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Practical tool in classification of animals for slaughter by fuzzy logic

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This paper treats of the classification of animals for slaughter, using concepts of fuzzy logic as a tool to assist in decision making. The entries (inputs) were made by measurements of body length and weight of animals. The output values corresponded to the classification as ideal weight for slaughtering. In this paper were developed three simulations involving three lambs from a group to be sent to slaughter. The two measures mentioned above were taken before slaughtering. The results were considered good, because it was possible to classify these lambs as ideal moments to slaughter.

Key words: Classification of animals, fuzzy logic, lamb slaughter, decision making.

INTRODUCTION

Currently, as in the companies as in day-by-day of the people, it is necessary constantly to take decisions. In the companies the decisions become much more important, since the future is dependent on decisions. If a wrong decision is taken, the consequences could be disastrous, causing damages or even the death of the company. Therefore it is necessary to use the logic so that the correct decision is taken.

In the decision moment, the entrepreneur makes use of assumptions, approaches or simplification, provoking doubts regarding the validity of the results. The uncertainties can occur when the entrepreneur is facing a probabilistic problem. In general, it is not possible to describe with exactness the probability distribution of some involved important variable in the problem, consequently, not being possible to apply the correct methods for the problem analysis. In this context, it is presented fuzzy logical (or diffuse logic), which provides subsidies to solve problems with high degree of uncertainty, without losing important information during the data manipulation (Barros and Bassanezzi, 2006; Xu et al., 2008).

Usually problems using historical record of the data use a bayesian equivalent model. The advantage of the method used in this study, compared to the equivalent model bayesian, is that the solution obtained in the fuzzy case does not always occur in the baysian case that often, it must perform numerical approximations of integrals, which does not occur in the used fuzzy model. In the fuzzy approach, limited information is often sufficient to obtain satisfactory results (Santos and Rodrigues, 2004).

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The method of fuzzy logic used in this paper does not make use of the propagation algorithm of artificial neural network based on multi-layer algorithm (ANN) to the default sort using empirical mode decomposition to the feature for each classification from another one, based on EEG where mimicry of data is quite impossible because it depends on users thought. In order to do this paper we have taken four regions of the brain such as frontal, brain, parietal, occipital and we have observed each and every individual has unique pattern (Gupta et al., 2014; Kumari et al., 2014; Kumari and Vaish, 2014; Semwal et al., 2014).

There are woks, as in as in Bellustin and Kalafati (2011), that use artificial neural networks to develop algorithms for classification of gender, age and race through the image of the human face.

The fuzzy logic theory used this paper uses computing resources to provide answers to problems with the high degree of uncertainty, fast and robust and ease to simulate real situations to guide the decision. Fuzzy logic allows the development of systems that represent human decision where conventional classical logic and mathematics are insufficient or inefficient decision-making (Oliveira Jr., 1999).

This paper was carried out similarly to the Gabriel Filho et al. (2011) that developed a system based on *fuzzy* rules applied on 147 nellore beeves to determine the body mass index of ruminant animals in order to obtain the best time to slaughter. The input variables were weight and height, and as output a new body mass index which may serve as a detection system at the time of livestock slaughtering, comparing one another by the linguistic variables "Very Low", "Low", "Average ", "High" and "Very High".

There is infinity of enterprise activities where the application of fuzzy logic is possible such as: credit evaluation, cash flow control, risk analysis, supply control, marketing evaluation, suppliers evaluation, quality control, inventories optimization, classification of products and animals, etc.

With regard to the classification of products, a promising area would be to offer to the animal breeders, for example, a trustworthy method of animal classification for slaughter, since this activity is carried out by empirical methods, taking in account only physical aspect and the age of the animal.

Therefore, the aim of this study was to use fuzzy logic concepts to provide the farmer a tool to assist in decision making before slaughtering.

Sheep farming system

Sheep breeding is, currently, a promising activity of the Brazilian agribusiness, provided by low investment in infrastructure and a good profitability to the breeders, coming meanly from meat production. As far as the sheep capacity of transforming foods of low quality into protein of high biological value as meat and milk, the animals can be reared in association with cattle in one same property, without damages for none of the species. Comparatively, this association provides a better economic return to the producers, instead of only cattle.

The growing appreciation and demand for lamb has been intensified the production systems of this animal, seeking greater flexibility in the finishing and marketing of meat, because the lamb provides one of the best carcass yield and excellent production efficiency due to its high growth rate (Hastenpflug and Wommer, 2010).

