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# An investigation of genetic algorithms for the optimisation of multi-objective fisheries bioeconomic models

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# An Investigation of Genetic Algorithms for the Optimization of Multi-objective Fisheries Bioeconomic Models

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**Abstract.**

The use of genetic algorithms (GA) for optimisation problems offer 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 achievement function in goal 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, however, for the same reason they are not contained by local optima.

In this paper, a non-linear goal programme of the North Sea demersal fishery is used to develop a genetic algorithm for optimisation. Comparisons between the GA approach and traditional solution methods are made, in order to measure the relative effectiveness. General observations of the use of GA in multi-objective fisheries bioeconomic models, and other similar models, are discussed.

*Keywords:* genetic algorithms, optimisation, goal programming, fisheries, bioeconomic modelling.

## 1. Introduction

Fisheries resources have the potential to yield substantial benefits to the community when managed effectively (Arnason [2]). Fisheries management has been introduced into many of the worlds' fisheries in an attempt to capture some, if not all, of these potential benefits. This has required policy makers to identify the key objectives of fisheries management in order to develop management plans. The existence of multiple objectives is a common feature of many fisheries management problems (Crutchfield [12]). Commonly declared objectives in the field include resource conservation, food production, generation of economic wealth and reasonable incomes, maintain employment and sustain the community (Charles [8]). The complexity of the natural fish resource and the diversity of interest groups involved dictate that a compromise between such objectives must be sought.

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The major conflict occurs between the attempts to conserve the stocks and the desire to satisfy the needs of the fishing community with respect to jobs and income. There is an obvious political reluctance to impose a policy resulting in a significant reduction in employment levels in areas where alternative employment opportunities are generally poor. There is also a significant cost involved in major structural change, which can often be overlooked (Pascoe [27]).

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 at achieving the various objectives. The foundations of fisheries bioeconomic modelling comes from the economic theory of the open-access or common-property fishery developed by Gordon [17] and Schaefer [32]). 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. For example, the price obtained may vary according to level of catch, resulting in a non-linear revenue function. Alternatively, additional non-linearities may be introduced into the species growth functions, such as the case where the biomass of one species biomass may be dependant on another. A review of fisheries applications using multi-objective programming techniques is given by Mardle and Pascoe [23].

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 often traditional solution methods are unable to achieve the global optimum. In this case, typically linear approximations are 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.

In this paper, a GA model is developed for the North Sea fishery. The model described in this paper is based on an original multiple objective bioeconomic model of the North Sea fishery (Mardle, Pascoe, Tamiz and Jones [24]). This was developed as a non-linear weighted goal programming model, and is used to compare the alternative solution strategy of a genetic algorithm.

An overview of genetic algorithms is given in section 2, and an introduction to the field of fisheries bioeconomic modelling is given in section 3. The model of the North Sea demersal fishery is discussed in section 4 in order to compare the two approaches of genetic algorithms and goal programming. Results are presented and compared for the approaches in section 5. Finally, section 6 offers a brief discussion and conclusions on the merits of each method analysed.

## 2. Genetic Algorithms

A genetic algorithm is a search method, typically an optimisation, which seeks the fittest *individual* of a developing *population*. Initially, the population is generally comprised of a randomly generated set of possible solutions (individuals). Given a *fitness statistic*, which measures the fitness of each individual in the population, the objective is to maximise (or minimise) this value. Subsequently, another population is genetically bred, from this set of solutions, using 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. Typically, each individual takes a genetic representation often using binary data storage, i.e. zeros and ones denoting *chromosomes*, although alternative storage implementations may be incorporated. The population consists primarily of fixed length strings. Variable (or *gene*) bounds are important to the performance of the GA, as the use of 'well-bounded' variables is key to effective individual management.

The operations applied in this general iterative process are briefly described:

i) Construct initial population - in general randomly generated, however it may be based on a known solution set.

1) 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.

2) Develop new population, for the next generation - the type of genetic operation is probabilistically chosen, selecting a single individual or two individuals for breeding;

    - Selection - 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. Examples of such techniques are 'roulette wheel' selection, 'fitness ranking' selection and 'tournament' selection.
    - 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.

3) Termination criteria - if the solution level is attained, or the maximum number of generations is reached, or a given number of generations without fitness improvement is performed, then stop, else go to step 1.

Population size selection is probably the most important parameter to determine, as generally this parameter must reflect the size and complexity of the problem. The tradeoff between extra computational effort with respect to increased population size is a problem specific decision to be ascertained by the modeller. 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 [22]).

