

The use of "Generating Techniques" in Fishery Policy Analysis: Study Case for the Yellowfin Tuna Fishery

Enríquez-Andrade, Roberto Ramón¹ Vaca-Rodríguez, Juan Guillermo^{1,2}

¹ Universidad Autónoma de Baja California, Km 103, Carretera Tijuana-Ensenada. Ensenada, Baja California, México

² Programa Nacional de Aprovechamiento del Atún y de Protección de Delfines. Km 107, Carretera Tijuana-Ensenada, campus CICESE Ensenada, Baja California, México

Abstract. Multiobjective decision analysis (MDA) is a useful assessment method when fishery managers need a systematic investigation of the trade-offs involved in the selection of alternative policy options. An important class of techniques within MDA is vector optimization, consisting of mathematical programming models with vector valued objective functions. From the management perspective vector optimization models are suited for situations when the decision rule requires that each objective be kept as high (or low) as possible. Solving vector optimization problems usually entails finding a set of Pareto optimal solutions. If decision makers have monotonic preferences then these solutions are highly relevant to the decision making process. In this paper a vector optimization model of the eastern Pacific yellowfin tuna fishery is used to generate Pareto optimal solutions and evaluate the trade-offs (shadow prices). Three conflicting policy objectives are considered, (a) minimizing dolphin incidental mortality, (b) minimizing by-catch of all non-dolphin species, and (c) maximizing total yellowfin tuna catch. Results are presented and discussed by means of non linear trade-off curves.

Keywords: Multiobjective decision making, by-catch, tuna-dolphin controversy.

1. INTRODUCTION

Historically the yellowfin tuna (*Thunnus albacares*) fishery in the eastern Pacific Ocean (East of 150°W, between 40°N and 30°S) has been one of the most important in the world, currently it accounts for approximately 270,000 mt of yellowfin tuna annually, roughly 20% of the YFT global production. The main fishing gear used is the purse-seine, with longlines occupying a distant second. Purse-seine is a gear designed to fish at the surface on large schools. This gear is specially useful in the tropical eastern Pacific, where the thermocline is shallow and the thermally sensitive species of tuna are forced into surface waters. The main target species for the fishery are yellowfin tuna and to a lesser extent skipjack and bigeye tuna.

Since the end of World War II the nations involved in the fishery have been making joint efforts to preserve and efficiently exploit the stocks of tuna in the region. With this purpose, in 1949 a Convention for the establishment of the Inter-American Tropical Tuna Commission (IATTC) was signed. These efforts however have not been harmonious. The issues of allocation, jurisdiction, access to the resource, and more recently, the incidental catches of dolphins and several other species have been the main source of conflicts.

Initially, purse-seine fisherman in the eastern Pacific Ocean mostly caught tunas by setting their nets around free swimming schools, a mode of fishing known as *school fishing*, or by fishing near floating objects such as tree trunks under which tunas often congregate, a mode known as *log fishing*. With the advent of modern purse-seine vessels, fisherman developed a technique, that took advantage of the association of dolphins with schools of large yellowfin tuna. In this technique, known as *dolphin fishing* or *fishing on dolphins*, the net is set around the tunas and the dolphins, then an attempt is made to release all the dolphins and tunas are loaded onto the vessels. In the early years the rate of dolphins incidentally killed was very high. More than 500 thousand dolphins were estimated dead in the 1960 season (Joseph, 1994).

In 1976 the member governments of the IATTC agreed to address the problem of dolphin mortality in the tuna fishery in the eastern Pacific, with the following objectives (Joseph, 1994): "(1) to maintain a high level of tuna production, and also to (2) to maintain dolphin stocks at or above levels that assure their survival in perpetuity,

(3) with every reasonable effort made to avoid needless or senseless killing of dolphins". A successful reduction in dolphin mortality was achieved in the fishery in response to pressure from environmental groups and the U.S. congress (Joseph, 1994; Hall, 1998). Total dolphin mortality and mortality per set decreased significantly in the early nineties (Hall, 1998), achieving lower levels than those established in international agreements (Anonymous, 1999). Present dolphin mortality levels are considered "statistically zero" and not significant in terms of population effects (Hall, 1998; Anonymous, 1999).

