Use of evolutionary methods for bioeconomic optimization models: an application to fisheries

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Abstract

Bioeconomic optimization models are regularly used in fisheries policy analysis. However, the use of these models has been restricted in fisheries, as in other similar fields, where there are a large number of non-linear interactions. In this paper, the basic features, advantages and disadvantages of the use of the evolutionary methods, specifically genetic algorithms, are discussed. A large non-linear model of the UK component of the English Channel fisheries is developed using genetic algorithms. The results are compared with those from a linearized version of the model solved using traditional optimization techniques. The results suggest that genetic algorithms may provide better solutions for large non-linear bioeconomic models that cannot be solved using traditional techniques without the use of simplifying assumptions.

Keywords: Genetic algorithms; Optimization; Bioeconomic modeling; Fisheries; Open access

1. Introduction

The foundations of fisheries bioeconomic modeling comes from the economic theory of the open-access or common-property fishery developed by Gordon (1954) and the models of sustainable yields in fisheries developed by Schaefer (1954). This, and subsequent theory (Clark, 1990), has been used to develop a range of both simulation and optimization models of fisheries around the world. The simulation models have largely been used to estimate the effects of changes in conditions in the
fishery (either natural, economic or management induced) on the biological resource and economic performance of the fleets. Assumptions are made about the allocation and level of fishing activity. In contrast, optimization models have been used to estimate potential yields and/or profitability in the fishery, and the allocation and level of fishing activity has been endogenously determined using the model.

Of particular interest in this study is the use of optimization models. Many of these models have been developed as mathematical programs. Linear programming (LP) models have been developed for prawn fisheries (Clark and Kirkwood, 1979; Haynes and Pascoe, 1988), lobster fisheries (Cheng and Townsend, 1993), and multispecies finfish fisheries (Brown et al., 1978, Siegel et al., 1979; Murawski and Finn, 1985; Sinclair, 1985; Geen et al., 1991; Frost et al., 1993). These models were based on either a linear relationship between catch and effort, or a linearized relationship using techniques such as separable programming (Williams, 1994).

The development of fast, non-linear programming (NLP) algorithms has resulted in a number of NLP models being developed for a range of fisheries. These include 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., 1999). Dynamic NLP models have also been developed. For example, the model developed by Pascoe et al. 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.

Most of the LP and NLP models noted above were used to examine the optimal (e.g. profit maximizing) equilibrium level of effort in a fishery. In such models, the performance of individual boat groups within a model is less important, and the model is optimized globally. Additional problems arise, however, when the performance of individual boat groups are important. This introduces a number of additional non-linearities into the model and increases the potential for local optima and locally infeasible solutions.

Individual boat performance may be important when trying to estimate the fleet configuration in an open-access or “regulated open access” (Homans and Wilen, 1997) fishery. Such a model may be required when estimating the effects of particular management policies that change the incentives of fishers, and hence an estimate of fisher response is based on some optimizing behavior.

Under the traditional Gordon–Schaefer framework, the open access situation is characterized by zero economic rents being generated in the fishery. Additional fishers enter the fishery up to the point where all rents are dissipated. This has been used to approximate the open access condition in optimization models, where some variable (such as fishing effort or boat numbers) is maximized subject to the condition that total fishery profits are zero (e.g. Haynes and Pascoe, 1988). However, the Gordon–Schaefer model is predicated on a fleet of homogeneous boats. In many multi-species multi-gear fisheries, it is unlikely that a single boat type would dominate in the long run as the different gears tend to catch different species in different proportions. Hence, equilibrium would be characterized by a heterogeneous fleet. In
such a case, it is likely that some boat groups would be earning intra-marginal rents, but the marginal boat in the fishery would be earning zero rent (Hannesson, 1993; Coglan and Pascoe, 1999). Any additional boats to the fishery would earn negative rents so would not enter the fishery.

