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Fisheries Multiple Criteria Decision Making Under Uncertainty

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ABSTRACT

Fisheries management decisions in commercial marine fisheries are carried out on an extremely complex biological, economic and social system. However, fisheries decision making is most often focused on reactionary policy-making in response to crises. Accordingly, there is a recognized need in fisheries management to develop decision alternatives that may be evaluated in terms of the multiple impacts on the various components of the fishery. The development and evaluation of decision alternatives takes place in a problem solving context. As in any appropriately defined problem, it is necessary to identify the multiple objectives, the constraining factors, and the form of decisions. It is then necessary to describe a model of the system. The management science literature has contributed much toward the formulation and analysis of multicriteria decision making. These approaches range from multiattribute utility methods to interactive tradeoff approaches using fuzzy set theory.

In this paper we present a wholistic view of multicriteria decision making for fisheries under uncertainty. The modelling approach is predicated on the nature of the problem to be solved. Strategic problems, e.g., making decisions about the size of annual global quotas over a planning period, are formulated as nonlinear optimization problems. Multiple objective functions are measured in weighted value terms measuring economic viability of fish harvesting, fish processing, and sector employment levels. Strategic problems are constrained by biological considerations for stock size and measured by stock abundance indices from stock assessments. Taken together this problem formulation represents a multiple criteria approach to the development of and evaluation of strategic bioeconomic alternatives for the fishery. Short-term operational or in-season problem resolution (e.g., opening and closing of areas to fishing) requires a multicritera decision making perspective. The ongoing operational view of the fishery provides a valuable source of learning and feedback to the general direction of the strategic plan. For example, the abundance status of the stock can be taken into account on the basis of repeated measurements made by fishermen through their fishing activities, catch, by-catch, economic considerations (price, market strength, quality of product) and ecosystem indicators (presence of prey, condition of habitat, water temperature, etc.) These multiple criteria all provide useful real-time information that in turn, can be used to assist in-season management decision making. Applications of strategic and in-season multicriteria decision making will be illustrated by examples from the Scotia-Fundy commercial herring fishery in NAFO divisions 4WX.

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1. Introduction

Management of commercial marine fisheries acts on an extremely complex biological, economic and social system. Perhaps as a consequence, actual fisheries decisions are most often characterized as reactionary central agency policy-making in response to crisis situations that require direct intervention. Nevertheless, there is a well-recognized need in the literature for fisheries management to set out procedures for developing innovative decision alternatives and evaluating them in terms of the multiple criteria on all components (biological, economic, social, operational) of the fishery system (Stephenson and Lane 1995, Lane and Stephenson 1995).

Stephenson and Lane (1995) attribute the limitations of current management approaches and the ongoing problems of dealing with multiple criteria in fisheries to several causes. They cite these as the inherent variability and complexity of the system, the inability to define appropriate operational objectives to guide fisheries management, the lack of accountability in decision making, and the institutional imbalance created by a predominance of biological advice versus a lack of stakeholder involvement in decision making.

In the context of multicriteria problem solving, Ozernoy (1992) describes two barriers to effective decision making: structural barriers and methodological shortcomings. As Ozernoy states,

The methodology of multiple-criteria decision making can be divided into three steps: 1) structuring the decision problem; 2) formulating a preference model, and 3) evaluating and comparing alternatives. Structuring the decision problem includes the specification of objectives and attributes, the generation of alternatives, and the assessment of consequences of each alternative in terms of multiple criteria. A formal preference model is developed in order to represent the decision maker's values and elicit relevant information about the decision maker's preferences. Finally, evaluating and comparing alternatives provides the ordering of decision alternatives required in a problem. Ozernoy (1992, p.159).

In this framework, the difficulties experienced in fisheries management problem solving are attributed almost entirely to structural barriers. Examples of structural difficulties and the inability in fisheries to define the decision making problem abound. In a workshop entitled "Risk Evaluation and Biological reference Points for Fisheries Management", Smith et al (1993, pp. vi-vii) pointed out that the "major source of uncertainty identified was associated with the lack of hard objectives for the management of fish stocks". As a principal component of problem structure, the inability to set objectives negates almost any possibility that even the most refined model may assist decision making.

Wooster's (1988) volume on the proceedings of a workshop on 'Fisheries Science and Management: objectives and limitations' contains several discussions on the differences bewteen objectives and constraints in fisheries management. Appropriate arguments are presented for delineating between value-based objectives (maximization of economic or social benefits to society)

and biologically-based limitations or constraints. In that same volume Larkin argues for an anthropocentric approach to fisheries management (as opposed to an ichthyocentric one). He states:

It is a contradiction in terms to to speak of biological objectives of fisheries management. Much more logical to speak of biological constraints to management...The real questions are: what should be the biological constraints and what should be the social objectives. The answers are: whatever is necessary to preserve future biological options until we know more biology and, whatever seems appropriate to the society at the time. (Larkin 1988, p.289)

In spite of these clear designations crucial to defining problem structure, the fisheries research and fisheries biology literature maintains a preoccupation with setting "biological objectives" and enumerating lists of standardized "reference points" for management purposes independent from other aspects of the fishery problem. Indeed, many ICES member countries set annual stock catch limits on the basis of single standardized biological reference points.

