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Setting Quotas in a Stochastic Fishery

by

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ABSTRACT

The purpose of this paper is to present a practical method for setting approximately optimal policy decisions in a quota regulated fishery in which the stock-recruitment relationship, somatic growth, parameter uncertainty, stochastic variation, and mean-variance trade-offs in catch are explicitly considered. The proposed method converts a dynamic optimization problem into one that can be solved using unconstrained optimization methods. The effects of errors in estimation of stock size, parameter uncertainty, and stochastic recruitment on optimal quota policies are demonstrated.

1 Introduction

The rational management of a fishery requires the amalgamation of economic and social considerations with prediction of changes in fish populations. This must be carried out with populations whose size is not known with precision and whose dynamics are subject to stochastic changes. Although excellent theoretical research has been done on the inclusion of economic factors in stochastic fisheries models, these methods have seldom been applied to the routine management of a fishery (see Clark (1985) for a review). The purpose of this paper is to present a practical method for setting approximately optimal updated policy decisions in which stochastic variation and parameter uncertainty are explicitly considered. I shall investigate the incorporation of information other than estimates of stock size, e.g. age structure, in setting quotas. For example, for a given stock biomass, it might be desirable to set a lower quota than if the stock comprised mainly older age classes. Similarly, if stock-recruitment relationship is autocorrelated, then it may be desirable to incorporate the last observed residual from the stock recruitment relationship into the quota setting process.

The approach used here is to limit attention to a parametric family of policy functions, e.g. let the quota for any year be a parametric function of the observed stock size. The optimization problem that is solved is to choose the parameters describing the policy function so that the desired objective, e.g. long-term catch, is maximized. This approach is known as parameter optimization (Bellman 1957), and has been previously used in fisheries problems by Ruppert et al. (1985). Here, this technique will be used in the context of a Bayesian decision problem.

Furthermore, we would not only like to set a quota each year, but we would also like to provide fishermen with estimates of the likelihoods of future catch levels. This would allow fishermen to make better investment decisions. The methods discussed here will be applied to a quota regulated fishery in which the quotas are updated each year. However, the methods could also be applied in other situations, e.g. effort regulated fisheries.

There is a major limitation to the approach discussed here; only passive learning will be considered here, not active learning (the modification of stock levels to improve parameter estimates of the fishery model, e.g. the stock-recruitment function). Ludwig and Walters (1982) have shown that a management strategy employing active learning can improve long-term yields when compared with a management strategy that allows minimal variation in the spawning stock. However, the abundance of most marine stocks has fluctuated widely in the last few decades because of changing management practices and environmental variation. Thus, it would be much more difficult to justify the deliberate manipulation the spawning biomass of these stocks for the purpose of improved parameter estimation.

2 Formulation

I consider a population described at time t by a vector of ages or stages, x_t. The vector x is assumed to be measured with error, i.e.

$$y_t = x_t + \varepsilon_t \tag{1}$$

where ε_t is a vector or measurement error. It is assumed here that the statistical properties of ε_t can be adequately estimated.

The fishery is assumed to be regulated by a quota that is updated each year based upon new knowledge of the population dynamics and new estimates of population size. The population dynamics are described by a discrete time stochastic equation

$$x_{t+1} = (x_t, Q_t, \zeta_t), \tag{2}$$

where the ζ_t is a random component (possibly vector) in the dynamics, e.g. a stochastic term describing variable recruitment.

The parameters describing the population dynamics are assumed to be estimated for the available data. At the time a quota is set, the uncertainty in the parameters is described by a prior distribution, π_0. Empirical estimation of the prior distribution is described by Ludwig and Walters (1982) and Charles (1983b).