In such a case, maximizing effort in the fishery subject to zero fishery profits would result in higher levels of effort than theoretically could exist in equilibrium. For total fishery profits to be zero, some boats would need to earn negative rents in order to offset the positive intra-marginal rents of other boats. This would not be a true equilibrium situation as the boats earning negative rents would not stay in the fishery in the long run.

To overcome this problem, the profitability of individual boat groups needs to be estimated within the model, and the condition needs to be set that these individual profits must not be negative. This requires an estimate of the individual boat catch, which is a function of the average catch rate and the individual level of effort. In most fisheries bioeconomic models, the average catch rate is a non-linear function of the total level of effort in the fishery. Hence, the individual catch rate is a highly non-linear variable, being a function of both its own effort and the total level of effort in the fishery. This increases the problems associated with the traditional solution algorithms for solving NLP models.

In this paper, a genetic algorithm (GA) model is developed for the UK fleet operating in the English Channel fishery. The model investigates the profit maximizing and open-access equilibrium level of effort in the fishery, and is based on a bioeconomic model developed as an LP problem (Pascoe, 1997). The GA approach is discussed in contrast to traditional solution methods and an attempt is made to evaluate the effectiveness of the GA procedure. General observations of the use of GA for the optimization of large NLP models and specifically fisheries bioeconomic models are discussed.

2. GAs

The introduction of GAs in modern form is generally attributed to Holland (1975), which he termed, “adaptive systems”. Since the early 1980s, and particularly in the last 10 years, substantial research effort has been applied to the investigation and development of GAs and related areas (e.g. Goldberg, 1989; Koza, 1992; Michalewicz, 1996).

A GA is a search procedure, typically used in an optimizing form, which finds the best 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. 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

1 These random variables can also be generated around given starting values.
algorithm identifies the individuals with the optimizing 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 population encompasses a range of possible outcomes. Local optima are not identified per se, as their ‘fitness’ (or objective function 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 NLP, identified as those associated with the highest objective function value. Successive generations improve the fitness of individuals in the population until the optimization convergence criteria is met. Due to this probabilistic nature, GA tends to the global optimum (Fig. 1).

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 (minimum or maximum) fitness. ‘Mutations’ to the ‘chromosomes’ of the genes are probabilistically undertaken with low probability, enabling random modification to the individual during the reproduction process. This allows combinations of variable values to exist in the ‘genetic pool’ which may not be otherwise represented from the crossover process.

The general algorithmic process of the GA follows an iterative procedure that involves four principal stages (Fig. 2):
1. Evaluate fitness of individuals — each individual solution in a population is evaluated and thus assigned a measure of fitness. Typically, in an NLP scenario, this measure will reflect the objective value of the given model. An elitist strategy is often implemented to maintain the best solution at a given stage in the population.

2. Select two individuals — individuals of the current population are selected as suitable subjects for development of the next generation based on their fitness. This follows the principles of Darwinian natural selection where the fittest have a greater probability of survival. Different methods of selection proposed (see Baeck and Hoffmeister, 1991, for an overview) include random selection, where a given number of individuals are selected at random and the best chosen, and proportional ranking, linear ranking and uniform ranking where probabilities for each individual are calculated from which selection is made (e.g. by the cumulative addition of the probabilities up to a random threshold).

3. Crossover — selected individuals are then combined using a given crossover strategy to create new individuals for the next population. Typically, two such crossover strategies are; n-point crossover, where the bits between points are alternately exchanged or not exchanged, and uniform crossover, where a bit mask is used to determine the individual to copy at a given bit. Simple (asexual) reproduction can also occur which replicates an individual in the new population.

4. Mutation — given a small mutation probability factor, a new individual may be probabilistically modified to a small degree.

The optimization is terminated when either: (1) a predefined solution level is attained; (2) a specified number of generations is reached; (3) the population as a whole reaches a defined level of convergence; or (4) a given number of generations without fitness improvement is performed. Criterion (2) is the most general of these
terminating conditions, as convergence typically slows significantly when approaching the optimal solution. Theoretically, population convergence appears to be the natural terminating condition. However, this may not be appropriate in some cases if the population converges too quickly to a given solution, therefore removing a large amount of the variation required to develop better solutions. This can be a potential difficulty in GA for the identification of what is close to the optimal solution. This makes the population size used in the model a crucial parameter, as generally it 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 modeler, as doubling the population size will approximately double the solution time. Enough variation must be maintained in the population to allow convergence towards the optimum.

