Maximising the Landed Value from Prawn Fisheries Using a Variation on the Simulated Annealing Algorithm

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Simulation is used to improve the management of prawn fisheries by indicating patterns of fishing effort which prevent the harvest of under-sized animals, conserve sufficient breeding stock, and maximise the sustainable yield. Attempts to use conventional optimisation methods to find the optimum pattern of weekly fishing efforts have been ineffective because of the many extraneous local maxima. Through the use of global optimisation methods such as simulating annealing we have been able to find fishing effort patterns which maximise predicted catch values. Despite being continuous variables, the optimum levels of weekly fishing efforts usually assumed either values of zero or else the maximum fishing effort allowed. Sensitivity of the predicted maximum catch value and the pattern of fishing effort achieving this were examined for a range of parameter values representing the fishing (net selectivity and catchability) and biological (natural mortality and growth rate) processes. The greatest catch values obtainable were constant for a wide range of values of trawl net selectivities and catchability parameters, however, the optimum fishing season to obtain these maxima altered. In contrast, changes in biological parameters had a large effect on the maximum catch value despite compensation in the optimum pattern of weekly fishing efforts.

1. INTRODUCTION

The prawn fisheries of Australia are worth in excess of $350M annually. In order to prevent overfishing and to improve catch values, management of these fisheries usually employs closed seasons and spatial closures. Simulation of these fisheries has improved our ability to structure fishing effort in ways that prevent the harvest of under-sized animals, conserve sufficient breeding stock, and maximise the sustainable yield from the fishery. The problem to be solved is that of finding the global minimum of a multivariate function which has many extraneous local minima, a situation in which conventional optimisation methods are ineffective. Through the use of global optimisation methods such as simulating annealing we have been able to find patterns of weekly fishing effort which maximise catch values. A simulated annealing (SA) algorithm developed by the authors was used to find the temporal fishing pattern that maximises the landed value for the fishery and was used to explore the sensitivity of the solutions to the parameter values represented in the fishing and biological processes modelled.

2. MATERIALS AND METHODS

2.1 Prawn fishery model

The function representing the fishery was very similar to the age-structured discrete time simulation models described in Watson and Restrepo [1995] and Watson et al. [1993]. The parameter values assumed were those used in Watson et al. [1993] and approximate a small commercial fishery for *Penaeus esculentus*, the brown tiger prawn, in northern Australia. Our model used weekly time steps.

Though the brown tiger prawn often has two major recruitment periods, usually one recruitment period dominates. For simplicity, our model of recruitment consisted of prawns aged 0 weeks, and was assumed to approximate a normal distribution with a range of 19 weeks and week 10 was the modal week. In total 200,000 recruits were modelled (equal numbers of males and females).

Let i (i = 1, 2,...,52) denote the calendar week of fishing and j (j=1, 2,...,80) denote the prawn's age (weeks).

Carapace length (cl) of prawns, L_j, was assumed to follow the von Bertalanffy growth function

$$L_j = L_\infty\left(1-e^{-k(j-t_0)}\right) \qquad (1)$$

where L_∞ is the asymptotic length, k is the slope and t_0 is the age at length zero.

Fishing mortality was calculated as

$$F_{i,j} = s_j q f_i \qquad (2)$$

a product of: net selectivity (retention) s_j, catchability (vulnerability) q, and fishing effort f_i (units of 1000 hrs).

Net selection was modelled as a logistic function

$$s_j = \frac{1}{1+e^{-\lambda(L_i-\sigma)}} \quad (3)$$

with λ is the slope of the curve and σ represents the 50% selection length (the length (mm cl) at which 50% of the prawns are retained by the net).

Weekly natural mortality, M_i was defined as

$$M_i = \alpha\, e^{-\beta\, L_i} \quad (4)$$

where β was assumed to be 0.2773 and α was varied in sensitivity trials (Table 1).

Table 1: Best estimates and ranges of parameters used in sensitivity trials

Parameter	Range (10^{-2})	Best Est (10^{-2})
50% selectivity (σ)	1075 - 5375	2150
catchability (q)	1.25 - 6.25	2.50
natural mortality (α)	5.3 - 26.5	10.6
growth parameter (k)	2.54 - 12.7	5.08

Prawns caught were assigned a value depending on their length and price grade category based on values obtained from the Western Australian fishing industry (Table 2).

Table 2: Size ranges for price grade categories

Length Range (mm cl)	Price ($/kg)
0 - 24.0	5.00
24.1 - 28.0	7.50
28.1 - 37.0	10.00
37.1+	17.50

In order to simulate the age structure of prawns in the wild, where animals can live for up to 80 weeks, simulations were for a three-year period and catch values were used from the third simulated year only.

