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Application of genetic algorithms for solving large non-linear fisheries bioeconomic models

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Application of genetic algorithms for solving large non-linear fisheries bioeconomic models

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Abstract
The development and use of fisheries bioeconomic optimisation models is well established. However, the use of these models has been restricted in fisheries where there are a large number of non-linear interactions. In most cases, the use of linear approximations or simplification of the model has been necessary in order to derive a solution. An alternative to traditional optimisation models is the use of genetic algorithms. These solve in a manner quite different from the traditional approach, and hence can overcome some of the problems associated with traditional solution systems. In this paper, the basic features, advantages and disadvantages of the use of genetic algorithms in fisheries bioeconomic modelling are discussed. A large non-linear model of the UK component of the English channel fisheries is developed using a genetic algorithm. The results were compared to those estimated using a linearised versions of the model solved using traditional linear programming techniques. The results suggest that genetic algorithms may be a suitable way for solving large non-linear bioeconomic models that cannot be solved using traditional techniques.

Keywords: Genetic algorithms, optimisation, bioeconomic modelling

1. Introduction

Fisheries resources have the potential to yield substantial benefits to the community when managed effectively (Arnason 1993), and management measures are designed to attempt to capture some, if not all, of these potential benefits. Bioeconomic models have been developed for a number of fisheries as a means of estimating the optimal level of exploitation of the resource and assessing the effectiveness of various management plans.

Given the relationships between catch and effort, prices and costs of fishing, a profit maximising level of effort can be determined for the fishery. Problems of this type are generally modelled as non-linear (possibly multi-objective) mathematical programming problems. However, if the model is large in size and/or significantly non-linear (i.e. non-smooth non-linear functions), then traditional solution methods are often unable to achieve the global optimum. In this case, linear approximations are typically included into the model in order to make solution possible.

Genetic algorithms (GA) do not suffer from these deficiencies, and have been shown to be highly applicable to examples of large non-linear models. Genetic algorithms are an evolutionary optimisation approach, probabilistic in nature, which are an alternative to traditional optimisation methods. GA are most appropriate for complex non-linear models where location of the global optimum is a difficult task, as due to the probabilistic development of solutions, GA is not restricted by local optima. Given the large number of non-linearities that can exist in fisheries bioeconomic models, GA appears to be a potentially useful approach.

Hence, the use of GA for optimisation problems offers an alternative approach to the traditional solution methods. GA follow the concept of solution evolution, by stochastically developing generations of solution populations using a given fitness statistic, for example the objective function in mathematical programmes. They are particularly applicable to problems which are large, non-linear and possibly discrete in nature, features that traditionally add to the degree of complexity of solution. Due to the probabilistic development of populations, GA do not guarantee optimality even when it may be reached. For the same reason they are not contained by local optima.

The list of topics to which genetic algorithms have been applied is extensive. These include job shop scheduling, time-tabling, the travelling salesman problem, portfolio selection, agriculture etc. However, in the field of fisheries there are relatively few examples, and of these none consider bioeconomic model optimisation. In the field of agriculture, Mayer et al. (1996) developed a bioeconomic dairy model in order to compare alternative solution methods. The four methods compared were that of GA, where a general GA tool (GENESIS - Grefenstette 1984) was used, the simplex method, a gradient method and simulated annealing. It was concluded that the GA performed well, with optimal values reported averaging 99.7% of the global optimal.

In this paper, a GA model is developed for the UK part of the Channel fishery. The model described in this paper is based on a bioeconomic model of the fishery developed as a linear programming (LP) problem (Pascoe 1997). Comparisons between the GA approach and traditional solution methods are made, in order to measure their relative effectiveness. General observations of the use of GA in fisheries bioeconomic models, and other similar models, are discussed.

2. Genetic Algorithms

The introduction of GA in modern form is attributed to Holland (1975), which he termed adaptive systems. Since the early 1980s, and particularly in the last ten years, substantial research effort has been applied to the investigation and development of genetic algorithms (see, for example, Goldberg 1989, Michalewicz 1996 and Koza 1992).

