.79	442
• Minimum	1	10.4	3.5	55

Catch composition changes over the year due to different patterns of seasonal abundance. However, information on the stock conditions in each month was not available, so a stock variable could not be included in the analysis. To allow for variations in availability, the DEA model was run categorically. That is, the model was run separately for each month, so that only boats that fished in the same month would be compared. It was assumed that stock abundance was relatively constant over the month so that the timing of fishing did not affect the catch composition. Spatial variations in catch composition were also not considered. The analysis is limited to one area of the Channel (the western half) and it is assumed that species abundance did not vary substantially across this area.

The model was also run separately for the two fleet segments such that otter trawlers were not directly compared to netter-liners. A combined analysis would have required the assumption of a common production process, which clearly is not realistic. Capacity output was estimated at the individual vessel level (based on the observed catch and the estimated capacity utilization and technical efficiency measures) and aggregated to the fleet level. From this, aggregate measures of capacity utilization can be derived from the aggregated actual and capacity output estimates.

From the model output, capacity utilization (CU) varied considerably by species and between the two fleet segments examined (Table D.3). For most species, the otter trawlers were operating at less than 90 percent capacity (e.g. cod, hake and ling) and for some species less than 80 percent capacity (e.g. cuttlefish, plaice and whiting). However, much of this underutilization of capacity arose out of using the inputs inefficiently rather than not using enough variable inputs. If the inputs had been used efficiently, then the unbiased capacity utilization for the target species would have been greater than 90 percent. In contrast, the netter-liner fleet segment was generally operating at above 90 percent capacity, and if inputs were used efficiently, would be operating at almost 100 percent capacity for most of the target species.

Table D.3 – Estimated capacity output (tonnes) and capacity utilization by species

	Observed output a	TE Capacity output b	TE output c	CU $1/\theta_1$ a/b	Unbiased CU θ_2/θ_1 c/b	Unbiased capacity output a/(c/b)
Otter trawlers						
Cod	89.5	108.3	98.2	0.83	0.91	98.4
Cuttlefish	472.2	649.6	596.4	0.73	0.92	513.3
Hake	15.1	17.5	16.0	0.86	0.91	16.6
Ling	33.8	38.1	35.7	0.89	0.94	36.0
Monk	218.4	260.1	237.3	0.84	0.91	240.0
Plaice	121.7	158.0	144.6	0.77	0.91	133.7
Sole	15.2	18.6	17.1	0.82	0.92	16.5
Whiting	650.6	822.0	757.0	0.79	0.92	707.2
Other	2 449.4	3 550.4	3 038.5	0.70	0.86	2 906.3
Netter-liners						
Cod	38.0	41.2	40.4	0.92	0.98	38.8
Cuttlefish	25.3	26.7	25.7	0.95	0.96	26.4
Hake	3.8	3.9	3.8	0.98	0.99	3.8
Ling	84.6	88.2	86.9	0.96	0.99	85.5
Monk	57.5	59.3	58.8	0.97	0.99	58.1
Plaice	8.5	9.2	8.8	0.92	0.96	8.9
Sole	3.4	3.5	3.4	0.98	0.99	3.4
Whiting	59.3	66.1	63.0	0.90	0.95	62.4
Other	786.7	894.2	856.4	0.88	0.96	819.5

While the fleets are significantly different in their operations, the capacity output from the two fleets can be aggregated at the species level (as the species is a homogenous output). The combined capacity output and derived capacity utilization for the two fleet segments is presented in Table D.4 From this, overall unbiased capacity utilization averages out at between 88 percent for the ‘other’ species, and between 92 and 97 percent for the key species examined.

The purpose in this example was to demonstrate how aggregate measures of capacity can be derived for individual species that are exploited by more than one fleet segment and in different combinations with other species. Further, the capacity measures can be aggregated over several fisheries provided each fishery is estimated separately. The resultant set of information can be compared to overall target capacity measures for the species. Further, the fleet level information provides guidance as to which fleet segments exploiting the fishery may be in most need of capacity management measures.