The introduction of genetic algorithms is attributed to Holland [19], 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. Goldberg [16] is widely recognised as giving a concise introduction to the field, as well as more advanced topics. Other notable texts include books by Michalewicz [26] and Koza [22], who discusses the associated field of genetic programming.

GA solvers such as GENESIS (Grefenstette [18]), GENOCOP (Michalewicz[26] and FORTGA (Carroll [7]) 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 has been designed to cater for non-linear constraints applying techniques to maintain feasibility of individual solutions.

The list of topics to which genetic algorithms have been applied is extensive, including job shop scheduling, timetabling, the travelling salesman problem, portfolio selection, agriculture etc. However, in the field of fisheries there are relatively few examples, none of which consider bioeconomic model optimisation. In the field of agriculture, Mayer, Belward and Burrage [25] 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) was used, the simplex method, a gradient method and simulated annealing. It was concluded that the GA performed well, coming second, with optimal values reported averaging 99.7% of the global optimal.

## 3. Fisheries Bioeconomic Models

As noted in the introduction, the beginning of modern fisheries bioeconomic modelling is generally attributed to Gordon [17] in 1954. A concise development of this and subsequent theory is given by Clark [10].

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 significantly useful from a management perspective. Examples include: a model of a herring fishery [3]; Tasmanian rock lobster fishery [5]; Orange Roughy management [6]; Hawaiian lobster fishery [11]; and Maldivian tuna fishery [31].

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. Eide and Flaaten [14] modelled the Barents Sea fishery and Pascoe [27] used linear programming to optimise resource allocation in the English Channel. Non-linear programming models have also been developed for an Italian Mediterranean fishery[29]; Australian prawn fisheries [13]; a shark fishery [28]; and the North Sea demersal fishery [24].

Currently, multi-species fisheries bioeconomic models are a vital aid for management to perform effective decision analysis. The fact that many fisheries are overfished has placed a significant importance on developing accurate predictive models. Therefore, there is a need to include ranges of species affected by alternative fishing methods and a growing awareness of predator/prey relationships. Such factors increase the size and complexity (non-linearity) of such bioeconomic models substantially. For example, the model of the English Channel fishery (Pascoe [27]) could only be solved by assuming no stock dynamics and linear approximations for the catch-effort functions and constant fish prices. Similarly, the model of the Italian fishery (Placenti, Rizzo and Spagnolo [29]) was solved as a series of separate models. While the model of the North Sea fishery (Mardle, Pascoe, Tamiz and Jones [24]) required a number of simplifying assumptions.

As models have become increasingly more detailed, the types of questions which fisheries managers hope to find answers to have also become more complex. Typical scenario (or what-if) analysis questions are "what are the effects of... changing mesh size in a multi-species fishery?; introducing individual transferable quotas?; the interactions between competing gear types?; discarding fish?; and conflicting multiple objectives (especially trade-offs)?"

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.

## 4. North Sea Demersal Fishery Model

The North Sea is a multi-species multi-gear fishery of great importance to many countries. Commercial activity in the region is mostly undertaken by fishers from the countries bordering the North Sea, namely: UK, Denmark, The Netherlands, France, Germany, Belgium and Norway. The fishery is managed according to the guidelines of the Common Fisheries Policy (CFP) as each is a member of the EU, except Norway who cooperates with the defining of suitable management measures.

The fishing activity relevant to human consumption is concentrated on eight species; cod, haddock, whiting, saithe, plaice, sole, nephrops and herring. The first seven species are demersal species (i.e. bottom dwelling) whilst herring is a pelagic species (i.e. surface dwelling). Hence, the fishing operation for herring is different than that of the other species. The roundfish stocks of cod, haddock and whiting are heavily fished with approximately 60% of their biomass removed each year, making recruitment very important. Cod, plaice and herring are currently considered to be overexploited and at risk of collapse. Stocks of the other demersal species are below the level that produces the maximum sustainable yield. The species are dependent on each other, with considerable interaction in the food chain.

The North Sea demersal fishery bioeconomic model described in this paper, is a long run equilibrium model. That is, the equilibrium level of each species' biomass and catch is estimated given the level of fishing effort expended. The stock dynamics are developed using standard multispecies logistic growth models [24], where nonlinear regression analysis was used to estimate the model parameters.

The structure of the bioeconomic model considers the seven most important demersal species i in the North Sea (cod, haddock, whiting, saithe, plaice, sole and nephrops), includes the North Sea's seven coastal states[3] j (Belgium, Denmark, England, France, Germany, Netherlands, Norway and Scotland), and takes account of the four associated major fishing methods or gear types k (otter trawl, seine, beam trawl and nephrops trawl).