The sensitivity of the maximum catch values and weekly fishing effort patterns to values of: σ (50% net selectivity), q (catchability), α (natural mortality factor), and k (growth parameter) were examined individually by using a range of values between a factor of 0.5 and 2.5 of the assumed best estimate using 21 equal steps (Table 1).

2.2 Optimisation procedure

The SA algorithm was adapted from Sumner et al. (in press) and was used to search the 52 dimensional parameter space corresponding to the weekly fishing efforts to maximise the annual catch value. SA is more effective than local search methods because it is more likely to find the global maximum of a multivariate function that has many extraneous local maxima. Since most optimisation software is developed for minimisation rather than maximisation problems the catch value was multiplied by negative one so standard software could be used.

The method adopted here is a combination of SA and the pattern search method of Hooke and Jeeves [1961]. The SA algorithm allows a thorough exploration of the parameter space and the pattern search method is used to locate a candidate global minimum. SA is analogous to the physical annealing process whereby a material is heated to a temperature just below its melting point, and then cooled slowly to allow the molecules to align themselves, crystallise and attain a minimum energy state. SA was proposed by Kirkpatrick et al. [1983] as a method for solving combinatorial optimisation problems. More recently it has been applied to continuous optimisation problems with many variables (Vanderbilt and Louie, 1984 and others). A control parameter analogous to the annealing temperature determines the probability of an uphill move away from a local minimum, which is high at a high temperature and approaches zero as the temperature is reduced. The annealing algorithms developed by Kirkpatrick et al. and others have the ability to migrate through a sequence of local minima in search of the global solution.

2.3 Annealing Schedule

The annealing schedule specifies a high initial value for the control variable T^0, a reduction coefficient $0 < r < 1$ for slowly decreasing the value of T, and the maximum number of steps in the annealing schedule m. The selection of an annealing schedule is a very difficult problem and one for which there is no "best" choice for all problems. The decrement function used here is defined by

$$T^{\phi+1} = r\,T^{\phi}, \quad \phi = 0,1,\ldots,m \quad (5)$$

Large m values allow the control variable to decrease slowly and thus enable the algorithm to search a broad area, accepting a relatively large number of uphill moves, and hence avoiding being trapped in a local minimum. This increases the probability of finding the global optimum but only at the expense of a large number of model evaluations.

The SA process is stopped when the current point is close to the final minimum and T is too low to allow the algorithm to escape from its region of attraction. (A region of attraction is defined as the subregion of the feasible parameter space surrounding a local minimum, such that applying a strict descent algorithm to each point within that subregion will yield the minimum.) A local search algorithm can then be used to find the minimum. Such an approach improves efficiency without compromising reliability. The final value of T should be close to zero to ensure proper completion of the SA process.

2.4 The SA algorithm

The algorithm developed is a subtle modification of the direct search method of Hooke and Jeeves [1961]. It uses the pattern search method to maintain a strong downhill bias and to locate the bottom of the valley containing the best function evaluation during the local search phase. The surface is explored by two basic operations: exploratory steps that examine each variable in turn and a pattern move that attempts to accomplish further function minimisation using the information acquired by the exploratory stage. This has the effect of moving the candidate point in a downhill direction towards a local minimum. The Hooke and Jeeves method offers an efficient means for finding the downhill direction. Uphill pattern moves are accepted according to an acceptance probability determined by the annealing temperature T. This causes the algorithm to take an occasional uphill step while maintaining a downhill bias.

The algorithm is constrained to remain in the pre-specified domain of plausible parameter values by using a penalty step function that returns a large value to the annealing program when a model evaluation with parameter values outside the domain is requested. The domain consists of the set of parameter values that satisfies $0 \leq \theta_i \leq \ell \quad (i = 1,2,\ldots,p)$ where ℓ is the maximum weekly effort available in the fishery (10,000 hrs) and $p = 52$, the number of parameters to be fitted.

3. RESULTS

3.1 Simulated Annealing

The simulated annealing algorithm used was able to maximise the catch value by finding optimal values for the 52 parameters corresponding to the levels of weekly fishing effort. The algorithm consistently returned the same estimates of the solution. The annealing schedule with $T^0 = 5000$, $r = 0.6$, and $m=5$ provided an estimate of the optimal distribution of fishing effort within 1,000-2,000 function evaluations.

Using the best estimates of parameters (Table 1), a maximum annual catch of $144,789 was predicted. The optimal pattern of weekly fishing effort was a season starting in week 38 and concluding in week 3 the following year. Weekly fishing effort within this period was always 10,000 hrs, the maximum allowed in the simulation.

3.2 Trawl Net Selectivity

As σ, the 50% selectivity length (mm cl), was increased, the maximum value obtainable from the fishery stayed constant but only if the fishing season was increased (Figure 1). After the selectivity of the net was no longer adequate to catch the prawns efficiently the value obtainable from the fishery decreased even though the fishing season continued year round. The value of the fishery was relatively insensitive to trawl net selectivity over a wide range of values (including the best estimate used in other sensitivity trials).

