

# Determination of feeding strategies in aquaculture farms using a multiple-criteria approach and genetic algorithms.

Manuel Luna, Ignacio Llorente, Ángel Cobo

## **ABSTRACT:**

*Since the 1990s, fishing production has stagnated and aquaculture has experienced an exponential growth thanks to the production on an industrial scale. One of the major challenges facing aquaculture companies is the management of breeding activity affected by biological, technical, environmental and economic factors. In recent years, decision-making has also become increasingly complex due to the need for managers to consider aspects other than economic ones, such as product quality or environmental sustainability. In this context, there is an increasing need for expert systems applied to decision-making processes that maximize economic efficiency of the operational process. One of the production planning decisions more affected by these changes is the feeding strategy. The selection of the feed determines the growth of the fish, but also generates the greatest impact of the activity on the environment and determines the quality of the product. In addition, feed is the main production cost in finfish aquaculture. In order to address all these problems, the present work integrates a multiple-criteria methodology with a genetic algorithm that allows determining the best sequence of feeds to be used throughout the fattening period, depending on multiple optimization objectives. Results show its utility to generate and evaluate different alternatives and fulfill the initial hypothesis, demonstrating that the combination of several feeds at precise times may improve the results obtained by one feed strategies.*

**Keywords:** *aquaculture management; operational research; genetic algorithms; multiple-criteria; decision-making; feeding strategies;*

## **1. Introduction**

The exponential and uncontrolled growth of fisheries in the second half of the previous century put the sustainability of fish stocks at risk. Since the 1990s, fishing production has stagnated and there has been an exponential growth of aquaculture. Traditionally, marine fish farming was practiced extensively, mainly in lagoons and coastal ponds. However, production and consumption patterns have changed over time and, nowadays, intensive production is the most used method thanks to the development of new technologies. This change to intensive farming has led to the rapid development of the aquaculture industry, becoming a relevant industry around the world that is able to meet the demand for fish. In this context, sea cage farming has increased its importance in the aquaculture sector in which it has a major comparative and competitive advantage at global level: the cost reduction, with no energy costs for pumping, aeration, or post-rearing water treatment. In contrast, similar to other areas of the primary sector, fish farms management is complex due to the broad range of internal and external factors that influence the decision-making process. In this way, main decisions throughout the breeding process are affected by the interactions of technical, biological, environmental and economic factors.

Over the last decades, operational research (OR) experts have already developed management tools and Decision Support Systems (DSSs) in order to respond to producers' demands on the automation and optimization of many strategic and operational decisions. In this regard, main company decisions have been also widely analysed in many OR studies, such as site selection (Stagnitti, 1997), facilities design (Ernst et al., 2000) or hatchery management (Schulstad, 1997). Most of these OR models applied in aquaculture have been traditionally based on accumulated experience in fishing and other primary sector activities, such as agriculture or forestry, to increase the efficiency and profitability of fish farming on an industrial scale (Bjørndal et al. 2004). These tools provide expert information in an easy-to-use manner to end users and, with the technological advance in Big Data and Artificial Intelligence, they have managed to improve aquaculture companies' capacity to make decisions and develop control systems (Zhou et al., 2018).

Among those decisions stands out the selection of the most suitable feeding strategy, since feed is the main operational cost in in finfish aquaculture, which can achieve 30%–60% of total production costs (Goddard, 1996). In this regard, great research efforts have been made to determine, from the manufacturer's point of view, the ingredients that would form the optimal feed formulation. For example, several researchers have analysed feed formulations assessing the efficiency of diet formulations based on the results of a feeding trial on laying hens (Criste et al., 2016), measuring the effect of feed formulation in productivity (Abayomi et al., 2015) or applying optimization techniques to design an optimal diet composition with the objective to ensure the maximal survival rate and (Hormiga et al., 2010). However, in practice, most producers do not produce their own feed, but rather acquire the feed already formulated by the industry. This, in conjunction with the fact that there are a wide range of feeds in the market, implies that feeding strategies are a complex set of selections of different feeds for the fattening period, also called feeding paths, and, therefore, the number of potential possibilities is extensive and the results of those aspects can vary hugely depending on the final decision.

The central objective of this work is to provide decision makers with a model to address that combinatorial optimization problem. To this end, on the basis that feed selection depends on different factors at the precise moment at which feed is used and it is chosen among a finite set of alternatives provided by specialized manufacturers, metaheuristic techniques stand out as the best alternative to provide a solution. These techniques sacrifice the guarantee to find the optimal solution for the sake of getting good solutions in a significantly reduced amount of time (Blum and Roli 2003) compared to classic optimization techniques, many of whom are not applicable in these problems or lead to computation times too long for practical purposes. For these reasons, the present work applies a genetic algorithm (GA) methodology, a metaheuristic search and optimization technique based on principles present in natural evolution, to feeding decisions in order to generate and evaluate different feeding paths based on a fitness function.

GAs are one of the most popular heuristic approaches for optimization with application to many decision areas focused on process and product design, operations planning and control, and

operations improvement, as stated in the bibliographical review carried out by Lee (2018). With regard to aquaculture, genetic algorithms have already been used successfully in different optimization problems, as well. Atia et al. (2012) used them to optimally design solar water heating systems and Liu et al. (2011) addressed the water quality prediction using a hybrid approach based on support vector regression and GAs. In this context, there are different applications that have integrated ecological factors in the optimization processes too, such as the prediction of the potential distribution of invader species (Chen et al. 2006), or the prediction of fish distributions (D'Angelo et al. 1995). Lastly, other nature-inspired metaheuristics have been also used successfully in various practical problems related to aquaculture, such as the determination of the production strategies that maximize the present profits of the farming process considering as decision variables the fingerlings size, seeding times and harvesting weights (Cobo et al. 2018). However, despite its application to different aspects of the activity, the enormous potential of these techniques to contribute to the improvement of the efficiency of the feeding decision-making process has still not been adequately exploited.

However, there are still other challenges to be faced. Nowadays, producers should also attend to stakeholders' demands not only in terms of profitability or cost efficiency, but also in terms of environmental responsibility or product quality, aspects that they can sometimes find contradictory. This has led to a lack of management capacity due to the increasing complexity of those decisions and the need for extremely large amounts of data. Consequently, more and more producers demand for expert's systems that take into account the new ways of production, such as cleaner production (CP) alternatives, integrating all these criteria to combine the efficient use of natural resources and the generation of economic benefits (Canal Vieira and Gonçalves Amaral, 2016).