Price per tonne of fish landed is variable, using published price flexibilities to estimate the effect of changes in the level of landing on price [21]. Average prices in each country and costs were estimated from 1995 statistics [1]. Gear selectivity by species and gear type was taken from an earlier simulation model of the fishery (Frost et al. [15]), and differences in catch rates by boats from different countries were estimated as a scaling factor (by comparing derived catch with observed catch). The equilibrium biomass was estimated as a function of fishing effort.

There are four objectives included in the goal programming model: maximise profit, maintain historic relative quota shares amongst countries, maintain employment in the industry and minimise discards. All of the species in the model currently have yearly Total Allowable Catches (TACs) assigned with historically proportional divisions to the relevant countries. TACs are the principal management control implemented as part of

[3] England and Scotland are included separately for analysis

the resource conservation and management system by the EC, and are generally set for each discrete stock of each species. It is considered politically important for employment and thus boat numbers to remain similar on a yearly basis, or preferably increase slightly, as large labour movement may result in substantial costs on the community.

The complete mathematical representation of the model, described as a non-linear weighted goal programme, is given in Mardle, Pascoe, Tamiz and Jones [24].

### 4.1. Goal Programming Solution Approach

The introduction of goal programming (GP) is generally attributed to Charnes, Cooper and Ferguson [9], and has since been developed by many researchers. Recent comprehensive discussions are given by Ignizio and Cavalier [20] and Romero [30]. The Archimedean (or weighted) GP model minimises the sum of absolute deviations from given target (goal) values, using the Simonian philosophy of 'satisficing'.

$$\text{Min } z = \sum_{i=1}^{k} (u_i n_i + v_i p_i) \tag{1}$$

subject to,

$$f_i(\mathbf{x}) + n_i - p_i = b_i \qquad ,i = 1 \ldots k \tag{2}$$

$$\mathbf{x} \in \mathbf{X} \tag{3}$$

$$\text{x, n, p} \geq 0 \tag{4}$$

where $f_i(\mathbf{x})$ is a typical objective function or goal (often linear), $\mathbf{x} \in \mathbf{R}^n$ is the set of decision variables, $\mathbf{n}, \mathbf{p} \in \mathbf{R}^m$ are deviational variables, and $\mathbf{u}, \mathbf{v} \in \mathbf{R}^m$ are the respective deviational variable predetermined weights.

Weighted GP is probably the oldest and one of the most widely used multi-objective modelling techniques. The linear form is directly related to linear programming (LP) and therefore can be solved using a standard LP solver, which are generally robust and highly effective. Similarly, the non-linear WGP paradigm is directly related to non-linear LP, however solution is significantly more difficult to the linear case. Traditional nonlinear programming solution methods, such as the conjugate gradient method, are appropriate for solving the nonlinear weighted GP model. The North Sea demersal fishery resource allocation model [24] was developed in GAMS [4] and solved using the CONOPT solver. The model statistics of the non-linear weighted goal programme are shown in table 1.

| | |
|---|---:|
| Rows | 682 |
| Objectives | 4 |
| Goals | 72 |
| Nonzero elements | 3851 |
| Upper bounds | 7 |

**Table 1: North Sea demersal fishery model statistics -- GP approach**

### 4.2. Genetic Algorithm Solution Approach

GENOCOP III (Genetic algorithm for numerical optimization of constrained problems - Michalewicz [26]) was used as the primary optimisation algorithm for the model implementation. The fitness function is based on the GP model with four objectives: maximise profit, maintain employment, minimise discards and maintain historic quota shares.

| | | |
|---|---|---|
| landings_jki | probabalistic | |
| boats_jk | probabalistic | |
| days_jk | probabalistic | |
| f_i | deterministic | days_jk |
| biomass_i | deterministic | f_i, (biomass_i) |
| catch_jki | deterministic | days_jk, biomass_i |
| price_ji | deterministic | landings_jki |
| revenue_jk | deterministic | landings_jki, price_ji |
| cost_jk | deterministic | boats_jk, days_jk, revenue_jk |
| profit_jk | deterministic | revenue_jk, cost_jk |

**Table 2: GA structure of the North Sea demersal fishery model**

The model's variable dependencies are shown in table 2, where f_i denotes fishing mortality. The 288 probabalistic variables landings_jki,boats_jk and days_jk are each assigned lower and upper bounds for the optimisation process (see section 4 for index descriptions), and contain the main information required for the model. The deterministic variables, managed by the fitness function, are each dependent on existing variables.

