Intl. Trans. in Op. Res. xx (2020) 1–24

A fuzzy approach to decision making in sea-cage aquaculture production

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Received DD MMMM YYYY; received in revised form DD MMMM YYYY; accepted DD MMMM YYYY

Abstract

Despite the rapid growth of productivity and business production scale of aquaculture companies in the last few years, their economic results have still experienced very high volatility. This can be partly explained by the increasing complexity of management issues and the strong changes in seafood consumption patterns. But, above all else, companies' results are affected by the conditions of high uncertainty in the decision-making processes, due to the large number of biological, technical, economic and environmental influencing factors, many of them beyond the control of managers. In this context, the number of variables, scenarios and the volume of data to be considered in decision making is increasing and, therefore, technological advances are becoming much more accepted and requested. This work presents a fuzzy model that allows aquaculture producers to easily manage the uncertainty regarding climate change and market price scenarios when they are facing production decisions, such as the choice between traditional or ecological production. To that end, this novel approach uses the fuzzy pay-off method to estimate the companies' economic performance and a discrete multicriteria decision-making technique (fuzzy TOPSIS) to integrate economic, environmental and product quality criteria in the selection of the most appropriate production alternative.

Keywords: aquaculture; multicriteria decision-making; fuzzy TOPSIS; fuzzy pay-off

1. Introduction

Aquaculture is the animal production that has grown the most in recent years due to the evolution of extensive and semi-extensive systems towards industrial scale production. At present, its production level has reached that of fisheries and it has been pointed out by FAO as the economic activity that

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can guarantee the sustainability of fishery resources. This process has been possible mainly thanks to the development of new production technologies. However, the rapid growth of productivity has significantly increased the complexity of aquaculture companies' management, which is affected by biological, technical, environmental, economic and market factors, many of them, beyond the control of managers. Furthermore, the greater activity has been accompanied by an increase in the volume of information that managers cannot process on their own efficiently. As a consequence, companies increasingly demand new simulation and optimization tools that help to improve the efficiency of decision making processes in aquaculture operations.

In addition to the complexity of the operations, the evolution of several uncontrollable factors for the production process is increasingly uncertain, such as water temperature or market prices. More specifically, water temperature is always highlighted as one of the key variables affecting sea cage aquaculture results both in terms of fish growth and mortality. In the case of this exogenous factor, in the short-term the company can overcome that lack of control by forecasting its value based on historical data, but it is nearly impossible to predict the exact values the will encounter in the future, mainly due to the direct effect of climate change. According to the latest IPCC report (IPCC, 2019), over the 21st century, the ocean is projected to be subject to unprecedented conditions with increased temperatures (virtually certain) and possible extreme events. Moreover, FAO have concluded in their technical report FAO (2018a) that climate change will potentially have both favourable and unfavourable impacts on aquaculture, but the available information indicates that unfavourable changes will outweigh the positives. At the same time, the strong development of the aquaculture sector has also increased market competitiveness and volatility in sale prices, facilitated by the increase in international trade (Fernández-Polanco and Llorente, 2019) and its dependence on the size of commercial fish (Janssen et al., 2017), which have important implications when planning production.

Furthermore, uncertainty increases even more when producers face new investments or new forms of production which will evolve according to how well they meet consumer demands, this makes it more difficult to predict their evolution over the next few years. This can be seen in some cases, such as organic aquaculture, which has had a high volatility of results and still has not taken off, even though organic production is leading changes in many sectors. In this regard, despite the fact there are consumers that have the capacity and willingness to pay for organic aquaculture products (Zander and Feucht, 2017), one of the main unknowns is if the plus that is produced in the final sale price would allow producers to address the increase in costs of this type of production. This situation is generated in part by a lack of tools that allow aquaculture managers to consider targets different from the economic ones, such as product quality or organic production, when making operational and strategic decisions.

Many studies worked in modelling the influence of several factors such as fish size, water temperature and feed in the fish grow (Seginer, 2016). However, these works in general present limitations in predicting the expected weight of the fish during the production process and, therefore, take some operational decisions. In recent years, researchers have developed a greater number of works that apply new bioeconomic models, and new simulation and optimization techniques to aquaculture (Granada et al., 2018; Llorente and Luna, 2015). These studies have provided new tools that improve the efficiency of decision-making processes. However, these decision-making support systems usually apply deterministic models that do not take into account the real uncertainty that exists in the different biological, technical, economic and environmental factors that lead to a high variability of results obtained in theoretically similar situations. This constitutes a limitation not only when applying them in practice, but also when considering certain criteria, such as the operational risk of some decisions, in decision-making models. Regarding this uncertainty, although in the short term it is easier to estimate (with a high probability) the value of some of the factors that influence aquaculture processes and their deviations, there are situations that greatly hinder that consideration.

In this context, the aim of this work is the development of a methodology for the decision-making process in aquaculture that takes into account the uncertainty regarding climate change and market price scenarios when they are facing production decisions, such as the choice between traditional or ecological production. Pelissari et al. (2018) identify the different types of uncertainty that occur in input data of multi-criteria decision making (MCDM) problems and the most appropriate techniques to deal with each one of these uncertainties. They identify three types of uncertainties in input data: due to ambiguity, randomness and partial information, and propose a framework that indicates techniques used in different decision-making contexts for each uncertainty. Taking into account the type of uncertainty in the data, the need to deal with numerical ranges and the possibility that decision-makers express hesitancy in stating their preferences, the proposed framework recommends the use of fuzzy set theory and its extensions. For this reason, the present work uses the fuzzy pay-off method first to allow aquaculture producers to estimate the company's economic performance , then the fuzzy TOPSIS technique to integrate that estimation with other fuzzy criteria, such as the environmental sustainability and product quality (Luna et al., 2019b). This models constitutes a novel approach to fish farming in sea cages and allows producers to overcome a growing need for new decision-making methodologies and support systems.

After this introduction, the second section presents a review of the literature on applications of operational research in aquaculture. After that, section 3 explains two methodologies for decision-making under fuzzy criteria: the fuzzy pay-off method and fuzzy TOPSIS. The fourth section then describes the fuzzy model developed for aquaculture production in sea cages. Once the methodology developed has been shown, the next section presents the results of a practical example developed to test the efficiency of the model. The last section discuss the main implications of the research and present the main conclusions.

2. Operational research models in aquaculture

Fish farming began to develop industrially in the early nineties in different species such as salmon, seabream or seabass, thanks to the development of cage production technology at sea. At present, it is one of the technologies that brings greater value to aquaculture, since the production and profitability of these species grew strongly during the last 15 years. However, despite this rapid expansion of aquaculture production, there isn't much substantial literature in the field of operational research and applied economics compared to other industries (Mathisen et al., 2016). This can be partly explained by the fact that during the early stages all efforts were focused on the factors that guarantee its biological viability and allow it to develop the production on an industrial scale (Luna, 2002). However, over time, production technology became universal and prices began to decrease, so the main aquacultures industries, such as the salmon-farming industry, are entering into the maturity phase and their growth has slowed down showing an annual rate of 4% (FAO, 2018b). In this new context, the research efforts are pursuing new objectives such as the productivity and profitability improvement.

During the last decades, a large part of the increase in the expansion of the production of some species can be explained by the productivity gains, with higher survival and growth rates (Asche et al., 2003). In that context, the application of operational research models to aquaculture, integrating biological models for fish growth and economic models linking the biological production process to the market, has proven to be a success (Bjørndal et al., 2004). The first works in this area were applied to the modelling of the production of shrimp (Karp et al., 1986; Leung and Shang, 1989) and to optimize the harvesting times of salmon, under different cost scenarios (Bjørndal, 1988) or in relation with the feeding strategy (Arnason, 1992; Mistiaen and Strand, 1998).