In this respect, the present study integrates a multiple-criteria decision-making (MCDM) methodology to formulate the fitness function that the genetic algorithm uses to evolve to a near-optimal solution. This methodology enables producers to condition their decisions to many criteria involved in the production process, such as economic, product quality or environmental sustainability ones. Furthermore, these techniques are ideal for this sector since they allow producers to weight each, different and very often opposed, criterion based on the subjective perception of the relative importance of them with the goal of combining several objective functions into a fitness function in order to prioritize the feeding alternatives. Some research studies, such as Ishizaka et al. (2011), have already shown the benefits of these methods in establishing rankings of alternatives through various experimental analysis and the emergence of new ways of production has led to the development of various MCDM tools applied to some problems of aquaculture, such as site selection (Dapueto et al. 2015; Shih, 2017), planning of regional aquaculture development (El-Gayar and Leung, 2001)

The methodology developed in this work represents an innovation in aquaculture since it manages to integrate the use of different optimization criteria, crucial for the development of new ways of production, and the possibility of having a variable feeding path throughout the fattening process

in the finfish-feeding decision-making process. After this introduction, the paper is structured as follows. First, section 3 describes the methodological approach, combining MCDM techniques and GA. Then, although the developed methodology could be applied to the culture of many aquaculture species, it is tested in the case of gilthead seabream farming in sea cages in section 4. Lastly, the conclusions and future research lines are given in section 5.

## 2. Materials and methods

To address this problem, the MCDM+GA optimization methodology designed has been implemented in a tool that combines all the techniques required in order to carry out the collection of real data and the simulation of the main management issues of the farm and the search for useful solutions with a population-based metaheuristic optimization algorithm, which allow farmers to try with different feeds throughout the production period rather than choosing only one, in the optimal way possible.

Prior to developing the described methodology, the vast amount of data needed and their complex relations makes necessary to develop a relational database and to clarify the problem. The structure of the database consists of four groups of tables: First, a central axis to identify the aquaculture farm and its main characteristics. Then, two groups representing the uncontrollable variables, such as the water temperature or salinity, which cannot be manipulated by the decision maker, but do affect the system performance, and therefore are required for forming a reliable decision (Casini et al. 2015). Lastly, five tables containing the information about the current status of each cage and the specific feeding, growth and loss rates according to the available feeds.

The development of an appropriate database is crucial to allow the tool to easily use specific information but it also assists in the clarification of the problem by gaining a detailed understanding of the different relationship between variables. In this regard, it is possible to define the problem as a combinatorial optimization problem, in which the producer has a finite set of feed  $\{F_1, F_2, \dots, F_m\}$  and the objective is to select the feed to be used in each week of the fattening period of the selected cage. The decision variables  $x_i \in \{1, 2, \dots, m\}$  represent the feed used in week  $i$ , for  $i=1, 2, \dots, n$  and a feeding path  $X$  is a vector  $X \in \{1, 2, \dots, m\}^n$ . Results obtained for each feeding path are estimated based on the explanatory variables included in the bio-economic model, which will be explained later.

Once the decision problem has been clarified, the methodology is structured as follows (Fig. 1):

- a. The first step to perform this process is to establish the criteria to be taken into account and weight each one based on the preferences of the farmer using MCDM techniques.
- b. Secondly, prior to the process of optimization, the development of a bio-economic model is needed to reasonably simulate the results for each feeding strategy.
- c. Lastly, an optimization process is developed based on a multiple-criteria fitness function according to which the initial population of feeding alternatives evolve, with the use of GA's crossover and mutation operators, until finding a useful solution.

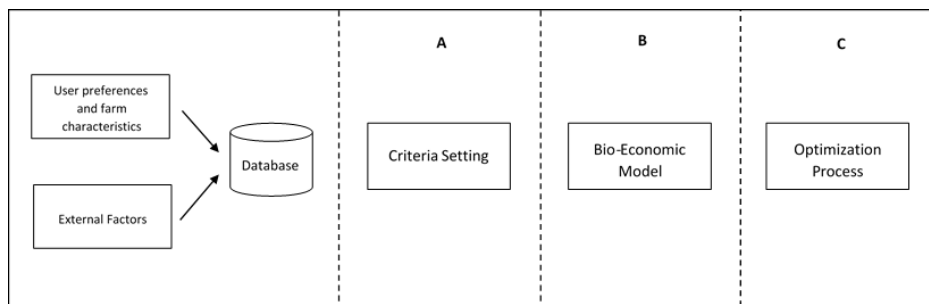


Fig 1. Software architecture according to the methodological approach.

## 2.1. Criteria selection and weighting

Within the supply of feed for the fattening of sea bream, there are notable differences in terms of prices, estimated fattening rates and nutritional composition. Furthermore, the choice of the most suitable feed can be conditioned by other factors, such as the environmental conditions of the farm or even the market.

This section presents three groups of criteria (economic, environmental sustainability, and product quality) used for choosing the most suitable feed and the method used to weight their subjective importance. In practice, this methodology allows decision makers to choose some of these factors for consideration or add new criteria before ranking them according to their individual needs.

### 2.1.1 Proposed criteria

From a conventional economic point of view, the main objective of aquaculture enterprises is profit maximization. In this respect, an economic sub-model has been included to estimate the **operational profit** by taking into account the costs incurred in the feeding process and the revenue obtained from the sales, calculated as a function of the average mass, its expected dispersion, and the market price in dollars per kg. The total weight in the cage is directly influenced by the growth, dispersion and mortality rates, so it will depend on the selected feed and the variations inherent to the fish source and species. Market prices considered are based on commercial classes, seasonal price and type of production (e.g. conventional or organic). This study considers only the feeding costs, making the assumption that others are not influenced by the chosen feed.

On the other hand, as an alternative to that conventional point of view, sustainable and organic procedures aim to reduce the negative environmental impacts of aquaculture production. In this regard, sharing best practices and their application in aquaculture companies throughout the breeding process is a key determinant as well as the appropriate selection of feed producers, as they also use energy and emits carbon dioxide (Boyd, 2015). In this regard, we have divided the environmental sustainability criteria into three sub-categories:

- Official ecolabels have been designed to certify organic products from a trusted third party. The Commission Regulation (EC) No 889/2008 of 5 September 2008 have set specific rules on feeds for carnivorous aquaculture animals. They shall be sourced by

products from: **organic aquaculture, fisheries certified** as sustainable or organic feed materials of plant origin (60% maximum). Furthermore, the maximum stocking density is 15 kg/m<sup>3</sup> for sea bass and seabream. This labels involves a disadvantage for the high cost of certification.

- In contrast, many consumers and producers prefer other strategies related to the environment surrounding aquaculture farms. Lembo et al. (2018) showed that in order to minimize the environmental impact of aquaculture, stakeholders placed the highest value on the prevention of chemical waste, namely **nitrogen and phosphorus**, and on the increase of **feed efficiency** in terms of fish meal and oil used.
- Along these lines, prior to the arrival to the farm, feed production has also an environmental impact that is commonly measured by the **energy use** (MJ equiv.), and the **global warming potential impact** (CO<sub>2</sub> equiv.) of the greenhouse gas emissions, among others (Abdou et al., 2017).