The exercise of developing sophisticated methodologies as aids for multi-criteria decision making would appear to be ineffective (Ozernoy 1992) until such time as the issues of problem structuring in fisheries can be agreed upon. With this *caveat* having been stated, the purpose of this paper is to present fisheries decision problems with specific interest in defining problem structure toward formulating multi-criteria decision problems. Following a brief review of multi-criteria research in the operations research literature, fisheries problems taken from the Canadian 4WX Scotia-Fundy commercial herring fisheries are used to illustrate fisheries management decision making in a multi-criteria setting.

2. Methodologies in Multi-Criteria Decision Making (MCDM)

The development and evaluation of decision alternatives takes place in a problem solving context. As in any appropriately structured and defined problem, it is necessary to identify the multiple objectives, the constraining factors, and the form of decisions. It is then necessary to describe a model of the system. Finally, the results of the model need to be interpreted, evaluated and compared in order to help decision makers make ultimate choices.

The development of MCDM methodologies and applied research falls within the domain of management science/operations research. Management scientists have contributed much toward the formulation and analysis of multicriteria decision making and the presentation of tools for supporting multi-criteria problems. At the same time, the rapidly evolving field of MCDM is very new. The first conference devoted entirely to MCDM was held in 1973 (Cochrane and Zeleny 1973). Since then biannual international MCDM conferences have taken place and proceedings have appeared (e.g., Angehm 1990, Fandel and Spronk 1985, Hwang and Yoon 1981, Hwang and Masud 1979). Many professional conferences in management science, engineering, and computers regularly carry tracks and tutorials on MCDM advances and applications. And, journals such as European Journal of Operational Research (1991), Mathematical and Computing Modeling, Computers and Operations Research, Naval research Logistics, INFOR (Kersten and Michalowski 1992), Management Science (Starr and Zeleny 1977 and Stronk and Zionts 1984), and Interfaces (Bodily 1992) have all recently

published special issues on this topic.

Methodologies in MCDM range from the two main "schools": multiattribute utility methods (Keeny and Raiffa 1976, Fishburn 1970, Samson 1988, Clemens 1986) to outranking methods (Roy 1985, Roy and Vincke 1981). Interactive tradeoff approaches (Saaty 1980), ideal point comparison methods (Zeleny 1982), hierarchical approaches (Saaty 1980, Ehtamo and Hamalainen 1995), fuzzy set analyses (Sakawa 1993), and visual interactive programming methods (Hamalainen 1999, Bell 1991, Elder 1996, 1992, Belton and Vicke 1989) have all become popularized as applied approaches to MCDM problem solving.

In recent years, more and more "user-friendly" software has been made available as decision support for MCDM problems. These include Saaty's "Expert Choice", Istel's "SEE-WHY", and "VISIT", British Steel's "FORSIGHT", Insight International's "OPTIK" and "INORDA", Elder's "V.I.S.A", Hamalainen's "HIPRE 3+" as well as other smaller systems that are commercially available and/or sold as modules of larger mathematical programming or decision support software systems.

From this brief review, it is clear that potential decision makers have a wide range of options when it comes to selecting a choice of MCDM models both from the point of view of methodology and presentation. The breadth of most MCDM approaches for providing decision support, including problems in fisheries, precludes any attempt to categorically select one method or one presentation as the ultimate "problem solving" procedure. In any case, we argue that the issue for fisheries management, as alluded to previously, is not due to a lack of appropriate methodology, but the lack of clear definition of the multicriteria fisheries problem. The purpose of this paper then is to explore further the problem structure for specific fisheries problems.

In this paper we examine two multicriteria fisheries problems:

- 1. Strategic decision making: Setting annual stock TAC (Total Allowable Catch) limits
- 2. Operational decision making: Stock assessment and opening and closing fishing areas

In examining these problems we focus on particular fisheries rather than on a general problem formulation approach. In this sense, it is felt that each fisheries multiple objective problem is unique in itself and must be defined in the context in which the problem arises. At the same time, we apply specific MCDM methodologies as decision support approaches without advocating any one methodology or presentation system over any other. In the end, it is the decision maker who makes the ultimate decision on the basis of a clearly defined problem and additional information from the MCDM decision support system.

3. Strategic Decision Making: Setting TAC Schedules

Setting annual TACs is viewed as a highly strategic exercise for planning in a fishery system over a medium term (approximately 3 to 5 years) planning period. Setting TACs has obvious implications for meeting biological stock targets, for determining commercial investment and payback incentives, and for affecting individual fishermen's operating decisions.

As a strategic multiobjective problem, setting TACs involves a "rolling" horizon, i.e., one that is continually planned for into the future, but not necessarily attained as originally predicted. As with all "business" planning predictions and goals, conditions change requiring continual updating and adapting of goals and objectives to realize feasible outcomes. This is also how we view TAC decision making in fisheries. The following example presents a multiple objective problem formulation for TAC planning with data taken from the 4WX herring fishery. Further details on this fishery are provided in Stephenson et al. (1993).

Problem definition: The task of the fisheries management committee (comprised of a biologist, an operations manager, an economist, harvesting sector and processing sector representatives, and local community representatives) is to set out the revolving five year TAC plan. The committee has previously agreed to act under the following guidelines (determined by consensus with all stakeholders):

Biological targets: the target stock size in 5 years time for juveniles and adults combined (ages 1+) is 360 000 t and for adults (ages 4+) is 260 000 t from current estimates at the beginning of year 1 of 325 000 t and 221 000 t respectively.

Economic targets: the average viability measured in levels of year end cash (after income taxes) of the harvesting fleet and the processing sector will be monitored; the breakeven target level (including reasonable return on investment) is at \$5.5 million in total discounted cash over the five year planning period; and, average levels of annual employment should be maintained at 7500+ equivalent person years over the five year planning period.