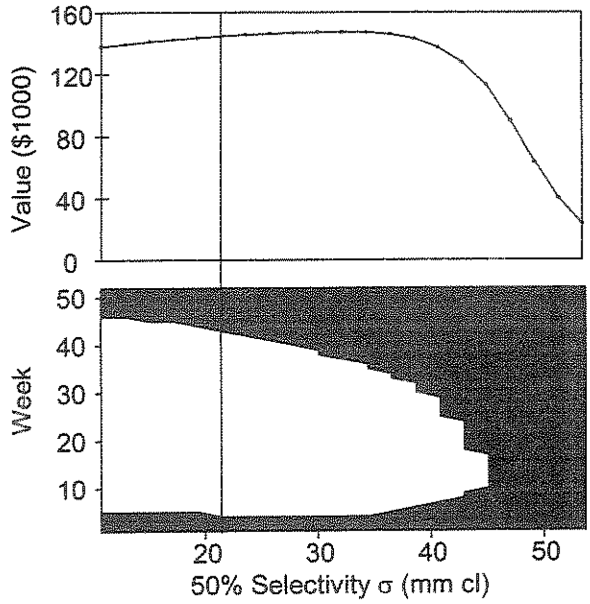

Figure 1: Effect of varying σ, the 50% net selectivity factor, on the maximum annual catch value (line graph) and the pattern of weekly fishing effort (stippled = fishing) producing the maximum landed catch value. The vertical line indicates the best estimate of selectivity used in other simulations.

3.3 Catchability

As catchability (q) increased the maximum annual catch value increased slowly towards an asymptote while the fishing season required to achieve the maximum value was slowly reduced (Figure 2). Above catchability values of about .03, there was little change in catch value or the optimum fishing pattern with increased catchability.

3.4 Natural Mortality

As natural mortality used in the simulations increased the maximum value obtainable from the fishery decreased asymptotically toward a very low value. This decrease in catch value happened despite an extension to the optimum fishing season (Figure 3). The value for the fishery was quite sensitive to assumed values of natural mortality. There was a transition point in the optimum weekly fishing pattern when natural mortality parameter α exceeded approximately 0.17 wk^{-1} and at that point the fishing season was extended.

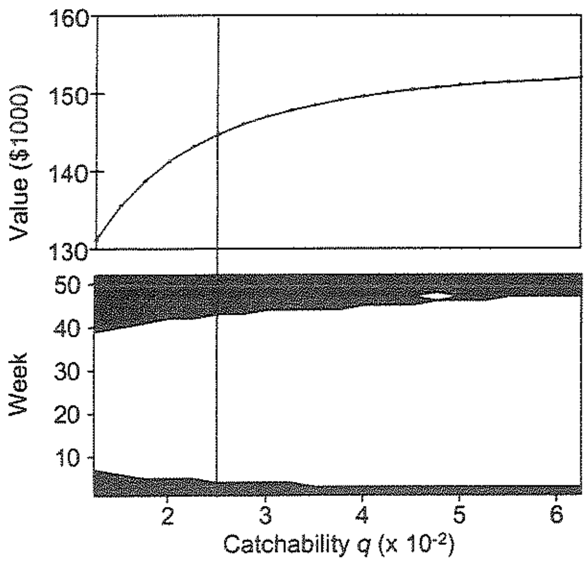

Figure 2: Effect of varying q, catchability, on maximum annual catch value (line graph) and the pattern of weekly fishing effort (stippled = fishing) producing the maximum landed catch value. The vertical line indicates the best estimate of catchability used in other simulations.

3.5 Growth Rate

As the growth parameter k increased, the value of the fishery increased in a linear fashion while the fishing season was slowly extended (Figure 4). Value of the fishery was very sensitive to changes in assumed growth rates. There was a transition point when the k parameter exceeds about 0.38 and at this point the optimum fishing season did not commence until after week 40.

4. CONCLUSIONS

Simulated annealing was effective in finding solutions for weekly fishing effort patterns providing the maximum catch value. In our solutions the individual weekly effort values were usually resulted in an assignment of either zero hours or the maximum allowed (10,000 hrs) making the problem essentially binary in nature (fish or do not fish). This indicates that in future, where a simple recruitment pattern is assumed, it may be possible to fit as few as two parameters (one representing the week that fishing starts and the other the duration in weeks) when maximising catch values.