The socio-economic utility of a quota will generally be a concave increasing function of the quota. The utility function, $U(Q_t)$ will generally be determined exogeneously to the management of the fishery, i.e. by a combination of economic analysis and political decision making. The utility will be assumed not to change with time. The degree of concavity of the utility reflects risk-aversion, which is defined as

$$r(Q) = -U''(Q)/U'(Q). \tag{3}$$

The amount of wealth, e.g. quota, society is willing to forego to avoid risk is $\frac{1}{2}r(Q)\sigma^2$, where Q is the present quota and σ^2 is the variance of the risk. In general, risk version will be a decreasing function of the quota levels, i.e. it is usually socially important to maintain a minimum level of fishing. To satisfy this requirement, only utility functions which satisfy this property will be considered (this is ensured if $r'(Q) < 0$; Hull et al. (1973). It will be useful to scale the utility function such that it can be compared to fishery management techniques that maximize only catch, i.e. in which the utility function is the identity. To do this we examine two utility functions that have the identify function as their limit. Two utility functions which satisfy the above conditions are

$$U(Q) = \frac{Q}{1 + vQ} \tag{4}$$

where v is the maximum quota capacity of the fleet or market (this function approaches the identity as $v \to 0$, and

$$U(Q) = (Q + v^{-1}v^{-1}/(v-1)^{v} \tag{5}$$

which is more useful in describing fisheries without a maximum capacity (in this case the U approaches the identity as $v \to 1$).

The objective of the fishery manager is to choose quotas, $Q_t, t = 1$ to N, which satisfy:

$$\max_{Q(t),t=1,\ldots,N} E\sum_{t=1}^{N} U(Q_t) \tag{6}$$

where E is the expectation operator and N is the time horizon of the management plan. The expectation is actually a multiple expectation, first, with respect to the errors in observation $\varepsilon_t, t = 1, \ldots N$; second, with respect to the stochastic portion of the population dynamics $\zeta_t, t = 1, \ldots N$; and third, with respect to the prior distribution π_0.

Note that if the initial stock size and age structure is not known with certainty, then the expectation will also have to include the prior probability distribution for those estimates. This will be particularly important when stock projections are made.

3 Method

Approximate solutions to the stated problem are generally impossible; approximations must be used (Kendrick 1981). The approach taken here is to develop methods that can be used by managers that are not experts at stochastic control theory.

The approximation used here is that the optimal sequence of quota decisions can be approximated by an appropriately chosen quota policy decision function

$$Q_t = Q(y_t; \nu) \tag{7}$$

where ν is a set of parameters describing the decision to function which are chosen such that

$$\max E \sum_t U[Q(y_t; \nu)], \tag{8}$$

where the population dynamics are given by (2). The maximization in (8) is a specialization of that in (6) in which the quota has been constrained by equation (7). Note that (8) does not depend upon possible improved estimates of the parameters describing population dynamics i.e. as if all future quota decisions will be based on the present level of information. The number of stochastic elements in the expectation will be sufficiently large that the expectation must be calculated by Monte-Carlo simulations (Stewart, 1983).

The quota policy for the simple case where there is only one age or stage class to consider, $Q(y; \nu)$ should have the following properties:

1. The quota should be a nondecreasing function of y.
2. If the estimated stock size y is below some critical stock size y_c, then the quota should be zero.
3. Above the critical stock size y_c, the quota should increase proportional to a power $(y - y_c)^\beta$, where β may be greater than one.

A two-parameter function that satisfies (1) and (2) is

$$Q(y; \nu) = \begin{cases} 0 & \text{if } y \le y_c \\ \upsilon_2(y - y_c) & \text{if } y > y_c \end{cases} \tag{9}$$

where $y_c = \upsilon_1$.

A three-parameter function that satisfies properties (1), (2), and (3) is

$$Q(y; \nu) = \begin{cases} 0 & \text{if } y \le y_c \\ \upsilon_2(y - y_c)^{\upsilon_3} & \text{if } y > y_c \end{cases} \tag{10}$$

where $y_c = \upsilon_1$.