A genetic algorithm is an optimisation procedure which finds an optimal solution from a developing 'population' of alternative solutions. The initial population is comprised of 'individuals' each with a given randomly-assigned combination of values for each of the control (or probabilistic) variables[1]. These combinations of values are contained within a series of binary strings that form the 'genetic code' of the individual. Also associated with each individual is a 'fitness statistic' which typically represents the value of the objective function. The algorithm identifies the individuals with the optimising fitness values. Thus by using alternative selection schemes the fittest individuals are chosen to produce the next generation of individuals. Those with lower fitness will naturally get discarded from the population.

The end result of this process is (in theory) the estimation of a set of variables that optimises the objective function being considered. As a result, the GA technique has advantages over traditional non-linear solution techniques that cannot always achieve an optimal solution[2]. A simplified comparison of the GA and the traditional solution techniques is illustrated in Figure 1. Non-linear programming solvers generally use some form of gradient search technique to move along the steepest gradient until the highest point (maximisation) is reached. In the case of linear programming, a global optimum will always be attained. However, non-linear programming models may be subject to problems of convergence to local optima, or in some cases, may be unable to find a feasible solution. This largely depends on the starting point of the solver. A starting point outside the feasible region may result in no feasible solution being found, even though feasible solutions may exist. Other starting points may lead to an optimal solution, but it is not possible to determine if it is a local of global optimum. Hence, the modeller can never be sure that the optimal solution produced using the model is the "true" optimum.

For the genetic algorithm, the population encompasses a range of possible outcomes. Local optima are not identified *per se* as their 'fitness' (or objective value) will be inferior to the higher values closer to the global optimum. With an appropriately sized population, the set of variables at or near the global optimum are, in the case of non-linear programming, identified as that with the highest objective function value. Successive generations improve the fitness of individuals in the population until the optimisation convergence criteria is met. Due to this probabilistic nature, GA tends to the global optimum.

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[1] These random variables can also be generated around given starting values.

[2] Linear programming techniques, such as the simplex method and the interior point method, will always result in an optimal solution, provided such a solution exists and assuming convexity in the model's constraints. Linear programming models do not incur the same problems of local optima as non-linear programming models.

The procedure of genetic breeding is based on the Darwinian principle of survival of the fittest. Ideas and principles of reproduction (crossover) of the selected individuals at each generation are incorporated, with a (small) mutation factor. The result of this 'mating' is another set of individuals that contain the modified 'genes' (representing the variable values) based on the original subjects with better (min. or max.) fitness. 'Mutations' to the 'chromosomes' of the genes are probabilistically undertaken with low probability, enabling random modification to the individual during the reproduction process.

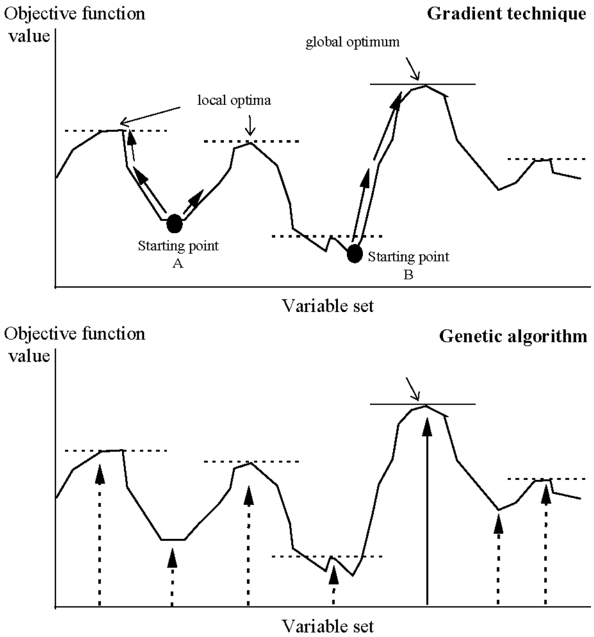

Figure 1. Comparison of gradient search technique and genetic algorithm approach.

The genetic algorithm follows an iterative procedure that involves four stages:

Evaluate fitness - each individual solution in a population is evaluated and thus assigned a measure of fitness. Typically in a non-linear programming scenario, this measure will reflect the objective value of the given model.
Selection - Individuals of the current population are selected as suitable subjects for development of the next generation based on their fitness. Various selection alternatives have been proposed. This follows the principles of Darwinian natural selection where the fittest have a greater probability of survival.
Crossover - Two selected individuals are combined by using a crossover point to create two new individuals. Simple (asexual) reproduction can also occur which replicates an individual in the new population.
Mutation - Given a small mutation probability factor, a new individual may be probabilistically modified to a small degree.