In recent times, such methodologies were continually expanded with the main objective of determining the production plan that maximizes the value of production (Bjørndal and Asche, 2011). In addition, as Llorente and Luna (2015) highlight in their review study, some of the methodological developments included all the technical work needed to transfer the knowledge to the industry. In this way, different Decision Support Systems were developed to assist managers in their decision-making about crucial aspects, such as the seeding and harvesting schedules (Yu et al., 2007, 2010), sustainable management (Conte and Ahmadi, 2010), site selection (Halide et al., 2009) and sequencing a large number of batches in an optimal way (Cobo et al., 2019). However, no suitable solution has yet been proposed to fully fit with the realities of the huge variety of problems affecting aquaculture companies. In this regard, more attention should be paid on aspects, such as the application of multi-criteria decision making models (MCDM) and or the consideration of the uncertainty in growth and mortality, which are being increasingly studied in other industries of the primary sector (Bjørndal et al., 2012).

Regarding the MCDM techniques, several exhaustive reviews on the literature of aquaculture business management have highlighted the lack of models that allow producers to take conscious decisions based on multiple criteria (Mardle and Pascoe, 1999; Mathisen et al., 2016). Now, a few authors have integrated multi-criteria methodologies in their OR models as, for example, Dapueto et al. (2015), Shih (2017) or Luna et al. (2019a,b). But, there is a clear imbalance between economic or financial studies and those that takes into account the social and environmental criteria (Peñalosa et al., 2019).

On the other hand, the research studies and projects that address the high uncertainty in aquaculture business management made little progress. Thus, the works of Sparre (1976), using the Markov approach for optimizing the harvest, and Hatch and Atwood (1988) incorporating risk with a risk programming model into an aquaculture decision-making technique, were groundbreaking projects. The Markov approach has been repeatedly applied in several works (Leung and Shang, 1989; Leung et al., 1990; Jensson and Gunn, 2001; Bravo et al., 2013) in which future uncertain growth depends solely on the latest growth measurement. However, this is not sufficient to address all the existing sources of uncertainty, as already explained in the introduction.

3. Decision-making under fuzzy criteria

3.1. Fuzzy modelling

All the aspects already mentioned point to a gap of appropriate models in aquaculture, which the present work has the aim of closing with the utilization of fuzzy numbers and MCDM methodologies to address the uncertainty of aquaculture processes and reduce the volatility of companies' results in a novel way in this sector. To this end, the theory of fuzzy sets is used to assess the results of multiple criteria in

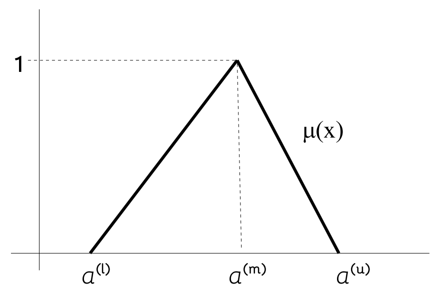

Fig. 1. Graphical representation of the fuzzy triangular number $\left\langle a^{(l)}, a^{(m)}, a^{(u)} \right\rangle$.

different scenarios. In this way, the fuzzy pay-off method, a specific methodology developed by Collan et al. (2009), is applied to address the particular complexity of the profitability analysis, since it is focused on using different cash-flow scenarios as a basis for creating a possibilistic pay-off distribution for an investment. It relies on the fact that possibility theory and fuzzy numbers can be used to model imprecise investment cash-flows (Kuchta, 2000) and, in addition, is compatible with uncertainty scenarios based on expert assessments. These are important advantages over other methods in the present case since the estimation of the evolution of some crucial factors is especially complex. Furthermore, it has already been used for investment analysis and valuation in the case of patents (Collan and Heikkilä, 2011) and information systems (You et al., 2012) or R&D projects (Collan and Luukka, 2014), among others.

Zadeh (1965) introduced the theory of fuzzy sets to model the concept of vagueness, the characteristic of human thought. A fuzzy set A is characterized by a membership function $\mu_A(x)$ which associates a real number $\mu_A(x) \in [0,1]$ to any element x in a referential set X. The value $\mu_A(x)$ is interpreted as the membership grade of x in the set A. A fuzzy number is a fuzzy set with referential set $X = R$ and a membership function μ satisfying the following properties: normal ($\exists x_0 \in R$ with $\mu(x_0) = 1$), upper semi-continuous, fuzzy convex ($\mu(\lambda x + (1-\lambda y)) \geq \min\{\mu(x), \mu(y)\}$) and compactly supported (the closure of $\{x \in R : \mu(x) > 0\}$ is compact). Fuzzy numbers allow us to face problems in which the variables or criteria are not precisely defined.

One of the most popular types of fuzzy number is the triangular fuzzy number, that is defined by three real numbers, expressed as $\hat{a} = \left\langle a^{(l)}, a^{(m)}, a^{(u)} \right\rangle$, where $a^{(l)}$ is the lower limit, $a^{(m)}$ the most promising and $a^{(u)}$ the upper limit value. The membership function of $\hat{a}$, shown in Fig. 1, is given by:

$$\mu_{\hat{a}}(x) = \begin{cases} 0 & \text{if } x < a^{(l)} \text{ or } x > a^{(u)} \\ \frac{x - a^{(l)}}{a^{(m)} - a^{(l)}} & \text{if } x \in [a^{(l)}, a^{(m)}] \\ \frac{a^{(u)} - x}{a^{(u)} - a^{(m)}} & \text{if } x \in [a^{(m)}, a^{(u)}] \end{cases} \tag{1}$$

The assumption of triangular fuzzy numbers is a simplification, which can be frequently found in the literature and which facilitates fuzzy arithmetic calculations (Meixner, 2009). It is possible to use the operation laws following Zadeh's extension principle via this simplification which makes calculations much easier. Given the triangular fuzzy numbers $\hat{a} = \left\langle a^{(l)}, a^{(m)}, a^{(u)} \right\rangle$ and $\hat{b} = \left\langle b^{(l)}, b^{(m)}, b^{(u)} \right\rangle$, the basic addition and non-negative scalar multiplication operations are also triangular fuzzy numbers:

$$\begin{aligned}\hat{a}+\hat{b} &= \left\langle a^{(l)}+b^{(l)}, a^{(m)}+b^{(m)}, a^{(u)}+b^{(u)}\right\rangle \\ \lambda\hat{a} &= \left\langle \lambda a^{(l)}, \lambda a^{(m)}, \lambda a^{(u)}\right\rangle \text{ with } \lambda \geq 0\end{aligned}$$

The result of the multiplication $\hat{a}*\hat{b}=\langle a^{(l)}b^{(l)}, a^{(m)}b^{(m)}, a^{(u)}b^{(u)}\rangle$ is not necessarily a fuzzy number, however we can accept this operation as an approximate value.