Operational targets: some fishing areas will be closed to access during a portion of the spawning period.

TAC policy options were developed as alternative strategic policies each aimed at attaining the desired stock level targets. A mathematical programming formulation was used to calculate deterministic solutions.

Deterministic Modelling: Deterministic model results are obtained by projection of the "best estimate" input population values over the five year projection period using a mathematical programming model. The model uses stock data including initial estimates for numbers at age, average weight at age, partial recruitment, natural mortality and fishing mortality data to determine year-over-year stock at age distributions for (i) numbers of fish, (ii) stock biomass, and (iii) catch (weight and numbers). The population dynamics model is based on the following system of equations:

(1)
$$N_{0x} = R_t = c\alpha S_{t-1}(1-\gamma\beta S_{t-1})^{1/\gamma} \exp(z\sigma)$$

$$N_{at} = N_{a-l,t-l} \exp(-M - PR_a F_t)$$

(3)
$$C_{as} = w_a N_{as} (1 - \exp[-M - PR_a F_i]) \frac{PR_a F_i}{M + PR_a F_i}$$

for t=0,1,2,...T, and a=0,1,2,...A, where t=0 denotes the initial (current period), and t=T the final year of the planning horizon, and a=0 denotes births and a=A the oldest age of fish in the stock.

Equation (1) represents the stochastic version of a generalized stock-recruitment function (Schnute 1985) as the mechanism used to generate the yearly reproductive capacity of the stock. $N_{0,t}$ denotes the numbers of births at the beginning of each year t as a function of the spawning stock biomass (herring ages 4+) and the scale, productivity, and shape parameters α , β , γ respectively of the stock-recruitment function; z is the standard normal variate and σ is the standard deviation in the lognormally distributed error term. Different families of stock-recruitment functions are obtained from equation (1) by either substituting values for the shape parameter, or through mathematical limits.

Equation (2) defines the year-over-year changes in each cohort of the stock. The changes in the numbers of stock is a function of M, the continuous rate of natural mortality (assumed as elsewhere to be constant across all ages in the population), the partial recruitment at age, PR_a (constant over all years of the planning period), and the fishing mortality level, F_t for fully recruited ages of the stock. Using (2) and the expected weight at age (at the beginning of each year, and on average over each year), corresponding biomass levels for different age groups can be determined.

Equation (3) defines the catch weight at age, $C_{a,t}$ for a given level of fishing mortality by year. The average weight per fish at age a, w_a is determined over the entire yearly catch period. The adjusted weight at age at the beginning of each year, w_a^b is approximated by the midpoint between successive age's average weights, i.e., $w_a^b = (w_{a-1} + w_a)/2$. This equation also provides the basis for determining (i) catch numbers at age in a given year, and the total catch (TAC) resulting from fishing mortality, F.

In order to generate the results of the iterative set of related formulae (1)-(3), an initial distribution of the stock numbers, $N_{\bullet,0}$ at the beginning of year 0 (e.g., from the most recent VPA) is required along with either (1) a schedule of fishing mortalities, F_{\bullet} to apply annually to the harvestable fraction of successive cohorts, or (2) a desired level of annual TACs. If the TAC schedule is provided explicitly, then the corresponding fishing mortalities are determinable that yield the specified TACs.

A deterministic problem formulation to determine the schedule of TACs over the planning period while simultaneously satisfying biological constraints was developed. The overall objective of the deterministic optimization problem is to maximize the discounted sum of annual economic value to the fishing industry over the planning period by choosing decision variables for the fishing mortality, F_t. This objective function explicitly incorporates resource allocation considerations among competing gear types. For a given allocation policy, the deterministic optimization results provide insight into the characterization of the optimal, feasible solution. The multiobjective functional for this nonlinear dynamic optimization problem for TAC setting is written as follows:

(4)
$$Z = MAX_{F_i} \sum_{i=0}^{T-1} \exp(-\partial t) \sum_{n=1}^{A} R_{a,i}(F_0, F_1, ..., F_{T-1})$$

where $R_{a,t}$ is the value-based reward from fishing attributed to the various gear sectors of the fishery and δ is the continuous rate of discount of annual TACs. $R_{a,t}$ is a function of the suballocation of TACs to herring purse seiners, gillnets, and weirs and their individual (estimated) price and cost data.

The objective function (4) is constrained by biological constraints that take the form of biomass targets specified over the planning period. For the herring problem, these constraints may be defined as follows:

- (5) Total Stock Biomass $\sum_{a=1}^{A} w_a^b N_{at} \ge B_t(1^+), t \in \{0,...,T\}$
- (6) Adult Biomass $\sum_{a=4}^{A} w_a^b N_{at} \geq B_t(4^+), \ t \in \{0,...,T\}$
- (7) Policy Variable $0 \le F_t \le r$, t = 0, 1, ..., T-1

The left hand sides of constraints (5) and (6) are expressions for the total stock biomass of herring, and the adult stock biomass respectively at time t. The right hand sides of these constraints are the specific biomass targets for each time t. Since each N_{at} is a nonlinear function of the fishing mortality, F, then these constraints are also nonlinear in the decision variables, F_t. Equation (7) declares annual upper (r) and lower (0) bounds on the annual fishing mortality decision variables. These constraints are used to construct feasible policy scenarios, such as increasing, decreasing, constant, or pulse TAC strategies over time. In each case, the schedule of annual TACs are derived together with and dependent on the stock targets. Figure 1 illustrates selected candidate strategies for the Scotia-Fundy herring TAC planning problem. It remains to consider the multiobjective value-based implications of biologically "feasible" alternative TAC schedules.