Several surveys of sheep of swamp of Mato Grosso do Sul (Brazil) have been carried out, showing that such animals have high reproductive seasonality (Santiago Son, 2010), their lambs are early and have good meat production (Pinto, 2009), have similar body biometrics to genetically improved exotic lambs, have good yield potential with respect to the characteristics of carcass and meat quality, with potential for the exploitation of the cutting sheep industry (Vargas Junior et al., 2011).

In the sheep industry is the lamb animal category that has greater acceptance in the consumer market, having better organoleptic characteristics, with lower production cycle and greater production efficiency due to its high growth rate (Cartaxo et al., 2011).

The experiment was conducted with lambs Technological Centre for Sheep (CTO), in the Farm School Três Barras (University Anhanguera –Uniderp), in Campo Grande, Mato Grosso do Sul (Brazil), in December 2011.

One of the problems that the sheep breeder faces is the decision making in relation to the correct moment in selecting the ready animals for slaughter, mainly, when there is a large number of animals in the fattening stage, needing an efficient and faster method of classification. The use of the concepts of fuzzy logic can facilitate this decision.

Topics fuzzy logic

The fuzzy logic is based on the theory of the fuzzy sets where, if one determined element belongs to this set, it must be verified the degree of pertinence of the element in relation to the set. Differently of the classic theory, where the pertinence degree is binary, that is, it belongs or it does not belong to the set. In the fuzzy sets the pertinence degree is the reference to verify how much “this element is possible” to belong to the set. The pertinence degree is calculated by determined function that generally returns a real value that varies between 0 and 1, being 0 to indicate that the element does not belong to the set, and 1, that it belongs to the set (Barros and Bassanezi, 2006).

The results gotten for the fuzzy logic imitate a behavior based on rules (inferences) instead of results gotten through complex mathematical models. It can be said even though that the objective of the fuzzy logic is to generate a logical exit from a set of information not accurate, missing or with noises (Yen et al., 1995). Some fuzzy logic concepts are important to the development of this paper.

A fuzzy set X of a universe U is expressed as a set of ordered pairs where each element of X has its degree of pertinence to the set varying from 0 to 1, Equation (1).

$$X = \{(x, \mu(x)\} \mid x \in U \ e \ \mu(x) \in [0, 1] \quad (1)$$

Like this:

$$\mu(x) \in [0,1] \text{ then } \mu(x) = \begin{cases} 0 & se \quad x \notin X \\ 1 & se \quad x \in X \end{cases}$$

As it happens with the conventional theory of sets, operations between fuzzy sets such as union, intersection, complement and algebraic product can be made.

The union of two sets A and the B, fuzzy subgroups of X, will result in a fuzzy set whose pertinences will be the maximum values of the respective pertinences of the sets in question, Equation (2).

$$(A \cup B)(x) = \max(A(x), B(x)) = A(x) \vee B(x), \forall x \in X \quad (2)$$

The intersection of two sets A and the B, fuzzy subgroups of X, will result in a fuzzy set whose its pertinence will be the minimum value of the respective pertinences of the sets in question (Equation 3).

$$(A \cap B)(x) = \min(A(x), B(x)) = A(x) \wedge B(x), \forall x \in X \quad (3)$$

The complement of a fuzzy set A, є subgroups of X, denoted for A, will result in a fuzzy set whose its pertinence will be the subtraction of 1 for the pertinence of the set in question (Equation 4).

$$A^{/}(x) = 1 - A(x), \forall x \in X \quad (4)$$

The algebraic product of two sets A and the B, fuzzy subgroups of X, denoted for A*B, will result in a fuzzy set whose its pertinence will be the product of the respective pertinences of the sets in question (Equation 5).

$$(A * B)(x) = A(x) * B(x), \forall x \in X \quad (5)$$

Other operations, such as limited products, drastic product, algebraic sum, limited sum, concentration and expansion can be found in Barros and Bassanezzi (2006).