Lastly, fish products quality is easily perceived by the appearance, odor, flavor, and texture but it is still very difficult to contemplate objective criteria in this area. As Shahidi (2011) explained, fatty acids, particularly **omega-3**, are considered as health-promoting dietary components so some feed producers present an approximate amount of omega-3 transmitted with the use of their feed during the whole fattening process based on their own empirical studies. Besides that, Grigorakis (2011) has showed that re-feeding fish that previously received plant oil with diets containing **fish oil over a period of 90 days** could be adequate to almost fully restore the initial muscle fatty acids in both gilthead seabream and sea bass. These two criteria have been included as an approach to two different points of view about the maximization of the fish quality.

Once selected, the corresponding criteria are organized into a hierarchical structure (Fig 2) which will facilitate the evaluation of their relative importance.

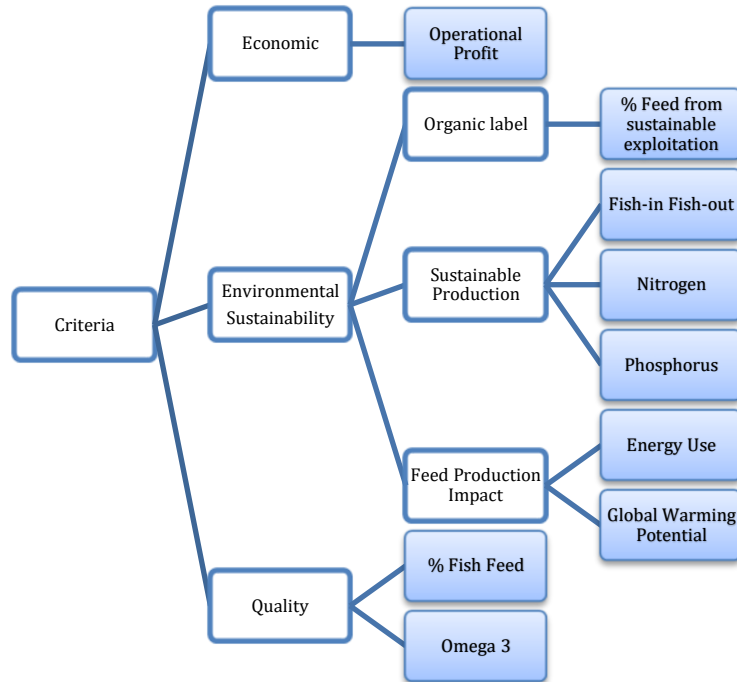


Fig. 2 Criteria hierarchy – tree structure: Highlighted boxes correspond to finally included criteria (Luna et al., 2019)<sup>1</sup>

### 2.1.2 Weighting method

The developed methodology uses the Analytic Hierarchy Process (Saaty, 1980) to turn human judgements, comparing the importance of each criterion with the others in the same level by pairs (table 1), in numerical values that will be easily integrated in a final weight for each criterion.

Intensity	Importance of one over another	Explanation
1	Equal Importance	Two activities contribute equally to the objective
3	Moderate importance	Experience or judgement slightly favour one criterion over another
5	Essential or strong importance	Experience or judgement strongly favour one criterion over another
7	Very strong important	An activity is strongly favoured and its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values	When compromise is needed

Table 1: AHP Marks Interpretation - Saaty (1987)

To address that process, an application of the AHP has been developed based on Cabral et al. (2016). It creates a matrix where the pairwise comparison values are stored associated with each

<sup>1</sup> The Fish-in Fish-out ratio represents the feed efficiency, measuring the amount of fish based feed needed to produce a unit weight of the cultured species.

hierarchical level of criteria. In such way, each entry  $a_{jk}$  represents the importance of the  $j^{\text{th}}$  criterion relative to the  $k^{\text{th}}$  criterion (1).

$$C^R = \begin{bmatrix} 1 & a_{12} & \dots & a_{1m} \\ 1/a_{12} & 1 & \dots & a_{2m} \\ \dots & \dots & 1 & \dots \\ 1/a_{1m} & 1/a_{2m} & \dots & 1 \end{bmatrix} \quad (1)$$

As simultaneously optimizing all the criteria is impossible, it is necessary to group these subjective judgments of the decision-maker on the importance of the criteria and from there define a heuristic process of searching for good solutions. In this regard, the developed methodology aggregates the values to form a vector of relative weights for each criterion considered in the matrix. In the present case, the weight vector is estimated as the normalized components of eigenvector corresponding to the largest eigenvalue of the matrix, according to the Saaty's approach. Furthermore, it also estimates a measure of the consistency in the decision maker's judgements (Wang et al., 2007)

## 2.2. Bio-economic simulation

In order to simulate the fattening process for each alternative of feeding and estimate its results or consequences, a bio-economic model has been developed. In this regard, the bio-economic model of the process of farming in sea cages integrated in the present work is based on the model proposed by Llorente and Luna (2013, 2014) and Cobo et al. (2015).

Initially, that model consisted in a biological sub-model of the process of farming in sea cages, which considers feed and growth rates as a percentage of the weight of the fish depending on the weight and environmental conditions, and an economic sub-model that quantifies the revenue and costs involved. However, MCDM techniques explore new factors, such as those related to environmental sustainability or product quality, that affect the decision-making process in aquaculture. As a consequence, the bio-economic model has gone one step further to estimate every important factor, based on the characteristics of each feed, while the biological process is simulated. In this regard, it also takes the assumption that producers cannot address the control of any of the abiotic factors affecting the growth process, for example, temperature, light, salinity, and oxygen, in an economically efficient way (Brett, 1979). Neither is it possible to choose the maximum biomass density, which is equal to the maximum insurable biomass density (Luna, 2002) or to the maximum allowed density in the case of organic labelled production.

However, some different assumptions have been taken. First of all, now it is possible to change the feed during the fattening process in order to reach the farmer goals. In this way, some farmers use a different feed during the colder months trying to maintain the growth and mortality rates or to reduce costs. On the other hand, the model considers only one a time investment, in which producers will take the harvesting time decision attending to their economic needs or agreements, so harvesting weight will be slightly different for each feeding strategy. Nevertheless, this methodology is also adaptable to a different model that considers an infinite series of investments



or time-dependent harvesting. In addition, the developed methodology allows decision-makers to consider, when such data is available, specific functions based on empirical findings in aspects such as feeding, growth, loss or dispersion.

Thus, feed composition and quality are considered crucial variables, dependent on the feed selected by the producer and the total amount consumed, since they will be used to simulate the economic, environmental and quality factors of each alternative in a daily basis. Finally, they are summed for the whole period getting as much values for each criterion as alternatives are generated in the optimization process.

### **2.3. Optimizing feeding strategies**

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics. GAs starts with a random population of strings, known as chromosomes, and thereafter successive populations are generated. To perform an effective search for better and better structures, they first require payoff values (objective function values) associated with individual strings (Goldberg, 2012).