Simulation Modelling: The next phase of the multiobjective decision support process involves analysis of candidate alternative TAC schedules through modelling the probabilistic events in the system over the planning period. A simulation model is developed to provide probabilities on corresponding outputs of the system. Input data for the main probabilistic components are modelled by randomizing key model elements. Biological parameter values representing natural mortality, initial stock abundance, gear selectivity, and average weight at age are defined in terms of input probability distributions from which realizations are taken to define a particular trial of the stock size simulation. Similarly, economic data components for effort, catchability, prices and costs were randomized according to empirical data observations. These provided simulated socioeconomic value results for the TAC alternatives (Figure 2). (See also Lane and Kaufmann 1993 where a similar analysis on Northern cod is carried out).

(4) Risk Assessment: The output measures of the Monte Carlo simulation experiments provide the results for the first stage of the decision risk analysis: risk assessment. Risk assessment provides a picture of the probabilistic outcomes of decision alternatives under the series of randomized biological and economic inputs. The outcomes are typically presented in the form of cumulative probability distribution functions on the space of the output variables. Figure 2 illustrates such curves for each alternative for the key output measures: (a) target juvenile stock abundance at start of year 6 (end of year 5); (b) target adult stock abundance at start of year 6; (c) total discounted cash from harvesting and processing over the five year period; and (d) average total person years of employment over the five year period.

Examination of the results of Figure 2 reveal no clear stochastically dominated alternatives with respect to stock abundance - all three alternative TAC schedules are relatively close in distributions. With respect to the biomass targets at the start of year 6, the simulation and the probability results show that under any of the three alternatives the possibility that the ages 1+ and 4+ biomass targets will be met is less than 50%. The "constant" strategy's performance with respect to these targets is slightly below target. However, with respect to discounted economic performance and employment levels, the "constant" strategy outperforms the other two schedules although the results for final year of the planning period is marginal. The "increasing" TAC schedule is not strictly dominating, but it is clearly superior especially in comparison with the "decreasing" strategy as can be noted from Figures 1c and 1d where the "constant" curve is nearly everywhere to the left (increasing cash and employment values) of the "increasing" strategy curves.

(5) Risk Management: The alternative TAC schedules for herring must be evaluated to provide a quantitative ranking that reflects not only their probability of occurrence (from risk assessment) but also the relative acceptability of the outcomes of various alternatives (risk management). The methodology is provided by the process of utility function analysis (Keeny 1977 and Walker et al. 1983). "Utility" is an abstract measure of the relative strength of preference/desirability for a particular decision alternative as a function of its weighted outcomes. Considerable effort is required to develop representative utility functions which will incorporate ecological, economic and social concerns (Keeny 1977, Bodily 1992). It is example, consider the "utility curves" of Figure 2. These curves are representative of decision makers' valuations of the key output measures of the problem, namely, (a) the ages 1+, juvenile and adult biomass at the end of the planning period (i.e., start of year 6), and (b) adult stock abundance, ages 4+ targets at start of year six, (c) the total discounted cash position of the industry (harve ting and processing operations combined), and (d) the average annual level of employment in the fish, by In practice, utility curves may be derived empirically from an analysis of decision makers' tradeoffs.

The most direct procedure for risk promagement is to evaluate the expected utility of each alternative by computing the vector prodes of the probabilities from the simulation analysis corresponding to the measured performance that the probabilities from the simulation analysis to the measured performance of their utility values. The results, presented in Figure 4, so the multidimensional utility valuation for each transfer and their decision options.

(6) Multiattribute Utility Evaluation: It is along the functions and comparison of variability of expected utility, leads to information which will permit decision makers to make an informed, overall evaluation and ranking of the alternatives prior to taking the final decision. By way of illustration, suppose the fisheries management a ministree agreed that among the four critieria, the two biomass measures (for 1+ and 4+ fish) had a meighting and that these measure should account for 70% of the total valuation of a strategy. As we approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the weight of the annual employment result the approve that the industry's discounted cash had twice the approve that the industry's discounted the approve that the approve

Let α_i denote the weight attached to 'vexpected utility u_i on criteria i such that the sum of the α_i over all criteria is 1. Then we may write the form of the multiattribute utility function U(a)

for alternative a simply as, $U(a) = \sum_{i=1}^{4} \alpha_i u_i(a)$ with the vector of weights derived from the decision makers' expressed tradeoffs given as $\alpha = (0.35, 0.35, 0.20, 0.10)$. The selection of the utility maximizing strategy follows from the calculating $U^*(a) = \max\{U(a), a = 1, 2, 3\}$.

For the case of Scotia-Fundy herring, the $U^*(a) = \max\{555,56,56,05\} = 565$. Accordingly, the "constant" TAC strategy yields the highest ranked weighted utility. Intutively, its performance in terms of the biomass targets is not very different from the other alternatives. It is arguably a superior strategy with respect to the socioeconomic measures of discounted cash and employment levels. However, the expected annual cash trend declines over the planning period to a slightly negative position in the last year. This additional observation may require a revision in strategy choice that will depend on the feedback of the decision makers involved that may include plans in the short run to prepare for this eventuality or other strategies designed to improve the trend, e.g., marketing arrangements, etc. It is obvious that a shift in the assigned weights to the criteria will result in a changed ranking. MCDM software routines expend a relatively large proportion of their effort (using graphical and tabular methods) in examining the sensitivity of such rankings through the criteria weights. This information will help decision makers determine the robustness of their rankings and provide further opportunity for adjustment and reconciliation due to other factors.