The relations between two sets A and B, fuzzy subgroups of X, can represent associations, interactions X⊃A and X⊃B interconnections between the elements of the two sets. The difference of these relations for the classic sets is in the degree of association between the elements X and Y. In the classic sets the association is 0 or 1, while the fuzzy association varies from 0 to 1 (Equation 6).

$$R_{A\times B}(x,y) = \{((x,y), \mu(x,y)) \mid (x,y) \in A \times B e \ \mu_{A\times B}(x,y) \in [0,1]\} \quad (6)$$

The pertinence of the union of A and B it is given by the maximum of the relevancies between them (Equation 7).

$$\mu_{A\cup B}(x,y) = \max\{\mu_A(x), \mu_B(y)\} \quad (7)$$

The pertinence of the intersection of A and B it is given by the minimum of the pertinences between them (equation 8).

$$\mu_{A\cap B}(x,y) = \min\{\mu_A(x), \mu_B(y)\} \quad (8)$$

There are others fuzzy relations that had not been treated here, since they are outside of this paper target.

The projection is an operation that reduces the dimension of a relation. From a relation of two dimensions it is possible to obtain two relations of dimensions one. Equations (9) represent the projections on coordinates X and Y, respectively from a relation of two dimensions.

$$\mu R_1(x,y) = \underset{y}{máx}\,[\mu R(x,y)] \text{ And } \mu R_2(x,y) = \underset{x}{máx}[\mu R(x,y)] \quad (9)$$

In the first equation x is kept fixed and the maximum of y is determined in its entire domain, in the second, y is kept fixed and the maximum of x is determined.

Given two fuzzy relations involving the cartesian products A×B and B×C, with XEA, YEB and ZEC, it is possible to get a new A×C relation. Some versions of compositions exist and some of them will be presented as follow.

Given two relations of fuzzy pertinences, $\mu(R_1(x,y))$ *and* $\mu(R_2(y,z))$, then the pertinence of the composition $(R_1 \circ R_2)(x,z)$ is given by the Equation (10).

$$\mu((R_1 \circ R_2)(x,z)) = \vee \{\mu(R_1(x,y)) \wedge \mu(R_2(y,z))\} \quad (10)$$

Where $\vee$ indicates the maximum of the result between clasps, $\wedge$ indicates the minimum of the relevancies of the two relations between clasps. In the calculation of $\mu(R_1 \circ R_2)(x,y)$ it is used the algorithm of the multiplication of matrices.

Given two relations of fuzzy pertinences $\mu(R_1(x,y))$ *and* $\mu(R_2(y,z))$, the Max composition – Product, $\mu((R_1 \circ R_2)(x,z))$ is given by Equation (11).

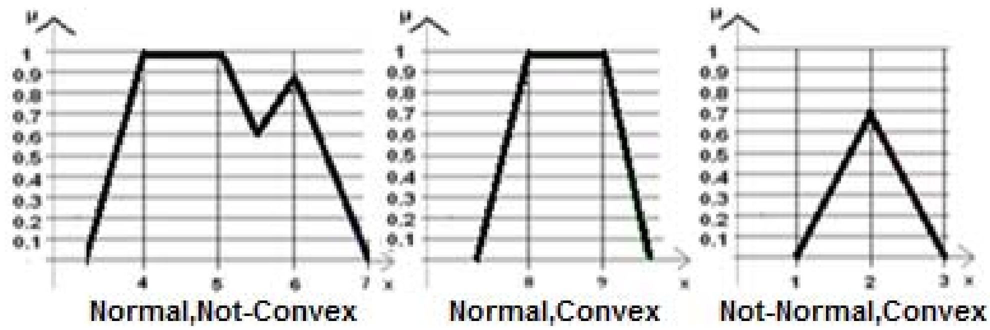

Figure 1. Types of fuzzy sets.

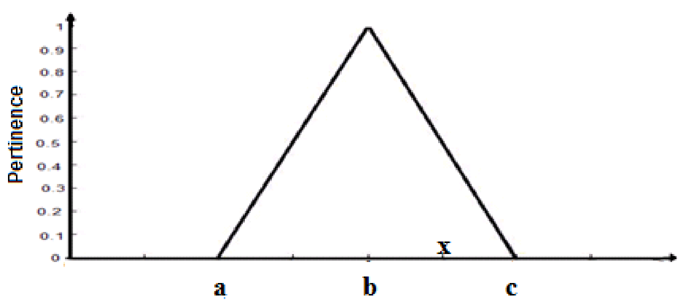

Figure 2. Graphical representation of the function of triangular pertinence.

$$\mu(R_3(x,z)) = \mu((R_1 \circ R_2)(x,z)) = \vee[\mu(R_1(x,y)) \times \mu(R_2(y,z))] \quad (11)$$

Other types of compositions can be found in Barros and Bassanezzi (2006) and Semwal et al. (2015).