A four-parameter function that is more flexible is

$$Q(y; \nu) = \begin{cases} 0 & \text{if } y \le y_c \\ \frac{(\upsilon_2(y - y_c))^{\upsilon_4}}{\upsilon_3 + (y - y_c)} & \text{if } y > y_c \end{cases} \tag{11}$$

where $y_c = \upsilon_1$.

The approach used here was to first restrict the quota decision function to 9, then fit 10 and 11; the more complicated decision function was accepted only if it significantly improved the expected utilities summed over time.

Rupert et al. (1984) suggest the use of a technique known as stochastic approximation to obtain solutions to a problem similar to that described here except that they limited stochasticity to recruitment. However, the method of stochastic approximation does not seem to be easily applicable to more complex problems, e.g. parameter uncertainty. Here, it was found that adequate solutions to the maximization could be obtained by simpler methods.

The suggested algorithm for finding the approximate maximum of (6) is as follows:

1. Choose a reasonable parameterization of the quota decision function $Q(y; \upsilon)$, e.g. such as eq. 10.
2. Generate and store realizations of all random elements; i.e. $\varepsilon_t, \zeta_t, (t = 1...N)$ and π_0.
3. Maximize (6) with respect to υ approximating the expectation by summing over the simulated realization generated in step (ii).
4. Repeat steps (ii) and (iii) to determine if sample size of Monte-Carlo simulations was sufficient.
5. Repeat (ii) - (iv) using alternative parameterizations of the quota-decision function.

The above algorithm is a stochastic version of parameter optimization (Bellman 1957), has several advantages over alternative methods. First, it does not require a deep knowledge of stochastic optimization theory to apply. Second, by choosing and storing the stochastic portions of the problem, the maximization in step (iii) is deterministic. Third, it can be relatively easily implemented because at the heart of the algorithm lies an unconstrained maximization routine. Fourth, the variation in quota levels are easily investigated.

Implicit in Eq. 8 is that errors in estimating stock abundance are sufficiently small that the quota will actually be caught. If this is not the case, then the quota in Eq. 8 must be replaced by the actual (or simulated) catch. This requires a model relating the quota and the "true" abundance to the simulated catch.

4 Simulation

In order to demonstrate the use of the methods and to illustrate principles of setting quotas in a stochastic environment, I consider a model with two stages: $x_{1,t}$, the number of pre-recruits at time t, and $x_{2,t}$, the number of post-recruits at time t.

The dynamics of the post-recruits, x_2, is

$$x_{2,t+1} = P_1 x_{1,t} + P_2(x_{2,t} - c_{2,t}) \tag{12}$$

where P_i is the natural survival of stage i, and $c_{2,t}$ is the catch of the fully recruited class at time t. If P_2 is zero, then the model can be used to simulate semelparous species such as Pacific salmon while if P_2 is close to one, the model can simulate long-lived species. Recruitment is assumed to follow a Beverton-Holt relationship with residual variation assumed to be a zero mean, autocorrelated, lognormal distribution. That is

$$x_{1,t+1} = \frac{x_{2,t}}{\alpha + \beta x_{2,t}} \exp(\zeta_t - \frac{1}{2}\sigma_\zeta^2) \tag{13}$$

where ζ_t is the realization of a stochastic process generated by

$$\zeta_{t+1} = \phi\zeta_t + a_t \tag{14}$$

where ϕ is the autocorrelation and a_t is a realization of Gaussion white noise with mean zero, variance σ_a^2, and no autocorrelation. The relationship between the variance of ζ and the variance of a is given by

$$\sigma_\zeta^2 = \frac{\sigma_a^2}{1 - \phi^2} \tag{15}$$

(Box and Jenkins 1976). In order to investigate the role of autocorrelation on setting quotas it is useful to vary the amount of autocorrelation for a fixed level of environmental variation σ_ζ^2. σ_ζ^2 will be constrained to remain constant as ϕ changes, i.e. for each ϕ, σ_a^2 will be chosen using (14) so that σ_ζ^2 is constant.