Dolphin incidental mortality has been reduced in two different ways: first, by improvements in the nets and fishing techniques that have allowed for a declining dolphin mortality per set on dolphins. Additionally, mortality can be reduced by changing the main fishing mode of fishing. This involves a geographical redistribution of the fishing effort. In spite of the dramatic success in reducing dolphin mortality rates, the industry still faces considerable pressure to lower this mortality to levels approaching zero. To comply with "dolphin-safe" requirements an important segment of the fleet changed its fishing patterns (ie. switching to fishing on logs and free schools). Additionally, new fleets joined the fishery using Fish Aggregating Devices (FADs), a variation of fishing on logs, resulting in mounting by-catch levels of species other than dolphins (including discarded portions of the yellowfin tuna catch), as well as reduced yellowfin tuna yields (Joseph, 1994; Hall, 1996; Hall, 1998).

There is currently an obvious management trade-off in the fishery among the main biological policy objectives: on one side reducing dolphin mortality, on the other maintaining low by-catch levels and a high productivity of the yellowfin stocks. By means of Multiobjective Decision Analysis (MDA) —in particular vector optimization techniques— we estimate the magnitude of the trade-offs associated given current technology and fisherman behavior.

2. MULTIOBJECTIVE DECISION ANALYSIS IN FISHERIES MANAGEMENT

Multiobjective decision analysis (MDA) is useful in situations where policy decisions must be made upon more than one objective that cannot be reduced to a single dimension (Meier and Munasinghe, 1994). Its main purpose is the identification and display of the trade-offs that must be made among objectives when they conflict. An important class of techniques within MDA is vector optimization. Vector optimization uses mathematical programming models with vector valued objective functions. From the decision-making point of view vector optimization problems are useful when the decision rule implies that each objective is to be kept as high (or low) as possible (Chankong and Haimes, 1983).

The general optimization problem is presented in (1) to (3). Equation (1) is a vector consisting of K ($k = 1, 2, \dots, K$) individual objective functions. In fishery problems, these functions may represent objectives such as yield biomass, net revenues, jobs, food production, maintaining spawning biomass and so on. The decision variables or policy instruments (eg. fishing effort, quotas, mesh size, season length, number of boats) are represented by the n -dimensional vector $Y = (y_1, y_2, \dots, y_n)$. In dynamic problems this vector, in addition to the decision variables, is made up of the state variables (i.e. the variables determining the state of the system through time). Equation (2) defines a set of m constraints. Equations 2 and 3 define the feasible region in decision space Ω_d (defined in the n -dimensional Euclidian space, (4)). In dynamic problems, the constraint condition typically includes the system's dynamics, expressed as a system of differential or difference equations (Conrad and Clark, 1989).

$$(1) \text{ Max. } Z(Y) = Z(z_1(Y), z_2(Y), \dots, z_K(Y)) \quad Y = y_1, y_2, \dots, y_n$$

$$(2) \text{ s. t. } g_i(Y) \leq 0 \quad i = 1, 2, \dots, m$$

$$(3) y_j \geq 0 \quad j = 1, 2, \dots, n$$

$$(4) \Omega_d = \{Y | g_i(Y) \leq 0, \forall_i\}$$

Given that vector optimization problems consist of conflicting and often non-commensurate criteria, a single optimal solution seldom exists. An optimal or superior solution is one which results in the maximum value of each objective function simultaneously (Evans, 1984). Therefore solving vector optimization problems usually entails finding their set of Pareto optimal solutions (Lai and Hwang, 1994; Chankong and Haimes, 1983; Evans 1984), also known as efficient solutions (Evans, 1984), non-dominated solutions and noninferior solutions (Lai and Hwang,