Each fuzzy set is characterized by its pertinence function, which will determine how much one determined element belongs to the set. Different types of pertinence functions exist.

Any set of fuzzy numbers can possess a pertinence function that will represent it, since that it is *normal* and *convex*. A fuzzy set is said normal when its function of pertinence allows to classify if one definitive element belongs totally to the set, and it is called convex when its pertinence function does not have more “growth or decrease” from resultant values throughout the given universe (Rodrigues et al., 2011). Figure 1 shows the graph of fuzzy sets.

In this research the function of triangular pertinence was used, whose graph represents a normal and convex set (Equation 12).

$$\mu tri(x,a,b,c) = \max\left\{\min\left\{\frac{x-a}{b-a}, \frac{c-x}{c-b}\right\}, 0\right\} \quad (12)$$

Figure 2 shows the graph of a triangular function when a=2, b=4 and c=6.

Linguistics variables are changeable whose values are words in natural language represented in fuzzy sets. For example, the temperature of one determined process can be a linguistic variable assuming values low, high and average. These values are described for intermediary of fuzzy sets (Gomide et al., 1995, Kruel et al., 2008).

The main objective of the linguistics variables is to supply a systemic way approach for characterization of phenomena badly defined, allowing the treatment of complex systems for analysis through mathematical terms (Shaw and Simões, 1999; Tanscheit, 2007).

The first stage of the fuzzy reasoning is the fuzzification, in which is considered precise inputs (not fuzzy) resultants of measurements or comments, in which for each value of one data occurs the activation of a pertinence function, so that it is possible to make the input data mapping for the fuzzy values (Santos and Rodrigues, 2004; Tanscheit, 2007).

The fuzzification consists of transforming numerical data into a term of natural language. For example, the weight and the height of an animal are called fuzzy variables, which are attributed the sets of fuzzy values as “very”, “little”, “high” or “low”.

Identified the fuzzy variable in a problem, it is necessary to determine the possible fuzzy values for these variables. In this case, for the fuzzy variable “weight”, it can be classified in three fuzzy values that are: “Light”, “Median” and “Heavy”, while the fuzzy variable “body length” could be classified in “Short”, “Median” and “length”. For each fuzzy value will exist pertinence function so that it is possible the mapping of the input data, that are numerical values, for the fuzzy values. In this paper, it will be used the triangular function by its simplicity and easiness of understanding (Rodrigues et al., 2011).

The inference is a stage that serves of support for the decision making. In this stage, the pertinence degrees of each element are determined to the set for posterior use of the rules of the type If - Then.

According Oliveira Júnior (1999) and Shaw and Simões (1999), the rules are created of empirical form, being able to be provided by specialists in form of linguistics

Table 1. Relations of more used implications.

Name	Implication of operations	Output
Zadeh (max-min)	máx{min{μ(A(x), μ(B(y))}; {(1-μ(A(x))}}	And
Mandami (min)	min{μ(A(x), μ(B(y))}	And
Larsen (produto)	μ(A(x)×μ(B(y))	Or

sentences as basic information in the development of a fuzzy inference system. The inference process makes nothing more of what to evaluate the Lights of "compatibility" of the inputs with the antecedents of some rules, being activated the consequents with proportional intensities to the same ones. The result is a fuzzy set that will be converted into scaling (condensed or defuzzified value), providing the system output.

Given two fuzzy sets A and B and respective complementary A' and B', for the accomplishment of fuzzy inference, exist two inference procedures between these sets: The Modus Ponens Generalized (MPG) and the Modus Tollens Generalized (MTG). The MPG has the following rule: if X is A then Y is B. This rule allows the implication of fuzzy values that are: If X is A' then Y is B', allowing, thus, to determining the consequent one. The MTG has the following rule: if x is A then the Y is B that allows the implication: If y is B' then x is A', determining the antecedent.

Therefore, the first stage is to determine the pertinence function $\mu(B^{'}(y))$ through of exit rules of the type "If - Then" (Equation 13):

$$\mu(B^{'}(y)) = \vee_x \left\{\mu(A^{'}(y)) \wedge \mu(x, y\right\} \quad (13)$$

Observing that $\vee_x$ means the calculation of the maximum of Y when X varies in its entire domain $\wedge$ represents the minimum of the two involved elements.