The optimisation is terminated if the solution level is attained, or if the maximum number of generations is reached, or if a given number of generations without fitness improvement is performed. Generally, the last of these criteria applies as convergence slows to the optimal solution.

Population size selection is probably the most important parameter. Generally this parameter must reflect the size and complexity of the problem. The trade-off between extra computational effort with respect to increased population size is a problem specific decision to be ascertained by the modeller, as doubling the population size will approximately double the solution time. Other parameters include the maximum number of generations to be performed, a crossover probability, a mutation probability, a selection method and possibly an elitist strategy, where the best is retained in the next generation. The most common type of fitness function is the error/distance shortfall functions (Koza 1992).

GA solvers such as GENESIS (Grefenstette 1984), GENOCOP (Michalewicz 1996 and FORTGA (Carroll 1997) are publicly available for non-commercial use. Many modifications and enhancements are typically incorporated into these algorithms in order to improve performance, including alternative selection processes and more complex utilities to maintain feasibility when dealing with constraints. GA solvers are particularly applicable to unconstrained problems, as constraints, of the traditional linear programming style, are difficult to incorporate into the model. The obvious approach is to penalise a sum of infeasibilities more than the objective value. However, such a weighted sum may give rise to very slow convergence to optimality. GENOCOP III (Michalewicz 1996) has been designed to cater for non-linear constraints applying techniques to maintain feasibility of individual solutions.

3. Fisheries Bioeconomic Models

The foundations of fisheries bioeconomic modelling comes from the economic theory of the open-access or common-property fishery developed by Gordon (1954) and Schaefer (1954). A concise development of this and subsequent theory is given by Clark (1976). These models are based on a logistic population growth model. The sustainable yield is equivalent to the level of growth in the population, which varies with the size of the population. From this, a parabolic long run catch-effort relationship can be developed. Other non-linearities can be incorporated into the traditional models.

The simplest of bioeconomic models are based on non-linear catch-effort relationships for single species. In recent years, models of this kind have been applied successfully to a number of predominantly independent fish stocks. However, they are often generalised as many interactions are ignored. Nevertheless, they can be useful from a management perspective.

Significant research on multi-species models has also been undertaken. Due to the more complex nature of such models, with species interaction and typically larger fisheries, such models are larger and more difficult to solve.

Many of these models have been developed as mathematical programmes. Linear programming models have been developed for prawn fisheries (Clark and Kirkwood 1979, Haynes and Pascoe 1988), lobster fisheries (Cheng and Townsend 1993), multi-species finfish fisheries (Brown et al. 1978, Siegel et al. 1979, Sinclair 1985, Murawski and Finn 1985, Geen et al. 1991, Frost et al. 1993). Non-linear programming models have also been developed for a range of fisheries, including prawn fisheries (Christensen and Vestergaard 1993, Reid et al. 1993, Dann and Pascoe 1994), shark fisheries (Pascoe et al. 1992), and finfish fisheries (Placenti et al. 1992, Mardle et al. 1997).

Most of the linear and non-linear programming models noted above were used to examine the optimal equilibrium level of effort in a fishery. However, dynamic (non-linear) programming models have also been developed. For example, the model developed by Pascoe et al. (1992) estimated the optimal harvesting strategy over time for the Australian southern shark fishery based on a dynamic age structured model. Diaby (1996) also developed a dynamic age structured model of the Ivorian sardinella fishery to examine the effects of the current management on economic profits compared with those from an “optimally” managed fishery.

Currently, multi-species fisheries bioeconomic models are a vital aid for management to perform effective decision analysis. The fact that many fisheries are over-fished has placed a significant importance on developing accurate predictive models. However, due to the complexities inherent in many problems, traditional optimisation methods may require approximation of the model to achieve solution.

Few attempts have been undertaken to develop GA models of fisheries. Pascoe (1996) developed a simple fisheries bioeconomic model using a commercial GA solver in order to compare the package with a traditional non-linear programming package. Mardle et al. (1998) developed a multi-objective GA model of the North Sea fishery to examine optimal fleet levels.