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 NLP package. Mardle et al. (2000) developed a multi-objective GA model of the North Sea fishery to examine optimal fleet levels. These models examined only the optimal scenarios at the global fishery level. They did not attempt to use the techniques to identify the long run open access situation in the fisheries examined.

3. Bioeconomic model of the English Channel fisheries

Both the LP and GA 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 Fig. 3. Pascoe (1997) discusses an earlier version of this optimization model on which the models in this paper are developed.

The fleet was subdivided into six fleet segments, based on three size classes, and two generic gear types: static gear (pots, nets and line) and mobile gear (otter trawl, beam trawl and dredge). The fleet were largely multi-purpose boats that used a combination of gear types. However, most boats tended to use either static or mobile gear types. Table 1 gives the lengths of the modeled variable indices.

Catches of each of the 29 species included in the model are estimated based on the level of fishing activity in each métier\(^2\) in each season. A total of 28 separate UK métiers have been identified in the Channel (Tétard et al., 1995), 21 of which are included in the model. The catch effort relationships are non-linear, based on the Coppola and Pascoe (1998) production function. Initial attempts at solving a NLP 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 LP model using the separable programming technique (Williams, 1994). The

\(^2\) Métiers are distinct fishing activities defined by gear used, area fished and main species targeted. As the English Channel is a multi-species fishery the boats catch a range of species; therefore the métier in which the boats operate reflects this catch combination.
non-linear functions, however, were incorporated directly into the GA version of the model.

The objective function of the profit-maximization simulations was, of course, the maximization of total fishery profits. For the LP model, this was defined as total fishery revenue less total fishery costs (Eq. (1a)), while for the GA model total fishery profits was estimated as the sum of individual boats’ profits, estimated as the sum of their individual revenues and costs (Eq. (1b)). These are given by:

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**Table 1**

Index structure of the model

<table>
<thead>
<tr>
<th>Index</th>
<th>Code</th>
<th>Length</th>
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<tbody>
<tr>
<td>Species</td>
<td>$s$</td>
<td>29</td>
</tr>
<tr>
<td>Season</td>
<td>$q$</td>
<td>4</td>
</tr>
<tr>
<td>Gear</td>
<td>$g$</td>
<td>2</td>
</tr>
<tr>
<td>Size</td>
<td>$l$</td>
<td>3</td>
</tr>
<tr>
<td>Métier</td>
<td>$m$</td>
<td>21</td>
</tr>
</tbody>
</table>

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where $\Pi$ is the measure of fishery profits, $\pi_{l,g}$ is the profit of a boat in size class $l$ using gear type $g$, $p_{s,q}$ is the price received for species $s$ in season (quarter) $q$, $Q_{s,q,m}$ is the total quantity of species $s$ landed in métier $m$ in season $q$, and $C_{s,q,l,g}$ is the catch of species $s$ in season $q$ by boats of size class $l$ using gear type $g$.\(^3\) Variable costs are determined by the running cost per day ($r_{g,l}$) of boats using gear type $g$ of size class $l$, and the total number of days fished ($D_{m,q,l,g}$) in métier $m$ in season $q$ by boats of size class $l$ using gear type $g$. Fixed costs ($F_{l,g}$) include non-cash costs (e.g. depreciation and the opportunity cost of capital). The crew share, $\tau$, is taken as the average crew share of net revenue for the fleet as a whole in the LP model, but varies by boat size for the GA model ($c_l$). The key control variable in the model is the number of boats in each size class/gear type ($B_{l,g}$), although the allocation of effort between activities is also endogenous in the model (see below).