In this regard, there are also different evolutionary metaheuristic techniques that can be used to address multiple-criteria problems, some of them using genetic algorithms such as NSGA-II (Deb et al., 2002). These techniques are mainly oriented to obtain a well distributed set of non-dominated solutions that approximate the Pareto front in practical problems in a great variety of fields. In fact, evolutionary multi-objective optimization is one of the most active fields of research within evolutionary computation (Abraham et al., 2005).

However, evolutionary multi-objective algorithms usually require working with a small number of objectives, because when this number grows there is an exponential increase in the number of non-dominated solutions found by the algorithms, which blocks the mechanism they have to reach the solutions of the Pareto front (Ishibuchi et al., 2008). In practice, these evolutionary algorithms are not very useful for the resolution of problems with more than three objective functions, so in the present work, we have chosen to combine the objectives in a fitness function with an MCDM technique and thus approach the problem with GAs.

#### **2.3.1. Evaluation function**

Genetic algorithms require an optimization objective according to which the population evolves. The fulfillment of this objective is measured by the fitness function  $F(X)$ , which assigns a fitness value to each individual based on the parameters derived from its chromosome. In the present study, that function is built for each feeding path taking the Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) as a reference (Hwang and Yoon, 1981).

Traditionally, TOPSIS considers two hypothetical alternatives: one with the best values for all the attributes (the positive-ideal) and one with the worst values for all the attributes (the negative-ideal), to later apply the fitness function for each alternative. Based on the definition of those ideal solutions, depending on each producer's profile, it is possible

to obtain a ranking of alternatives. The ranking of alternatives depends on the attainment of relative proximity indexes using a TOPSIS approach which allows us to construct the relative proximity intervals.

Later, the fitness function is applied for each alternative. This function is defined as the relative closeness to the ideal solution (2)

$$F(X) = \frac{d^-(X)}{d^-(X) + d^+(X)} \quad (2)$$

where  $d^-(X)$  and  $d^+(X)$  represents the separation of criteria values of  $X$  from the negative ideal and positive ideal solutions, respectively. This ratio varies between 0 and 1 and alternatives with a ratio closer to 1 would be preferred. Accordingly, and from the best alternatives, the optimization algorithm continues generating new solutions in order to evolve to a near-optimal one (Lamata et al., 2018).

In the present study, a TOPSIS has been integrated in an evolutionary methodology. This causes that there are not a fixed number of combination or alternatives, but they are generated sequentially. In order to overcome this problem, two hypothetical ideal alternatives, positive and negative, are generated from an initial step where only one feed can be used during the whole period. This enables to estimate the initial values for each criterion, as many as feeds are available, and to generate the hypothetical alternatives with the best and worst values with a supplement of  $\pm 75\%$ , assuming that a combination of different feeds will achieve better results than the utilization of only one. The only exception is the criterion of organic production feed ratio, whose ideal value is considered 1 and the anti-ideal value 0.

### 2.3.2. Evolving process

Once the fitness function has been fixed, the process continues with the generation of a random set (population) of feeding paths (individuals) and an estimation of their fitness according to that evaluation function. The second step of the GA methodology is to improve the initial population sequentially. This algorithm receives three operators to guide the algorithm towards a solution to the given problem:

- a. Selection: The selection process determines which individuals participate in reproduction to generate the next population according to their fitness values. In general, this process takes advantage of the fittest solutions by giving them greater weight when selecting the next generation and hence leads to better solutions to the problem (Siriwardene and Perera, 2006)

The developed methodology includes an elitism factor. Elitist selection strategies ensure that a percentage of the fittest alternatives continue to the next generation without any crossover or mutation. Once again, the disadvantage is the possibility of genetic

convergence but some studies have proven that elitism appears to be an important factor to improve evolutionary multiple-objective optimization (Parks, 1996; Zitzler et al., 2000)

- b. Crossover: the classic genetic crossover is performed using a random crossing point to create new individuals for the next generation by taking more than one parent solutions and combining them into a child solution. A high crossover rate encourages good mixing and the genetic algorithm is more likely to create a better solution.
- c. Mutation operators. The mutation randomly changes the feed of a week encouraging genetic diversity amongst solutions. High mutation rates prevent GA of converging to a local minimum but it could destroy good solutions.

Furthermore, to initiate the process it is necessary to assign the value of certain parameters, such as the crossover and mutation probabilities or the size of the population. The population size is the number of individuals that form part of each set generated. More individual means more cost, in time, but also increase the population diversity.

During this process, each solution, therefore, needs to be awarded a score, to indicate how close it came to meeting the overall specification of the desired solution, by applying the fitness function (2). This score, allow the process to decide the optimum moment to stop, by a stopping criterion, instead of continue during a fixed number of generations. The stopping criterion is settled as a number of generations without any improvement and when it is met, the algorithm provides the final set of feeding strategies.

Finally, the ranking of the alternatives is presented with information about the feed to be used each week and the values of each criterion in the final alternatives is provided to the decision maker.

### **3. Application to gilthead seabream feeding strategies.**

In order to test the developed methodology, several theoretical scenarios on decision-maker preferences are considered for the election of an optimum feeding strategy. They will be applied for the feeding decision-making process in a gilthead seabream farm in the Mediterranean during a period of 52 weeks and with the possibility of using three different feeds currently available in the market. As will be explained below, information used comes from real sources, such as oceanographic buoys, feed manufacturers or other research studies- the planning in a farm.

This process starts with the collection of relevant data, both from the farm and from external factors, and the estimation of the final weights for all the criteria in each scenario. Secondly, an objective function is calculated with the bio-economic model. Then, the process of optimization is developed with the generation and evaluation of alternative feeding paths in order to find an optimum strategy. Lastly, as a discussion of the utility of this methodology, results are compared with the alternative of using only the most adequate feed for each scenario.

#### **3.1. Farm information**

First of all, the specific characteristics of one farm of gilthead seabream have been simulated (Table 2) based on common characteristics of Mediterranean farms in Spain. In this way, the problem to optimize would be the performance of a unique sea cage of Gilthead seabream with juveniles of 30g during a year. The maximum biomass density depends on the type of production as the regulation requires, generally being 20 Kg/m<sup>3</sup> unless in the case of organic production where would decrease to 15 kg/m<sup>3</sup>.

External factors included in the database are the water temperature and the characteristics of the available feeds. Information on sea temperature has been collected from the oceanographic buoys network of the Spanish Port Authority, that covers the principal locations of marine aquaculture in Spain. In the present study, only the data registered during 2017 by the buoy placed at the simulated location, in the Mediterranean Sea near Tarragona (Fig. 2), have been used.