4. Bioeconomic Model Of The English Channel Fisheries

Both the linear programming and genetic algorithm versions of the bioeconomic model of the UK component of the English Channel fisheries share many similar characteristics. The general components of the models are illustrated in Figure 2. The mathematical description of the linear programming model, data sources and validation are given in Pascoe (1997). The genetic algorithm model uses similar equations to those presented in Pascoe (1997).

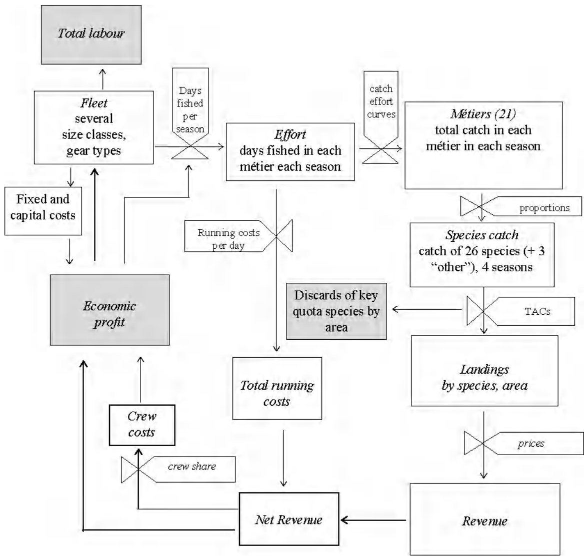

Figure 2. The Channel fisheries bioeconomic model.

In the original linear programming model, the fleet is subdivided into 6 size classes in each of the 5 administrative regions along the coast. These boats can use combinations of 6 gear types (beam trawl, otter trawl, dredge, lines, nets and pots) to operate in 21 métiers. The boats can change gear and métier each season although boats are restricted to using either static gear or mobile gear.

In the genetic algorithm model, the fleet was subdivided into only 3 size classes. Gear use was limited to 2 generic gear types: static gear (pots, nets and line) and mobile gear (otter trawl, beam trawl and dredge). While the model can theoretically incorporate the same data structure as the LP model, it was necessary at this investigative stage to reduce the size structure of the GA model in order to effectively implement the GA.

For the purposes of the analysis, it was considered acceptable to use a simpler version of the model which still maintained the key elements of the problem. A simplified form of the LP was also developed with the same regional, size class and gear type groups as the GA model in order to allow a direct comparison of the model results.

Catches of each of the 29 species included in the model are estimated based on the level of fishing activity in each métier in each season. The catch effort relationships are non-linear, based on the Coppola (1995) production function. Initial attempts at solving a non-linear programming version of the model were unsuccessful due to the large number of non-linearities. As a result, the non-linear catch effort relationships were incorporated into the linear programming model using the separable programming technique (Williams 1994). The non-linear functions, however, were incorporated directly into the genetic algorithm version of the model.

Landings of some species were limited by total allowable catches (TAC), with the difference between landings and catch being implicitly discarded. Revenue was estimated based on the level of landings and the price. Running costs were determined as a function of revenue and the level of effort while fixed and capital costs were determined by the fleet size and structure. Revenues and costs determine the level of economic profits in the fishery, which affect the level and distribution of effort.

The models are largely based on individual boat catch and effort data relating to 1992. The model has a short run perspective only as information on stock dynamics for nearly all key species is not currently available. Cost data were derived from the economic survey of the fishery (Pascoe et al. 1996). Market information (such as prices) was derived from total value of landings statistics for the UK (MAFF 1996, and earlier issues) as well as value of landings by port information provided by MAFF. All economic data are indexed to represent values in 1994-95 prices.

5. The Solution Process

The different models' variable dependencies are shown in Table 1, with the index definitions given in Table 2. For the simplified LP model and the GA model, the data were aggregated or averaged over the new groupings. In total, the reduced LP and GA models include 876 probabilistic variables (i.e. landings, boats and days). Each probabilistic (or control) variable is assigned lower and upper bounds for the optimisation, and contain the main information required for the model. The deterministic variables, managed by the fitness function, are each dependent on the values of the control variables.

Table 1. GA structure of the Channel fisheries model.