4. Operational Decision Making: Spatial-Temporal Considerations

Stock assessment is an inexact art. In the discussion of the multi-criteria strategic TAC setting exercise above, the latest stock assessment results formed a key input to the longer term planning process. For aggregate stock considerations, VPA and cohort methods are used to provide deterministic estimates of stock abundance. However, at the level of the fishery, additional information is available that is ignored aggregate abundance estimation methods. This additional information is in the form of spatial and temporal (seasonal) data from regular stock dynamics behaviour. Understanding this information provides independent means for updating and estimating stock status throughout the season. The following multicriteria model incorporates uncertainty and multiple measures into an updating stock estimation procedure. As above, the case of Scotia-Fundy herring is used to illlustrate this MCDM problem.

Problem definition: The task of the herring fisheries management committee is to monitor seasonal spatial-temporal fishing activity and incorporate fishing observations into an updating procedure for stock abundance status. This information is indispensable for making in-season decisions on when to open or close particular areas to the fishery, e.g., spawning grounds or feeding aggregations.

Stochastic aspects of the fishery resource may be described by two major components: (1) the underlying and unobservable dynamics of the stock, and (2) the observations about the underlying process that are subject to observation error. Define the elements of the model and model notation as follows:

The Core Process: Consider a planning period of T weeks during a season and, let $t \in T = \{0,1,...,T\}$

denote the weekly periods of the season. Consider a stock comprised of cohorts of juvenile and adult herring. Let $z \in Z$ represent an independent segment of the stock with $|Z| = N_Z$ (finite) denoting the number of discrete population segments, e.g., juvenile and adult stock. Represent the state of stock abundance by the population of the components of the stock. Let X_t be an N_Z -dimensional random variable defined on a sample space Ω . Let the random variable X_{α} , an element of the vector X_t , denote a discrete level of abundance of population segment z, an (unobserved) state of the system at period t. Assume that X_{α} takes on only discrete values in the finite set $1,2,...,N_X$, where N_X (finite) is constant for all periods t and all population components z.

The "core" stochastic process $\{X_t, t \in T\}$ describes the dynamics of fish abundance over the season. The state-to-state dynamics of the process of the system between periods t-1 and t is assumed to be a finite state Markov chain with stationary transition probabilities

$$(8) p_{ij} = Pr\{X_i = j \mid X_{i-1} = i\}$$

where p_{ijk} is the probability of moving from state $X_{t-1}=i$ in period t-1, to state $X_{t-1}=i$ in period t and i,j are members of the set of N_Z -tuples, N with $|N|=(N_X)^{**}(N_Z)$. The process of stock abundance dynamics is completely described by the $|N| \times |N| = (N_X)^{**}(N_Z)$. The process of stock abundance dynamics is completely described by the $|N| \times |N| = (N_X)^{**}(N_Z)$. The process of stock abundance dynamics is completely described by the $|N| \times |N| = (N_X)^{**}(N_Z)$, and the initial probability distribution over N at time t=0 which is denoted by the vector $\pi(0)=(\pi_1(0),\pi_2(0),...,\pi_{N_Z}(0))$ where $\pi_1(0)=Pr(X_0=i)$, $i\in N$.

The Observation Process: The core process provides a mapping for the various auxiliary data that together form the "observation process". The core and observation processes are linked by a measure of reliability of observation on core. This takes the form of probability distributions of observation states to given core states forming the observation matrix.

Let Y_t be an N_Y dimensional random variable which denotes the signals or observations of the actual state of the system at period t. These signals are a function of the levels of stock abundance and total catch by weight and may include, for example, all sources of auxiliary data that provide information about the actual state of stock abundance, e.g., research survey results, abundance indices, CPUE, average catch per "standardized" set. Let the random variable Y_{z_t} , an element of the vector Y_t , denote a discrete level of the signal for population segment z at period t. Assume that Y_{z_t} takes on only discrete values in the finite set 1,2,..., N_Y , where N_Y (finite) is constant for all t and all z. The stochastic process $\{Y_t, t \in T\}$ is known as the observation process of the system.

Information regarding the actual abundance, X_t is obtained when Y_t signals are made during fishing activities. The probabilistic relationship between X_t (not observed) and Y_t (observed) is assumed to be known. The state-to-observation function for each period t relates observations Y_t to actual state X_t by the probabilistic relationship

(9)
$$q_{int} = Pr\{Y_i = m \mid X_i = j\}$$

(assumed to be independent of all X_i , $t' \in T$ and $t' \neq t$) where q_{jmt} is the probability that catch level $Y_t = m$ will occur in period t given that the actual state of abundance is defined by $X_i = j$ in period t; $m \in M$; and $j \in N$. The observation process is described by the signal or observation matrix for each period t, $Q_t = [q_{jmt}]$.

In the herring fishery, fishermen (seiners, gillnetters, weirs operators) are privy to a wide range of local observations that have implications for abundance. The multiplicity of observations (e.g., the 'feediness' of the fish, presence or absence of predators, spawning state, length at age, location in the water column, etc.) all contribute to describing the observation process.