The relation of implication is a rule of the If - Then. To determine an implication relation must rather determine the type of fuzzy implication relation. The relations of fuzzy implications receive as input the values from entries (inputs) $\mu A(x)$ received from the fuzzification and the values of output $\mu(B(x))$ contained in the inference, and the result of the operation is the data of exit of the implication relation. In Table 1 some main operations types of implication are presented.

According to Shaw and Simões (1999), in fuzzification the value of the linguistics variable of inferred exit for the fuzzy rules will be translated in a number. The objective is to get only a numerical value that better represents the inferred fuzzy values of the linguistic variable of exit.

Diverse methods of defuzzification have been considered in the literature, but it is important to choose the method that better adjusts to the problem. In this paper, the method of the Center of Area (Centroid) was used for the defuzzification of the fuzzy variable which is located in the geometric center fuzzy values exits, represented for a convex polyhedral region in the pertinence graph of the inference exit (Figure 3).

The calculation of the abscissa x* of the centroid is expressed by Equation (14).

$$x^* = \frac{\sum_{i=1}^{n} x_i \times \mu_{Output}(x_i)}{\sum_{i=1}^{n} \mu_{Output}(x_i)} \quad (14)$$

Where: x_i , $(i = 1,2,\cdots,n)$ is the numerical value of the variable in each situation i, and $\mu_{Output}(x_i)$ is the value of the pertinence function for the value of x_i in each situation i.

MATERIALS AND METHODS

In this paper the concepts of the fuzzy logic was applied with the objective to classify lambs for slaughter, using measurement data of weight (kg) and body length (cm) of lambs from Farm Três Barras, University Anhanguera-Uniderp, Campo Grande, (MS), Brazil.

The first stage considers input not fuzzy, or not accurate, resultant of measurements or comments, in which, for each presented value, the activation of a pertinence function occurs, so that the inputs data mapping for the fuzzy values will be possible (Rodrigues et al., 2011).

The second stage is the inference, from which the decision making is processed taking into account the determination of the pertinence degrees of each set that, with the input data, the rules of the If-Then type are carried out. According to Shaw and Simões (1999) and Rodrigues et al. (2011), the rules are created of empirical form, being able to be provided by specialists in form of linguistics sentences, which constitutes a basic aspect in the development of a fuzzy inference system.

The third stage is the defuzzification, which in accordance with Shaw and Simões (1999) the values of the linguistics variable of exit, inferred for the fuzzy rules, will be translated for numbers (Rodrigues et al., 2011). In this paper the method of the Center of the Area (Centroid) was used in accordance with Figure 3.

RESULTS AND DISCUSSION

With the purpose to test the methodology, its application

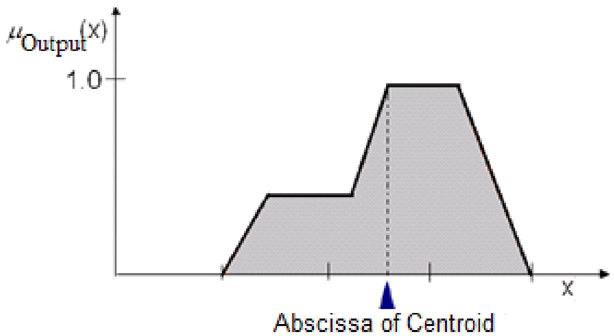

Figure 3. Method of defuzzification for the center of area (Centroid) Source: Adapted of Shaw and Simões (1999).

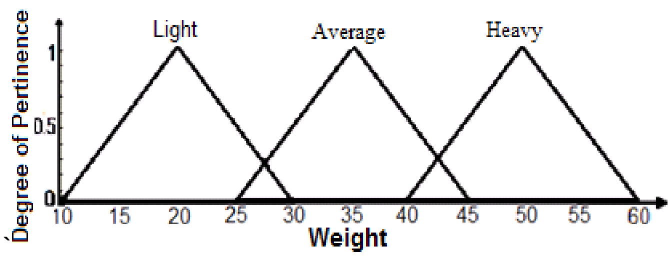

Figure 4. Graph of inputs triangular functions relative to the pertinence of weight variable.

Table 2. Pertinencies table for the variable “weight” using fuzzy set.