Variable	*Type*	*Dependencies*
$landings_{sta}$	probabilistic	
$boats_{trzg}$	probabilistic	
$days_{mtrzg}$	probabilistic	
$boatsize_{rz}$	deterministic	$boats_{trzg}$
revenue	deterministic	$landings_{sta}$, $Price_{st}$
net_revenue	deterministic	revenue, $days_{mtrzg}$, $Daycost_{gz}$
rent	deterministic	net_revenue, $Costs_{z}$, Crewshare, $boatsize_{rz}$
$effort_{mt}$	deterministic	$days_{mtrzg}$, $FishingPower_{mrz}$
$total\_catch_{mt}$	deterministic	$effort_{mt}$
$catch_{sa}$	deterministic	$total\_catch_{mt}$, $CPUE_{mts}$
$total\_crew_{r}$	deterministic	$boatsize_{rz}$, $CrewNo_{z}$

Table 2. Index structure of the model.

Index	*Code*	*Length* LP_{FULL}	LP_{RED}, *GA*
Species	s	29	29
Season	t	4	4
Area	a	3	3
Region	r	5	1
Gear	g	6	2
Size	z	6	3
Métier	m	21	21

The LP model was developed and solved using the GAMS (General Algebraic Modelling System) package (Brooke at al. 1988). GENOCOP III (Genetic algorithm for numerical optimisation of constrained problems, Michalewicz 1996) was used as the primary optimisation algorithm for the model implementation. The fitness function is based on the profit maximisation objective.

An arithmetic crossover technique is implemented in GENOCOP III, which is capable of maintaining feasibility with defined constraints. However, this operation requires feasibility of individuals before optimisation. Therefore, two stages were developed for the GA optimisation. The first ignored the defined constraints and managed them explicitly in the fitness function to attain feasibility by means of a simple sum of infeasibilities technique. The second stage then used the solution attained to restart the optimisation with the defined constraints. The 123 defined inequality constraints describe the maximum number of boats of a given size class available in a season (12 constraints), a landings limit based on TACs for species defined in fishing areas (87 constraints) and the maximum number of days fishing per season by a boat class (24 constraints).

The principle optimisation parameter settings of the model are set to minimisation, population size 50, and maximum number of feasible generations 100. These settings were developed from a number of optimisation test cases. For the size of model, the chosen population size is small. However in tests the convergence characteristics of the smaller population with a greater number of generations, was more computationally efficient than that of a larger population.

6. Results

Results for three optimisation models and 1995 summary statistics for the key economic indicators are presented in Table 3. The LP model (LP_{FULL}) uses the complete data structure defined in Table 2. The GA model and reduced LP model (LP_{RED}) use the reduced data structure (Table 2). In all models, the objective is the maximisation of economic profits.

Table 3. LP and GA model results.

	1995[a]	Profit maximising fleet LP_{FULL}	LP_{RED}	*GA*
Revenue (£m)	69.3	63.9	61.0	60.8
Economic profits (£m)	1.7	31.3	25.8	25.9
Fleet size				
<10m	1673	604	1163	1134
10m-20m	392	44	57	57
>20m	101	4	1	1
Employment	4853	1312	2491	2432

a) Estimated from survey data (Pascoe et al. 1997)

Reducing the information contained within the LP model makes a significant difference to the results (Table 3). The approximations of size class and gear type in LP_{RED} have affected the optimal fleet structure and consequently the level of economic profit achievable.

Due to the size and complexity of the LP models, the catch-effort functions were included as piecewise linear approximations (see Section 4). Consequently, the total catch reported for métier *m* in season *t* is an underestimate of the true function value[3]. In contrast, the GA model uses the specific non-linear representation of the catch-effort functions, and therefore should arrive at a superior optimal solution. Given this, the information from the optimal solution of LP_{RED} was used to start the GA model with an advanced solution. Thus, the individuals of the GA's initial population were developed to approximate this result. Hence, feasibility in the GA is given, and then maintained in the fitness function where necessary through management of the probabilistic variables.

The effect of the linear approximation on the optimal level of profits and optimal fleet size can be seen by comparing the results for the GA model with those of the LP_{RED} model. The economic profits estimated using the GA model were approximately £0.06m greater than those estimated using the LP_{RED} model, a difference of less than 1 per cent. The optimal fleet size were also similar, with the optimal number of small boats estimated using the GA model being slightly less than that estimated using the LP_{RED} model. The similarities in the results suggest that the linear approximations used in the LP models were fairly accurate. A total of 40 segments were used in the estimation of the linearised catch-effort curves.