The calculation of the distance between two fuzzy numbers can be performed in different ways. In this work we will use the vertex method used by Chen (2000):

$$d(\hat{a},\hat{b})=\sqrt{\frac{1}{3}\left[(a^{(l)}-b^{(l)})^2+(a^{(m)}-b^{(m)})^2+(a^{(u)}-b^{(u)})^2\right]} \tag{2}$$

On certain occasions, it may be appropriate to replace a fuzzy number with an exact number (crisp number). Defuzzification is the process of converting a fuzzy number into a single crisp value in the referential set. There are many different methods of defuzzification available, we will use the centroid of area (COA) method that provides a crisp value based on the center of gravity of the fuzzy set. For continuous membership function $\mu_{\hat{a}}(x)$ is defined as:

$$df(\hat{a})=\frac{\int_{-\infty}^{\infty} x\mu_{\hat{a}}(x)dx}{\int_{-\infty}^{\infty} \mu_{\hat{a}}(x)dx} \tag{3}$$

In the case of triangular fuzzy numbers we can calculate the gravity center of the fuzzy number over any subinterval $[p,q]$ in the following manner:

$$df_{[p,q]}(\hat{a})=\frac{2}{a^{(u)}-a^{(l)}}\int_p^q x\mu_{\hat{a}}(x)dx \tag{4}$$

Another crisp measure associated with fuzzy numbers is the possibilistic or fuzzy mean of a fuzzy number $\hat{a}$, that is computed using the concept of α-cuts. Given a fuzzy number and a value $\alpha\in[0,1]$, the $\alpha-$cut is defined as $[\hat{a}]^\alpha=\{x\in R:\mu_{\hat{a}}(x)\leq\alpha\}$ and is a closed interval $[a_1(\alpha),a_2(\alpha)]$. According to Carlsson and Fullér (2001) the possibilistic (or fuzzy) mean value of fuzzy number $\hat{a}$ with α-cuts $[\hat{a}]^\alpha=[a_1(\alpha),a_2(\alpha)]$ is defined as

$$E(\hat{a})=\int_0^1(a_1(\alpha)+a_2(\alpha))\alpha d\alpha \tag{5}$$

In the particular case of a fuzzy triangular number $\hat{a}=\langle a^{(l)},a^{(m)},a^{(u)}\rangle$, the α-cuts are

$$[\hat{a}]^\alpha=[a^{(l)}+\alpha(a^{(m)}-a^{(l)}), a^{(u)}-\alpha(a^{(u)}-a^{(m)})]$$

and the fuzzy mean is

$$E(\hat{a})=\frac{1}{6}(a^{(l)}+a^{(u)}+4a^{(m)}) \tag{6}$$

3.2. Fuzzy pay-off method

The fuzzy pay-off method was introduced by Collan et al. (2009) as a method for the valuation of projects and assets. They define the real option value (ROV) from a fuzzy net present value (NPV) as

$$ROV = \frac{\int_0^\infty \mu_{\hat{A}}(t)dt}{\int_{-\infty}^\infty \mu_{\hat{A}}(t)dt} \times E(\hat{A}_+) \tag{7}$$

where $\hat{A}$ represents the fuzzy NPV, with membership $\mu_{\hat{A}}(x)$ and $E(\hat{A}_+)$ representing the fuzzy mean value of the positive side of $\hat{A}$. When the whole fuzzy number is above zero, then ROV is the fuzzy mean of the fuzzy number calculated by expression (5), and when the whole fuzzy number is below zero, the ROV is zero.

Hassanzadeh et al. (2012) use the fuzzy pay-off method to effectively value R&D projects and include expressions to compute $E(\hat{x}_+)$ with trapezoidal fuzzy numbers. These expressions can easily be adapted to the case of triangular numbers $\hat{x}$:

$$E(\hat{x}_+) = \begin{cases} E(\hat{x}) = \frac{1}{6}(x^{(l)} + x^{(u)} + 4x^{(m)}) & \text{if } x^{(l)} \geq 0 \\ \frac{1}{6}\left(x^{(l)} + x^{(u)} + 4x^{(m)} + (x^{(m)} - x^{(l)})\left(1 - \frac{x^{(m)}}{x^{(m)} - x^{(l)}}\right)^3\right) & \text{if } x^{(l)} < 0 \leq x^{(m)} \\ \frac{1}{6}(x^{(u)} - x^{(m)})\left(1 + \frac{x^{(m)}}{x^{(u)} - x^{(m)}}\right)^3 & \text{if } x^{(m)} < 0 \leq x^{(u)} \\ 0 & \text{if } x^{(u)} < 0 \end{cases} \tag{8}$$

The calculation of ROV using (7) implies the multiplication of the possibilistic mean of the positive outcome $E(\hat{x}_+)$ by the fraction of positive area of the distribution of the NPV. In the case of a fuzzy triangular number $\hat{x}$ this fraction is

$$\frac{\int_0^\infty \mu_{\hat{x}}(t)dt}{\int_{-\infty}^\infty \mu_{\hat{x}}(t)dt} = \frac{2}{x^{(u)} - x^{(l)}} \int_0^\infty \mu_{\hat{x}}(t)dt \tag{9}$$

where

$$\int_0^\infty \mu_{\hat{x}}(t)dt = \begin{cases} \frac{1}{2}(x^{(u)} - x^{(l)}) & \text{if } x^{(l)} \geq 0 \\ \frac{1}{2}\left(x^{(u)} - x^{(l)} - (x^{(m)} - x^{(l)})\left(1 - \frac{x^{(m)}}{x^{(m)} - x^{(l)}}\right)^2\right) & \text{if } x^{(l)} < 0 \leq x^{(m)} \\ \frac{1}{2}(x^{(u)} - x^{(m)})\left(1 + \frac{x^{(m)}}{x^{(u)} - x^{(m)}}\right)^2 & \text{if } x^{(m)} < 0 \leq x^{(u)} \\ 0 & \text{if } x^{(u)} < 0 \end{cases} \tag{10}$$

3.3. Fuzzy discrete multicriteria decision-making: fuzzy TOPSIS

Discrete MCDM are used to assess a finite set of alternatives in order to select a suitable alternative to fulfil a desired goal with regard to multiple (and often conflicting) criteria. MCDM is recognized as a significant and active area of operational research and management science. Different decision-making methods have been developed and used for different real-life problems and there are no superior methods (Ishizaka and Siraj, 2018). The choice of a specific method depends on different factors concerning the problem and the method's characteristics.

Given the great diversity of MCDM methods, the first question is related to choosing the most appropriate method based on the characteristics of the problem. Although Haddad and Sanders (2018) propose a methodology to recommend the most suitable MCDM when risk and uncertainty are anticipated, Ceballos et al. (2018) argue that the question remains open. In their paper, they compare a set of MCDM methods sharing three features: same fuzzy information as input data, the need of a data normalization procedure, and quite similar information processing. Specifically, they compare different fuzzy versions of MULTIMOORA, VIKOR, WASPAS and TOPSIS methods and conclude that given a new decision problem, a good strategy would be to solve it with as many methods as possible. Other comparative studies can be taken as a reference. Rodrigues-Lima et al. (2014) present a comparative analysis of two widely applied methods for supplier selection: fuzzy TOPSIS and fuzzy AHP. Their analysis is based on seven factors: adequacy to changes of alternatives or criteria, agility in the decision making problem, time complexity, support to group decision-making, limitation in the number of criteria and alternatives, and modeling uncertainty. According to their conclusions, although both methods are adequate to deal with imprecision, subjectivity and group decision, fuzzy TOPSIS performs better than fuzzy AHP in most cases except when there are few criteria and suppliers. Fuzzy AHP is prone to ranking reversal when a new alternative is included, while fuzzy TOPSIS produces consistent preference order. Another advantage of fuzzy TOPSIS is that there is no limitation in the number of criteria and alternative suppliers without a change in the decision problem hierarchy structure. A similar comparative study between fuzzy TOPSIS and data envelopment analysis (DEA) reveals that TOPSIS outperforms DEA in terms of both calculation complexity and sensitivity to changes in the number of suppliers (Rashidi and Cullinane, 2019). Finally, Pätäri et al. (2018) perform a comparison of median-scaling (MS), TOPSIS, AHP, and add.DEA in the context of portfolio selection and, at least for their particular sample data, AHP and TOPSIS outperform MS and add.DEA. Another advantage of the TOPSIS method is its possibility of offering a graphical display that is very appealing to decision makers (Eiselt and Marianov, 2014).

For the reasons outlined above, in this work we decided to use a fuzzy extension of TOPSIS. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a multicriteria decision making method originally developed by Hwang and Yoon (1981) that considers two hypothetical alternatives: the positive-ideal (with the best values for all the attributes) and the negative-ideal (with the worst values for all the attributes), to later measure a closeness ratio in order to choose the alternative with the shortest distance from the positive ideal solution and longest distance from the negative ideal solution.