1994). A feasible solution is Pareto optimal if there exists no other feasible solution that will produce an increase in one objective without causing a decrease in at least one other objective (Evans, 1984; Cohon, 1978). More formally, y^* is Pareto optimal if there exists no other feasible solution y , such that (5) holds.

$$(5) Z_k(Y) \geq Z_k(Y^*), \quad \forall k=1,2,\dots,K, \quad \text{and} \quad Z_k(Y) > Z_k(Y^*) \quad \text{for at least one } k$$

An important characteristic of Pareto optimal solutions is that in moving from one Pareto optimal alternative to another the objectives must be traded-off against each other. A typical multiobjective optimization problem has many Pareto optimal solutions; the set of all these solutions is known as the Pareto optimal set.

If decision-makers have monotonic preferences, then only Pareto optimal solutions are relevant to the decision making process. Monotonicity of preferences states that for each objective function z_k an alternative having larger value of z_k is always preferred to an alternative having a smaller value of z_k , with the value for all other objective functions remaining equal. In a given policy problem only one of the Pareto optimal solutions can be selected by the decision-makers. The solution that is actually selected (some times through some additional criteria) among the set of Pareto optimal solutions is called the best-compromise solution (Cohon, 1978) or preferred solution (Lai and Hwang, 1994). Note that in the context of vector optimization the selection of the best-compromise solution among the Pareto optimal solutions is not the result of a formal maximization problem, but rather the result of a subjective evaluation of the importance of the objectives by the decision-makers.

In the general vector optimization problem presented in (1)-(3), if a solution y^* is Pareto optimal then there exists a set of multipliers $\lambda_i \geq 0$, $i = 1,2,\dots,m$ and $w_k \geq 0$, $k = 1,2,\dots,K$, with strict inequality holding for at least one k , such that the conditions in (6)-(8) hold. Equations (6)-(8) are necessary for Pareto optimality. These conditions are also sufficient if the K objective functions are concave, Ω_d is a convex set, and $w_k > 0$, $\forall k$ (Cohon, 1978).

$$(6) Y^* \in \Omega_d$$

$$(7) \lambda_i g_i(Y^*) = 0, \forall_i$$

$$(8) \sum_k w_k \Delta Z_k(Y^*) - \sum_i \lambda_i \Delta g_i(Y^*) = 0$$

In the context of public policy decision making, Ballenger and MacCalla (1983) refer to the Pareto optimal set as the "policy frontier." The policy frontier explicitly reveals the trade-offs associated with policy alternatives (Chankong and Haimes, 1983).

2.1. Generating Techniques

An important family of solutions to vector optimization problems are the generating techniques. These techniques, that follow directly from the Kuhn-Tucker conditions (Equations 6 to 8), are expressly designed for finding Pareto optimal solutions. Generating techniques do not require prior statements about preferences, utilities, or any other value judgements about the objectives (Evans, 1984). The articulation of preferences is deferred until the range of choice, represented by the policy frontier, is identified and presented to decision-makers. The role of the analyst is to concentrate on the formulation and evaluation of alternatives, and when results are reported they need not recommend a specific alternative as the best. Analysts, instead, find in the more comfortable and defensible position of information providers. The responsibility of selection rests with the decision-makers.

The Weighing Method: Zadeh (1963) shows that the condition given in (8) implies that the solution to the following problem (9) and (10) is, in general, Pareto optimal where $w_k \geq 0$ for all k and strictly positive for at least one k . In essence this means that a multiobjective optimization problem can be transformed into a scalar optimization problem where the objective function is a weighted sum of the components of the original vector-valued function (Cohon and Marks, 1975). The optimal solution to the weighted problem is a Pareto optimal solution to the multiobjective optimization problem, provided that all the weights are nonnegative. The Pareto optimal set can be generated by parametrically varying the weights w_k in the objective function (Gass and Saaty, 1955).

$$(9) \text{ Max. } Z(w, Y) = \sum_k w_k z_k(Y)$$

$$(10) \text{ s.t. } Y \in \Omega_d$$

The weighting method is not an efficient method for finding an exact representation of the Pareto optimal set. However, it is often used to obtain an approximation of this set: a number of different sets of weights are used until an adequate representation of the Pareto optimal set is obtained.

