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DECISION SUPPORT SYSTEM FOR FISHERIES MANAGEMENT

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ABSTRACT

This paper presents a decision support system that is oriented toward fisheries policy and management decisions. The important current issues involve the development of an optimal harvesting plan for the fishing industry. A simulation optimization has been built to assist authorities in scheduling for a fleet of hundreds of vessels in terms of time and location of fishing, as well as amount and target species to be fished. Marine fisheries are highly complex and stochastic. A simulation model, therefore, is required. Simulation-based optimization utilizes the simulation model in obtaining the objective function values of a particular fishing schedule. A Genetic Algorithm is used as the optimization routine to determine the optimal fishing schedule, subject to fleet capacity and conservation requirements. The decision support system is then applied to the real situation in the Northeastern U.S.

1 INTRODUCTION

The US fishing industry is a $25 billion wholesale business which employs 300,000 people. In 2003 it had over $3.3 billion in landing revenues with a total of 4.3 million tons of fish caught.

There is an opportunity to improve management approaches to address issues created by the complexity and uncertainty inherent in the fishery management system. The complexity stems from the dynamic nature of the marine environment and numerous groups with conflicting interests. To accomplish management objectives a set of control mechanisms have been developed. Some of them are:

1. Fishing effort restriction. Fishing permits limit the number of fishing vessels, and the number of days at sea (DAS) a vessel can fish.
2. Gear restrictions. Requirements on type and size of nets to avoid catch of small fish.
3. Area specific restrictions. Controlling where fishing can take place at any given time in the year.

The Decision Support System (DSS) is a computer program that transfers information from research surveys, and commercial fishing reports into advices for policy makers on decisions of when, where and how much fishing effort should be allocated. The core of the DSS is the component that intensively applies simulation modeling and operations research techniques.

The Decision Support System for Fishery Management will assist the government agencies and the fishing industry to use sound data and management science techniques in making policy decisions for fishing activities.

2 CONCEPTUAL FRAMEWORK

We consider the fishery management systems to be comprised of seven components: (1) sampling design and research survey to collect data that are independent of commercial fishing, (2) database and data management system, (3) a systems identification and statistical models to acknowledge the current situation, (4) simulation, optimization modules where decision analysis is applied to provide the optimal management solutions, (5) allocation of fishing permits accordingly, (6) implementation of fishing activities, and (7) fishing trip report requirement as a feedback control to evaluate and adjust management measures (Rothschild et al. 1996).

In this paper we focus our discussion on component (4) to demonstrate how simulation based optimization is applied to improve productivity of fishing.

3 INPUT DATA

The School for Marine Science and Technology, University of Massachusetts Dartmouth has been conducting the High Resolution Trawl Project since 2002 as a collaboration with commercial fishing fleet. The project has gathered fishery, oceanographic and meteorological data for each fishing tow. This study monitored 355 fishing trips on Georges Bank with a total of 7215 usable tows as shown in Figure 2. Shaded areas in Figure 2 have been closed from fishing since 1994, although some portions were opened in short period of time.