Different fuzzy extensions of TOPSIS can be found in the scientific literature; variations of fuzzy TOPSIS focus on the determination of ideal solutions, distance measurement or the use of different type of fuzzy numbers. We have chosen to use the methodology proposed by Chen (2000) due to its simplicity and applicability. The methodology is briefly described below.

Input A fuzzy decision matrix and weight vector:

$$\hat{\mathbf{X}} = \begin{pmatrix} \hat{x}_{11} & \hat{x}_{12} & \cdots & \hat{x}_{1m} \\ \hat{x}_{21} & \hat{x}_{22} & \cdots & \hat{x}_{2m} \\ \cdots & \cdots & \ddots & \cdots \\ \hat{x}_{n1} & \hat{x}_{n2} & \cdots & \hat{x}_{nm} \end{pmatrix}; \quad \hat{\mathbf{w}} = \begin{pmatrix} \hat{w}_1 \\ \hat{w}_1 \\ \vdots \\ \hat{w}_m \end{pmatrix}$$

where $\hat{x}_{ij}$ represents the fuzzy rating of alternative i under criterion j, and $\hat{w}_j$ the importance fuzzy weight of criterion j.

Step 1 Construct the normalized fuzzy decision matrix $\hat{\mathbf{R}} = (\hat{r}_{ij})_{n\times m}$, where

$$\hat{r}_{ij} = \begin{cases} \left\langle \frac{x_{ij}^{(l)}}{u_j^+}, \frac{x_{ij}^{(m)}}{u_j^+}, \frac{x_{ij}^{(u)}}{u_j^+} \right\rangle & \text{if} j \text{ is a benefit (max) criterion} \\ \\ \left\langle \frac{l_j^-}{x_{ij}^{(u)}}, \frac{l_j^-}{x_{ij}^{(m)}}, \frac{l_j^-}{x_{ij}^{(l)}} \right\rangle & \text{if} j \text{ is a cost (min) criterion} \end{cases}$$

with $u_j^+ = \max_i x_{ij}^{(u)}$ and $l_j^- = \min_i x_{ij}^{(l)}$

Step 2 Construct the fuzzy weighted normalized decision matrix $\hat{\mathbf{V}} = (\hat{v}_{ij})_{n\times m}$, where $\hat{v}_{ij} = \hat{r}_{ij} * \hat{w}_j$ are normalized positive triangular fuzzy numbers in $[0, 1]$.

Step 3 Identification of fuzzy ideal ($\hat{v}_j^+$) and anti-ideal ($\hat{v}_j^-$) values for each criterion. In the case of benefit criterion $\hat{v}_j^+ = \hat{1} = \langle 1, 1, 1\rangle$ and $\hat{v}_j^- = \hat{0} = \langle 0, 0, 0\rangle$, and in the case of cost criterion $\hat{v}_j^+ = \hat{0}$ and $\hat{v}_j^- = \hat{1}$.

Step 4 Calculate the closeness coefficient of each alternative:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

where $D_i^+ = \sum_j d(\hat{v}_{ij}, \hat{v}_j^+)$ and $D_i^- = \sum_j d(\hat{v}_{ij}, \hat{v}_j^-)$ using the distance measure (2).

Step 5 Rank the alternatives according to the closeness coefficient (the alternative with the higher value is preferred).

TOPSIS and fuzzy TOPSIS are based on synthesizing criteria; the ratings for all the criteria are aggregated into a single overall grade (closeness coefficient) allowing a bad rating for one criterion to be compensated for a good rating in another.

4. Product decisions in a fuzzy context

When addressing product decisions, it is necessary to take into account the physical, service and subjective attributes of each product. In the case at hand, these aspects depend on decisions such as the species of fish we are going to produce or the size category that we have as a production objective. However, recently, the decision between traditional and organic products has gained special importance for producers. This decision is mainly marked by only two decisions, the fry that will be introduced into the cage and the feeding strategy that will be carried out. However this has great importance due to several factors:

- The decision has to be taken at first, since it affects the initial costs of buying fingerlings, and is hardly reversible without assuming the loss of part of those costs.
- Most of the company's costs will be determined by the feeding strategy, which represents between 30%–60% of total production costs (Goddard, 1996).
- Uncertainty is multiplied when the producer faces new forms of production that depend on a new factor: the valuation of customers about the plus price that these products deserve.

For these reasons the choice of the most appropriate feed has important implications for business results. In this section we propose two fuzzy approaches to select one of the available feeds already formulated by the industry.

4.1. Fuzzy farming model

In order to simulate the results obtained with the different farming alternatives in aquaculture it is necessary to apply a biological model and three different submodels that simulate the economic, environmental and quality behaviour of the fattening process in the cages. This model is based on the bioeconomic model described in previous studies developed by Luna et al. (2019b) but fuzzy elements are now introduced.

The model takes the assumption that there are a range of abiotic factors (temperature, light, salinity, and oxygen) in which, as the process is done in sea cages, the producer cannot influence 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 ecologic labelled production. Of these external factors, the one with the greatest influence on the growth of the fish is the seawater temperature since the producer must plan the juvenile seeding and fattening processes based on an fuzzy estimate of these temperatures at the location of the farm. In addition, now it is assumed that the value for growth and mortality rates depending on fish weight and temperature provided by feed suppliers are not an exact number. These rates depend on many factors that are hardly predictable with accuracy. In order to overcome this problem, a fuzzy extension of the previous model has been developed using triangular fuzzy numbers. This allows the model to consider the variation on the growth rates depending on the variation of the water temperature.

On the other hand, the market price is the other main external factor that plays a key role and cannot be accurately predicted. This factor is crucial for determining the optimal input mix for maximizing the value of the stock and the price uncertainty may induce further changes in optimal harvesting patterns (Bjørndal et al., 2004). In this regard, it is possible to estimate the expected price taking as reference past prices, but always considering those prices as fuzzy numbers. In addition, prices tend to be different depending on the type of production (ecologic/non-ecologic) and the range of fish weights. For example, in the case of gilthead seabream weights below 300g cannot be traded, and prices of gilthead seabream with more than 400g are higher than serving size (between 300 and 400).

In complex decision-making contexts decisions must be data-driven. The use of an appropriate database is crucial to allow the model to easily use specific information but also assists in the clarification of the problem. In the present case, as can be seen in Luna et al. (2019b), we use a database with a structure consisting 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 that affect the system performance and therefore are required for forming a reliable decision (Casini et al., 2015). Lastly, the group of tables containing information about the status of each cage and the specific feeding, growth and loss rates according to the available feeds. Information used in this work has been collected from primary sources, such as oceanographic buoys or feed manufacturers, or secondary sources of information, i.e., other research studies.

Taking all these into account, the fuzzy model uses the following notations:

Model notation

$\hat{T}_t$ fuzzy seawater temperature in period $t = 1, 2, \ldots$.

$\hat{N}_t$ fuzzy number of fish in the cage at time period t.

$\hat{w}_t$ fuzzy fish weight at time period t.

$M(w, T)$ mortality rate as function of fish weight and temperature.

$pf(w_0, eco)$ fingerling price depending on the weight and the type of production.

n number of available feeds (alternatives).

eco_f binary variable indicating whether the feed is suitable for ecologic production or not, $f = 1, 2, \ldots, n$.

$price_f$ price of feed f.

$R_f(w, T)$ feed ration recommended by the feed producer based on fish weight and temperature, $f = 1, 2, \ldots, n$.

$GR_f(w, T)$ estimated growth rate as function of fish weight and temperature, $f = 1, 2, \ldots, n$.

w_{min} minimum commercial weight.

$\hat{p}(w)$ fuzzy estimated selling price depending on fish weight.

$\hat{eplus}$ fuzzy "plus" (%) that consumers would be willing to pay for an eco-labeled product.