The Constraint Method: An alternative interpretation of third Kuhn-Tucker condition for Pareto optimality (Equation 8) implies that Pareto optimal solutions can be obtained by solving (11) and (12). Where L_k is a lower bound on objective k (Cohon and Marks, 1975). This represents an alternative transformation from a vector-valued objective function to a scalar objective function. The Pareto optimal set can be found by changing L_k parametrically. Thus, the constraint method operates by optimizing one objective while all the others are constrained to some value.

$$(11) \text{ Max. } Z_h$$

$$(12) \text{ s.t. } Y \in \Omega_d, Z_k \geq L_k, \forall k \neq h$$

The Hybrid method: A technique that combines the characteristics of the weighing method and the constraint method (Zadeh, 1963) can be used to generate Pareto-optimal solutions for a multiobjective optimization problem. Chankong and Haimes (1983) call this procedure the hybrid method. According to the hybrid method Pareto-optimal solutions for a multiobjective programming model can be characterized in terms of optimal solutions of the problem presented in (13) and (14) where w_k represents a set of arbitrary positive "weights" (at least one strictly positive), and L_h is a lower bound on the objective h . Pareto optimal solutions can be generated by the parametric variation of w_k and L_h (see Chankong and Haimes, 1983 for a proof).

$$(13) \text{ max. } Z(w, y) = \sum_k w_k z_k(y)$$

$$(14) \text{ s.t. } y \in \Omega_d, Z_h \geq L_h, \forall h \neq k \quad (14)$$

3. A VECTOR OPTIMIZATION MODEL OF THE EASTERN PACIFIC YELLOWFIN TUNA FISHERY

A three-objective dynamic vector optimization model with fixed technology is developed to analyze the implicit trade-offs among biological objectives in the eastern Pacific yellowfin tuna fishery. The objectives considered are: (a) minimizing dolphin mortality; (b) minimizing by-catch levels; and (c) maximizing total YFT yield. These objectives are represented by 15 to 17, where $OBJa$ is the level of dolphin mortality (to be minimized); $OBJb$ is the level of by-catch (to be minimized); and $OBJc$ is the yellowfin tuna yield (to be maximized). The description of the components of these objectives is presented below.

$$(15) \text{ OBJa} = \sum_{t,w} TB_{b="dolphins",t,w}$$

$$(16) \text{ OBJb} = \sum_{t,w} TB_{b="non-dolphins",t,w}$$

$$(17) \text{ OBJc} = \sum_{t,a,w} CB_{t,a,w}$$

The vector valued objective function incorporating the objectives given in (15) to (17) is presented in (18).

$$(18) \text{ Max } Z(Y) = Z(-OBJa(Y), -OBJb(Y), OBJc(Y))$$

The population dynamics of yellowfin tuna are represented by (19), where X is the YFT population age structure in number of organisms; CN is catch in number of organisms; M is the natural mortality coefficient; t is time in years; a is age in years; w is type of set or fishery (log-sets, school-sets, dolphin-sets and longline); and e is Euler's number (c.a. 2.71828).

$$(19) X_{t+1,a+1} = \left(X_{t,a} - \sum_w CN_{t,a,w} \right) e^{-M}$$

The initial age structure was taken from virtual population analysis (Anonymous, 1999). Five main age classes were considered. An average of the last five available years was taken, with a total of 60,040,040 organisms of age class 1; 19,700,000 of age class 2; 5,034,000 of age class 3; 575,000 of age class 4; and 27,000 of age class 5. One last age class (5+ or cumulative age class) was considered with 11,000 organisms. M was set as 0.8 and considered as a constant (Wild, 1994; Anonymous, 1999). Recruitment was considered constant using an estimated average for the last decade of 85,000,000 (Anonymous, 1999) since no stock-recruitment relationship has been found yet (Wild, 1994, Anonymous, 1999). Other recruitment schemes will be used for future approaches.