Parameter	Value
Seeding Date	15/06/2018
Harvesting Date	15/06/2019
Time horizon	52 weeks
Cage production capacity	200 m <sup>3</sup>
Juvenile weights	30 g
Feasible harvest sizes	(300, 1000) g
Location	Tarragona (2720)

Table 2: Farm Characteristics

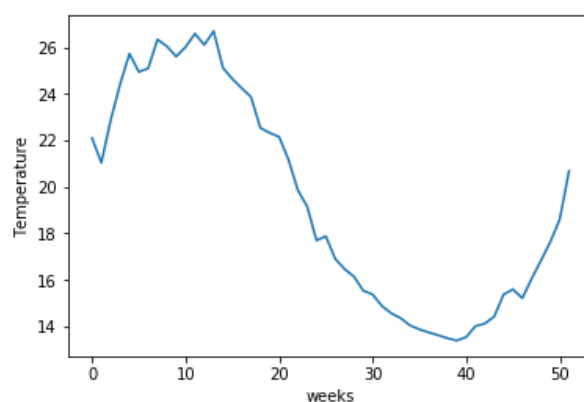


Fig. 4: Avg Temperature - Port Buoy 2720

In respect of feeding alternatives, the main rates and characteristics have been estimated based on the information provided directly by the feed production (table 3). However, there is one exception: feed production criteria have been estimated based on the study conducted by Pelletier and Tyedmers (2007). In that study, the approximate the value for both “feed production impact criteria” depending on the feed ingredients as the aggregated impact in raw material production, processing and transportation stages. All this data has been obtained for three different feeds:

- Feed 1 (F1) represent the more commonly used feed since they function well under normal circumstances and some of them are available at a very competitive price.
- Feed 2 (F2) have an increased percentage of fish protein so, although it has a higher price, growth rates are good even in unfavourable weather conditions.
- Feed 3 (F3) is a high quality and price feed, entirely made with products from organic fisheries/production. This feed present always better results, especially in warm conditions.

Feed Info	F1	F2	F3
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Price USD/Kg	1.11	1.19	1.49
% Fish origin feed	25.0%	38.0%	55.0%
% Plant origin feed	50%	62%	45%
% Poultry origin feed	25.0%	0%	0%
% Organic Feed	0.0%	0.0%	100.0%
Total Nitrogen (g per kg of feed)	77.5	73.6	99
Total Phosphorus (g per kg of feed)	16.30	16.80	17.50
Energy Use (MJ equiv. per kg of feed)	19,451	9,422	24,815
Global Warming (kg CO <sub>2</sub> equiv. per kg of feed)	1,665	0,800	1,705
Omega-3 (g per kg of fish growth)	10.2	14.9	17.3

Table 3: Feeds info

### 3.2. Theoretical scenarios of producer's preferences.

Once the main conditions have been specified, two theoretical scenarios of producer preferences have been simulated for such farm. To estimate the final weights in each scenario, criteria are compared by pairs, scoring the importance of each criterion related with another one.

In the present study, two conflicting tendencies have been analysed with respect to fish production: the traditional production procedures with the only objective of maximizing the annual profit and the organic production trend commonly used to differentiate the product with an organic label, which constitute an alternative to conventional aquaculture.

The scoring process follows a hierarchical structure, starting from the three groups of criteria and ending on the disaggregated criteria. This system reduces the number of evaluations just to the numbers under the main diagonal inasmuch as the others are deducted by the property of reciprocity ( $a_{ji}=1/a_{ij}$ ).

First of all, when comparing the three groups of criteria (table 4), the economic criterion is evaluated with the highest value in the first scenario, while the group formed by the environmental sustainability criteria is the most important in the second one.

Scenario 1				Scenario 2			
	Economic Criterion	Environmental Criteria	Quality Criteria		Economic Criterion	Environmental Criteria	Quality Criteria
Economic Criteria	1	9	9	Economic Criteria	1	1/9	½
Environmental Criteria	1/9	1	1	Environmental Criteria	9	1	4
Quality Criteria	1/9	1	1	Quality Criteria	2	1/4	1

Table 4: Pairwise judgements – main groups

Secondly, the environmental sustainability criteria have been evaluated in both scenarios. In the first one all the environmental criteria have low importance and only the fish-in:fish-out stands out inasmuch as it represents an efficiency ratio. On the other hand, the criterion that has a more prominent weight in the second scenario is the proportion of feed produced by organic production as requires the European Commission Regulation for the labelling of organic products (table 5).

	Scenario 1						Scenario 2					
	Organic Feed	Fish-in Fish-out	Total N (g)	Total P (g)	Energy Use	Global Warming	Organic Feed	Fish-in Fish-out	Total N (g)	Total P (g)	Energy Use	Global Warming
Organic Feed (%)	1	1/9	1/3	1/3	1/6	1/6	Organic Feed (%)	1	9	9	9	9
Fish-in Fish-out	9	1	3	3	2	2	Fish-in Fish-out	1/9	1	1	1	1
Total Nitrogen (g)	3	1/3	1	1	1/2	1/2	Total Nitrogen (g)	1/9	1	1	1	1
Total Phosphorus (g)	3	1/3	1	1	1/2	1/2	Total Phosphorus (g)	1/9	1	1	1	1
Energy Use (MJ equiv.)	6	1/2	2	2	1	1	Energy Use (MJ equiv.)	1/9	1	1	1	1
Global Warming (kg CO <sub>2</sub> equiv.)	6	1/2	2	2	1	1	Global Warming (kg CO <sub>2</sub> equiv.)	1/9	1	1	1	1

Table 5: Pairwise judgements – environmental sustainability criteria

Lastly, although a minimum quality is always required when selling fish products, quality criteria are more important under the circumstances of differentiation of the second scenario (table 6).

	Scenario 1		Scenario 2	
	% Fish origin	Omega 3 (g)	% Fish origin	Omega 3 (g)
% Fish origin feed	1	1/9	% Fish origin feed	1
Omega 3 (g)	9	1	Omega 3 (g)	8

Table 6: Pairwise judgements – product quality criteria

After applying the AHP methodology, the weights associated with each criterion in each scenario are those shown in Table 7. As can be observed, the distribution of weights perfectly fulfils the perception of relative importance of the criteria in the proposed scenarios. This greatly facilitates an evaluation work that could be very difficult to do directly on all of the criteria.

Criterion	scenario 1	scenario 2
<b>Economic Criteria</b>	<b>81.8%</b>	<b>8.3%</b>
Profit	81.8%	8.3%
<b>Environmental Criteria</b>	<b>9.1%</b>	<b>75.0%</b>
% Organic Feed	0.3%	48.2%
Fish-in Fish-out Ratio	3.2%	5.4%
Total Nitrogen	1.0%	5.4%
Total Phosphorus	1.0%	5.4%
Energy Use	1.8%	5.4%
Global Warming Potential	1.8%	5.4%
<b>Quality Criteria</b>	<b>9.1%</b>	<b>16.7%</b>
% Fish origin feed	0.9%	1.9%
Omega 3	8.2%	14.8%

Table 7. AHP weights in both scenarios considered.

### 3.3. Objective Function

In order to carry out the optimization process successfully, a fitness function, which evaluates how close a given solution is to the objective solution, is needed. In this regard, the objective function is the business goal of the selected farm, in mathematical terms, of multiple and competing criteria combined.