This way, assuming that we know the initial state of the cage (initial number of fish $\hat{N}_0$ and estimated weight $\hat{w}_0$), the evolution of the state of the cage during the fattening process using feed f is modeled by equations

$$\hat{N}_t = \hat{N}_0 \prod_{k=0}^{t-1} \left(\hat{1} - \left\langle M(w_k^{(l)}, T_k^{(l)}), M(w_k^{(m)}, T_k^{(m)}), M(w_k^{(u)}, T_k^{(u)}) \right\rangle \right) \quad (11)$$

$$\hat{w}_t = \hat{w}_0 \prod_{k=0}^{t-1} \left(\hat{1} + \left\langle GR_f(w_k^{(l)}, T_k^{(l)}), GR_f(w_k^{(m)}, T_k^{(m)}), GR_f(w_k^{(u)}, T_k^{(u)}) \right\rangle \right) \quad (12)$$

Lastly, the mortality rate $M(w, T)$ also depends on the size of the fish and the seawater temperature and is estimated using biological studies and practical farming experiences.

4.2. Economic performance measurement using fuzzy pay-off method

From a conventional economic point of view, the main objective of aquaculture enterprises is profit maximization. In order to estimate operational profit, we have to consider the costs incurred in the feeding process and the revenue obtained from the sales. This study considers only the costs directly related to this decision, such as the purchase of fingerlings and feed, making the assumption that others are not influenced.

Regarding the decision-making process in aquaculture in contexts of uncertainty, it would be possible to apply the fuzzy pay-off method to choose the feed with the highest ROV calculated according to (7).

Assuming that fp represents the fattening duration, the total amount of food using feed f is a fuzzy number calculated as

$$\hat{F}_f = \sum_{k=0}^{fp-1} \left(\hat{N}_k * \left\langle R_f(w_k^{(l)}, T_k^{(l)}), R_f(w_k^{(m)}, T_k^{(m)}), R_f(w_k^{(u)}, T_k^{(u)}) \right\rangle \right) \tag{13}$$

and the feeding cost is $\hat{C}_f = price_f \hat{F}_f$. The total amount of food depends on the number of fish estimated at each moment, modeled by the fuzzy number $\hat{N}_k$, and on the amount of feed to be supplied following the feed manufacturer's prescriptions. These prescriptions are defined by non-fuzzy functions R_f, so the different scenarios (lower, upper and most promising values of fish weight and temperature) must be considered in their application.

We can consider that the feeding costs are distributed throughout the different quarters of the fattening period. We will denote the total feeding cost of the quarter q as $\hat{C}_{f,q}$. Another associated production cost is the cost of fingerlings. It should also be considered that the cost depends on the fingerlings' weight and their compliance with restrictions for organic production. Assuming that $pf(w_0, eco)$ represents the unit fingerling price, the production costs are

$$\hat{PC}_f = pf(w_0, eco)\hat{N}_0 + \sum_{k=0}^{nq} \hat{C}_{f,q} \tag{14}$$

where nq is the number of quarters of the feeding period.

The calculation of the operating income is affected by the uncertainty not only in the growth of fish, but also in market prices at the time of commercialization. The proposed model assumes that the price is different depending on the weight segment of the fish.

The income obtained from the sales is computed as:

$$\hat{I}_f = \left\langle \hat{p}(w_{fp}^{(l)})^{(l)}, \hat{p}(w_{fp}^{(m)})^{(m)}, \hat{p}(w_{fp}^{(u)})^{(u)} \right\rangle * \hat{N}_{fp} * \hat{w}_{fp} * (\hat{1} + eco_f \, ep\hat{l}us) \tag{15}$$

In order to compute this income, the sale price of the final product is considered a fuzzy number that depends not only on the uncertainty in the price itself, but also on the final weight that the fish will reach. The lower (upper) limit of the sale price is taken as the result of assuming the lower (upper) limit of the estimated price and the lower (upper) limit of the estimated fish weight. The last factor of the expression (15) allows us to consider the possibility of obtaining a fuzzy extra plus in income by opting for organic production (when $eco_f = 1$).

Cash flows allow us to calculate the fuzzy net present value (NPV) of each feeding option:

$$N\hat{P}V_f = \frac{\hat{I}_f}{(1+r/4)^{nq}} - pf(w_0, eco)\hat{N}_0 - \sum_{q=1}^{nq} \frac{\hat{C}_{f,q}}{(1+r/4)^q} \tag{16}$$

where nq is the number of quarters of the feeding period and r is the annual discount rate.

Finally, using (7) the real option value associated to each alternative can be computed and the one with highest value would be selected.

4.3. Integration of multiple criteria with Fuzzy TOPSIS

Although the economic performance of a company is usually the decision criterion in aquaculture studies, several authors have highlighted the need for a higher effort to include all aspects of sustainability in future research to help bring the industry closer to sustainable development (Peñalosa et al., 2019). In this regard, the choice between traditional and ecological production can be based on a wide range of different criteria.

Following on from previous work, such as the study developed by Luna et al. (2019b) to determine the decision criteria that play an important role in aquaculture processes, the present study considers six economic, environmental and product quality criteria.

- C_1 *Real option value (ROV)*: crisp number calculated using (7) and taking into account the cash-flows in the feeding process.
- C_2 *Feed conversion ratio (FCR)*: is a rate measuring the feed efficiency, in terms of the amount of fish based feed needed to produce a unit weight of the cultured species (Fish-in Fish-out ratio). This criterion responds to the idea that the most efficient use of resources, especially fishmeal and fish oil, is a decisive factor for sustainable aquaculture (FAO, 2018b).
- C_3 *Chemical waste (nitrogen and phosphorus)*: In line with the previous criterion, stakeholders placed the highest value on the prevention of chemical contamination, namely nitrogen and phosphorus, in order to minimize the environmental impact of aquaculture (Lembo et al., 2018).
- C_4 *Potential warming*: prior to arriving on 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 (CO2 equiv.) of the greenhouse gas emissions, among others (Abdou et al., 2017). The inclusion of specific criteria, such as a carbon footprints indicator, have proven to have benefits for both the consumer and producer (Madin and Macreadie, 2015).
- C_5 *Omega-3*: as Shahidi and Alasalvar (2010) 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. We consider the amount of omega-3 in the feed as selection criterion.
- C_6 *Proportion of fish origin*: as fatty acids are one of the main pre-harvest factors affecting quality, the amount of fishbased feed that is used in the last months of production has been included as a quality criterion. Grigorakis (2010) has shown 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. We consider the proportion of fish origin ingredients in the feed as selection criterion.

These criteria can be divided into two categories: benefit criteria (more is better) $\{C_1, C_5, C_6\}$ and cost criteria (less is better) $\{C_2, C_3, C_4\}$.

The values of the criteria in each alternative can be calculated taking as reference the total amount of feed $\hat{F}_f$ that should be used during the fattening period calculated as (13) and the deterministic information provided by the feed producer. As these quantities depend on the environmental conditions and the size of the fish, they are also considered fuzzy numbers.

Another important aspect to consider is the fact that, if you want to offer an eco-labeled product, the Commission Regulation (EC) No 889/2008 of 5 September 2008 have set specific rules on feeds for carnivorous aquaculture animals. The most important one is that they shall be sourced by-products from organic aquaculture, fisheries certified as sustainable or organic feed materials of plant origin. Therefore, in addition to the values of the 6 criteria, each feeding alternative must include a value of the binary variable eco_f, indicating whether the feed is suitable or not for obtaining the ecological label.

The values calculated for the criteria allow the construction of the fuzzy ratings matrix $\hat{\mathbf{X}}$ to later apply the TOPSIS methodology as shown in the following section.

5. Practical example

Once the model has been developed, we tested its efficiency under real operating conditions when an election between 3 production alternatives was taken: two of them would lead the decisor to produce a traditional product of greater or lesser quality, and the third one allowed him to obtain an eco-label for the product, thus obtaining a possible increase in the sale price.