Catch in number CN is represented by (20), where P is the percentage of organisms caught per age and type set or fishery (Hall, 1996; Ortega-García, 1996; Anonymous, 1989) for one unit of effort, reflecting the historically integrated effects of oceanographic phenomena and fisheries on population structure.

$$(20) CN_{t,a,w} = P_{a,w} \cdot NP_{t,w}$$

NP is the number of units of effort generated by the model. NP is the free variable generated by the model to maximize or minimize the objectives, considering the constraints.

Catch in biomass (mt) CB is given by (21) where wg_a are average weights per age (Anonymous, 1999): 1.4175 kg for age class 1; 9.8175 kg for age class 2; 31.7475 kg for age class 3; 64.1825 kg for age class 4; 97.5500 kg for age class 5; and 124.9725 kg for age class 5+.

$$(21) CB_{t,a,w} = \frac{CN_{t,a,w} \cdot wg_a}{1,000}$$

By-catch level TB is represented by (22) where bl is a data base with by-catch levels per 1,000 mt of yellowfin loaded (Anonymous, 1999); and b is by-catch species sub-divided into “dolphins” and “non-dolphins”. The “dolphins” by-catch represents the number of dolphins incidentally killed per type of set or fishery per 1,000 mt of YFT loaded. The “non-dolphins” by-catch is an integrated index representing all non-target and target species discarded, arbitrarily weighted depending on their trophic level following the theoretical 10% energy-flow rule (e.g. 100 kg of small fishes = 10 kg of medium fishes = 1 kg of big fish). Since complete by-catch levels for the longline fishery were not available or not reliable, and since the main focus was on the purse-seine fishery, it was decided for this exercise not to include the longline by-catch on the by-catch index. However, this will have the effect of underestimating over-all trade-offs when longline is used as a main fishery option, but not when estimating trade-offs among purse-seine set-types.

$$(22) TB_{b,t,w} = bl_{b,w} \cdot \sum_a CB_{t,a,w}$$

The constraints used for the exercise described are represented in (23) to (27). Equations (23) and (24) constraint the YFT biomass (in mt) to be greater than or equal to a certain arbitrary “security” level, (24) does this specifically for the last year ($t=10$) of the model. Equations (25) and (26) constraint the catch (mt) to just above historical records for longline (Anonymous, 1999), and for all types of sets or fisheries to 290,000t representing the catch quota for the region agreed on meetings of IATTC (Anonymous, 1999). Finally, (28) specifies that each age-class must have at least one organism on it.

$$(23) \sum_a (x_{t,a} \cdot wg_a) \geq 100,000t$$

$$(24) \sum_a (x_{10,a} \cdot wg_a) \geq 200,000t$$

$$(25) \sum_{t,a} CB_{t,a,w=longline} \leq 50,000t$$

$$(26) \sum_a CB_{t,a,w} \leq 290,000t$$

$$(27) X_{t,a} \geq 1$$

The constraint method was used to trace three arbitrary segments of the policy frontier, given the specification of the model described above. The trade-offs were calculated on the basis of the marginal values from the output of the model. Some discrete solutions from the policy frontiers were selected to show average annual values of selected variables resulting from the optimization exercise. A ten-year time horizon was considered.