Weight (Kg)	Light	Average	Heavy
20	1	0	0
25	0.5	0	0
30	0	0.5	0
35	0	1	0
40	0	0.5	0
45	0	0	0.5
50	0	0	1

Table 3. Pertinences for “body length” using fuzzy sets.

Body length (cm)	Small	Median	Great
30	1	0	0
35	0.5	0	0
40	0	0.5	0
45	0	1	0
50	0	0.5	0
55	0	0	0.5
60	0	0	1

was proceeded in the classification of lambs for slaughter, using three common subgroups in relation to the variable “Weight” (ranging from 10 to 60 Kg); to classify a lamb at the moment of slaughter, with the use of the fuzzy sets “Light”, “Average” and “Heavy”, with respective pertinences (all ranging from 0 to 1), established by professionals of the study area, whose pertinencies are represented in Table 2.

Equation (15) presented the data classification for lamb weight as to inputs values:

$$\begin{aligned}
\mu tri_{Light}(x;10,20,30) &= máx\left\{\min\left\{\frac{x-10}{20-10},\frac{30-x}{30-20}\right\},0\right\}\\
\mu tri_{Average}(x;25,35,45) &= máx\left\{\min\left\{\frac{x-25}{35-25},\frac{45-x}{45-35}\right\},0\right\}\\
\mu tri_{Heavy}(x;40,50,60) &= máx\left\{\min\left\{\frac{x-40}{50-40},\frac{60-x}{60-50}\right\},0\right\}
\end{aligned}\tag{15}$$

Figure 4 presents the classification graph of the weight inputs data and respective pertinencies.

Also, using the fuzzy set, there are three subsets for the classification of lambs for slaughter in relation to “Body length” (ranging from 20 to 70 cm), such as “Small”, “Median” and “Great”, with respective pertinences (all ranging from 0 to 1) (Table 3).

The data classifications of body length as inputs values are presented in Equation (16).

$$\begin{aligned}
\mu tri_{Small}(x;20,30,40) &= máx\left\{\min\left\{\frac{x-20}{30-20},\frac{40-x}{40-30}\right\},0\right\}\\
\mu tri_{Median}(x;35,45,55) &= máx\left\{\min\left\{\frac{x-35}{45-35},\frac{55-x}{55-45}\right\},0\right\}\\
\mu tri_{Grat}(x;50,60,70) &= máx\left\{\min\left\{\frac{x-50}{60-50},\frac{70-x}{70-60}\right\},0\right\}
\end{aligned}\tag{16}$$

Figure 5 presents the graph of the triangular functions of body length inputs to the respective pertinences.

In this manner, for the inputs of “weight” and “body length” variables, it will be necessary to determine the fuzzy variable that will be the “states”, and to choose the actions through the fuzzy values, in the case, five values as “Very lean”; “Lean”; “Ideal”; “Fat” and “Very fat”, which also will have pertinences functions.

Table 4 presents the used inferences in this paper, which correspond to the biometric parameters of the lamb in relation to the inputs variables “weight” and “body length”. In this paper inference function was used in the triangular form. Figure 6 presents the possible results of the defuzzification in linguistic variable ranging from -15 to 15, relative to inferences in Table 3.

In this study the inference function was used in the triangular form (Figure 6). The Table 5 shows the possible outcomes of defuzzification outs in linguistic variables relating to inferences evaluated (Table 3). For example, the input data for a lamb with weight of 25 kg and body length of 40 cm; the degrees of pertinences was calculated, making x = 25 in Equations (15) obtaining:

$$\mu tri_{Light}(25;10,20,30) = máx\left\{\min\left\{\frac{25-10}{20-10},\frac{30-25}{30-20}\right\},\ 0\right\} = máx\{\min\{1.5,\ 0.5\},\ 0\} = máx\{0.5,\ 0\} = 0.5$$

$$\mu tri_{Average}(25;25,35,45) = máx\left\{\min\left\{\frac{25-25}{35-25},\frac{45-25}{45-35}\right\},0\right\} = máx\{\min\{0,\ 2\},\ 0\} = máx\{0,\ 0\} = 0$$

$$\mu tri_{Heavy}(25;40,50,60) = máx\left\{\min\left\{\frac{25-40}{50-40},\frac{60-25}{60-50}\right\},\ 0\right\} = máx\{\min\{-1.5,\ 3.5\},\ 0\} = máx\{-1.5,\ 0\} = 0$$