From Table 3, it can be seen that the maximum economic profits estimated using the models were substantially higher than those estimated for 1995 from survey data (Pascoe et al. 1997). As would be expected, a substantial reduction in boat numbers would be required to achieve the maximum level of profits. However, the optimal fleet size was sensitive to the level of aggregation in the model. The optimal number of small boats estimated using the most disaggregated form of the model was almost half that estimated using the reduced form of the LP and the GA models. While this is not the subject of investigation in this paper, the result is interesting nevertheless.

As GA is a stochastic search technique, no two solutions will generally follow exactly the same path even though status at termination would be expected to be very similar. Hence, three runs of the GA model were performed in order to evaluate the convergence effects. The models all converged to the same level of economic profits.

The difference in time taken to solve the model types WAS significant, with the GA taking over 10 minutes to show convergence to 'optimality'. In contrast, the LP models solved in less than a minute. Improvements in model performance, however, are expected with continued development of the GA model.

The GA approach has an advantage over the LP solution process when variables must take integer values. The GA model can be solved equally as fast with either integer or continuous variables. In contrast, the LP models were solved with continuous variables, with integer approximations taken from the continuous results. While integer programming techniques exist (e.g. branch and bound), these are generally time consuming. Where integer values for the control variables are important, GA models may be considerably faster than traditional approaches.

7. Discussion and Conclusions

As models have become increasingly more detailed, the types of questions which fisheries managers hope to find answers to have also become more complex. The development of detailed multi-species multi-gear models to answer these questions is limited by the available solution techniques. New techniques can expand the range and relevance of fisheries models in solving real-world issues.

[3] The accuracy reflects the number of data points used to form the piecewise linear approximation.

The model of the UK part of the Channel fishery has been used to investigate the potential usefulness of genetic algorithms for the solution of large-scale, non-linear problems. This paper compares a known solution, found by a traditional optimisation approach, to solutions attained by a genetic algorithm. It is clear that GA offer a potential alternative to the traditional optimisation approaches.

Fisheries bioeconomic models are not unique in the fact that generally simplifying assumptions must be made to find a solution using many optimisation techniques. This is due to the models' natural size and complexity. Where solution is not possible by traditional approaches, GA may be able to offer a viable alternative. As in this case, it would not be expected for a constrained mathematical programming problem to be solved faster by GA, which is a probabilistic search method, than by a traditional optimisation approach, which is a guided search method and has been developed and successfully applied to many models of this type.

There are a number of factors which must be taken into consideration when developing a GA model; there are typically many standard parameters which can be modified to affect the performance of the optimisation (see section 2), variable specification (probabilistic or deterministic), tight variable bounds, weighting strategies and constraints. Unconstrained problems are particularly suitable for GA consideration as constraints require the management of possible infeasibility, which may slow down the optimisation process considerably. Generally, a standard genetic algorithm is taken for specific development of the problem under investigation where the modeller should take advantage of model structure for effective implementation.

Constraints are difficult to incorporate into a GA code, as generally it is left to the fitness function to manage and quantify possible infeasibility. For problems where a large feasible set of solutions exist, constraints do not pose the same problem as for a small feasible set. This is because the fitness function must generally determine the level of infeasibility and optimality as one fitness statistic. If feasible solutions are easily determined, then fitness is easily described.

The majority of existing GA tools are written in C/C++ and developed on UNIX workstations, and are available free for non-commercial activity. The modeller typically implements the model directly into the code of the computer program. Although, C/C++ is a robust programming language for algorithmic software development, this adds to the expertise required by the modeller. Typically, facilities such as a user-friendly interface are not available to the novice user. This is definitely a disadvantage over the usability and history of traditional modelling approaches. General commercial GA solvers do exist, although their applicability to specific large-scale constrained is unclear.

This paper has investigated the potential applicability of genetic algorithms for the application to fisheries bioeconomic models. Further development of a specialised solver will improve the speed and number of variables that can be practically considered in a range of problems. The ultimate aim is to encourage the development of broader and more comprehensive fisheries models for use in management decision making. Such a tool will both contribute to the methodological development of bioeconomic modelling as well as having immediate practical benefits in terms of increasing the range of management questions that can be addressed by such models.

8. Acknowledgements

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