When multiple observations such as these are involved (Richards 1991), they can be weighted together (e.g., as in the multiattribute utility process described above) to form an overall observation (discretized) index that then provides a composite picture (in the form of probabilities on core states) of stock size.

Naturally, the stochastic nature of the inputs (stock dynamics) lead to stochastic outputs (e.g., stock effects, economic performance of various TAC schedules). The variability and range of these outputs must be captured. Traditionally, valuation schemes are required here through statements of the problem objectives. In the decision making arena uncertainty valuations are recognized as being a function of the possible outcomes, and the decision maker's interpretation of these, though the evaluation of the decision maker's utility functions. Measuring the utility of decisions is not difficult, but it does require prior disclosure and feedback from the decision maker about the valuation of particular outcomes.

The Decision Space: In order to develop a decision evaluation objective measure, we first define the space of possible decision alternatives. Let A be a finite set which denotes all actions (i.e., all choices for opening or closing fishing areas) available to decision makers in each period t. Denote a particular decision in this set for period t by $a_{\alpha} \in A$. Action a_{α} is defined as the total removals by population component z in period t.

The controllability of the core and observation processes depends on the choice of a_{z} in each period. Thus, if X_t is the current state of the core process and action a_t (over all z for simplicity) is chosen at the end of the current period, then the core process moves to a new state X_{t+1} with probability $p_{ijt+1}(a_t)$ dependent on action a_t . Similarly, the state-to-observation process may depend on actions taken, $q_{jru+1}(a_t) = q_{jru+1}$. Thus, in general,

(10)
$$P_{i}(a_{i-1}) = [p_{ij}(a_{i-1})] \text{ and } Q_{i}(a_{i-1}) = [q_{im}(a_{i-1})]$$

denote the probability transition matrices of the core process and the signal matrices of the observation process, respectively as a function of the actions chosen.

Let $y_t \in M$ denote the level of signals, Y_t observed at period t. And, let I_t be the vector of information accumulated from successive decisions and signals in the system up to and including time period t, with $I_t = (y_0, ..., y_t, a_0, ..., a_{t-1})$.

The discrete space process (for states and observations) can be "reduced" to, a continuous space MDP using a sufficient statistic that summarizes all information history of the problem. One form of a sufficient statistic is the expression of Bayes' Theorem:

(11)
$$\pi(t) = \Pr(X_i = j \mid I_i), j \in N$$

the conditional probability that the abundance level $X_t = j$ occurs at period t, given information I_t . $\pi(t)$ may be considered as the new state variable of the transformed system. Using Bayes' formula, the sufficient statistic is defined by the transfer function τ_t as follows for $t \in \{1,2,...,T\}$; $i,j \in N$; $m \in M$; and $a_{t-1} = a \in A$:

(12)
$$\tau_{i}(\pi | m, a) = \pi_{j}(t+1) = \frac{q_{jml}(a) \sum_{i} p_{ijl}(a) \pi_{i}}{\sum_{i,j} q_{jml}(a) p_{ijl}(a) \pi_{i}}$$

Intuitively, Bayes' formula examines the observed outcome of the fishing decision, i.e., catch, and then asks what would be the probability that the catch was due to a particular cause, namely, an unobserved level of abundance. In this manner probability distributions of actual abundance are updated after every fishing period (week). The $\pi_j(0)$ priors on the initial abundance levels at the start of the season are assumed to be known explicitly.

Policy Dynamics: Once a complete policy has been developed, application of the decision rules depends on the actual evolution of the system and the corresponding observations (Bertsekas 1976, p.113). Initially, a prior probability distribution, $\pi(0)$ on the population size, X_0 is provided. Next, a policy is assigned for the current period, then observation data are collected. The action combines with the state to provide current multiobjective rewards. The subsequent state of the system is derived as a function of the previous state and policy. Successive observations and results are recorded, actions taken, etc., to the end of the planning period.

Solution Procedures: The proposed solution procedure for developing fisheries management advice combines the results of alternative solution methods in the presentation of overall advice for fisheries management decisions. A step-by-step solution procedure is as follows:

- 1) Use information about stock discreteness and spawning stock dynamics to build the probability transition matrix P. Use simulation to include observed variation in spatial-temporal dynamics.
- 2) Estimate the reliability (state-to-observation) matrix, Q using available empirical data on survey reliability and fishermen feedback (e.g., Rivard and Foy 1987).
- 3) Develop a multiattribute weighting scheme to assign multiple observations of the fishery to "fuzzy" (Kosko 1993, Sakawa 1993) observation classes.
- 4) Update the priors from spatial observations each period and produce probability distributions of stock status.
- 5) Develop a multiattribute decision rule for opening and/or closing fishing areas taking into account the impacts on fishermen's earnings/losses and the stock status.

5. Discussion

This paper attempts to present multicriteria problem constructions for fisheries management decision making. While it is not the purpose of this paper to apply particular MCDM techniques to specific fisheries problems, we do point out in the problem formulations where MCDM problem analyses are required. In this respect, we have explored two aspects of fisheries decisions: strategic (TAC setting over a planning period) and operational problems (for stock assessment and in-season maintenance of fish population areas). In doing so, we point out:

- 1. The lack of strategic planning that has taken place in most government-managed fisheries historically.
- 2. The need for much more focus on operational aspects of fisheries, in particular, the wealth of multi-criteria spatial-temporal information available (but essentially unused) at the level of the operation of the fisheries.
- 3. The inappropriate institutional arrangements in fisheries not conducive to MCDM problem formulation and resolution.