For the estimation of the open access equilibrium, the objective function of the LP model was defined as the maximization of total fishery revenue ($R$), i.e. a function of price and total landings (Eq. (2a)). However, in order to accommodate the condition that $\pi \in \mathcal{R}^+$ in the GA, the objective function in the GA model maximizes the sum of individual boats’ revenue ($R_{l,g}$) minus the total profit level achieved ($\Pi^w$). This is a weighted measure to maintain the non-negativity condition, where the weight ($W_{l,g}$) has a value of 1 if the boats in a fleet segment (i.e. size $l$ and gear $g$) have non-negative profits, and a large negative value (i.e. $-1000$) if the boats in a fleet segment have negative profits. The GA objective function is defined by Eq. (2b).

\[
\begin{align*}
\text{max } R &= \sum_{s} \sum_{q} \sum_{m} p_{s,q} Q_{s,q,m} \\
\text{s.t. } \Pi &= 0 & (2a) \\
\text{max } R - \Pi^w &= \sum_{l} \sum_{g} R_{l,g} B_{l,g} - \Pi^w = \sum_{l} \sum_{g} \left( \sum_{s} \sum_{q} p_{s,q} C_{s,q,l,g} \right) B_{l,g} - \sum_{l} \sum_{g} W_{l,g} \pi_{l,g} & (2b) \\
\text{s.t. } \pi_{l,g} &\geq 0.
\end{align*}
\]

\(^3\) Note that both catch ($C_*$) and landings ($Q_*$) are used at different levels for both the LP and GA model descriptions.
In Eq. (2a), the condition that profits (rents) are equal to zero under open access are based on the traditional Gordon (1954) model. In Eq. (2b), the condition that individual boat profits may be greater than zero allows for the existence of intra-marginal rents (i.e. producer surplus) that can exist as a result of heterogeneous technologies in the fishery (Coglan and Pascoe, 1999).

The use of the weighted term \( W_{l,g} \) in the objective function is twofold. Firstly, dealing with infeasibility in GA models is often problematic. The large penalty on boats with a negative profit helps force them out from the population. Secondly, because of the asymptotic nature of the yield curves used in the model (see below), similar revenues can be obtained with different levels of fishing effort. Lower levels of total fishery effort would be associated with higher levels of profits. The weighted term in Eq. (2b) penalizes these combinations by a greater extent, favoring the combinations that result in lower profits (and hence are associated with greater effort levels).

Catch-effort curves are estimated for each season on a métier basis, and are based on the production function proposed by Coppola and Pascoe (1998), represented in the model by:

\[
Q_{s,m,q} = a_{s,q,m} \left( 1 - \phi_{m,q}^{E_{m,q}} \right),
\]

where \( Q_{s,m,q} \), \( E_{m,q} \) is the total effective effort expended in métier \( m \) in season \( q \), \( \phi_{m,q} \) is a parameter determining the shape of the decay function \((0 < \phi_{m,q} < 1)\) and \( a_{s,q,m} \) is the maximum potential catch of species \( s \) from métier \( m \) in season \( q \). For the LP model, these were incorporated into the model using separable programming techniques (Williams, 1994), with 40 intervals per non-linear function\(^4\). The use of piecewise linear approximations in the LP model is likely to result in an underestimate of the true function value. The accuracy of the approximation is a function of the number of data points used to form the piecewise linear approximation. 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.

The level of total effective effort in each métier in each season is given by:

\[
E_{m,q} = \sum_{l} \sum_{g} f_{m,l} D_{m,q,l,g},
\]

where \( f_{m,l} \) is the relative fishing power of a boat of size \( l \) fishing in métier \( m \), \( D_{m,q,l,g} \) are the total number of days fished by boats using gear type \( g \) of size \( l \) fishing in métier \( m \) in season \( q \). The fishing power is 0 if the boat is not able to participate in a particular métier because of its gear type (e.g. trawls cannot be used in potting métiers).