3.1. Results and discussion

Figure 1 depicts a two dimensional representation of values for the three policy objectives considered in the vector optimization problem described in the previous section. The by-catch index and the dolphin mortality are presented in the “y” and “x” axis respectively, while the “z” axis presents yellowfin tuna yield. The curves in the figure represent three arbitrary segments of the resulting policy frontier. Each curve in the figure connects points of equal values of yellowfin tuna yield. This graphical construction highlights the non-linear nature of the trade-offs between dolphin mortality and by-catch of all other species. Each contains all Pareto optimal combinations of values for the two objectives while keeping yellowfin tuna yield constant. Since the aim was to minimize both dolphin mortality and by-catch index the curves of equal yield values are convex to the origin.

Figure 2 shows the segment policy frontier corresponding to an average annual yield of 175,000 mt. The Roman numerals I to V are used to label particular Pareto optimal solutions that will be used below to make some remarks about the nature of the solutions of the vector optimization model.

The conflict among the three objectives is clearly shown in Figure 1 and Figure 2, since there is no solution achieving the lowest values for dolphin mortality and the by-catch index, and at the same time achieving the greatest values for yellowfin tuna yield.

Average annual dolphin mortality increases from 17 in solution I to 2,700 in solution V (Table 1). The opposite trend is observed in the values of the by-catch index and the corresponding number of organisms discarded. Yellowfin tuna biomass reached its lowest level in solution I, and its highest level in solution V.

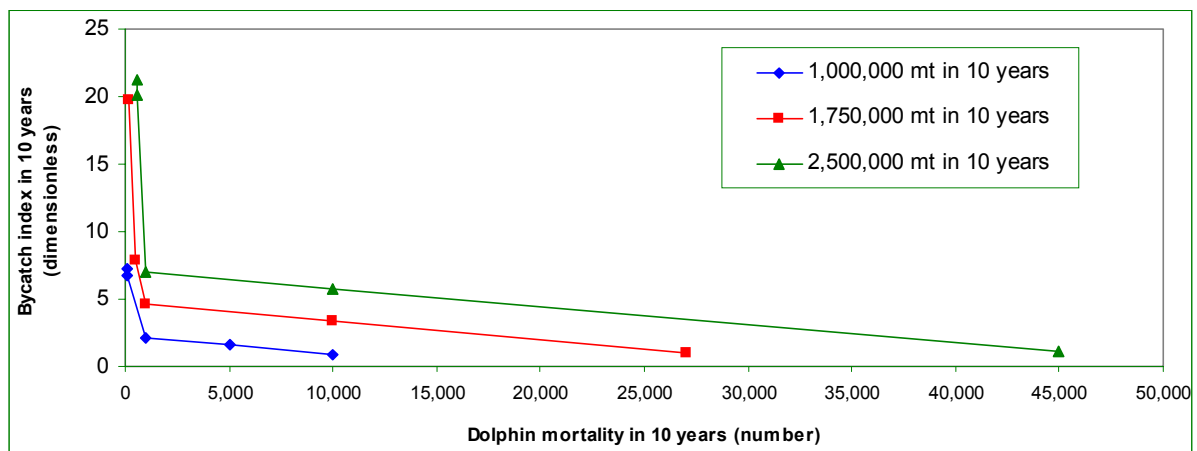


Figure 1. Policy frontiers for three different levels of yellowfin tuna yield.

Catch by type of set or fishery is the decision variable or policy instrument. The average catch necessary to

achieve a given Pareto optimal solution is shown in Table 2. Solution I was characterized by a high by-catch index and a low dolphin mortality, and its corresponding yellowfin tuna catch shows the dominance of log-sets. Solution III is dominated by school-sets, and was characterized by a moderate dolphin mortality and a low by-catch index. Finally, solution reference point V was characterized by a high dolphin mortality and a low by-catch index, and the catch was dominated by dolphin-sets. The other two solutions were characterized by transition trends of their neighbors.