Making x = 40 in the Equations (16) we obtain:

$$\mu tri_{Small}(40;20,30,40) = máx\left\{\min\left\{\frac{40-20}{30-20},\frac{40-40}{40-30}\right\},0\right\} = máx\{\min\{2,\ 0\},\ 0\} = máx\{0,\ 0\} = 0$$

$$\mu tri_{Median}(40;35,45,55) = máx\left\{\min\left\{\frac{40-35}{45-35},\frac{55-40}{55-45}\right\},0\right\} = máx\{\min\{0.5,\ 1.5\},\ 0\} = máx\{0.5;\ 0\} = 0.5$$

$$\mu tri_{Great}(40;50,60,70) = máx\left\{\min\left\{\frac{40-50}{60-50},\frac{70-40}{70-60}\right\},0\right\} = máx\{\min\{-1,\ 3\},\ 0\} = máx\{-1,0\} = 0$$

With the calculations of the pertinences it was found in the stage of the fuzzification the fuzzy values different of zero of the weight input, with “Light” classification, degree of pertinence 0.5; body length, with “Median” classification and degree of pertinence 0.5. The results are presented in the Table 6.

Thus, the fuzzification will be activated for the rule 5 (Table 4), which will pass to be analyzed. If the weight is “Light” and the body length is “Median”, “Then” the condition is “Thin” for slaughter – if no. The weight, the body length and the state are, respectively, x, y and z, while “Light”, “Median” and “Thin” are A1, A2 and B, respectively. In the fuzzification the values of the pertinences of A'1 and A'2, representing the “Light” and “Median” are, respectively, 0.5 and 0.5, while the pertinence of B', representing the “Thin” is not known. In this in case, it is applied the rule MPG: if x is A1 “and” y is A2, then z is B, consequently, if x is A'1 “and” y is A'2, then z is B'. As “and” represents the minimum, then with the pertinence of A'1 is 0.5 and of A’2 is 0.5, then, in this case, randomly, A'1 with pertinence 0.5.

For the determination of the pertinence of B' it is necessary to apply the pertinence function of B, choosing an operation of implication that can be the Mandani operation (min) in Table 1. The values of $A1 = \{(30;\ 0.5);\ (35,1);\ (40;\ 0.5)\}$, consequently, it is determined the values of $A'1 = \{(30;\ 0.5);\ (35,\ 0);\ (40;\ 0.5)\}$. Some values of B different of zero are $B = \{(4.0,\ 0.5);\ (5.0,0.5);\ (6.0;,0.5);\ (7.0,0.5);\ (8.0,0.5);\ (9.0,0.5)\}$. Then, the relation R of the intersection of A'1 is determined with B.

$$R_{A'1\cap B}(x,y) = \left\{\begin{matrix}((30,4.0),0.5);((30,6.0),0.5);((30,8.0),0.5);\\((35,4.0),0.5);((35,6.0),0.5);((35,8.0),0.5);\\((40,4.0),0.5);((40,6.0),0.5);((40,8.0),0.5)\end{matrix}\right\}$$

Summarizing the pertinences:

$$\mu\left(R_{A1\cap B}(x,y)\right) = \begin{bmatrix}0.5 & 0.5 & 0.5\\0.5 & 0.5 & 0.5\\0.5 & 0.5 & 0.5\end{bmatrix}$$

The pertinences of B' are calculated through the Max-min composition as follow:

$$\mu(B') = \mu(A'1 \circ R_{A1\cap B}(x,y)) = [0.5 \quad 0 \quad 0.5] \circ \begin{bmatrix}0.5 & 0.5 & 0.5\\0.5 & 0.5 & 0.5\\0.5 & 0.5 & 0.5\end{bmatrix} = [0.5 \quad 0.5 \quad 0.5]$$