We perceive the major stumbling block to the application of effective MCDM methods in fisheries to the difficulties associated with problem definition and structuring. Remedies for dealing with these problems will require a much more interdisciplinary structure to our fisheries management institutions. Without this, the necessary dialogue and discussions among biologists, economists, sociologists, ecologists, etc., in a concerted problem solving setting, cannot take place.

Within an interdisciplinary management structure it will furthermore be necessary to define the appropriate roles and responsibilities of all participants. In particular, in our view, it is not government agencies who will be ultimately "responsible" for defining particular objectives and constraints of the MCDM problems. Rather, government agencies should act as decision support experts charged with providing the stakeholders who operate the fishery system (and produce value from it) with the range of interpretations arising from both strategic and operational decision problems. On the basis of appropriately presented information, these stakeholder-decision makers will be best able to make effective multi-criteria decisions in a consensus setting.

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Annual TAC Schedule Alternatives

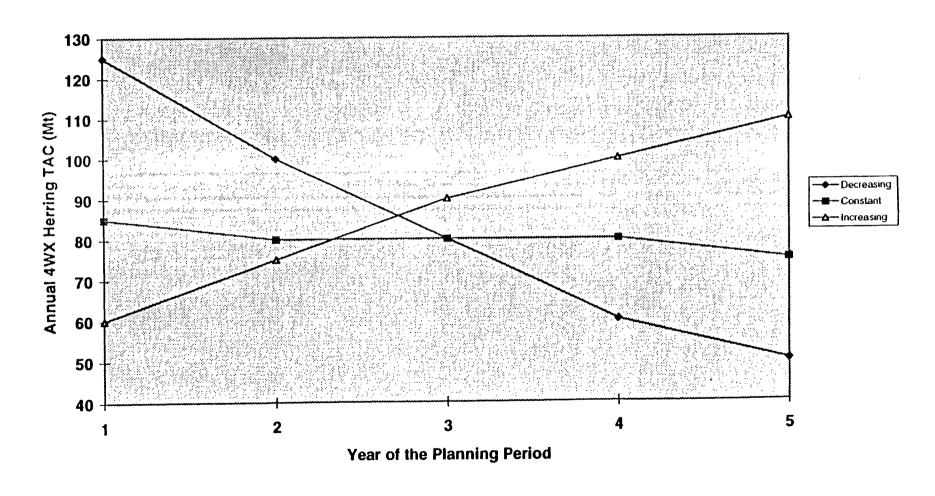
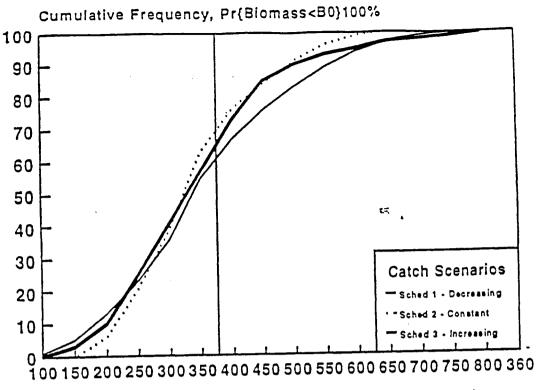


Figure 1



Ages 1+ Start of Year 6 Biomass (000s t)