With this aim, the conditions of a sea cage of gilthead seabream during a year was simulated based on historical data and possible scenarios on the evolution of key uncertain parameters. Finally, the optimal alternative was choosen for two theoretical producers.

5.1. Farm conditions

Gilthead seabream farming is commonly developed in the Mediterranean sea, due to its favourable natural conditions. Accordingly, the specific characteristics of the cage are based on common characteristics of Mediterranean farms in Spain as shown in Table 1.

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, the data registered during 2018 by the buoy placed at the simulated location, in the Mediterranean Sea near Tarragona, have been used to deduce triangular fuzzy numbers $\hat{T}_t$ for weeks $t = 1, 2, \ldots, 52$. The mean values $T_t^{(m)}$ of water temperature in each week of the farming period are shown in Fig. 2 and we consider the following fuzzy values to use in the fuzzy growth model:

$$\hat{T}_t = \left\langle T_t^{(m)} - 0.50, T_t^{(m)}, T_t^{(m)} + 1.00 \right\rangle$$

Table 1
Farm characteristics.

Parameter	Value	Parameter	Value
Location	Tarragona - Spain (2720)	Cages	1
Species	Gilhead sea bream	Cage capacity	200 m^3
Seeding Date	01/07/2019 (week 0)	Batches	1
Harvesting Date	01/07/2020 (week 52)	Fingerling weight (w_0)	30 g
Time horizon	52 weeks	Feasible harvest sizes	300-1000 g

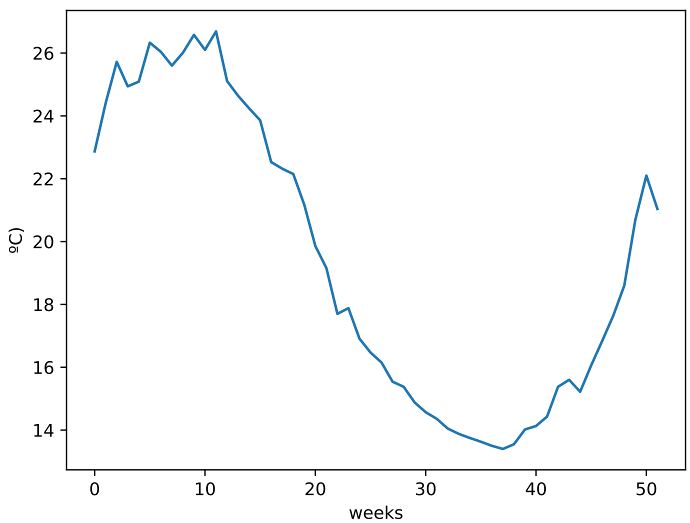

Fig. 2. Evolution of water temperature during the farming period in the location.

In relation to the sales prices of seabream, the minimum commercial size is 300g and three price segments are considered based on those from the Spanish wholesale market.

- Segment 1 (non-commercial size, less than 300g): although the income from the sale would be 0, the fish would have an accounting value and it will be assumed that this value is equal to the sale price of the first commercial segment (segment 2) with a penalty of 25%.
- Segment 2 (serving size, between 300 and 400g): price $\hat{p}(I_1) = \langle 3.57, 4.00, 4.24\rangle$ euros/kgs.
- Segment 3 (more than 400g): price $\hat{p}(I_2) = \langle 4.05, 4.60, 5.05\rangle$ euros/kgs.

In addition, the ecologic/organic plus price that consumers might be willing to pay is assumed equal to $\hat{eplus} = \langle 0.07, 0.15, 0.20\rangle$. This assumption is based on market studies conducted by different researchers (Zander and Feucht, 2017).

The proposed model has been tested for three different alternatives. The main difference between them concerns the selected feed stuff, assuming that there are only three feed stuffs available in the market. The first traditional feed stuff (F_1) represents the more commonly used, with the best quality-price ratio;

Table 2
Available feeds.

Feed	Type of production	eco_f	Max biomass density	Initial number of fingerlings	Unit cost of fingerlings
F_1	Standard	0	20 kg/m^3	12964	0.20 euros
F_2	Standard	0	20 kg/m^3	12400	0.20 euros
F_3	Organic/Eco	1	15 kg/m^3	8123	0.30 euros

Table 3
Production simulation depending on used feed.

Feed	$\hat{N}_{fp}$	$\hat{w}_{fp}$	centroid	$\alpha - cut: \ [\hat{w}_{fp}]^{\alpha}$
F_1	$\langle 12130, 12139, 12166 \rangle$	$\langle 298.11, 328.02, 361.25 \rangle$	329.13	$[298.11 + 29.91\alpha, 361.25 - 33.23\alpha]$
F_2	$\langle 11606, 11615, 11638 \rangle$	$\langle 317.60, 344.14, 378.99 \rangle$	346.91	$[317.60 + 26.54\alpha, 378.99 - 34.85\alpha]$
F_3	$\langle 7597, 7603, 7622 \rangle$	$\langle 363.86, 389.22, 430.96 \rangle$	394.68	$[363.86 + 25.36\alpha, 430.96 - 41.74\alpha]$

the second one (F_2) has an increased percentage of fish protein so, although it has a higher price, growth rates are good even under unfavorable weather conditions and the final product quality is better. On the other hand, the last feed stuff (F_3) is a high quality and price feed, entirely made with products from organic fisheries/productions, which is used for eco-labeled production.

However, the decision has implications beyond just selecting the right feed. The maximum numbers of fingerlings have been calculated by estimating the weight they can reach depending on the type of feeding and with the restriction of not exceeding the maximum established densities at the end of the fattening period. If organic production is chosen, EU standards reduce the maximum amount of biomass that is admissible and that, in turn, has effects on the maximum number of fingerlings that can be seeded in the cage. Furthermore, organic production also requires the use of a specific type of fingerling that is usually more expensive. In this case it is assumed that the ecological fingerling is priced 50% higher than a standard one of the same weight, whose price is around 0.20 euros/unit (Janssen et al., 2017). Table 2 shows information about the implications of opting for different types of feed.

Fig. 3 shows the evolution of the estimated weight of the fish for each alternative, representing in each case the most promising value $w_t^{(m)}$ of the fuzzy weight. As explained above, organic production implies the use of feed 3, less biomass density and, therefore, lower number of final fish (see Table 2). Nevertheless, feed 3 achieves the highest growth rates, it also has the highest quality and fish could be sold with a plus in the price, which should compensate for the increase in costs. In short, the choice of feed is not trivial, so the use of fuzzy decision-making methodologies is proposed.

5.2. Application of fuzzy pay-off method

Firstly, the great uncertainty that affects the aquaculture sector due to the aforementioned factors, has its greatest impact when estimating the economic performance of the production. On the one hand, if this uncertainty is not considered, an economic aspect as important as risk would be left out. On the other hand, the consideration of all possible scenarios, many of them unknown, becomes almost impossible. In order to address this problem, the fuzzy pay-off method has been applied to estimate the present value of each alternative.

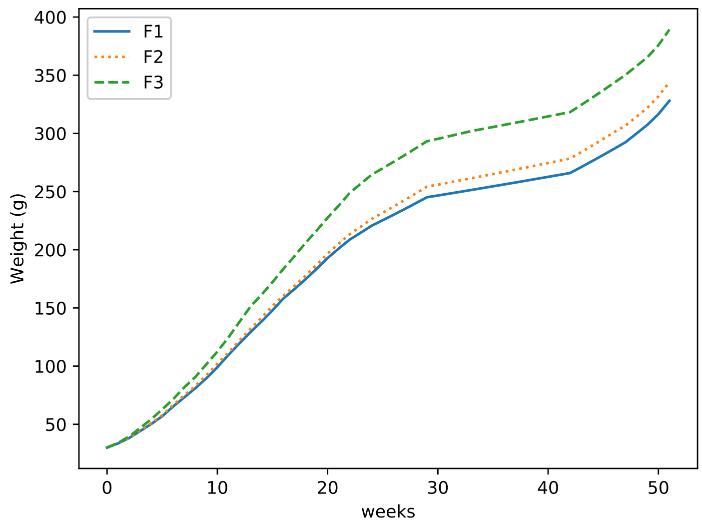

Fig. 3. Evolution of fish weight.