\(^4\) Earlier attempts at developing the model as a non-linear program were unsuccessful as the large number of non-linear equations resulted in the model being unable to find a solution. With 29 species, 21 métiers and four seasons, there are potentially 2436 non-linear yield curves (although not all species are caught in all métiers in all seasons).
The total number of days fished is determined by the number of boats in each size class using each gear type, $B_{l,g}$, and the average number of days fished per boat in each season by boats using a particular gear type and of a particular size, $d_{q,g,l}$. Given that the effort can be spread over a number of métiers within a season, the number of days fished in the métiers is limited by:

$$\sum_m D_{m,q,l,g} \leq d_{q,g,l} B_{l,g}. \quad (5)$$

Estimating catch at the boat level requires a number of steps. Total catch in each métier is based on the total level of effort. Since it is primarily a non-linear relationship, the average catch per unit of effort will also depend on the total level of effort, given by:

$$\text{CPUE}_{s,q,m} = \frac{Q_{s,q,m}}{E_{m,q}}, \quad (6)$$

where $\text{CPUE}_{s,q,m}$ is the catch per unit of effort of species $s$ in métier $m$ in season $q$.

As effort is allocated across métiers, the average effort employed by each boat in each métier also needs to be determined. This is estimated by:

$$\overline{D}_{m,q,l,g} = \frac{D_{m,q,l,g}}{B_{l,g}}, \quad (7)$$

where $\overline{D}_{m,q,l,g}$ is the average number of days fished in métier $m$ in season $q$ by boats of size class $l$ using gear type $g$. From these, the level of catch of each species can be estimated for each boat, given by:

$$C_{s,q,l,g} = \sum_m f_{m,l} \overline{D}_{m,q,l,g} \text{CPUE}_{s,q,m}. \quad (8)$$

That is, the average catch of each species in each season, by boats in each group, in each size class using each gear ($C_{s,q,l,g}$) is the fishing power of the boat times the number of days fished times the catch per unit of effort, summed over all métiers.

In the LP model, Eqs. (6)–(8) were estimated outside the optimization component of the model. The non-linear functions are largely non-separable, as they are functions of more than one endogenous variable (Williams, 1994). While CPUE could be estimated by separable programming (as it is effectively only a function of total effort), average effort is a function of total effort and total boat numbers (both endogenous) and individual boat catch is a function of average effort and CPUE (both endogenous).

Validation of the LP model was undertaken by comparing the estimated catch levels, effort distribution across métiers, and economic performance measures to known values with a given fleet configuration. The results from the model were very similar to these values, indicating that the model could at least replicate known events. Full details of the model validation are given in Pascoe (1997).
4. The solution process

The LP model was developed and solved using the General Algebraic Modeling System (GAMS) package (Brooke at al., 1992). The GA model was developed from a version of GENEsYs (Baeck, 1992). An initial investigation of the GA model (Mardle and Pascoe, 1998) used Genetic algorithm for numerical optimization of constrained problems (GENOCOP III, Michalewicz, 1996). This implementation was developed as a crossover from the LP solution to one using the complete set of non-linear functions, using the specialized operators in GENOCOP III to maintain feasibility in individuals. Therefore, this GA was developed using an advanced starting strategy. However, in test cases, GENEsYs was preferred for the general implementation, where such starting information is not used (or not generally available). A recent overview of alternative GA modeling systems is presented in Mardle and Pascoe (1999).

In total, the GA model includes 876 probabilistic variables (i.e. landings, boats and days) — where the boats group (24 variables — i.e. three sizes x two gears x four seasons) is restricted to take integer values only. Each probabilistic (or control) variable is assigned lower and upper bounds for the optimization, and contains the main information required for the model. All lower bounds are zero. The deterministic variables, managed by the fitness function, are each dependent on the values of the probabilistic (control) variables and the intrinsic data of the model.