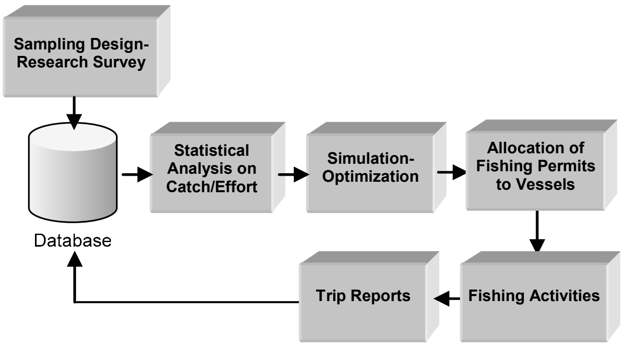

Figure 1: Components of the Decision Support System for Fishery Management

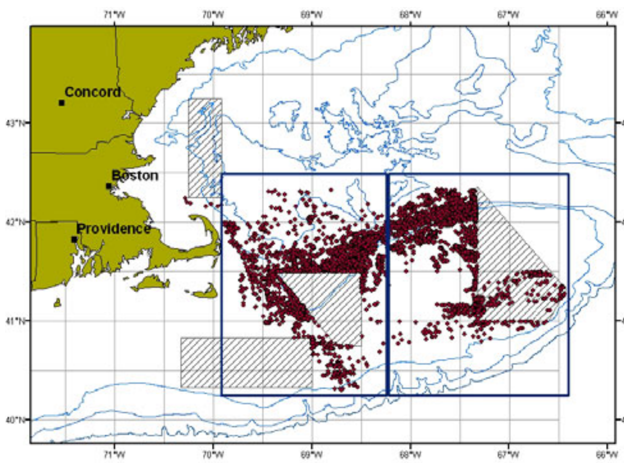

Figure 2: Georges Bank Map and Location of Fishing Tows Reported in This Study.

This is a multispecies fishing industry as several fish stocks overlap (more than 50 species are reported) and are concurrently exploited. The data shows spatial heterogeneity of fish densities, that in turn affect fishing behavior as well as catch. If Georges Bank is simply divided into two halves (West and East GB) as illustrated in Figure 2, the frequency of targeting species among fishing trips in each sub-area is as shown in Table 1, and catch data is in Table 2. Tables 1 and 2 present data for the three most valued species; cod, haddock and yellowtail flounder. Multispecies trips are defined as those that do not specify target species upon leaving port. Multispecies trips may catch any species.

Catch per fishing day (or Catch-Per-Unit-Effort, CPUE, in kgs/day) is a stochastic variable that follows the log-normal distribution (Figure 3). The mean of CPUE depends on location, time and targeting species of the fishing

Table 1: Frequency (%) of Target Species

Target species	West GB	East GB
Multispecies	49	51
Cod	17	20
Haddock	27	7
Yellowtail flounder	7	22

trips. Table 2 shows catch of cod per unit effort (CPUE) in two sub-areas, in each quarter of the year (Q1, Q2, Q3, and Q4) with different target species.

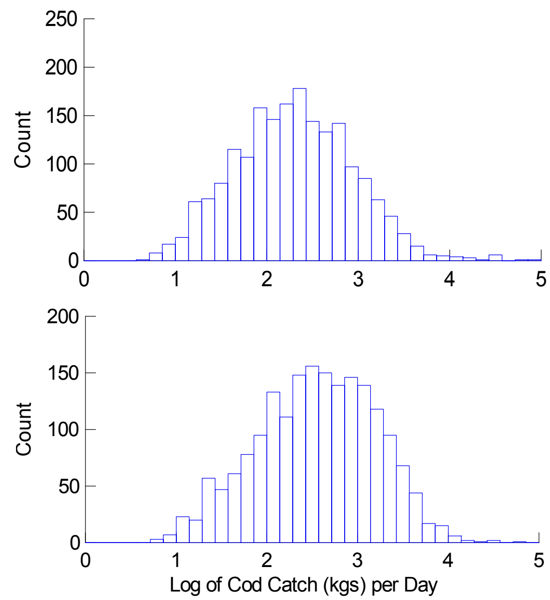

Figure 3: Catch-Per-Unit-Effort on West (above) and East Georges Bank (below) Is Log-Normally Distributed

Table 2: Mean of CPUE on West (above) and East GB (below) Depends on Time and Target Species.

Target species	Log(CPUE of cod, kg/day) on West GB Q1	Q2	Q3	Q4
Multispecies	1.93	1.79	1.56	1.47
Cod	2.70	2.69	2.76	2.54
Haddock	2.03	0.74	1.20	1.62
YT flounder	1.82	0.67	1.45	0.95

Target species	Log(CPUE of cod, kg/day) on East GB Q1	Q2	Q3	Q4
Multispecies	2.37	2.24	1.72	1.58
Cod	3.01	3.09	1.86	3.32
Haddock	2.42	1.09	0.85	2.30
YT flounder	1.06	1.01	0.15	0.39

4 MODEL STRUCUTURE AND OPTIMIZATION ALGORITHM

4.1 Simulation Model

It has almost become a standard practice to provide scientific advice in fisheries management by using Monte Carlo simulation that incorporates the uncertainties of dynamic ecosystems. A simulation model of the fleet and fishing activities has been constructed in a general context, not limited to the number of sub-areas and the number of species of interest. The simulation model is used to evaluate the status quo or any particular fishing schedule. The simulation model is also necessary for the optimization algorithm introduced in the next section.