If it was used other rules, others B’ would be gotten, corresponding others areas in the exit graph. As the operation of Mandani implication was used (min), the general exit of the inferences would be the union (or) of the inferences of the sets B', obtained by the rule fired. In this case, the pertinence of the exit will be equal to the pertinence of variable “Thin”, this is:

$$\mu_{Output}(u) = \mu_{Thin}(u)$$

To carry out the defuzzification, let us consider the set of points in the range (Table 5):

$$u = \{3,4,5,6,7,8,9,10\}$$

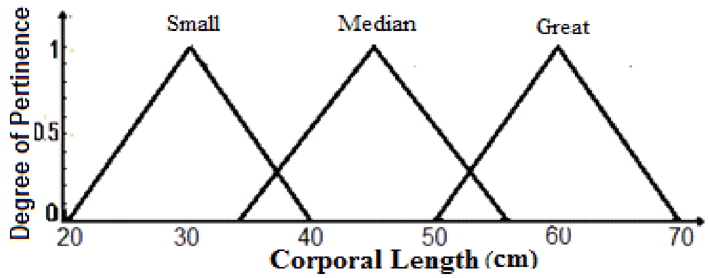

Figure 5. Graph of triangular functions relative to the pertinences of body length variable.

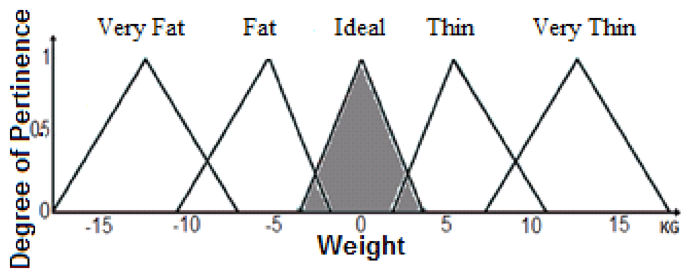

Figure 6. Graphs of relative exits to the evaluated inferences.

Table 4. Set of correspondent inferences of entries to the biometric parameters of the lamb in relation to the body length and weight variables

Rule	If: Peso (Kg)	If: Body length (cm)	Then: Condition
1	Light	Small	Ideal – Else
2	Light	Median	Thin – Else
3	Light	Great	Very Thin – Else
4	Average	Small	Fat – Else
5	Average	Median	Ideal – Else
6	Average	Great	Thin – Else
7	Heavy	Small	Very Fat – Else
8	Heavy	Median	Fat – Else
9	Heavy	Great	Ideal - Else

Table 5. Defuzzification in linguistic variables.

Weigth (kg)	
-20 ≤ peso≤ -7	Very fat
-10≤ peso≤ -3	Fat
-3 ≤ peso≤ 3	Ideal
3≤ peso≤ 10	Thin
7 ≤ peso≤ 20	Very thin

Table 6. The fuzzification.

Weight	Body length
$\mu tri_{Light}(25;10,20,30) = 0.50$	$\mu tri_{Median}(40;35,45,55) = 0.50$

And the use of Equation (14):

$$x^* = \frac{3\times0+4\times(0.5)+5\times(0.5)+6\times(0.5)+7\times(0.5)+8\times(0.5)+9\times(0.5)+10\times0}{0+0.5+0.5+0.5+0.5+0.5+0.5+0} = 6.5$$

Thus, $B^{'} = \{(5{,}0,\ 0.5); (6.0, 0.5); (8.0, 0.5)\}$

As the result was zero, the recommendation to the breeder is of that the lamb is thin, with 6.5 kg below of the ideal weight.

One second simulation was carried through considering a lamb with 40 kg of weight and 35 cm of body length. Carrying out analogous calculations to the previous simulation, the result of the defuzzification is $x^* = -5.0$, returning to the breeder the recommendation of that the lamb is with 5 kg above of the ideal weight.

Conclusions

The paper used fuzzy logic as tool in decision making to the farmer on the classification of lambs for slaughter, using for this rules of inferences determined by specialists in the activity of sheep industry. The results can be considered good, since it was possible to verify the power of the tool to aid in the decision.

Although the use of this tool still seems impractical for the moment due to the hard work of lamb measurement collection in the field, as would occur when the stress of the animals are being biometric measures taken, the results are promising because, with the evolution technology in the near future, they will be taken in digital form, using cameras that allow the reading of the main biometric measurements of the animals without causing any stress to them. Thus, news researches should be implemented.

Other research is required to improve decision making, considering other biometric variables, as in the present study it was decided to consider only two input variables length and weight of the body and an output variable, the animal's weight, because was done without computer assistance. These results can be implemented in computer and for ease of achieving faster results. In fact, there are some statistical packages such as Matlab, SPSS, etc., which have available fuzzy logic routines. It should be noted that this tool can be applied to a number of other sorting processes, provided that the set of rules is developed by specialists. .

Conflict of Interest

The authors have not declared any conflict of interest.

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