Figure 2a

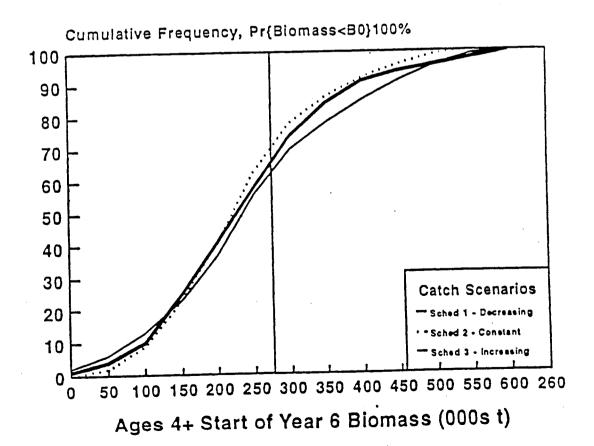


Figure 2b

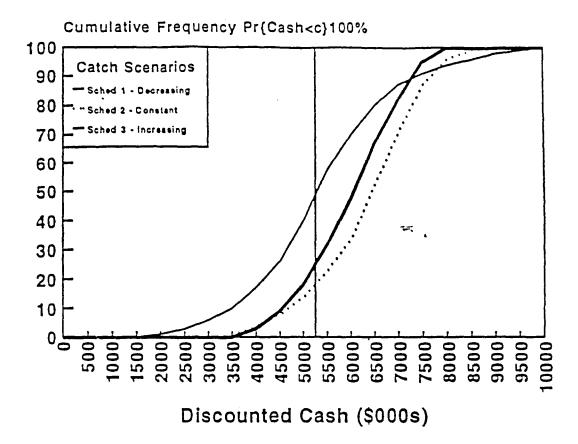


Figure 2c

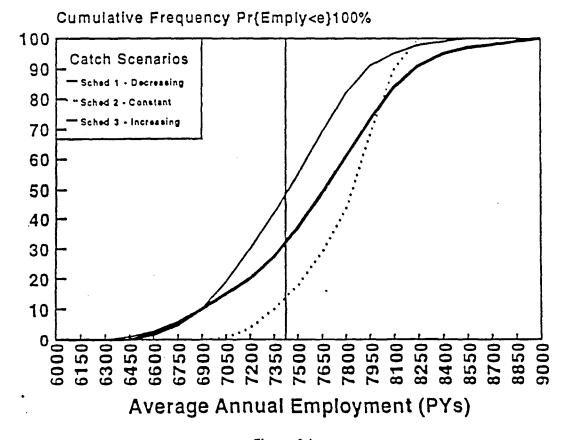
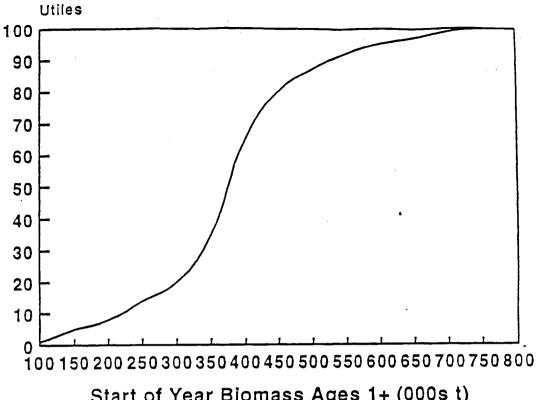


Figure 2d



Start of Year Biomass Ages 1+ (000s t)



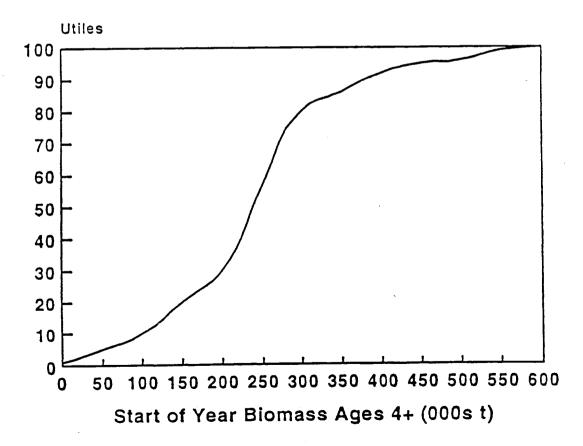
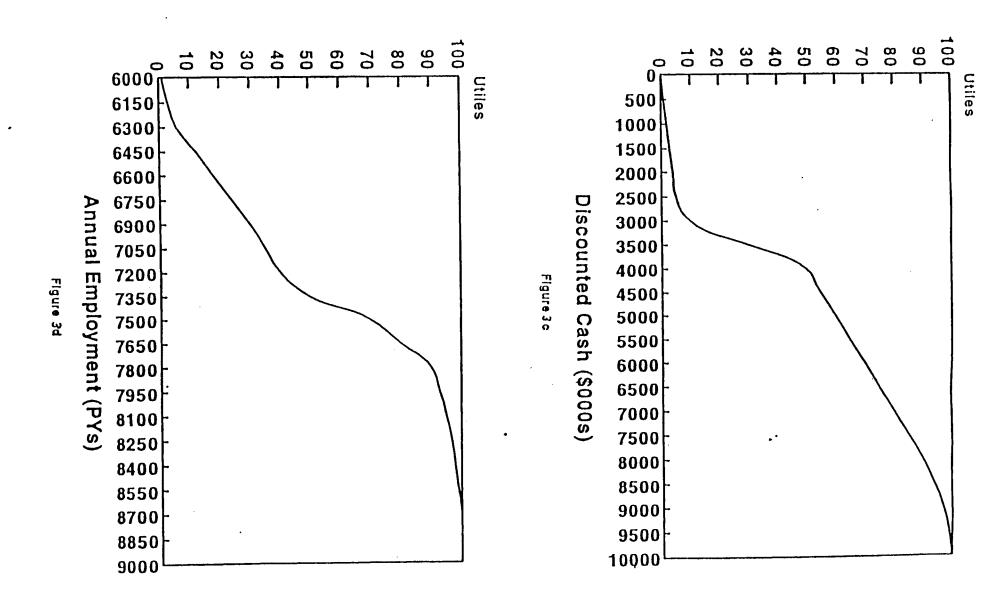


Figure 3b



Utility Curve Tradeoffs Schedules 1 - 3

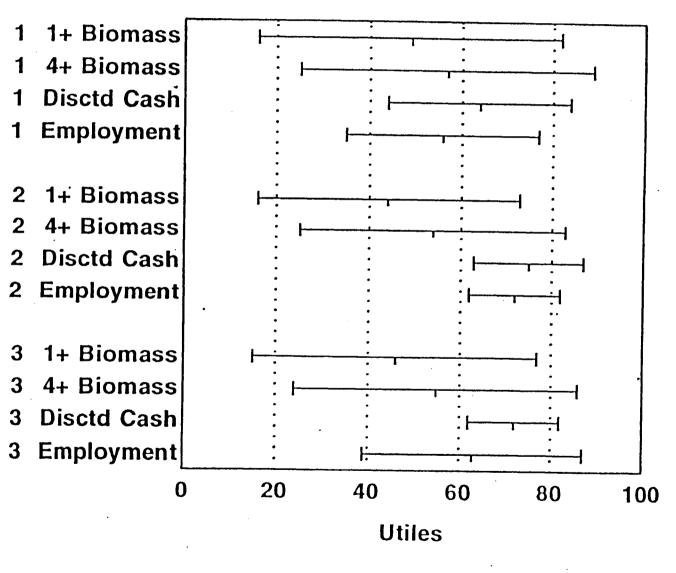


Figure 4