Table D.4 – Combined capacity output (tonnes) and capacity utilization by species

	Observed output	TE Capacity output	TE output	CU $1/\theta_1$	Unbiased CU θ_2/θ_1	Unbiased capacity output
Cod	127.5	149.5	138.6	0.85	0.93	137.1
Cuttlefish	497.5	676.3	622.1	0.74	0.92	539.6
Hake	18.9	21.4	19.8	0.88	0.93	20.4
Ling	118.4	126.3	122.6	0.94	0.97	121.4
Monk	275.9	319.4	296.1	0.86	0.93	298.1
Plaice	130.2	167.2	153.4	0.78	0.92	142.6
Sole	18.6	22.1	20.5	0.84	0.93	20.0
Whiting	709.9	888.1	820	0.80	0.92	769.6
Other	3 286.1	4 444.6	3 894.9	0.74	0.88	3 725.8

APPENDIX E: ESTIMATION OF TARGET AND LONG-RUN OVERCAPACITY: AN EXAMPLE FROM THE ENGLISH CHANNEL FISHERIES

Estimating overcapacity in fisheries requires an estimate of the potential sustainable level of output that might be possible in the long run, given that stocks have adjusted to changes in the fishing fleet. With multispecies fisheries, the long-run desired output level of each species may differ from the maximum sustainable yield, or maximum economic yield if considered in isolation, as this will also depend on the “optimal” fleet structure that harvests the resource. To assess these optimal fleets and yields, a bio-economic model of the fishery is required that takes into account stock dynamics as well as costs and revenues associated with undertaking different fishing activities.

The definition of “optimal” also depends upon management objectives. An optimal fleet size under an objective of profit maximization will be substantially smaller than one in which employment is considered the key objective. Similarly, the optimal sustainable yields under both scenarios would differ. More often is the case; however, that management must balance several, often conflicting, objectives. Multi-objective bio-economic models therefore play a significant role in assessing the level of overcapacity in species when several management objectives exist. A multi-objective bio-economic model was used to determine the “optimal” fleet configuration and size for key fleet segments operating in the fisheries of the English Channel.

Multispecies, multigear fishery

The English Channel hosts a broad variety of fishing activities aimed at targeting a number of species. Approximately 4,000 boats operate within the English Channel [WHEN?], comprised roughly of 50 percent United Kingdom boats, 45 percent French boats and five percent from other countries (most of these from Belgium). The fleet uses one (or more) of seven gear types: beam trawl, otter trawl, pelagic/mid-water trawl, dredge, line, nets and pots. In total, 92 species are landed by boats operating in the English Channel. However, approximately 30 species make up the majority of landed weight and value.

The English Channel fleet is comprised primarily of small vessels. Over two-thirds of the fleet are less than ten metres in length, and about half of these are less than seven metres. A large proportion of the under seven metres vessels operates essentially on a part-time basis, generally fishing for less than half of the number of expected full-time days.

The boats are, for the most part multi-purpose; they operate with different gears over the year, and in some cases, use different gears in the same month. Fishing activity has been classified into a number of métiers based on gear used and area fished, which can vary within the same month.[54]

The bio-economic model

The model, described in Pascoe and Mardle (2001), includes both French and United Kingdom fleets operating in the Channel and takes into account the fishing activity of other

[54] This classification was undertaken using cluster analysis to identify different activities within a given gear type.

EU Member States (which, combined, contribute around five percent of the fishing activity). All commercial species caught in the Channel are included in the model, and for some species (e.g. crustaceans) several identified stocks have been included. The model includes a combination of age-structured biological models, as well as surplus production models for some species. That is, all outcomes are sustainable in the long run (both biologically and economically). The model also was specified as an "optimization" model, because it produces the best outcomes given the objectives provided. The output of the model is: the sustainable catch of each species, the fleet size and structure that produces that catch and relevant socio-economic measures of performance, given the fleet structure and catch (e.g. profits, employment).