Both the pre- and post-recruits may be observed with error, i.e.

$$y_{1,t} = x_{1,t}\exp(\epsilon_{1,t} - \frac{1}{2}\sigma_{\epsilon_1}^2) \tag{16}$$

$$y_{2,t} = x_{2,t}\exp(\epsilon_{2,t} - \frac{1}{2}\sigma_{\epsilon_2}^2) \tag{17}$$

where the observational errors are realizations of a mean zero, non-autocorrelated, lognormally-distributed stochastic process. That is, ϵ_i is a mean zero, Gaussian noise with variable σ_i^2. Generally estimates of stock size of pre-recruitments will be worse than those of past recruits, i.e. $\sigma_{\epsilon_1}^2 > \sigma_{\epsilon_2}^2$.

The prior probability distribution for the stock recruitment parameters, α and β, is assumed to be a bivariate normal as follows:

$$\pi(\alpha,\beta) = (C/\sigma)^n \exp(-(\frac{1}{2})[\lambda_1(\alpha-\hat{\alpha})^2 + \lambda_2(\alpha-\hat{\alpha})(\beta-\hat{\beta}) + \lambda_3(\beta-\hat{\beta})^2]) \tag{18}$$

with

$$\lambda_1 = [(1-\rho^2)\sigma_\alpha^2]^{-1}, \lambda_2 = -[2\rho/(1-\rho^2)\sigma_\alpha\sigma_\beta], \lambda_3 = [(1-\rho^2)\sigma_\beta^2]^{-1} \tag{19}$$

where C is a normalization constant, n is the number of observations, and $\hat{\alpha}$ and $\hat{\beta}$ are the best estimates (Charles 1983b). The theoretical justification for using a bivariate normal for an empirical estimate of the prior uncertainty is that the uncertainty of maximum-likelihood parameter estimates can be very generally asymptotically approximated by a multivariate normal distribution. A further practical consideration is the wide availability of multivariate random number generators. However, in practice, the parameters of stock-recruit relationships may not be sufficiently well determined for the multivariate normal to be an adequate description of the likelihood surface.

In the simulations which are described below, the quota decision function will be restricted to the form of eq. 9 unless otherwise stated. The time horizon will be 100 years and the Monte-Carlo integration will use 250 replicates.

The parameters used for the Beverton-Holt stock-recruitment relationship (Table 1) have been discussed and plotted in a widely used text (Ricker 1975, Fig. 11.5, Table 11.7). The observational error variance, $\sigma_{\epsilon_2}^2$, corresponds roughly to that of a typical virtual population analysis, while the error variance of the pre-recruits corresponds to that of a groundfish research survey. The recruitment variability and autocorrelation is the median of 10 stocks examined by Koslow (1984). The parameter uncertainty was calculated from data in Beverton and Holt (1957) for North Sea plaice.

5 Simulation Results - Linear Utility

5.1 No Sochasticity

The simplest case is considered first: a semelparous species, i.e. one that dies after reproduction, with no observation error and with deterministic known dynamics and linear utility. In this case the proposed method should reproduce the known optimal solution (obtained using optional control theory), namely

$$Q_t = \begin{cases} 0 & \text{if } x_{2,t} \leq x_2^* \\ x_{2,t} - x_2^* & \text{if } x_{2,t} \leq x_2^* \end{cases} \tag{20}$$

where x_2^* is the optimal escapement of spawners (Goh 1980). This type of policy is known as a constant escapement policy, i.e. a constant number of spawners are allowed to return to spawn each year. In this case the optimal number of spawners is 387. The resulting quota decision function has a slope of one and x intercept of 387 if the observed numbers of spawners is greater than 387 and zero otherwise. This is the solution found by the proposed method (Fig. 1).

5.2 Stochastic Recruitment

Reed (1974, 1979), Ludwig and Walters (1982), Charles (1983a), and Clark and Kirkwood (1984) have considered the above problem with the addition of independent stochastic variation in recruitment. Their results are that the optimal solution is of the same form as (19) except that the optimal escapement level of spawners is usually reduced by a small amount (less than 5%) unless the coefficient of variation is quite large (greater than 100%). The solution produced here is consistent with these theoretical results (Fig. 1, model 2).