Let S be the number of species of interest, N the number of vessels, and D_{ij} the actual number of days-at-sea vessel i uses on fishing trip j. Days-at-sea D_{ij} includes fishing time, DF_{ij}, and steaming time, DS_{ij}, from port to fishing location and vice verse. The total number of days-at-sea used by one vessel in one year should not exceed the maximum annual permit D_{Max}.

Fishing location, time and target species are stochastic. Catch per fishing day is a random variable that follows the lognormal distribution with the density function:

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\log(x)-\mu}{\sigma}\right)^2}$$

where μ and σ are the mean and standard deviation of CPUE respectively.

μ and σ depend on fishing location, time and targeting species. When the simulation is run and the fishing location, time and target species is generated for each trip, these parameters are estimated based on the historical data.

Net profit on trip j of vessel i is given as revenues less operating cost.

$$P_{ij} = \sum_{s=1}^{S} CPUE_{ijs}.DF_{ij}.p_s - c_i.(DF_{ij} + DS_{ij})$$

where p_s is price of species s and c_i is operating cost per day for vessel i.

Total net profit P and total annual catch of each species C_s are calculated as

$$P = \sum_i \sum_j P_{ij}$$

$$C_s = \sum_i \sum_j CPUE_{ijs}.DF_{ij}\ .$$

4.2 Optimization Problem for Harvesting

The ultimate goal of this decision support system is to provide policy makers with the optimal temporal-spatial fishing schedule for a regional fleet complying with existing regulations about fishing effort and Total Allowable Catch on protected species. The optimization problem can be stated as follows.

4.2.1 Objective Function

The objective is to maximize the expected value of total net profit from fishing in one year.

4.2.2 Decision Variables

The decision variables that we can control to obtain the maximum objective value are the number of fishing dates allocated in each sub-area, in each period of time for each target species.

4.2.3 Constraints

Feasible solutions must satisfy the following constraints.

1. The fishing effort is controlled by the maximum total number of fishing days used by the whole fleet. This limit depends on the fleet capacity or agreements between industry and government authorities;
2. In order to protect fish populations that are currently at a low biomass level, such as Georges Bank cod, the total landings of these species are required not to exceed pre-specified limits called Total Allowable Catch (TAC). In stochastic terms, the probability that actual landings exceed TAC must be less than a threshold, for example, of 5%.

4.3 Simulation Based Optimization

Optimization problems in fisheries management, especially those that do not require assumptions on equilibrium conditions, often contain a great deal of stochastic factors, and non-linear interrelationships among components. These problems, therefore, are difficult to be solved analytically. A popular optimization approach in fisheries science is dynamic programming (Babcock and Pikitch 2000). Ruppert el al (1984) use stochastic approximation in maximizing the catch of Atlantic Menhaden. Azadivar et al. (2002) is the first introducing a simulation-based-optimization approach (Azadivar 1999) to solve the harvesting problem for Georges Bank scallops. In this approach, a Genetic Algorithm (GA) is employed as the optimization engine and it controls the optima searching process. Simulation is activated and returns the objective function's value in each evaluation.

GA is a class of stochastic search techniques inspired by natural evolution. Decision variables, i.e. fishing schedule in this case, are encoded as fixed length chromosomes. The search process takes place by selection, crossover and mutation operations (Goldberg 1989).