While estimating the optimal sustainable yield of each species, the model solution is primarily input-based rather than output-based. Fishing activity in the model was modified such that each vessel in the model solution was operating at full capacity utilization (expressed in terms of days fished). The resulting fleet size and structure thereby represented that which was required to harvest the "optimal" yield operating at full capacity. Because the benchmark is the existing fleet size and structure, input-based measures of overcapacity[55] are derived rather than output-based measures.

The model solution was based on key management objectives in place in the fishery. Conservation objectives are over-riding, and all solutions are sustainable in the long run. The economic objectives were specified as maximizing profits in the fishery, with each country having a separate profit target, based on its own potential maximum profit. (See Pascoe and Mardle, 2001.) Employment objectives were also included by setting target employment levels based on their current levels in the fishery. Finally, the EU principle of relative stability was imposed so that each country could not incur a greater proportion of benefit (or loss) than the other. Multiple objectives were incorporated into the model through specification of an "achievement function". Deviations away from the targets for each objective can then be minimized using a technique known as goal programming.

Multi-objective optimization

The model was run with the dual objectives of both increasing economic profits and maintaining employment. The economic profit objectives were taken as the maximum economic profits that could be achieved in each country. (See Pascoe and Mardle, 2001.) The employment objectives were taken as the current level of employment in each country. The additional objective – that each country can only incur the same proportion of the potential social cost – was also imposed to ensure that relative stability was maintained.

Essential to the achievement function was the definition of the weights associated with each goal. Different weights are likely to result in different optimal solutions. Because deviations from all goals are undesired, one appropriate method is to set all weights to unity since there is no need to differentiate their importance (Ignizio and Cavalier, 1994).

A number of different weights were applied in the model. The model was run with equal weights applied to both profit and employment goals. The model was also run with a lower

[55] More correctly, the measures indicate the degree of overcapitalization, which are considered an input-based measure of overcapacity.

weight on economic profits and with a lower weight on employment. A common weight was used for both countries with each objective. This ensured that neither country was given preference relative to the other.

Table E.1 – Multi-objective optimization results

	Current situation		Different weights on objectives					
			$w_{profit} = 0.5$; $w_{employment} = 1$; $w^s_{equity} = 1$		$w_{profit} = 1$; $w_{employment} = 1$; $w^s_{equity} = 1$		$w_{profit} = 1$; $w_{employment} = 0.5$; $w^s_{equity} = 1$	
	UK	France	UK	France	UK	France	UK	France
Boat numbers								
• otter trawl	129	207	64	173	40	134		98
• beam trawl	92	86	74	65	65	63	92	56
• dredge	18	253	18	253	18	253	18	253
• trawl/ dredge		300		295		255		127
• pots	65	159	65	157	65	141	65	132
• nets		172		168		108		62
• lines		51		43		43		39
• net/line	137		122		122		122	
• whelk pots		44		42		38		25
• seaweed		59		59		59		56
• fixed gear		216		194		194		172
• misc.		127		126		119		79
• inshore mixed	1 613		1 613		1 250		832	
Revenue (€m)								
• Channel fleet[a]	155.8	257.6	132.2	246.9	122.8	219.0	139.0	172.2
• External fleet	11.0	17.3	11.2	21.0	11.3	25.2	11.5	29.1
Profits[b] (€m)	-6.1	31.7	0.0	42.3	8.8	51.1	17.6	51.8
Capital[b] (€m)	195.5	319.2	149.1	260.4	113.9	182.1	114.3	102.1
Employment[b]	4 343	4 840	3 978	4 433	3 216	3 584	2 198	2 450

a) Includes revenue from English Channel fleet generated outside the Channel. b) Channel fleet only.