5.3 Stochastic Autocorrelated Recruitment

It is more realistic to consider autocorrelated environmental variation of recruitment, i.e. greater than zero. If the environmental variation (σ_ζ^2) constant, and the policy function is restricted such that it is only a function of the number of spawners, there is no change in the policy decision, i.e. it remains the same as in Figure 1 (model 2). The policy decision function is not changed in this case because there is no feedback to the quota decision function from the information on deviating from the stock-recruitment relationship.

The information present in the environmental autocorrelation can be used to improve the policy decision function by making the decision function dependent upon the observed deviation from the stock-recruitment relationship as well as the present stock of spawners. Define the logarithm of the deviation as

$$d_t = \log(y_{1,t}) - \log(\widehat{y_{1,t}}) \tag{21}$$

where $\widehat{y_{1,t}}$ is the recruitment predicted by the stock-recruitment relationship. A reasonable first step in examining a quota decision function that uses this information is to reduce the quota in years with lower recruitment than expected ($d_t < 0$) and to raise it in years in which recruitment is higher than expected ($d_t > 0$). Equation (9) can be modified in several way to do this, e.g.

$$Q(d_t, y_{2,t}; \nu) = \begin{cases} 0 & \text{if } \alpha > 0 \\ \nu_2(\frac{\alpha}{\nu_s + \alpha})^{\nu_4} & \text{if } \alpha < 0 \end{cases} \tag{22}$$

where

$$\alpha = (\nu_1 - \nu_5 d_t) - y_{2,t}. \tag{23}$$

The resulting optimal quota decision function significantly increased the expected quota of the policy by about 5% (Table 1). Sobel (1982) and Spulber (1982) considered this problem using the theory of Makov decision processes; their results using a more complex theory are similar to those found here.

5.4 Errors in Observation

Consider model 1 (Table 1) with only errors in observation included (model 4). In this case there is a qualitative change in the optimal policy (Fig. 1). In particular, the quotas are lower than these from model I when high stock sizes are observed and higher when low stock sizes are observed. This type of quota decision function is reasonable when one considers the direction of errors once the population has reached a steady state with respect to the quota decision function. That is, high observed stock sizes are likely to be overestimates and low observed stock sizes are likely to be underestimates. Thus, the quota decision function should be modified as in Fig. 1. This type of quota decision function produces results similar to the James-Stein estimators in statistics.

5.5 Stochastic Recruitment and Errors in Observation

If errors in observation and variable recruitment are considered simultaneously (model 5) the result is a quota decision function that is moderated form of that found in model 4 (Fig. 1). The inclusion of variation in recruitment along with error in observation means that more of the observed variation in stock size is real, and thus the results from model 4 should be moderated.

5.6 Parameter Uncertainty

The effect of parameter uncertainty in the estimates of the stock-recruitment parameters was investigated. A standard error of 20% with a correlation coefficient of -.9 had very little effect on the optimal decision policy; the shape of the optimal policy was almost identical to that produced above. The mean utility, the mean catch, and the standard deviation of the optimal catch was also almost identical. kHowever, if the correlation between the estimated paramters was not included in a realistic manner, e.g. no correlation was assumed, the decision function changed greatly. Thus, the estimated tock and recrutiment paramters may be adequate for obtaining quota decision functions, but if parameter uncertainty is included, then it must be included in a realistic fashion.

6 Simulation Results - Nonlinear Utility

The inclusion of nonlinear utility in the simulation with error the estimate of stock size and stochastic recruitment (model 5, Table 1) has a drastic effect on the policy function (Fig. 2, model 7). The simple constant escapement policy that is characteristic in simpler models (Eq. 16) becomes a more complex function with the result that the equilibrium number of spawners is approached gradually as opposed to that which resulted from the case of linear utility, in which the approach was as rapid as was biologically possible. The results found here are consistent with those found using optimal control theory (Clark 1985), but can be obtained without a deep knowledge of optimal control theroy.