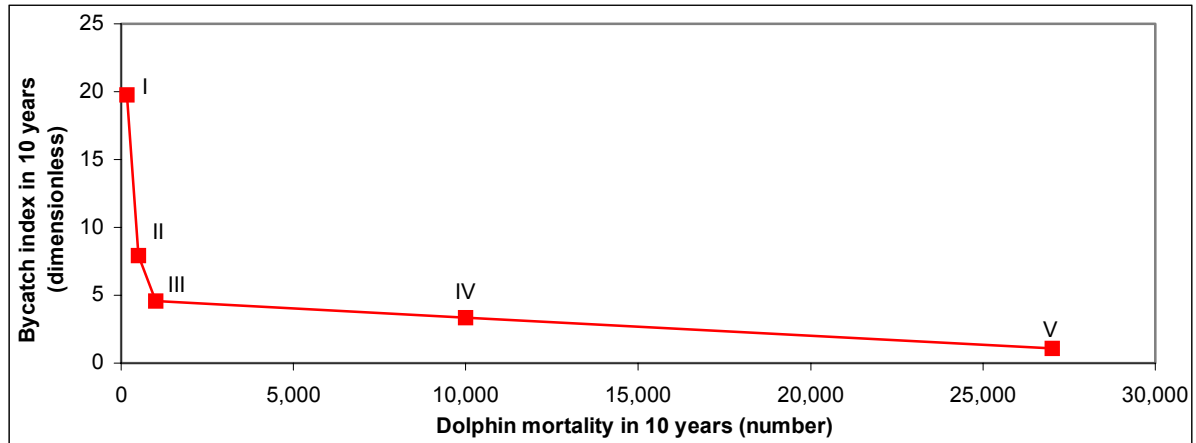


Figure 2. Policy frontier for the level of 1,750,000 mt of yellowfin tuna yield in 10 years, and five solution reference points.

Table 1. Average annual dolphin mortality, by-catch indexes, by-catch in terms number or tonnage of organisms, and yellowfin tuna (YFT) biomass resulting at each of the five reference solutions selected in Figure 2

Reference number	Dolphin mortality (number)	By-catch index (dimensionless)	Non-dolphin by-catch		YFT biomass (mt)
			Non-target (number)	Target (mt)	
I	17	1.976	5,995,358	62,655	425,644
II	50	0.793	2,365,383	27,617	629,037
III	100	0.460	1,341,344	17,868	662,267
IV	1,000	0.337	994,096	13,215	679,782
V	2,700	0.106	151,470	2,489	722,305

Table 3 shows the average annual by-catch to give the reader an appreciation of the meaning of the by-catch index values in terms of numbers of organisms. The same two trends described above (Table 1) holds true for each species separately.

Table 2. Average annual catch (and its standard deviation) by each type of set for the five reference solutions.

Reference number	Average catches per year (mt)				Catch standard deviation (mt)			
	Longline	Dolphin-sets	Log-sets	School-sets	Longline	Dolphin-sets	Log-sets	School-sets
I	50,000	0	109,453	15,547	0	0	89,000	34,287
II	50,000	0	27,363	97,637	0	0	48,018	109,381
III	45,005	1,654	3,492	124,848	15,796	5,225	11,044	117,396
IV	45,005	40,868	3,492	85,634	15,796	87,695	11,044	107,426
V	45,005	114,939	3,492	11,564	15,796	122,051	11,044	26,387

In solution I, the marginal cost of reducing dolphin mortality is 108,770 non-target organisms and 1,137 mt of

target species. However, for solution V the marginal cost drops significantly to only 197 non-target organisms and 3 mt of target species, given the same level of yellowfin tuna yield. Hall (1998) reported that the differential cost of fishing of 1 dolphin + 0.1 sailfish + 0.1 manta ray obtained with dolphin sets was approximately 1,833 non-target organisms and 15,620 target organisms (about 8 mt if we assume a weight of 2 kg per individual).