Both the process of estimation of the results for one feed alternatives in order to find the objective function and the evaluation of each alternative generated by the genetic algorithm, involves two steps where the bio-economic model takes action. In the first instance, it estimates the growth reached and the feeding amount needed in a daily basis. Then, the value of each criterion is calculated from that data.

In economic terms, profit is quantified both in unitary and aggregated terms, by the revenue and costs involved. Cost varies as a function of the used feeds, due to its different feeding amount and price. Meanwhile, revenue depends on the reached growth, its dispersion if available and the selling price, which relies on the type of production. For classical aquaculture, weekly selling prices correspond to the main Spanish wholesale market prices for the commercial classes of Seabream (300–400g, 400–600g, 600–1000g) in 2018. The prices are reduced by the average wholesale-producer margin as stated by MAPAMA (2012) and used as a proxy of the ex-farm price. In the case of organic aquaculture, Zander and Feucht (2018) have showed that the willingness to pay varies between 7% and almost 20%, depending on attribute and country. Therefore, the used price is on average a 15% higher than in classical aquaculture for the same period.

In the case of all other additional criteria mentioned above, grouped as environmental sustainability and product quality criteria, they can be estimated based on the information provided by the different feed producers as a percentage of the amount used of each feed.

As a result of this process, the main values for each alternative are estimated. Data shown in table 8 for the first scenario provides an idea of importance of choosing an adequate feeding path, being able to distinguish clearly different results for each criterion. This confirms the characteristics of the three different feed mentioned above. In the case of positive-ideal and negative-ideal, they are multiplied by  $\pm 75\%$  setting the objective functions. On the other hand, scenario two shows similar results with a reduction due to the smaller number of fishes seeded to meet the organic regulation requirements.

Criterion	Obj	F1	F2	F3	+ Ideal	- ideal
<b>Economic Criteria</b>						
Profit (\$)	<b>MAX</b>	9,921.03	9,613.06	8,067.96	<b>17,361</b>	<b>2,016</b>
<b>Environmental Criteria</b>						
Organic Feed (%)	<b>MAX</b>	0%	0%	100%	<b>1</b>	<b>0</b>
Fish-in Fish-out Ratio	<b>MIN</b>	52%	77%	105%	<b>13%</b>	<b>183%</b>

Total N (g)	<b>MIN</b>	650,069.23	604,280.52	567,337.66	<b>157,912</b>	<b>1,585,360</b>
Total P (g)	<b>MIN</b>	136,724.24	137,933.60	100,286.96	<b>34,181</b>	<b>280,240</b>
Energy Use (MJ equiv.)	<b>MIN</b>	163,154,800	80,861,140	227,074,800	<b>2.02E+07</b>	<b>3.97E+14</b>
Global Warming (kg CO <sub>2</sub> equiv.)	<b>MIN</b>	13,966,000	6,865,731	15,601,950	<b>1.72E+06</b>	<b>2.73E+13</b>
<b>Quality Criteria</b>						
% Fish origin feed	<b>MAX</b>	25%	38%	55%	<b>96%</b>	<b>6%</b>
Omega 3 (%)	<b>MAX</b>	1.02%	1.49%	1.73%	<b>3.50%</b>	<b>0.25%</b>

Table 8: hypothetical ideal alternatives for scenario 1.

Then, as stated in the methodological approach, the fitness is calculated as the relative closeness to those ideal solutions (2).

### 3.4. Search for useful solutions

Once the objective function and the method responsible for evaluating each alternative of the feeding strategy have been determined, the genetic optimization process begins with the search of useful solutions, based on the generation of alternatives and the evolution till the point where a better solution is not found in a determined number of generations. For the evolving process, the following parameters have been considered: population size of 30, crossover probability of 0.8, mutation probability of 0.03 and a limit of 15 generations without any improvement to stop the process. Furthermore, the best individual is always included in the next generation.

After applying the genetic algorithm with the parameter defined above a set of 30 potential solutions is obtained for each generation, which means that more than 1900 alternatives for each scenario have been evaluated. This means that, in most cases,

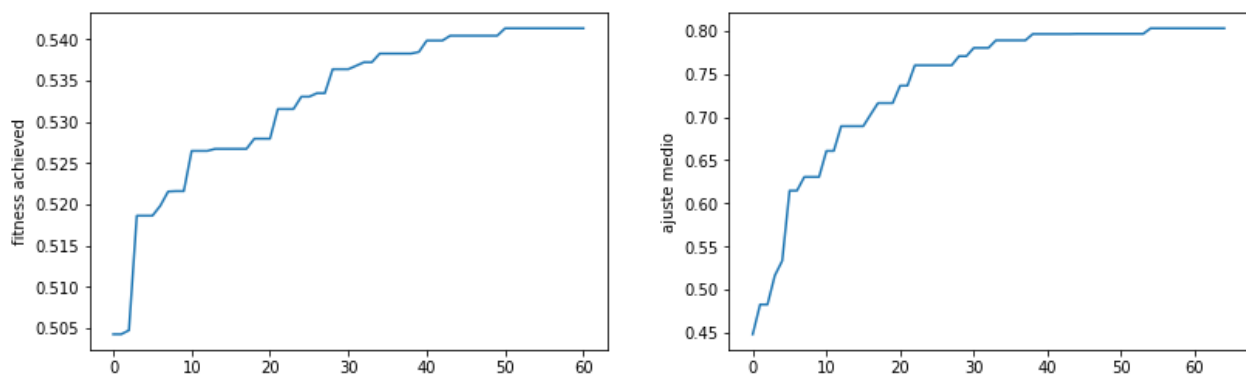


Figure 5. Evolution of the average fitness for scenario 1 and 2 respectively.

Furthermore, one of the problems faced by this type of tools is the computational cost, measured as the time needed to finish the process. This results have been obtained using an Intel Core i7 2.81GHz processor and 16 Gb SDRAM, and the average execution time was 290 seconds (table 9),, what does not seem too much.



Scenario	Generations	Number of alternatives	Execution Time (seconds)
First	61	1830	273.25
Second	63	1890	303.65

Table 9. Simulation numbers.

Finally, the algorithm provides the decision maker with a set of 30 potential solutions obtained and the best feeding strategy generated during the iterative process. The fact of offering to the decision-maker a set (population) of good alternatives or near-optimal schedules facilitates the final decision and allows considering new factors not initially included in the model. For each considered scenarios, the best solutions are those shown in table 10.

Scenario	Best solution – Feeding path	Fitness
First	F3, F3, F3, F3, F3, F3, F3, F3, F3, F3, F3, F1, F3, F1, F3, F1, F3, F2, F1, F1, F1, F1, F1, F3, F2, F2, F1, F1, F1, F1, F1, F1, F1, F2, F1, F2, F2, F2, F2, F2, F2, F2, F2, F2, F2, F2, F2, F2, F2, F2, F2, F2, F2	0.54218
Second	F3, F1, F3	0.8028

Table 10. Best solutions for both scenarios.