7 Iteroparous Species

In these simulations long-lived species are mimicked by allowing post-reproductive survival ($P_2 > 0$). Although this model does not include somatic growth (this is studied in the next section), it does allow the investigation of two important factors characteristic of longer-lived species. First, in many long-lived species the estimates of older cohorts may be quite good, e.g. via cohort analysis; however, these estimates of younger cohorts may be very poor. It may be desirable to use these two types of information differently when making policy decisions. Second, a species that does not die after reproduction will have more resilience to fluctuations in recruitment which will be contrasted here with our previous examples. Results will be presented verbally at the meeting.

8 Age-Structured Density-Dependent Models

The management of a multi-cohort, age-structured fishery is an enormously complex task even in the deterministic case. Usually drastic simplifications are made. For example, recruitment can be ignored and an equilibrium age structure assumed, as in the dynamic pool models of Beverton and Holt (1957). Another common simplification is to lump somatic growth, mortality, and recruitment into one variable, as in "general production model". The Schaffer model is the most commonly used example of this class.

Clark (1976), Botsford (1981), Deriso (1980), Feichtinger (1982), Hannesson (1975), and Getz (1980) have considered more realistic deterministic density-dependent age-structured models and have obtained useful results. Nevertheless, none of the models have come into general use and the results are not complete. The problem is the inherent difficulty of multi-dimensional dynamic optimization problems (Clark 1985); even when partial results are obtained they may be too complex to apply in practice. The inclusion of errors in observation, nonlinear utility, and stochasticity makes full solutions impossible in practice.

Here the problem is reduced to an unconstrained optimization of a policy decision function as before; the principle difficulty is to reduce the dimensionality of the problem so that the policy function is described by a reasonably small number of parameters.

The Beverton-Holt dynamic pool model reduces the age structure into one variable, exploitable biomass, which is a reasonable place to begin. One obvious extension is to consider a measure of deviations from the equilibrium age structure. For example, a population in which the exploitable biomass will be concentrated in older, slowly-growing age classes should be harvested differently from a population in which the exploitable biomass is concentrated in younger, faster-growing age classes. One solution to this problem is considered below.

It may be useful to also consider estimates of the pre-recruits as a variable in the policy function. Another obvious variable to consider is a measure of size selectivity of the fishery. (This was considered in the classic models of Beverton and Holt's model.)

We would like to reduce to a vector of age specific abundances into two numbers, one representing total biomass and another representing the potential for somatic growth. One obvious possibility is

$$S_t = \sum_{i=a_f}^{N} u_{i,t} w_i \tag{24}$$

$$G_t = \sum_{i=a_f}^{N} u_{i,t}(w_{i+1} - w_i)/S_t \tag{25}$$

where G_t is the relative growth potential next year for the stock, and a_f is the age at first fishing.

The state of the population is described by a vector of ages, x_i with elements $x_{i,t}, i = 1, 2, \ldots n-1$ is the number of fish in age class i at time t, and $x_{n,t}$ is the number of fish age n and older at time t.

The catch of each age i at time t, $c_{i,t}$, is assumed to be taken at the end the year in spawning concentrations. The dynamics of numbers at age is thus

$$x_{I+1,t+1} = P_i x_{i,t} - ci, t \tag{26}$$

for $i = 2, 3, \ldots n-1$

$$x_{n,t+1} = P_{n-1} x_{n-1,t} - c_{n-1,t} + P_n x_{n,t} - c_{n,t} \tag{27}$$

for $i = n$ where P_i is natural survival.

