DOKUZ EYLUL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

MULTI EXPERT DECISION MAKING BY USING 2-TUPLE FUZZY LINGUISTIC REPRESENTATION AND ITS APPLICATION TO OLIVE OIL SENSORY EVALUATION

Suzan KANTARCI

September, 2010
İZMİR

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M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled "**MULTI EXPERT DECISION MAKING BY USING 2-TUPLE FUZZY LINGUISTIC REPRESENTATION AND ITS APPLICATION TO OLIVE OIL SENSORY EVALUATION**" completed by **SUZAN KANTARCI,** under supervision of **PROF. DR. EFENDİ NASİBOĞLU** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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MULTI-EXPERT DECISION MAKING USING 2-TUPLE FUZZY LINGUISTIC REPRESENTATION AND ITS APPLICATION IN SENSORY ANALYSIS OF OLIVE OIL

ABSTRACT

This study aims at investigating the sensory analysis via Multi-Expert Decision Making Model based on 2-Tuple Fuzzy Representation. Sensory analysis, as it is used in various areas, is widely used in determining the class of Natural Olive Oil. Taking into consideration the importance of the quality of olive oil, which has a special place in Turkey's agricultural activities, the examination and application of sensory analysis, depending on fuzzy linguistic decision analysis, is conducted in the study.

In Chapter One, the general point of view about the content of the study is touched upon. In Chapter Two, information on concepts such as Computing with Words, Linguistic Variable, Fuzzy Linguistic Representation, Linguistic Hierarchies and Linguistic Computational Models is provided. In Chapter Three, the Multi-Expert Linguistic Decision Analysis Model is discussed in detail.

In Chapter Four, the Sensory Analysis Model based on Linguistic Decision Analysis is explained elaborately. The model in question is examined in terms of decision analysis phases. Chapter Five includes the explanation of sensory analysis of olive oil with reference to linguistic sensory analysis and the computer software regarding the aforementioned application is introduced. And finally, the results of the study are presented in last chapter.

Keywords: Fuzzy Linguistic Approach, Linguistic Decision Analysis, Linguistic Hierarchies, 2-tuple Linguistic Computational Model, Multi-Expert Decision Problem, Sensory Analysis, Quality of Natural Olive Oil.

2’Lİ BULANIK SÖZEL GÖSTERİM KULLANARAK ÇOK UZMANLI KARAR VERME VE ONUN ZEYTİNYAĞININ DUYUSAL DEĞERLENDİRMESİNE UYGULANMASI

ÖZ

2’li Bulanık Gösterime dayanan Çok Uzmanlı Karar Verme Modeli kullanılarak Duyusal Analiz üzerinde inceleme yapılmıştır. Duyusal Analiz birçok alanda kullanıldığı gibi Natürel Zeytinyağının sınıfının belirlenmesinde kullanılmaktadır. Ülkemiz tarımında da ayrı bir yere sahip olan Zeytinyağının kalitesinin zeytincilik sektöründe öneminden yola çıkılarak natürel zeytinyağının sınıfına ulaşmak için duyusal analize uyarlanan bulanık sözel karar analizine dayanan duyusal değerlendirme yöntemi irdelenerek uygulaması gerçekleştirilmiştir.

Birinci Bölümde çalışmanın içeriği hakkında genel bir bakış açısına değinilmiştir. İkinci Bölümde, Kelimelerle Hesaplama, Sözel Değişken, Bulanık Sözel Gösterim, Sözel Hiyerarşiler ve Sözel Hesaplama Modelleriyle ilgili bilgiler verilmiştir. Üçüncü Bölümde, Çok Uzmanlı Sözel Karar Analizi açıklanmıştır.

Dördüncü Bölümde, Sözel Karar Analizine Dayanan Duyusal Değerlendirme Modeli üzerinde durulmuştur. Duyusal Değerlendirme Modeli karar analizi basamaklarına uygun bir şekilde irdelenmiştir. Beşinci Bölümde, Zeytinyağına ilişkin Sözel değerlendirme modelinin sözel duyusal analizle bağlantılı olarak açıklaması yer almaktadır ve uygulamaya ait Bilgisayar Programının içeriği belirtilmiştir. Son bölümde ise tezin sonucu açıklanmaktadır.