As would be expected, the optimal fleet configuration depends on the relative weights given to the profit and employment objectives (Table E.1). An optimal fleet with a higher weight on employment was characterized by a large number of smaller boats, particularly in the United Kingdom. Conversely, increased weight on economic profits results in the total capital (and employment) in the fishery decreasing. Comparing the current situation with the case in which employment was given greater weight than profits (i.e. $w_{profit}=0.5$, $w_{employment}=1$), economic profits could be increased by 65 percent, with only an eight percent reduction in employment.

Extent of overcapacity

As noted previously, the extent of any overcapacity in the fishery will depend on the actual objective of fisheries management. From the above analysis, several different fleet configurations were identified based on different levels of importance assigned to each objective. Potentially, an infinite number of "optimal" fleets can be identified, but only one will be truly optimal.

The percentage of overcapacity can be estimated by dividing the current fleet number by the "optimal" fleet (Table E.2). From this, it can be seen that the estimate of overcapacity varies substantially based on the objectives of management. For example, if maximizing employment was the main objective, there is no overcapacity in the inshore fleet, but if maximizing profit was a main objective, there was considerable overcapacity in this sector.

Table E.2 – Extent of overcapacity in the UK fleet segments of the Channel fishery (%)

Fleet segment	*Weights given to each objective*		
	$w_{profit} = 0.5$; $w_{employment} = 1$; $w^{s}_{equity} = 1$	$w_{profit} = 1$; $w_{employment} = 1$; $w^{s}_{equity} = 1$	$w_{profit} = 1$; $w_{employment} = 0.5$; $w^{s}_{equity} = 1$
otter trawl	102%	223%	inf
beam trawl	24%	42%	0%
dredge	0%	0%	0%
pots	0%	0%	0%
net/line	12%	12%	12%
inshore mixed	0%	29%	94%

Usefulness of the results

The use of bio-economic models to assess the extent of overcapacity needs to be undertaken with some caution. Most optimization models are sensitive to the data provided, and a small change in the main parameters may result in a different optimal solution. For example, if the price of the fish species targeted by the otter trawlers increased, then the optimal number of vessels in this segment may also increase. Similarly, if fuel prices decreased, the optimal number of all mobile gear boats (otter and beam trawlers and dredges) could increase. Because prices and costs are likely to change in the future, the results of the models should not be seen as prescriptive, but rather, indicative of problem areas within a fishery.

Many biological parameters in the model are also subject to uncertainty. This again would affect the optimal fleet size and structure if errors were introduced into the model through inaccurate biological parameters. The robustness of the results to uncertainty in biological and economic parameters can be examined through either sensitivity analysis or stochastic simulation. Such techniques were not presented in this paper in order to keep the analysis fairly simple, but a stochastic analysis of the model results was presented in Pascoe and Mardle (2001).

With these limitations in mind, the development and use of bio-economic models can provide useful information to managers on the extent of overcapacity by fleet segment in a multispecies, multigear fishery.

APPENDIX F: POSSIBLE REPORTING FRAMEWORK

General information

Table F.1 – General description of the fisheries reported, current year

Fishery	Gross value of production	Number of vessels	Employment	Main gear types	Key species
X					
Y					
Z					
Total country					

Fishery level information

Input-based measures

Table F.2 – Input capacity indicators, fishery X

Fleet segment	Total tonnage (GRT)	Total Engine Power (kW)	Total standardized days fished (kW days)	Potential standardized days fished (kW days)	Latent effort (standardized days fished - kW days)	Capital utilization (%)
	a	b	c	d	d-c	c/d*100
A						
B						
C						
D						
Total fishery						

Table F.3 –Trends in input capacity over the last 5 years, fishery X

Fleet segment	Total tonnage (GRT)	Total Engine Power (kW)	Total standardized days fished (kW days)	Potential standardized days fished (kW days)	Latent effort (standardized days fished - kW days)	Capital utilization (%)
	a	b	c	d	d-c	c/d*100
Current – 4						
Current – 3						
Current – 2						
Current – 1						
Current year						

Table F.4 – Indicators of input-based overcapacity (MSY)