Table 4
Cash-flow projection with the different alternatives.

Feed	Fingerlings cost	Feeding cost Q1	Feeding cost Q2
F_1	$\langle 2592.80, 2592.80, 2592.80\rangle$	$\langle 1690.91, 1881.36, 1762.48\rangle$	$\langle 2309.29, 2451.68, 2495.50\rangle$
F_2	$\langle 2480.00, 2480.00, 2480.00\rangle$	$\langle 1771.80, 1956.20, 1846.45\rangle$	$\langle 2424.34, 2555.10, 2633.41\rangle$
F_3	$\langle 2436.90, 2436.90, 2436.90\rangle$	$\langle 1551.66, 1720.69, 1621.05\rangle$	$\langle 2205.53, 2329.84, 2477.17\rangle$
Feed	**Feeding cost Q3**	**Feeding cost Q4**	**Income**
F_1	$\langle 1323.80, 1554.09, 1957.07\rangle$	$\langle 1929.73, 2193.48, 2608.63\rangle$	$\langle 9689.90, 15927.55, 18634.54\rangle$
F_2	$\langle 1429.14, 1655.37, 2053.35\rangle$	$\langle 2054.66, 2303.25, 2725.17\rangle$	$\langle 13170.07, 15988.63, 18701.25\rangle$
F_3	$\langle 1330.30, 1375.86, 1791.31\rangle$	$\langle 1847.34, 2013.70, 2360.05\rangle$	$\langle 10568.00, 13612.62, 19905.72\rangle$

With this aim, Table 4 shows the projected cash-flows for each alternative over a period of 4 quarters under conditions defined in the previous section. The table shows fingerling cost, feeding costs in each quarter and the estimated income at the end of the fattening period.

Using the cash-flows of Table 4 and assuming an annual discount rate $r = 0.04$, the fuzzy NPV are calculated using expression (16) and ROV values using (7). Both values are shown in Table 5. Based on the results of this evaluation, the recommendation is to opt for the traditional production of gilthead seabream using the feed 2.

In today's conditions, however, it takes more than just choosing the alternative with the best value for the economic criterion. More than ever, economic criteria must be considered together with environmental sustainability or product quality criteria in order to provide the necessary flexibility that these methods need to be applicable in practice.

Table 5
Fuzzy real option value with the different alternatives.

Feed	NPV	$E(N\hat{P}V_f+)$	Factor	ROV
F_1	$\langle -358.25, 4830.88, 6716.91 \rangle$	4280.64	0.9965	4265.66
F_2	$\langle 2683.75, 4623.11, 6470.05 \rangle$	4607.71	1.0000	4607.71
F_3	$\langle 953.94, 3386.45, 8652.16 \rangle$	3858.65	1.0000	3858.65

Table 6
Fuzzy ratings matrix.

Feed	ROV (C_1)	FCR (C_2)	Chemical waste (C_3)
F_1	4265.66	$\langle 0.51, 0.51, 0.52 \rangle$	$\langle 694285.16, 773428.66, 844551.89 \rangle$
F_2	4607.71	$\langle 0.75, 0.76, 0.77 \rangle$	$\langle 661206.99, 729219.54, 797102.21 \rangle$
F_3	3858.65	$\langle 1.04, 1.05, 1.05 \rangle$	$\langle 612052.39, 656643.93, 728088.30 \rangle$
Feed	Potential warning (C_4)	Omega-3 (C_5)	Proportion of fish origin (C_6)
F_1	$\langle 12323931.64, 13728770.96, 14991246.17 \rangle$	0.01	0.25
F_2	$\langle 5851389.29, 6453270.28, 7054001.85 \rangle$	0.01	0.38
F_3	$\langle 8957504.98, 9610110.70, 10655712.86 \rangle$	0.02	0.55

5.3. Application of fuzzy TOPSIS

The next step to take multiple criteria and their potential complications into consideration is the application of the Fuzzy Topsis methodology. As outlined in the methodological approach to this research, this method deals with each new criterion as a triangular fuzzy number to synthesize and aggregate them into a single overall grade for each decision-maker, thus allowing for a better assessment of each alternative with the aim of selecting the most suitable one.

First, the fuzzy decision matrix $\hat{\mathbf{X}}$ with the fuzzy evaluations of each alternative (feed) with respect to each of the criteria $\{C_1, C_2, C_3, C_4, C_5, C_6\}$ is defined with the information shown in Table 6.

Then, in order to apply the fuzzy TOPSIS methodology and construct the fuzzy weighted normalized decision matrix, the decision maker must assess the importance of each criterion using weights. These weights are the only subjective parameters taken into account in the methodology. To facilitate the decision maker's task, linguistic variables can be used. Table 7 shows the linguistic variables for the importance weight of the criteria and the equivalent fuzzy triangular numbers together with the opinions of two decision makers.

In this work, the preferences of two theoretical producers have been simulated trying to represent the most common viewpoints and interests of producers in respect to gilthead seabream and other species nowadays (see Table 7). For this reason, in contrast to the first decision-maker which is focused on maximizing the company's profits, the second one is more concerned about the impact of aquaculture production on the environment and the quality of the final product he offers to his customers, all of which without ignoring the economic aspects.

According to these opinions, the vectors of criteria weights for each decision maker are

$$\hat{\mathbf{w}}_1 = (\langle 0.9, 1.0, 1.0 \rangle, \langle 0.0, 0.0, 0.1 \rangle, \langle 0.0, 0.0, 0.1 \rangle, \langle 0.0, 0.0, 0.1 \rangle, \langle 0.0, 0.0, 0.1 \rangle, \langle 0.0, 0.0, 0.1 \rangle)$$

$$\hat{\mathbf{w}}_2 = (\langle 0.7, 0.9, 1.0 \rangle, \langle 0.0, 0.1, 0.3 \rangle, \langle 0.9, 1.0, 1.0 \rangle, \langle 0.9, 1.0, 1.0 \rangle, \langle 0.7, 0.9, 1.0 \rangle, \langle 0.7, 0.9, 1.0 \rangle)$$

Table 7
Fuzzy weights of each criterion.

Linguistic variable	Fuzzy weight	C_1 (MAX)	C_2 (MIN)	C_3 (MIN)	C_4 (MIN)	C_5 (MAX)	C_6 (MAX)
		Importance					
Very low	$\langle 0.0, 0.0, 0.1\rangle$		$\otimes$	$\otimes$	$\otimes$	$\otimes$	$\otimes$
Low	$\langle 0.0, 0.1, 0.3\rangle$		$\odot$				
Medium low	$\langle 0.1, 0.3, 0.5\rangle$						
Medium	$\langle 0.3, 0.5, 0.7\rangle$						
Medium high	$\langle 0.5, 0.7, 0.9\rangle$						
High	$\langle 0.7, 0.9, 1.0\rangle$	$\odot$				$\odot$	$\odot$
Very high	$\langle 0.9, 1.0, 1.0\rangle$	$\otimes$		$\odot$	$\odot$		

Note: $\otimes$ decision maker 1; $\odot$ decision maker 2.

Table 8
Weighted fuzzy rating matrix after normalization.