Anahtar Sözcükler: Bulanık Sözel Yaklaşım, Sözel Karar Analizi, Sözel Hiyerarşiler, 2’li Sözel Hesaplama Modeli, Çok Uzmanlı Karar Problemi, Duyusal Analiz, Natürel Zeytinyağı Kalitesi.

CONTENTS

CHAPTER ONE

INTRODUCTION

Decision Analysis is a discipline appropriate for the decision theory that helps decision-makers to arrive at correct decisions when they have problems on deciding. In the "modeling of decision-making problems" phase, which is the starting point of decision analysis different approaches such as Analytic Hierarchy Approach, Expected Value Criteria Approach, Laplace, Minimax, Savage and Hurwicz approaches are used.

One of these modeling approaches is the Linguistic Decision Analysis Approach (Herrera & Herrera-Viedma, 2000). In this approach the decision-making problem is resolved depending on the linguistic information. Using linguistic expressions in decision-making problems gives way to words and sentences instead of numeric values. Thus, information that cannot be expressed assertively is presented more explicitly and more accurately. Specialists linguistically evaluate the criteria presented to solve the problem. In the literature linguistic decision-making approach is used in different areas such as "Group decision-making", "Multi-criteria decision-making", etc., in solving various problems in real life. Herrera and Herrera-Viedma (2000), developed this approach by adding two phases to the "Classical Fuzzy Decision Making" process mentioned in Roubens (1997), and thus emerged the Linguistic Decision Analysis Approach. According to Herrera and Herrera-Viedma (2000), using the phases of linguistic decision analysis in decision making problems with information modeled with linguistic letters contributes the decision makers to obtain more consistent results.

Many researchers conducted studies on decision-making analysis concentrating upon computation with words in various areas; for instance Yager (1994) on marketing, Herrera et al. (2001) on personal management, Herrera-Viedma et al.

(2007) on Web quality, Güngör and Arıkan (2007) on stock development, Büyüközkan and Ruan (2008) on project evaluation and selection, and Martínez et al., (2007, 2008) on sensory evaluation.

In Decision Analysis, the role played by the decision-making specialists is crucial. They choose the best option among a set of predetermined alternatives, depending on their experiences and knowledge. In cases, when there is more than one expert to decide, multi-expert decision-making issues arise. In resolving such issues, using linguistic information contributes in getting better results. Decision-makers may find opportunity to better explain themselves using linguistic expressions. Therefore, multi-expert decision making problems are solved, with the contribution of linguistic information, using appropriate linguistic computational models after assigning linguistic values to linguistic variables.

There are different models for use in computation processes that ascertain the combination and comparison status of linguistic variables. The most basic models in the literature are presented in a study by Herrera et al. (2009). The models presented here, may be briefly listed as a computational model named linguistic computational model depending on both membership functions and extension principle followed by a linguistic computational model depending on Type 2 fuzzy sets, a symbolic linguistic computational model depending on ordinal scales, and 2-tuple linguistic computational model.

Herrera and Martínez (2001b) argue that among the aforementioned computation models, 2-tuple linguistic computational model plays an effective role in analysing the information without loss. Their study also observed that this model give more consistent results compared to the other computational models.

One of the linguistic decision analysis processes in which the 2-tuple linguistic computational model is used, is Sensory Evaluation. In determining the quality of a product, Sensory Evaluation is used as an important means. In the literature, Sensory Evaluation appears in marketing as for Lee and Mahony (2005), as well as in quality determination. In evaluations depending on the specialists' perceptions, namely in Sensory Evaluation analyzing the linguistic expressions of the specialists with appropriate models, increases the consistency of the evaluation results. Herein, it is clearly seen that sensory evaluation poses a decision problem in terms of specialists' experiences and opinions on determining the quality of the goods.

One of the sectors in which sensory evaluation is used in determining the quality of a product in terms of the experiences and opinions of experts, is olive industry. In Olive industry, in determining the quality of the natural olive oil, a sensory analysis is conducted according to the information provided by expert connoisseurs. Martínez et al. (2008) argued the applicability of sensory analysis depending on linguistic expressions in the sensory analysis of olive oil. Their study also used the linguistic hierarchies mentioned in Herrera and Martínez (2001a) in order to ease the transmission of linguistic information. Martínez (2007), defined a sensory analysis process in which a linguistic approach, depending on the linguistic decision analysis. Accordingly, this study aims at examining the multi-specialist decision-making analysis on sensory evaluation via 2-tuple fuzzy linguistic representation model.