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 64 defined constraints described the maximum yearly boat landing capacity (i.e. each boat cannot exceed gross landings of more than 600 tonnes over the period), and the maximum boat operational period (i.e. each boat has a maximum number of days available for fishing over the period). The inequality of assuring that landings must be less than or equal to catch, and the non-negativity criterion of biomass was managed by the fitness function.

The principle optimisation parameter settings of the model are set to minimisation, population size 50, and maximum number of feasible generations 1000. 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 slightly more generation, was more computationally efficient than that of a larger population.

## 5. Results and Discussion

Results for four optimisations are presented; the goal programming approach (GP) and three runs of the genetic algorithm (GA1, GA2 and GA3). GP starts from an 'advanced' basis, using current (1995) data for the initial values. The optimisation results are given in table 3. Due to differences in the GP and GA solution algorithms, the variable structure and objective weighting schemes differ. For comparison, these modelling differences are developed to be as close as possible, in order to maintain the importance of each objective. The objective values given for the GP, in table 3, are re-computed using the same functions as the GA for comparative purposes. A percentage normalisation style technique was used to measure the objective levels, i.e. using the goal's target value to express the unwanted deviation(s) in percentage terms.

| | | | | |
|---|---|---|---|---|
| Iterations/Generations | 2576 | 1236 | 1240 | 1154 |
| - to feasibility | 1950 | 236 | 240 | 154 |
| Objective (Fitness) | 5.161 | 4.618 | 4.518 | 4.201 |
| - Profit Objective | 0.082 | 0.315 | 0.293 | 0.335 |
| - Employment Objective | 0.848 | 0.855 | 0.860 | 0.881 |
| - Discards Objective | 0.110 | 0.218 | 0.245 | 0.264 |
| - TAC Objective | 4.121 | 3.230 | 3.120 | 2.721 |
| Solution time (secs) | 63 | 827 | 869 | 772 |

**Table 3: GA and GP model solution statistics.**

It is clear from the apparent tradeoffs of the profit and TAC objectives in the models, that the GP model gives more importance to the profit objective than the GA model. The difference in time taken to solve the model types is significant, with the GA taking over 10 times longer than the GP to appear to converge to optimality, which may be an underestimate due to the predefined termination criterion. Feasibility in the GA is attained straightforwardly, however once the four objectives are introduced, the optimisation process becomes more complex as the GA converges to optimality.

The progress of the GA optimisation procedure for Run 3 is shown in figure 1. The sum of infeasibilities is resolved after 154 generations, where the imposed weighting scheme on the objectives in the model is highlighted. The employment and discards objectives are stable, but the total profit level in the fishery is increased through the degradation of the TAC objective which aims to maintain historic share of fish amongst countries.