Figure 6 shows the evolution of the temperature of the water over the 52 weeks and the recommended feed for each week for the final feeding strategy proposed by the algorithm in both scenarios. As can be seen, in scenario 2 the algorithm mainly recommends the use of F3 but in specific weeks it considers more appropriate the use of the other two feed. In scenario 1, however, we observe how the algorithm recommends first the F3 feed, probably due to its better growth rates in warm conditions, but it changes to F2 feed, which have similar results under cold conditions, when the water temperature decreases. In the mid-term it recommends the other one.

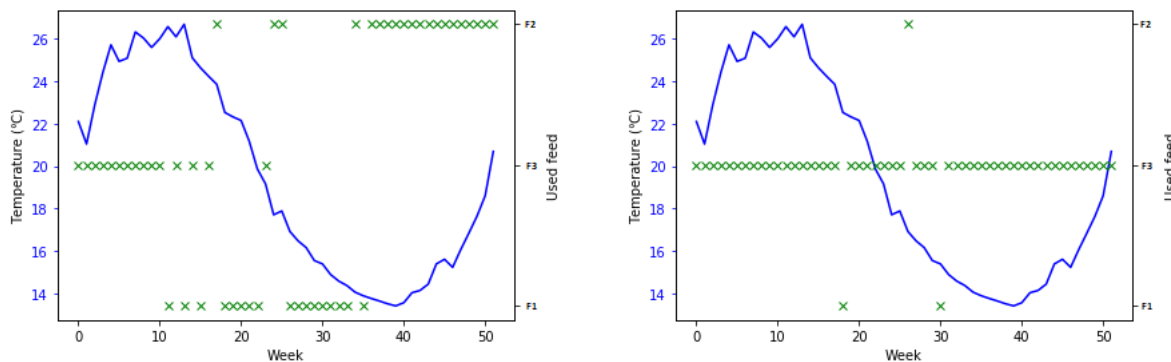


Fig 6. Selected feed and weekly temperature

These results confirm that the methodology developed is useful when setting a production objective in a complex environment where diverse and sometimes conflicting criteria intervene. In addition, the fitness function and the genetic algorithm have worked at the time of optimizing feeding strategies, evolving from the first generation and finding a good solution in an adequate time.

### 3.5. Results discussion.

After assessing the capacity of the developed methodology to analyse and prioritize new alternatives properly, some features that are relevant shall be discussed thoroughly. The most important is the validation of the hypothesis that a combination of different feeds should improve the results obtained with only one feed during the whole period. This requires a comparison between the selected mixed strategy for each scenario and the unique feed that the tool would have chosen if so requested. It should be taken into account that scenario 2, corresponding to organic production, requires a cage density under 15Kg/m<sup>3</sup> so the current number of fished is lower.

On the one hand, results for the first scenario are conclusive, the mixed strategy found by the developed methodology has resulted in significant gains in the improvement of the selected criteria, therefore confirming the initial hypothesis. In this case, the criterion with the highest importance is the economic one and it shows an improvement of 7,17% compared to the value estimated for AR feed. As can be seen in table 11, although there has been an increase in producer's costs, the increase in the weight achieved, and therefore in the benefits obtained, compensates the situation. Furthermore, product quality, where the second most important criterion can be found, becomes significantly larger.

Scenario 1	F1	Mixed Strategy	% Var	Result
Fishes	12,141	12,144	0.02%	Improvement
Unit weight reached	329.28	370.19	12.42%	Improvement
Total weight (Kg)	3,997.82	4,496	12.45%	Improvement
Cost (\$)	9,341.17	11,028.29	18.06%	Worsening
Cost per kg	2.06	2.16	4.99%	Worsening
Revenue (\$)	19,262.20	21,660.39	12.45%	Improvement
Revenue per kg	4.82	4.82	-	-
FCR (%)	210%	192%	-8.50%	Improvement
<b>Economic Criteria</b>				
Profit (\$)	9,921.03	10,632.10	7.17%	Improvement
<b>Environmental Criteria</b>				
Organic Feed (%)	0%	25%	(+25%)	Improvement
Fish-in Fish-out Ratio	52%	75%	42.94%	Worsening
Total N (g)	650,069.23	722,507.69	20.90%	Worsening
Total P (g)	136,724.24	149,525.28	11.14%	Worsening
Energy Use (MJ equiv.)	163,154,800	151,911,800	1.98%	Worsening
Global Warming (kg CO <sub>2</sub> equiv.)	13,966,000	12,036,020	8.55%	Worsening
<b>Quality Criteria</b>				
% Fish origin feed	25%	39%	56.22%	Improvement
Omega 3 (%)	1.02%	1.27%	24.99%	Improvement

Table 11: Improvements achieved – scenario 1.

This results can be more easily compared in figure 7. As an added benefit, it is possible to highlight that the company can't sell the fish until they reach the minimum weight for sale in the market

(300 g) and in this case it is reached several weeks before with the mixed strategy. This would give the producer greater flexibility and the capacity to react to possible adverse situations, which can be considered a measure that significantly reduces the risk incurred.