Nowadays, the sensory analysis of olive oil is conducted in accordance with the standards published by International Olive Oil Council. Sensory evaluation in line with these standards, in our country, appears in Olive Oil and Olive Pomace Oil Notice published in 3 August 2007. This Notice is due application in the near-future. The 3 years period granted for the adaptation process regarding sensory evaluation has ended in 3 August 2010 and Sensory Analysis will take its place in the required quality analyses for determining the quality of virgin olive oil.

This study, within the framework of the notice mentioned above and the sensory analysis of olive oil, addresses how the multi-expert decision-making problem depending on linguistic decision analysis is adapted to sensory evaluation using multi-granular linguistic representation via 2-tuple linguistic computational model and presents the resolution of the problem on the sensory evaluation of olive oil, with the computer software implemented.

CHAPTER TWO

COMPUTING WITH WORDS AND LINGUISTIC APPROACH

2.1 Introduction

In this chapter, before explaining the Linguistic Decision Analysis, one of the computing with words approaches, what computing with words is; how the linguistic variable used in this approach is defined and selected; and how the linguistic descriptors and their meanings are generated will be touched upon. Later, the aggregation operators which enable the operations on linguistic information will be discussed. After providing this basic information, in the further sections of the chapter, the linguistic computational models used in linguistic decision analysis will be addressed. At last, the "Linguistic Hierarchical Structure" concept, which comprises the linguistic structures on which the models will be implemented, will be scrutinized.

2.2 What is Computing With Words?

Computing with Words (CW) is a methodology that does computations using words and sentences instead of numbers. People generally prefer using words to express their thoughts. Since the expression of human thought alters according to the perception of the individual, it is difficult to use numbers in expressing some thoughts. Thus, quantitative expressions cannot be used. In situations where human perception is in question, it seems more plausible to use words in solving problems.

Words, in terms of their meaning, help people to meet on a common ground. This situation incorporates ambiguity since perception and expressions are altered dependently on individuals, experience and the nature. Therefore, Fuzzy Set concept asserted by Zadeh (1965) helps us to make computations with words which incorporate ambiguity.

The foundation of computing with words concept was laid in paper by Zadeh (1973). In this study linguistic variable and granularity was explained. In time many research has been published on computing with words. For instance, Mendel (2002) studied on making judgments using words; Yager (2004) examined the re-transformation process of Zadeh's Paradigm on computing with words. Grzegorzewski and Hryniewicz (2002) performed computing with words on vital signs.

Mendel (2007) argues that, it is the first time that Zadeh (1996) asserted that fuzzy logic approach is equivalent to computing with words. Zadeh (1996) argues that there are two main factors for computing with words: First, the situation of numbers being insufficient in explaining information; and second, the possibility of tolerance for fuzziness in real-like situations.

It is seen that Zadeh (2002), in terms of computing with words, aims at making computers to perform computing with words and to give outputs as words, by taking into consideration that humans express their thoughts via words when making a decision. At the same time, the relation between managing the perception and computing with words is emphasized. Considering Zadeh (2002), it can be said that, the main difference of computing with words from other approaches is its being based on fuzzy logic. Computing with words takes human mind which can manage both perception and numbers as a role-model. Computing with words offers a methodology that can reduce the difference between human mental activities and the operations of the machines by overcoming the ambiguities for solving the problems. The main concepts of Computing with Words may be enumerated as "granules" and "linguistic variables" with reference to Zadeh (1973).

Zadeh (1997) defines granule, one of the main concepts, as "the set of objects that are selected with the differentiability, similarity, proximity and functionality".

As it is referred in Herrera et al. (2009), granules both can be thought as a set of objects for quantitative computations, and they play a crucial role in overcoming the processes where human logic is prevalent. So much that, granules are way too fuzzy then the classical approach.