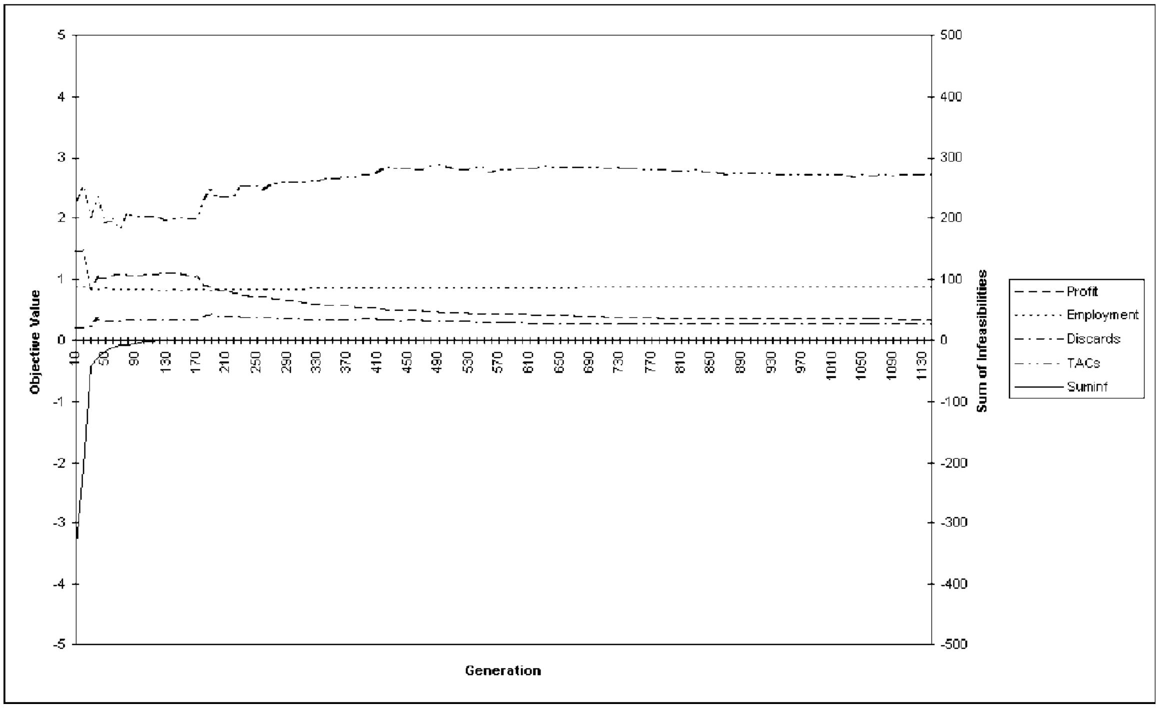


**Figure 1: Genetic algorithm progress in Run3.**

In developing the GP model, a profit maximising scenario was investigated in order to determine the potential profits in the fishery. This was subsequently used as the target value for the profit goal in the multi-objective analysis. The maximum profits that can be achieved in the fishery was estimated to be about ECU 261 million for the developed model. For most countries, the large reduction in employment required to achieve a profit maximising fleet would be unacceptable.

It is suggested by the model results shown in table 4, that the North Sea fishery is overfished, a fact generally considered to be true. This is highlighted by the long term equilibrium employment figures which are significantly lower than current levels. Also, except for plaice the models suggest a decrease in landings in order to maintain sustainability. Discards are much higher in the GA model than the GP model, due to the weighting scheme but also the differences in solution methodology of the catch/landings constraint implementation. The achieved economic profit over the GP and GA scenarios is significant, highlighting the importance of weighting strategies in the specification of the models

| | | | | | |
|---|---|---|---|---|---|
| *Economic profit, mECU* | n.a. | 239.9 | 178.9 | 184.7 | 173.7 |
| *Employment* | | | | | |
| Belgium | 776 | 119 | 129 | 90 | 94 |
| Denmark | 1670 | 258 | 301 | 268 | 256 |

| | | | | | |
|---|---|---|---|---|---|
| England | 3051 | 448 | 474 | 520 | 433 |
| France | 2488 | 330 | 179 | 234 | 67 |
| Germany | 2333 | 214 | 318 | 330 | 317 |
| Netherlands | 2523 | 693 | 382 | 394 | 319 |
| Norway | 1913 | 347 | 346 | 366 | 215.7 |
| Scotland | 4571 | 353 | 548 | 412 | 618.8 |
| *Landings (Discards), '000s tonnes* | | | | | |
| Cod | 88.0 (n.a.) | 51.1 (0.0) | 51.7 (7.0) | 57.9 (6.2) | 54.6 (6.9) |
| Haddock | 80.0 (n.a.) | 25.6 (0.1) | 40.7 (1.7) | 36.9 (5.1) | 46.6 (5.6) |
| Whiting | 42.5 (n.a.) | 18.3 (3.1) | 18.0 (7.3) | 13.4 (13.2) | 17.7 (6.6) |
| Saithe | 98.2 (n.a.) | 88.7 (5.8) | 66.8 (19.6) | 72.8 (19.5) | 44.8 (27.5) |
| Plaice | 111.1 (n.a.) | 152.4 (0.9) | 76.8 (80.7) | 70.2 (85.3) | 55.2 (91.7) |
| Sole | 31.3 (n.a.) | 28.0 (0.5) | 26.7 (0.3) | 27.8 (0.6) | 27.9 (1.2) |
| Nephrops | 13.7 (n.a.) | 3.0 (9.7) | 3.2 (5.6) | 1.9 (5.6) | 3.2 (6.8) |

n.a. not available

**Table 4: GA and GP model objective results.**

## 6. Conclusions

The model of the North Sea demersal fishery has been used to investigate the potential usefulness of genetic algorithms for the solution of large-scale, non-linear and multi-objective (specifically goal programming) problems. This paper compares a known solution, found by a traditional optimisation approach, to solutions attained by a genetic algorithm. As with the majority of multi-objective approaches, direct comparison of solutions is difficult due to the intrinsic differences of the methods. However, 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. However, in order to gauge effectiveness a comparison as described here must be made.

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/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 multi-objective models is unclear.

The probabilistic nature of the genetic algorithm approach is highlighted in the results, with convergence slowing to different objective levels, which is a feature of the many 'close to optimal' solutions that exist in the model. It is also clear that an excellent knowledge of the problem under investigation is required for effective implementation as a GA. Poor modelling of a large model will undoubtedly result in a slow optimisation process.

This paper has investigated the potential applicability of genetic algorithms for the the application to fisheries bioeconomic models. 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.

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