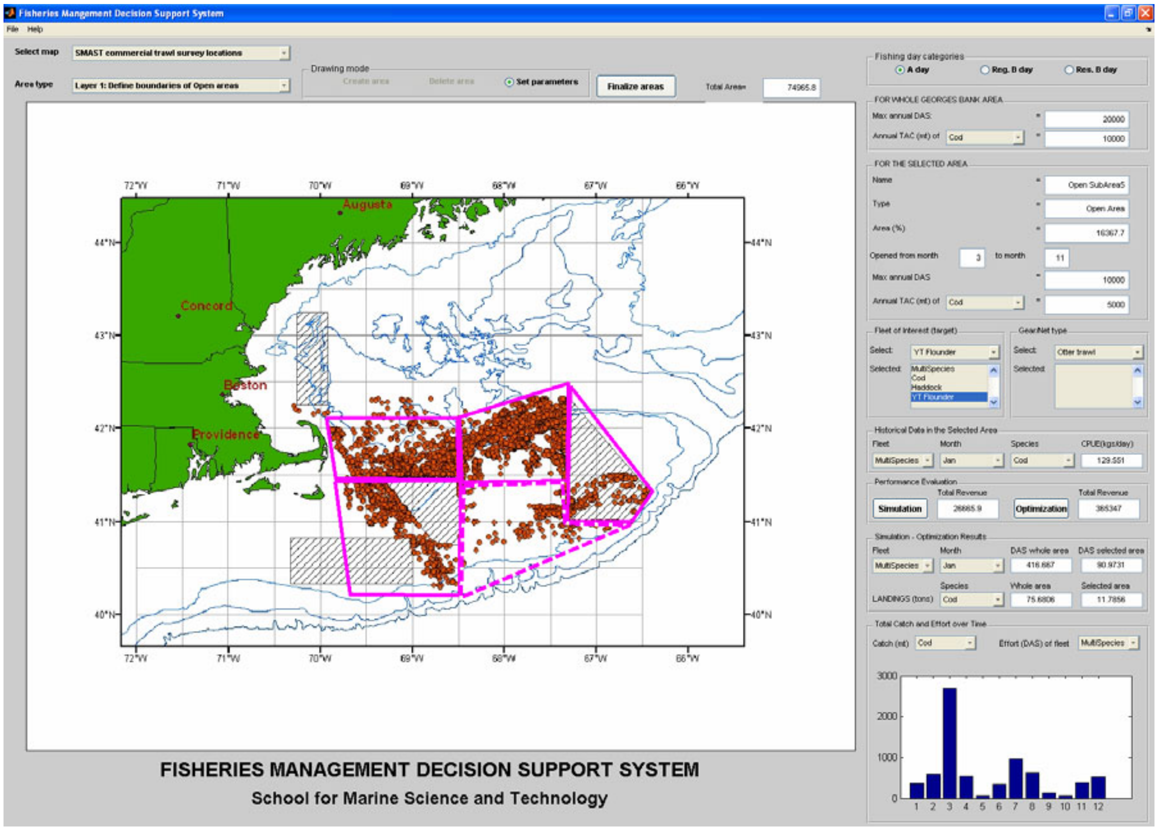

Figure 4: The Graphical User Interface (GUI) of the DSS program

There are several ways to handle constraints within GA (Michalewicz et al. 1996). In this study, constraint (a) can be checked when a new chromosome is created but constraint (b) cannot. The total landing for each species is determined by the simulation model and is available only after the simulation is run. If total landings exceed the limits, there are two options: either returning an objective function value of zero or adjusting the number of fishing days in order to maintain the feasibility. The latter proved to be more sufficient.

5 OUTPUTS AND RESULTS

The DSS program was developed in Matlab. The graphical user interface (Figure 4) allows policy makers to evaluate different spatial management alternatives by letting them create, delete and modify sub-areas. Figure 4 shows a plan of five sub-areas with arbitrary shapes and sizes. The maximum number of days-at-sea, and the total allowable catch of each species can be set for the whole area and/or for individual sub-areas. There are no limits on the number of sub-areas, the number of species and fleets of interest. Outputs of simulation and optimization functions, including catch and fishing effort allocated to each fleet in each sub-area, in each period of time, can be viewed as numbers or in graphs.

Figure 5 presents the results of 1000 simulation runs for a simple scenario in which the fishing ground is divided into two equal halves as in Figure 2 and the parameters are as in Tables 1 and 2. In order to meet constraint (b) (Section 4.2.3) that the probability of the annual catch of cod exceeds 10000 mt be less than 5%, the actual number of fishing days is 12000 per year. From the simulation results of the current process, the average catch of cod is 9122 mt, haddock is 5090 mt and yellowtail flounder is 9445 mt. The average total net profit P_{Sim} = \$109 847 000/year.