In the GA model, three constraint sets are identified and modeled which define 384 constraints. These describe the maximum number of boats of a given size class available in a season (12 constraints), the maximum number of days fishing per season by a boat class (24 constraints), and catch (348 constraints). The fitness function manages the feasibility of each constraint in the model. This is achieved by using a proportional modification approach which translates the control variables’ values to satisfy the constraints at their upper (or lower) bound level. This is an ordered procedure, which for the four sets of constraints required will only proportionally reduce the level a variable. All variables are positive with zero lower bound. Therefore, as each constraint is implemented as a ‘less than’ constraint, reassessment is not required and therefore feasibility is assured in the fitness measure. As the variables of each constraint are altered proportionally, no loss of variability within the GA solution arises, i.e. the distinctness of the individual when infeasible is maintained when ‘repaired’ to feasibility. A simple penalty is also attached to negative profit groups in the fitness function (Eq. (2b)) as this is not considered as a hard constraint in the model.

The principle optimization parameter settings of the model are a population size of 70 and maximum number of feasible generations 100,000. These settings were developed from a number of optimization 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. The default settings were used for other parameters, i.e. in GENEsYs the proportional selection strategy, simple n-point crossover and simple mutation were used.
5. Results

Results for the optimization models and 1995 summary statistics for the key economic indicators are presented in Table 2. Two forms of the model are investigated; the first investigates the profit maximizing fleet structure where a single objective (i.e. economic profits) is optimized, and the second considers the open access scenario. An LP model and GA model are solved for each case.

From Table 2, 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.

The optimal fleet configuration differed substantially between the LP and the GA models. Further, the LP model had a slightly higher maximum profit (and revenue) than the GA. These differences are largely a result not of the linearization of the catch curves, but the use of an average crew share (τ) in the LP. The smaller boats have a higher crew share of net revenue than the larger boats, as the labor input is of greater importance in the less capital-intensive small boats (and also the net revenue is lower so a higher share is required to attract labor). By removing larger boats from the fishery, the average crew share should increase. However, this was not possible in the LP model. Hence, the crew costs have been underestimated and profits overestimated. In contrast, profits, revenue and crew costs were estimated directly at the boat level in the GA model, with the appropriate crew share being applied for each boat group. Hence, there was less of an incentive in the GA model to utilize smaller boats, as their costs were effectively higher than in the LP. The GA model results are, therefore, likely to be a better representation of the “true” optimal fleet and maximum profit level.

The LP model approximating the open-access scenario considers the maximization of revenue subject to total economic profits being non-negative. In the model, catch and revenue increased asymptotically with increasing levels of effort. Hence, 

<table>
<thead>
<tr>
<th></th>
<th>1995a</th>
<th>Profit maximizing fleet</th>
<th>Open access</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>LP</td>
<td>GA</td>
</tr>
<tr>
<td>Revenue (£m)</td>
<td>69.3</td>
<td>61.0</td>
<td>59.0</td>
</tr>
<tr>
<td>Economic profits (£m)</td>
<td>1.7</td>
<td>25.8</td>
<td>24.7</td>
</tr>
<tr>
<td>Fleet size</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 10 m</td>
<td>1673</td>
<td>1163</td>
<td>798</td>
</tr>
<tr>
<td>10–20 m</td>
<td>392</td>
<td>57</td>
<td>113</td>
</tr>
<tr>
<td>&gt; 20 m</td>
<td>101</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Employment</td>
<td>4853</td>
<td>2491</td>
<td>1917</td>
</tr>
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</table>

* Estimated from survey data (Pascoe et al., 1997).
maximizing revenue not only ensures the maximum level of effort in the fishery, but also the allocation of effort is likely to be more representative of the true situation than what might be estimated by maximizing effort directly. Economic profit, aggregated into a single variable, was strictly positive in this model. However, at such a level of aggregation, negative profits could likely be apparent at a more detailed level of economic profit calculation (i.e. at $B_{l,g}$ level). Revenue is calculated as a total for the fishery as a whole based on catch of each species and the price received. Both the catch rate and prices varied quarterly in the model. Costs were based on boat characteristics (e.g. size and gear type). As noted earlier, profits could not be estimated at the boat level in the LP model as the additional non-linearities this created resulted in the model being unable to find a solution. However, the free-format modeling structure of the GA makes the modeling of this relationship straightforward.