The fishery is managed on a quota basis, in which the quota is the weight not numbers of fish caught. To calculate the age-specific catch from a given quota, an age-specific catch equation is assumed, i.e.

$$c_i = e q_i x_i, \tag{28}$$

where e is effort and q is the age-specific catchability. The total weight of the catch equals the quota, i.e.

$$Q = \sum_i c_i w_i = e \sum_i q_i x_i w_i. \tag{29}$$

where w_i is weight at age i.

The effort, e, can be determined from the above equation and used to calculate the catches,

$$c_i = \frac{Q q_i x_i}{\sum_i q_i x_i w_i}. \tag{30}$$

The above equation may have to be modified if the population experiences density-dependent growth.

A program has been written to apply the above approach to real fishery populations. Preliminary results will be presented verbally at the meeting.

9 Conclusions

1. The proposed method is sufficiently simple to be used to be use to set quotas policy.
2. Stochastic recruitment had a small effect on the shape of the optimal policy function.

3. Error in estimating stock size had a large effect of the shape of the optimal policy.
4. It is important to simultaneously include the effects of stochastic recruitment and error in observing stock size in setting quota policies.
5. The inclusion of parameter uncertainty is a Bayesian formulation had little effect on the optimal policy.
6. It is crucial to include risk aversion in the setting of quota policies via a nonlinear utility function

10 References

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Table 1. Models investigated for a semalparous species. Mean recruitment is assumed to follow a Beverton Holt stock-recruit function with α = 0.0006 and β = 0.4.

Model		1	2	3	4	5	6	7
Observational error variance	σ_ε^2	0	0	0	0.2	0.2	0	0.2
Recruitment variability	σ_ζ^2	0	0.4	0.4	0	0.4	0	0.4
	ϕ	0	0	0.8	0	0	0	0
Recruitment parameter uncertainty	σ_α^2	0	0	0	0	0	0.2	0
	σ_β^2	0	0	0	0	0	0.2	0
	ρ	0	0	0	0	0	-0.9	0
Utility	υ	0	0	0	0	0	0	0.002

FIG. 1, SEMELPAROUS SPECIES, LINEAR UTILITY

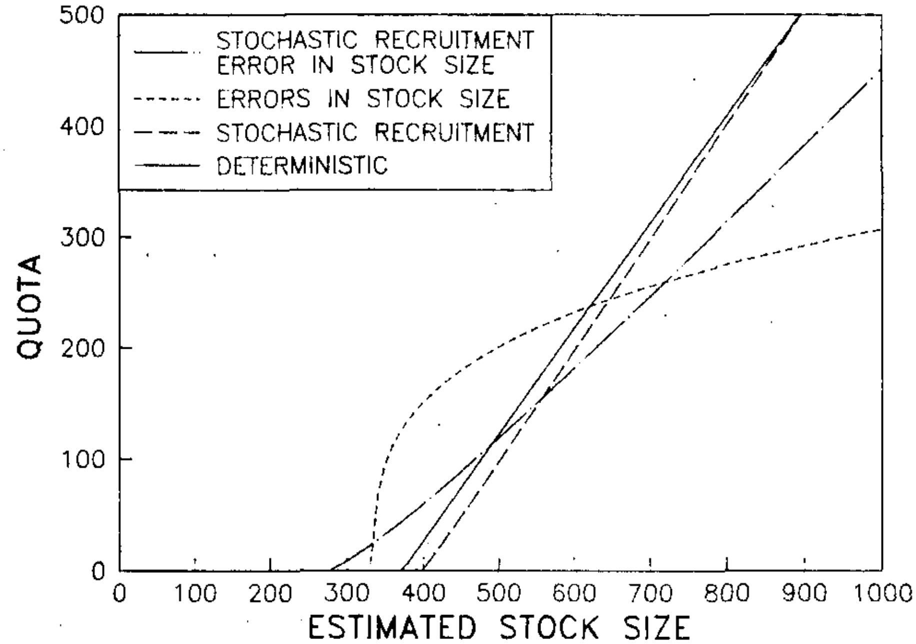

Fig. 2. Non linear Utility