The simulation-based optimization approach can improve the average total net profit by 54% compared to P_{Sim}, with P_{Opt} = \$169 578 000/year. The optimal fishing schedule is shown in Table 3 as the best result found during 100 GA iterations.

6 CONCLUSIONS

This paper presents one application of a simulation-based optimization approach for fisheries management, which overcomes the limitations of conventional optimization techniques in fisheries sciences. Since the optimization module (a Genetic Algorithm in this case) is independent of the simulation module, the combination of the two modules makes this approach general and robust to the complexity of simulation models for any biological process and fishing activity.

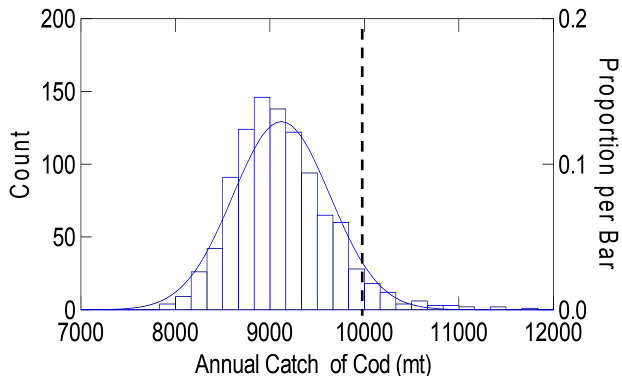

Figure 5: Result of 1000 Simulation Runs

Table 3: The Optimal Fishing Schedule.

Targeting species	Fishing days on West GB			
	Q. 1	Q. 2	Q. 3	Q. 4
Multispecies	590	74	27	596
Cod	487	392	232	211
Haddock	45	765	818	714
YT flounder	247	557	515	813

Targeting species	Fishing days on East GB			
	Q. 1	Q. 2	Q. 3	Q. 4
Multispecies	53	121	859	236
Cod	166	245	854	220
Haddock	854	781	404	578
YT flounder	229	443	299	823

The optimization approach is applied to a harvesting and scheduling problem for a fishing fleet. The comparison between the simulation of status quo and the result of the optimization program shows that the current fishing activities are far from the optimum and the net profit can be improved significantly by adjusting the time, location and targeting species.

The final product of this research is a Decision Support System for fisheries management authorities. The DSS program serves several purposes.

- Analysis function: executing simulation and exploration of possible options.
- Learning function: through the use of DSS one can get more insight into the functioning of the fisheries management system and outcomes of the management policies before implementation.

REFERENCES

Azadivar, F., T. Truong, K.D.E. Stokesbury, and B.J. Rothschild. 2002. Simulation based optimization in fisheries management. *Proceedings of the 2002 Winter Simulation Conference*. edited by E. Yücesan, C.H. Chen, J.L. Snowdon, and J.M. Charnes, 1268-1275.

Azadivar, F. 1999. Simulation optimization methodologies. *Proceedings of the 1999 Winter Simulation Conference*, edited by P. A. Farrington, H. B. Nembhard, D. T. Sturrock, and G. W. Evans, 93-100.

Babcock, E. A., and E. K. Pikitch. 2000. A dynamic programming model of fishing strategy choice in a multispecies trawl fishery with trip limits. *Canadian Journal of Fisheries and Aquatic Sciences*. 57: 357-370.

Goldberg, D. E 1989. *Genetic algorithms in search, optimization and machine learning*. Addison Wesley.

Michalewicz, Z., D. Dasgupta, R. G. Le Riche, and M. Schoenauer. 1996. Evolutionary algorithms for constrained engineering problems. *Computers & Industrial Engineering Journal*, 30 (2): 851-870.

Rothschild, B. J., J. S. Ault, and S. G. Smith. 1996. A system approach to fisheries stock assessment and management. In *Stock assessment, quantitative methods and application for small scale fisheries*. Edited by V. F. Gallucci, S. B. Saila, D. J. Gustafson and B. J. Rothschild. CRC press.

Ruppert, D., R. L. Reish, R. B. Deriso, and R. J. Carroll. 1984. Optimization using stochastic approximation and Monte Carlo simulation with application to harvesting of Atlantic Menhaden. *Biometrics*, 40: 535-545.

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