Maximum catch levels per year in the model were constrained by an *ad hoc* restriction based on catch quotas agreed on at IATTC meetings. However, there was no restriction regarding the minimal levels of catch per year. The resulting variation of catches may cause uncertainty, instability and a sense of risk to fishermen. Decision-makers may wish to explore other model outputs with different constraints.

Table 3. Average annual by-catch (non-target species in number of organisms) for each of the selected reference solutions.

Group or group of species	Reference numbers				
	I	II	III	IV	V
Dolphins	17	50	100	1,000	2,700
Mahi-mahi	1,098,240	338,104	119,332	92,829	8,061
Wahoo	589,909	156,793	31,186	27,456	1,637
Rainbow runner	87,181	27,708	10,624	8,152	733
Yellowtail	127,852	134,657	140,320	97,958	14,405
Other big fish	67,714	150,984	179,976	123,911	16,560
Triggerfish	1,737,810	454,695	82,310	74,101	3,252
Other small fish	2,174,440	1,005,941	683,142	501,934	92,718
Shark and ray	103,575	87,957	85,696	61,376	12,461
Marine turtles	203	286	319	231	60
Unidentified fish	4,522	2,802	2,366	1,762	487
Other fauna	16	95	121	85	15
Sword fish	43	80	93	67	15
Blue marlin	1,310	865	755	547	116
Black marlin	1,163	731	621	453	101
Striped marlin	412	694	798	570	130
Shortbill marlin	18	9	7	7	7
Sail fish	554	2,688	3,404	2,451	648
Unidentified marlin	275	214	202	152	49
Unidentified billfish	121	81	71	53	15
Total non-dolphin species	5,995,358	2,365,383	1,341,344	994,096	151,470

Table 4. Trade-offs between dolphin mortality and the by-catch index for the 10-year simulation period. Trade-offs are presented both as the by-catch index and as the corresponding number of non-target organisms and tonnage of target species.

Reference number	by-catch index units per marginal unit of dolphin mortality	Organisms per marginal unit of dolphin mortality	
		non-target species (number)	target species (mt)
I	0.0358417	108,770	1,137
II	0.0358417	106,937	1,248
III	0.000135938	397	5
IV	0.000135938	401	5
V	0.000135938	197	3

3.2. Conclusions

The resulting policy frontiers are useful in providing guidance to decision-makers and other policy actors to understand the implication of management decisions, structure the policy debate, and aid policy participants (e.g., biologists, lawyers, politicians, environmentalists, commercial and sports fishermen, processors, and consumers) in developing informed and balanced perspectives.

Results suggest that the marginal cost of reducing dolphin mortality in terms of non-dolphin species does not increase linearly, rather it increases gradually up to a point—after which most fishermen are setting their nets on logs— afterwards it increases rapidly. Solutions away from the extremes in the policy frontier, such as reference point III (dominated by school-sets) attain both low dolphin mortality and by catch index. However, information such as the length of yellowfin tuna caught at each set, availability and readiness to make any type of set, economic viability, and existing fishery management regulations should be used as additional criteria to make a selection.

Ballenger and MacCalla (1983) emphasize that changing the set of policy instruments and adding or changing any parameters to a vector optimization model could shift or redefine the shape of the policy frontier. That is, the policy frontier for a given fishery policy problem may shift or change shape with changes in technology, policy instruments, institutional constraints, preferences, environmental conditions etc. As stated before, this exercise assumes no technological changes in the fishery, adjustments are made on the basis of set-type (ie. dolphin sets, school sets or log-sets). This assumption represent accurately current fishing practices, which are largely motivated by the “dolphin safe” principle. Fishermen that want to comply with this principle need not to set their nets on dolphins.

This paper highlights the usefulness of vector optimization, in particular generating, techniques to evaluate trade-offs in fisheries management. Rather than suggesting an optimal solution, this approach concentrates on providing information to the decision makers regarding the range of choice and the consequences of policy options. Future research includes assessing a broader set of objectives in the eastern Pacific tuna fishery, such as revenue, profits and employment.

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