Granules are generally used as unified with fuzzy variables. The values that a fuzzy variable, open to human interpretation, comprise the granules and the fuzziness of the granules forms the characteristics of the direction that human conceptual thoughts are formed and organized upon. In computing with words methodology, the expression of a granule word g is shown as a constraint on a variable w.

The “linguistic variable”, the second main concept in computing with words, can be shortly explained as the variable, with the words and sentences used by people in daily life as its values.

Computing with words is used in various areas. As it is an approach with a distinctive viewpoint, it is applied to the decision making problems, recently. Herrera and Herrera-Viedma (2000) brought a distinctive perspective into decision analysis with linguistic approach by publishing a paper that account for the steps of the linguistic decision analysis. In the following chapters of this study, the steps of linguistic decision analysis and its application on multi-expert decision making problems will be dealt with.

2.3 Linguistic Variable

Zadeh (1975) defined the linguistic variable as; “a variable with words or sentences as its value instead of numbers in natural or artificial languages.” Although, linguistic variables are less definite than numerical ones, they are more convenient for individuals to make statements using their knowledge. In daily life, since people always think and they express their thought using words and sentences, it is difficult to access to exact information. Therefore, it seems more effective using linguistic variables to model human thought.

Zadeh (1975) characterizes the linguistic variable as given below:

Definition 1: A linguistic variable is characterized with a Pentad. $(L, H(l), U, G, M)$ L is the name of the variable; H(L) (or H) shows the term set of L, i.e., the set of the names of L's linguistic values, sequencing in the universal set of U with each of its value is aggregated with a fuzzy variable shown with *X* and a basic variable *u*; *G,* is the linguistic rule (generally takes the form of grammar) to derive the value of the names of L, and M is a rule to bind the names of the values of each L with their meanings, *M(X)* is a fuzzy subset of *U*.

In order to perform computing with words, it is necessary to characterise the fuzzy variables in accordance with **Definition 1** above. The linguistic variable forming stage is crucial in terms of getting correct results using computation with words. Therefore, one should place great emphasis on defining the linguistic term set, the convenience of the meanings of the selected terms and the selection of the membership functions depending on meaning rule shown with fuzzy numbers.

Herrera and Martínez (2001a) highlighted the importance of selecting appropriate descriptors for the term set and determining the meanings of the descriptors correctly.

2.3.1 Selecting the Linguistic Term Set

The main purpose in selecting the linguistic term set is to offer the minimum number of words to the individual, who will use the variable, to explain the statement he wants to express. Thus, the number of the linguistic terms should be few as possible but many for making differentiation in evaluation. The "Granularity of Fuzziness" can be thought as the differentiation levels in the fuzziness of the variable.

In linguistic term sets for Linguistic Models, odd numbers are used as element numbers, generally. 7, 9, 11, or not more than 13 are the most used element numbers. The observations made by Miller (1955) and the fact that humans organize the designated odd numbers to keep in memory coincide. In term sets with this number of elements, it is seen that the terms are symmetrically distributed around the mean term which is approximately 0.5.

2.3.2 Generating Linguistic Descriptors

Another important point is the generation of linguistic descriptors. Because, the descriptive variables generated, ascertain the “granularity of fuzziness”. Two different approaches, Context-Free Grammar Approach and Ordered Structure of Linguistic Terms Approach, are used to generate the linguistic descriptors after the element number of the linguistic term set is defined:

2.3.2.1 Context-Free Grammar Approach

This approach defines the linguistic term set via a context-free grammar. G is the grammar that generates the sentences. Grammar has a four-order notation presented as (V_N, V_T, I, P). V_N, means non-terminal symbols set, V_T, means terminal symbols set, *I* means the initial symbol, and *P*, the generation rules. The expanded Backus Naur Form (Bordogna & Passi (1993)) can be used for P generation rule.

If we explain by example, between V_N and V_T the main terms are defined as {many, medium, few… }, constraints are defined as { none, a lot, many, quite,…}, relations as {higher, lower,…} and links as {and, but, or,…}. After an initial term *I* is selected, a linguistic terms set can be generated as S={high, higher, not high, higher or medium,…} using P. The selection of these elements determines the shape of the linguistic term set. According to the observations of Miller (1955), the language derived should be easily understandable, notwithstanding that it need not be infinite.