	C_1	C_2	C_3	C_4	C_5	C_6
Decision maker 1						
F_1	$\langle 0.83, 0.93, 0.93\rangle$	$\langle 0.00, 0.00, 0.10\rangle$	$\langle 0.00, 0.00, 0.09\rangle$	$\langle 0.00, 0.00, 0.05\rangle$	$\langle 0.00, 0.00, 0.05\rangle$	$\langle 0.00, 0.00, 0.05\rangle$
F_2	$\langle 0.90, 1.00, 1.00\rangle$	$\langle 0.00, 0.00, 0.07\rangle$	$\langle 0.00, 0.00, 0.09\rangle$	$\langle 0.00, 0.00, 0.10\rangle$	$\langle 0.00, 0.00, 0.05\rangle$	$\langle 0.00, 0.00, 0.07\rangle$
F_3	$\langle 0.75, 0.84, 0.84\rangle$	$\langle 0.00, 0.00, 0.05\rangle$	$\langle 0.00, 0.00, 0.10\rangle$	$\langle 0.00, 0.00, 0.06\rangle$	$\langle 0.00, 0.00, 0.10\rangle$	$\langle 0.00, 0.00, 0.10\rangle$
Decision maker 2						
	C_1	C_2	C_3	C_4	C_5	C_6
F_1	$\langle 0.65, 0.83, 0.93\rangle$	$\langle 0.00, 0.10, 0.30\rangle$	$\langle 0.65, 0.79, 0.88\rangle$	$\langle 0.35, 0.43, 0.48\rangle$	$\langle 0.35, 0.45, 0.50\rangle$	$\langle 0.32, 0.41, 0.45\rangle$
F_2	$\langle 0.70, 0.90, 1.00\rangle$	$\langle 0.00, 0.07, 0.20\rangle$	$\langle 0.69, 0.84, 0.93\rangle$	$\langle 0.75, 0.91, 1.00\rangle$	$\langle 0.35, 0.45, 0.50\rangle$	$\langle 0.48, 0.62, 0.69\rangle$
F_3	$\langle 0.59, 0.75, 0.84\rangle$	$\langle 0.00, 0.05, 0.15\rangle$	$\langle 0.76, 0.93, 1.00\rangle$	$\langle 0.49, 0.61, 0.65\rangle$	$\langle 0.70, 0.90, 1.00\rangle$	$\langle 0.70, 0.90, 1.00\rangle$

Vector of criteria weights $\hat{\mathbf{w}}$ and matrix $\hat{\mathbf{X}}$ are used to construct the fuzzy weighted normalized decision matrices that can be seen in Table 8.

5.4. *Final decision*

Once the matrices have been created, they allow us to calculate the distance of each alternative from the fuzzy positive ideal and anti-ideal solutions, and calculate the closeness coefficient of each alternative; the results are shown in Table 9.

As can be observed, in the case of the decision-maker with more concern for the economical profit, the model proposes the use of feed 2. This results agreed with the classic economic theory about profit maximization and the decision that was taken using only the fuzzy pay-off method.

However, when the decision-maker also expresses concern about the environmental and quality factors (decision-maker 2), the suggestion of the model is the organic/ecologic production. This concurs with the findings of some of the studies cited above about the importance of considering these new criteria reflecting the changing situation in the market and the most current demands and principles based on sustainability.

Table 9
Results of TOPSIS method.

		Decision maker 1		
Alternative	Distance from ideal	Distance from anti-ideal	Closeness coefficient	Ranking
F_1	2.218561	3.875127	0.635925	2
F_2	2.169581	3.952186	0.645596	1
F_3	2.254245	3.856005	0.631072	3
		Decision maker 2		
Alternative	Distance from ideal	Distance from anti-ideal	Closeness coefficient	Ranking
F_1	2.791154	3.351400	0.545604	2
F_2	3.001972	3.193440	0.515452	3
F_3	2.239739	3.986385	0.640268	1

6. Discussion and Conclusions

Aquaculture is an economic activity that has grown exponentially in recent years thanks to the industrialization of production processes. The development of new technologies and the increase in the average size of companies has led to the increasing complexity of managing this activity. In addition, it is necessary to mention that the increase in production and trade, together with new patterns of consumption and social demands, have caused a greater competition. Furthermore, these changes in consumer behavior means that production strategies should not only consider profit maximization, but also sometimes meet certain environmental and quality criteria.

In this new context, the profit margin is increasingly tight, and the work of managers is more crucial than ever. The level of uncertainty of the results of the production strategies is not only conditioned by the high number of factors that affect production, but also by an increase in the volatility of those that are beyond the control of the managers.

These considerations have led many producers to become aware of the fact that they need the most advanced and appropriate expert systems to support their decision-making processes. Furthermore, those systems must have the capacity to deal with growing data volumes and have to be adaptable to new cultural contexts and for new purposes. In this regard, the results of the simulations carried out seem to confirm the goodness of the fuzzy methodologies for the determination of farming strategies in aquaculture farms in situations of uncertainty.

In this way, the methodology developed has proven to be a good alternative to take into account the risk or uncertainty when assessing the possible performance of the different production alternatives. Thus, it enables the decision-makers to consider three possible scenarios, the most possible one based on historical data and two extreme scenarios due to possible fluctuations in factors such as the water temperature, the market price or the customer valuation of new products. Furthermore, the fuzzy TOPSIS methodology has shown its great value in facilitating the assessment of the importance of each criterion by the producers through qualitative assessments.

All this does constitute substantial progress to meet specific needs or gaps in the development of OR models in aquaculture that consider simultaneously all aspects of long-term sustainability (Peñalosa et al., 2019). In addition, the development of this methodology also has significant implications in practice for both producers and regulators.

The importance of this approach to the aquaculture stakeholders has also been directly reflected in the results obtained, due to the crucial effect that the consideration of different scenarios has had in the decisions recommended to the company. In this regard, although the traditional methods that only take into account the economic profitability would recommend the first alternative (Table 5), which achieved a Net Present Value in the most likely scenario of about a 5%-40% increase, the consideration of the current uncertainty makes it inadvisable, due to the high volatility of its NPV ranging from about -358 to 6,716 USD. In that case, the second alternative stands out at the other extreme, with a NPV ranging from 2,683 to 6,470, which makes it more appropriate for risk-averse producers. In this way, the utilization of this methodologies allows aquaculture producers to accurately address the increasing uncertainty in their decision-making process which is a pressing need for the sector (Llorente and Luna, 2015).

The integration of multiple subjective and, sometimes, opposed criteria has also proven to give a greater degree of flexibility to decision making methodologies. In fact, this has sometimes led to a change in the optimal choice to another alternative that, despite not being the most appropriate in a goal, presents good overall results, as is the case of the second decision maker (Table 9). This responds to the actual need in aquaculture of combining complex optimization methods and multiple-criteria decision-making techniques in order to be able to make better decisions (Domínguez-May et al., 2020).

Furthermore, the application and testing of this method also constitutes a contribution to the discussion about the capacity of producers to move towards new forms of production without assuming too much risk. In this respect, the utilization of this type of methodology has proven that if the regulators are capable of determining objective criteria that enables producers to discern that they need to adopt new forms of production, the producers will be able to carry out effective strategic plans that reduce the risk. In this way, some institutions, such as FAO (2018b), have already highlighted this need for the different stakeholders (i.e. producers, governments and consumers) to look closely at production practices in order to bring them closer to a sustainable path.

Lastly, it should be noted that the application of these techniques is highly dependent on data. For that reason, the collection of reliable data, throughout real intelligent sensors and control systems, and the determination of objective indicators, are crucial factors in enhancing its effectiveness and efficiency. All this points out to the two lines of research, data collection and OR models, that would lead aquaculture farms to be data driven companies.

Acknowledgments

This paper is part of the MedAID project which has received funding from the European Union's H2020 program under grant agreement 727315. The authors also wish to thank the Ibero-American Program for the Development of Science and Technology, CYTED, and the Red Iberoamericana BigDSSAgro (Ref. P515RT0123) for their support of this work.

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