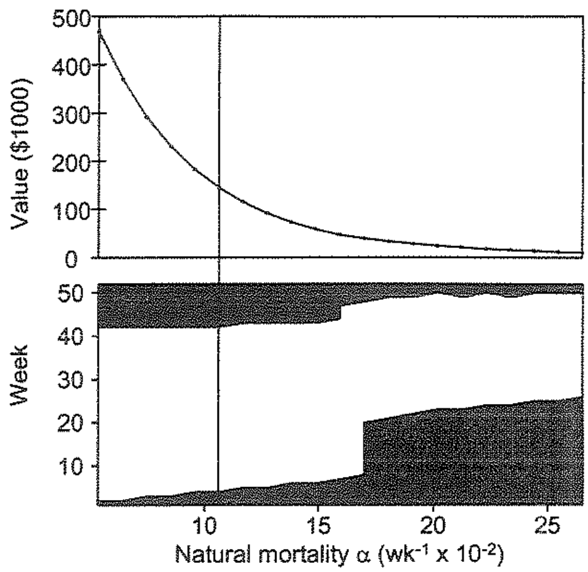

Figure 3: Effect of varying α, the level of natural mortality, on maximum annual catch value (line graph) and the pattern of weekly fishing effort (stippled = fishing) producing the maximum landed catch value. The vertical line indicates the best estimate the natural mortality used in other simulations.

The sensitivity of maximum catch values varied depending on the nature of the parameter being examined. For the model parameters tested which are directly related to fishing effort (catchability and net selectivity) there were large ranges of parameter values that had little effect on the maximum catch predicted but the optimum fishing season duration to produce this catch was altered with changes to the parameter values.

In contrast, maximum catch values were sensitive to changes in parameters describing biological relationships such as growth and natural mortality. Changes in the duration and starting date of fishing seasons could not compensate for changes in these parameters suggesting that a greater emphasis must be placed on obtaining accurate estimates of, for example, natural mortality than net selectivity if total catch value must be predicted.

When natural mortality or growth parameters were varied, there were abrupt changes in the fishing patterns corresponding to maximum catch values. Although further investigations are required, it appears that these shifts might develop from the discontinuous nature of the relationship between prawn length and value (Table 1). As the parameters tested varied, prawns of different lengths were successively affected, however, the value of these prawns changed abruptly depending on their price category, thereby altering the calculated catch value for that fishing pattern.

The use of the simulated annealing search technique is a promising tool for work in optimising fishing efforts in fisheries. In the future, extension of this approach to the multi-area problems (spatial closures) will allow managers further scope to improve catch values and sustain stocks.

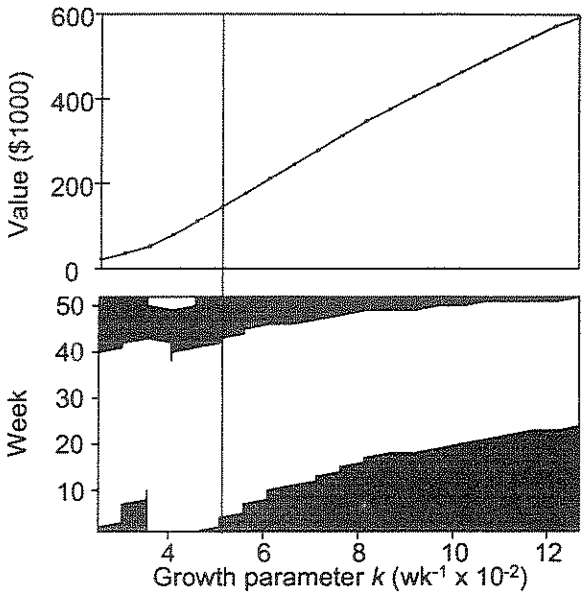

Figure 4: Effect of varying *k*, a von Bertalanffy growth parameter, on maximum annual catch value (line graph) and the pattern of weekly fishing effort producing the maximum landed catch value. The vertical line indicates the best estimate of *k* used in other simulations.

5. ACKNOWLEDGEMENTS

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6. REFERENCES

Hooke, R., and Jeeves, T.A., Direct search solution of numerical and statistical problems. *J. Assoc. Comp. Mach.*, 212-229, 1961.

Kirkpatrick, S., Gelatt, Jr., C.D., and M.P. Vecchi, Optimization by simulated annealing. *Science*, 220, 671-680, 1983.

Vanderbilt, D., and S.G. Louie, A Monte Carlo simulated annealing approach to optimization over continuous variables. *J. Comput. Phys.*, 56, 259-271, 1984.

Sumner, N.R., P.M. Fleming, and B.C. Bates, Calibration of a modified SFB model for 25 Australian catchments using simulated annealing. *J. Hydrol.*, (In Press).

Watson, R.A., D. Die, and V.R. Restrepo, Closed seasons and tropical penaeid fisheries: a simulation including fleet dynamics and parameter uncertainty. *N.A. J. Fish. Management* 13, 326-336, 1993.

Watson, R.A., and V.R. Restrepo, Evaluating closed season options with simulation for a tropical shrimp fishery. *ICES Marine Science Symposia* 199, 391-398, 1995.