This limitation of the LP model is highlighted by the existence of boats in the greater than 20-m size class. These boats were earning, on average, negative returns (as estimated outside the LP model per se) and hence would not be expected to be in the fishery in a true long run equilibrium situation. The majority of the fishing effort, and correspondingly the majority of revenue, is generated by the other boat groups. These boats produced an economic surplus. This would be equivalent to intra-marginal rent or producer surplus in other industries. However, the specification of the model, which required total fishery profits only to be non-zero, resulted in the positive surplus being offset by negative returns from the larger boat group. With profits calculated by boat class and gear type in the GA, a more refined measure of economic profit can be estimated. In the GA, where negative profits are modeled as unwanted effects, the long run number of boats in this size class is zero under open-access conditions (maximizing revenue).

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, a number of runs of the GA model were performed in order to evaluate the convergence effects and alternative parameter options to attempt to increase the search performance. Fig. 4 shows the progress of a typical GA where, in the initial generations, large improvements in the best solution found are achieved. However, the rate of improvements in fitness declines after the initial large gain, although fitness is still improved at regular intervals.

The difference in time taken to solve the model types was significant, with the GA taking up to an hour to show a satisfactory degree of convergence to ‘optimality’. However, the solution in Fig. 4 was obtained after several hours of optimization. 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 additional advantage over the LP solution process when variables must take integer values. The GA model is generally solved faster with integer variables than with continuous variables, as the search space is greatly reduced. 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.

6. Discussion and conclusions

The model of the UK part of the English Channel fishery has been used to investigate the potential usefulness of GAs for the solution of large-scale, non-linear problems. This paper compares the approach of traditional optimization methods, against the approach of GAs. It is clear that GAs offer a potential alternative to the traditional optimization approaches, principally in complex scenarios where it is not possible to describe the entire model within a traditional optimization modeling framework.

Fisheries bioeconomic models are not unique in the fact that generally simplifying assumptions must be made to find a solution using many optimization techniques. This is due to the models' natural size and complexity. The complexities result in simplifications that may distort the model results, as in the case of the optimal fleet configuration from the LP model in Table 2. 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 optimization approach, which is a guided search method and has been developed and successfully applied to many models of this type.

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.

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 optimization (Section 3), 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 optimization process considerably. Generally, a standard GA is taken for specific development of the problem under investigation where the modeler 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 (i.e. using a penalty approach). 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. A ‘repair’ approach was implemented in the fitness function which on determination of constraint infeasibility proportionally modified the variables under consideration to assure individual feasibility. While the focus of this paper has been on the application of GA to fisheries bioeconomic modeling, the results of the model analysis raise an interesting issue. Presumably, the existence of above-normal profits by some boats in a heterogeneous fishery will attract new entrants, even if the marginal boats are earning only normal profits. From the model results, the level of intra-marginal rents in the fishery under a theoretical open-access equilibrium situation is about 40% of the total economic profits (which include intra-marginal rent and resource rent) under the profit-maximizing scenario. These new entrants would take the form of the more profitable boats in the fishery, making the currently marginal boats extra-marginal (i.e. making economic losses and, hence, would leave the fishery in the long run). This has been termed the fisheries treadmill (Whitmarsh, 1998).

With changes in technical efficiency over time, it is likely that new boats will be developed that will be more efficient than existing older boats. In such a case, an equilibrium situation may never really exist. An open-access fishery, then, may be characterized by a mix of some boats earning intra-marginal profits (i.e. producer surplus) and some boats earning extra-marginal losses. If this is the case, an open-access disequilibrium may be a more appropriate situation to model, and the approach adopted by the traditional modeling approaches (e.g. assume that total fishery profits are zero) may be a better approximation of the fishery under open access than a model that is predicated on a more theoretical basis involving a long run equilibrium situation.

This paper has investigated the potential applicability of GAs for the application to large non-linear models, especially fisheries bioeconomic models. Further development of a specialized 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 modeling as well as having immediate practical benefits in terms of increasing the range of management questions that can be addressed by such models.

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