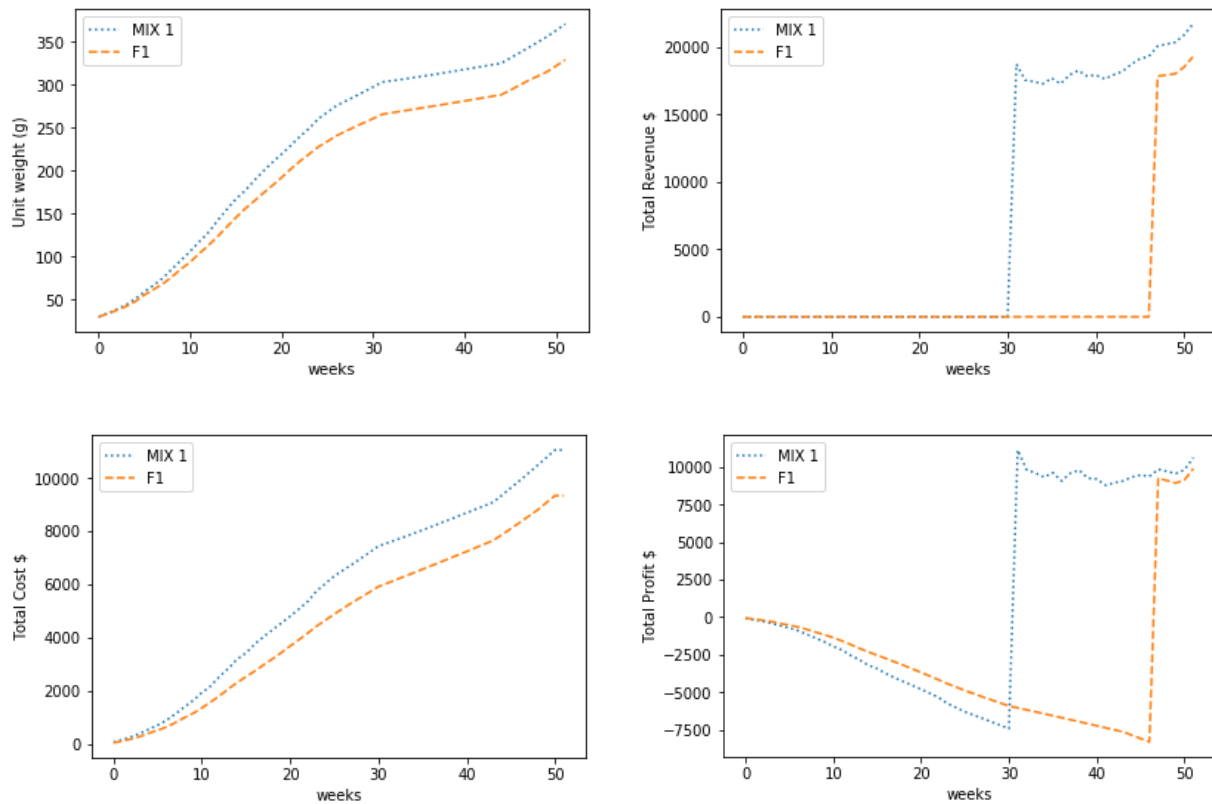


Fig. 7: Visual comparison of strategies – scenario 1.

On the other hand, scenario 2 presents small differences in main results since the EC feed has been chosen for almost the 90% of the period. Table 12 shows how the best alternative found by the genetic algorithm has slightly worsened the value for the most important criterion (Organic feed - 48,2%) while leading to more quality, that is the second criterion in importance (Omega 3 – 14,8%) and efficiency in costs. In this case, it is not possible to state categorically what is the best solution for the producer. However, the proposal of various alternatives increases the capacity of the latter to decide in situations of theoretical equality.

Scenario 2	F3	Mixed Strategy	% Var	Result
Fishes	7,606	7,606	-	-
Unit weight reached	395.40	391.81	-0.91%	Worsening
Total weight (Kg)	3,007.45	2,980.13	-0.91%	Worsening
Cost (\$)	8,596.02	8,407.70	-2.19%	Improvement
Cost per kg	2.52	2.48	-1.29%	Improvement
Revenue (\$)	16,663.99	16,512.62	-0.91%	Worsening
Revenue per kg	5.55	5.55	-	-
FCR (%)	191%	187%	-2.04%	Improvement

<b>Economic Criteria</b>				
Profit (\$)	8,067.97	8,104.92	0.46%	Improvement
<b>Environmental Criteria</b>				
Organic Feed (%)	100%	96,0%	-4.04%	Worsening
Fish-in Fish-out Ratio	105%	102%	-2.94%	Improvement
Total N (g)	567,337.66	555,359.39	-1.77%	Improvement
Total P (g)	100,286.96	99,381.80	-2.11%	Improvement
Energy Use (MJ equiv.)	142,206,900	138,049,200	-0.76%	Improvement
Global Warming (kg CO <sub>2</sub> equiv.)	9,770,815	9,596,298	-0.90%	Improvement
<b>Quality Criteria</b>				
% Fish origin feed	55%	54%	-0.93%	Worsening
Omega 3 (%)	1.73%	1.97%	13.94%	Improvement

Table 12: Improvements achieved – scenario 1

#### 4. Conclusions

In recent years, aquaculture has become a relevant industry called to meet the world demand for fish, though not without difficulty. As is the case with many primary sector activities, the management of fish farms is increasingly complex due to the broad range of internal and external factors that influence most decisions and the need for managers to consider aspects other than economic ones, such as product quality or environmental sustainability. For all of these reasons, the need for more efficient and productive management systems in order to automate and optimize many strategic and operational decisions has increased over the last few years.

Among these decisions, it is possible to highlight the selection of the most suitable feeding strategy. These decisions are of greater importance not only because of the direct effect on the breeding costs they have, since feed is the main operational cost in in finfish aquaculture, but also because of they are the maximum responsible for the quality of the final product and the effect on the environment that surrounds the farm, two of the criteria most valued by stakeholders. Furthermore, feeding decisions have an added complexity: The existence of many different feeds and the possibility of combining them during the fattening process cause that traditional optimization techniques are not applicable to this problem or lead to computation times too long for practical purposes.

In order to address this problem, the present work integrates a multiple-criteria methodology with an evolutionary metaheuristic technique that allows determining the best sequence of feeds to be used throughout the fattening period, depending on multiple optimization objectives. In spite of their wide applicability and simplicity, metaheuristic techniques are not being used in the management of aquaculture farms as widely as in other contexts. In particular, genetic algorithms are well suited to address complex problems that arise in the management of such farms. In this regard, this work states a model in which the preferences of the decision maker are included thanks to the AHP methodology and these preferences influence the definition of the fitness function that a genetic algorithm subsequently uses.

In this regard, the main results of the simulations carried out seem to confirm the goodness of the model for the determination of feeding strategies in aquaculture farms that are affected by variations in environmental conditions. In addition, these results help to confirm that the combination of several commercial feeds in the same feeding strategy may improve the results obtained by one-feed strategies that considers only one commercial feed along all the production process.

In the context of the management of aquaculture companies, the implementation of the developed model allows multiple criteria to be introduced in the decision-making process, thereby enabling producers to find solutions suited to their needs from the many alternatives in very short time. All this is translated in a contribution to the improvement of the efficiency and flexibility of the decision-making processes, both regarding operative and strategic decisions.

From the point of view of the management of production processes, the proposed model allows to identify the feeding strategy that optimize the economic performance of the farm. However, and different from previous works that only considered the economic criteria in the decision process, this model also opens the door for aquaculture managers to find the feeding strategy that provides the best results in terms of environmental sustainability or product quality. Considering several criteria in the same decision is not a minor issue. As in other production activities, those criteria in aquaculture are very often opposed and, in most of the cases, their importance is based on the subjective perception attributed by each manager. In such way, this model integrates multiple-criteria decision making techniques and genetic algorithms applied to the decision-making process, thereby enabling producers to find solutions suited to their needs. The computational time is also a key aspect, since the model finds a near-optimal solution by simulating a vast number of alternatives in a very short period of time. All this is translated in a contribution to the improvement of the efficiency and flexibility of the decision-making processes in aquaculture production, both regarding strategic and operative decisions.

Lastly, it is mandatory to consider some limitations and future lines of research as, for example, the incorporation of elements of fuzzy logic to introduce into the model the vagueness of any subjective judgment and the increase of the number of cages that would allow producers to make long-term planning in major aquaculture farms. This points to the need for more research studies on this line and sets out the future direction of them.

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