Fleet segment	Target tonnage (GRT)	Relative capacity (%)	Target Engine Power (kW)	Relative capacity (%)	Target standardized days fished (kW days)	Relative capacity (%)
	e	a/e*100	f	b/f*100	g	d/g*100
A						
B						
C						
D						
Total fishery						

Table F.5 – Indicators of input-based overcapacity (ASY)

Fleet segment	Target tonnage (GRT)	Relative capacity (%)	Target Engine Power (kW)	Relative capacity (%)	Target standardized days fished (kW days)	Relative capacity (%)
	e	a/e*100	f	b/f*100	g	d/g*100
A						
B						
C						
D						
Total fishery						

Output-based measures

Table F.6 – Current output (tonnes), current year, fishery X

Fleet segment	Species				
	1	2	3	4	…
A					
B					
C					
D					
Total fishery					

Table F.7 – Capacity output (tonnes), current year, fishery X

Fleet segment	Species				
	1	2	3	4	…
A					
B					
C					
D					
Total fishery					

Table F.8 – Capacity utilization (%), current year, fishery X

Fleet segment	Species				
	1	2	3	4	…
A					
B					
C					
D					
Total fishery					

Table F.9 – Relative capacity for fishery X

Species	Total capacity	Target capacity: Catch at		Relative capacity given	
		E_{MSY}	E_{ASY}/TAC	E_{MSY} (%)	E_{ASY}/TAC (%)
1					
2					
3					
4					
…..					

Note: target catch based on current stock and target input level. Where TACs exist, these may represent the target catch at E_{ASY}.

Table F.10 – Trends in capacity utilization and relative capacity over last 5 years, fishery X, species 1

Year	Total catch	Capacity output	Capacity utilization	Relative capacity at	
			(%)	E_{MSY} (%)	E_{ASY}/TAC (%)
Current year – 4					
Current year – 3					
Current year – 2					
Current year – 1					
Current year					

National level information

Input-based measures

Table F.11 – Input capacity indicators

Fishery	Total tonnage (GRT)	Total Engine Power (kW)	Total standardized days fished (kW days)	Potential standardized days fished (kW days)	Latent effort (standardized days fished - kW days)	Capacity utilization (%)
	a	b	c	d	d-c	c/d*100
X						
Y						
Z						
Total country						

Table F.12 – Indicators of input-based overcapacity (MSY)

Fishery	Target tonnage (GRT)	Relative capacity (%)	Target Engine Power (kW)	Relative capacity (%)	Target standardized days fished (kW days)	Relative capacity (%)
	e	a/e*100	f	b/f*100	g	d/g*100
X						
Y						
Z						
Total country						

Table F.13 – Indicators of input-based overcapacity (ASY)

Fishery	Target tonnage (GRT)	Relative capacity (%)	Target Engine Power (kW)	Relative capacity (%)	Target standardized days fished (kW days)	Relative capacity (%)
	e	a/e*100	f	b/f*100	g	d/g*100
X						
Y						
Z						
Total country						

Output-based measures

Table F.14 – Aggregate species output capacity utilization

Species	Total catch	Capacity output	Capacity utilization	Relative capacity at	
			(%)	E_{MSY} (%)	E_{ASY}/TAC (%)
1					
2					
3					
4					
….					

Table F.15 – Aggregated output capacity measures

Fishery	Current output	Capacity output	Capacity utilization	Target capacity at (US$)		Relative capacity (%)	
	(US$)	(USS)	(%)	E_{MSY}	E_{ASY}/TAC	E_{MSY}	E_{ASY}/TAC
X							
Y							
Z							
Total country							

Table F.16 – Summary of national capacity measures

Measure	Current capacity	Capacity utilization	Target capacity at		Relative capacity (%)	
		(%)	E_{MSY}	E_{ASY}/TAC	E_{MSY}	E_{ASY}/TAC
Output (US$)						
Input measures						
• Tonnage		n.a.				
• Engine power		n.a.				
• kW Days						

n.a. = not applicable

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