2.3.2.2 Approach Depending on the Ordered Structure of Linguistic Terms

In this approach, the elements of the term set are aligned on an indicator chart. Let us explain by example; if $a \langle b$ then $s_a \langle s_b$.

$$S = \{s_0 : \text{none}, s_1 : \text{very few}, s_2 : \text{few}, s_3 : \text{average}, s_4 : \text{high}, s_5 : \text{very high}, s_6 : \text{perfect}\}$$

When these situations are in question, the term set should satisfy the following characteristics:

1) There is a negation operator, i.e., $\text{Neg}(s_i) = s_j, j = T - i$.

(T+1 =The number of the elements of the term set.)

2) Maximization Operator= $\text{Max}(s_i, s_j) = s_i, s_i \geq s_j$.

3) Minimization Operator= $\text{Min}(s_i, s_j) = s_i, s_i \leq s_j$.

2.3.3 The Semantic of the Linguistic Term Set

After the number of elements of the linguistic term set and its descriptors are derived, the meanings of the elements of the linguistic term set should be predicated. In the literature, one comes across with three main approaches that predicate the meaning of the linguistic term set. These are named as *"semantic depending on membership functions and a semantic rule", "semantic depending on the ordered structure of the linguistic term set",* and *"mixed semantic".*

2.3.3.1 Semantic Depending on Membership Functions and a Semantic Rule

Mathematically, a fuzzy set U in the universal set E is characterized as $\mu_U(x) : E \to [0,1]$. Here the function μ_U is called the membership function of the fuzzy set U. The Fuzzy set U is the set of dual set that each element in E' forms with its membership degree.

$$U = \{(x, \mu_U(x)) : x \in E, \mu_U(x) \in [0,1]\}.$$

Propositions as "Ayşe is beautiful", "The weather is extremely hot" are called fuzzy propositions. One cannot offer certain statements for the truthfulness or falsity of these propositions. Each of the fuzzy terms generated with the fuzzy proposition is modeled with the “fuzzy set”. A set comprised by a fuzzy proposition is defined by mathematically assigning a value from the real numbers in the range of [0,1] that represents the degree of membership in the set to each individual belonging to the area studied. This value predicates the degree of convenience of the element on the part of the fuzzy set.

In this approach too, the semantic approach is generally used in situations where linguistic descriptors are derived by a generative grammar, acknowledging that each linguistic term is given via fuzzy subsets defined in the range of [0,1], predicated by the membership functions.

This approach follows the two steps given below:

(i) The primary fuzzy sets associated to the primary linguistic terms.
(ii) The semantic rule M, to generate the fuzzy sets of the non-primary linguistic terms from primary fuzzy sets.

Herrera and Herrera-Viedma (2000) argue that the semantic for primary terms is both personal and context-dependent, and the semantic for other terms is obtained by implementing the semantic rule M. At the same time, this approach aims at forming primary fuzzy sets by associating each term with the semantic rule which alters them.

The representation of the primary fuzzy terms depends on parameters, but it is difficult for humans to express their behavior and preferences within the same parameters. Due to concepts do not have the same universal distribution; same primary fuzzy terms may have different representations. With reference to Herrera et al. (1995) it can be said that users can distinguish the same linguistic term set in the same though environment, taking into consideration the linguistic variable concept that enables the evaluation of the approximate characterization of the information for indefinite preference.

Linguistic evaluations given by the users are only the approximate ones; the preference of membership function of each researcher may be different. Some authors such as Delgado et al. (1992) agree that isosceles trapezoidal membership functions grasp the fuzziness of the linguistic evaluations quite well. However, some others, such as Bordogna and Passi (1993) prefer the representations that have Gaussian distribution.

As Herrera and Martínez (2001a) put forth in their study, the representation type that is used widely is the linguistic evaluations with triangular membership functions.

The formula for the triangular fuzzy number is as below:

$$f(x; a, b, c) = \begin{cases} 0, x \leq a \\ \dfrac{x-a}{b-a}, a \leq x \leq b \\ \dfrac{c-x}{c-b}, b \leq x \leq c \\ 0, c \leq x \end{cases}$$

The triangular fuzzy number, is shown as (a, b, c) by b having 1 membership degree. In the example below, the triangular fuzzy numbers are presented mapped with the letters in the term set.

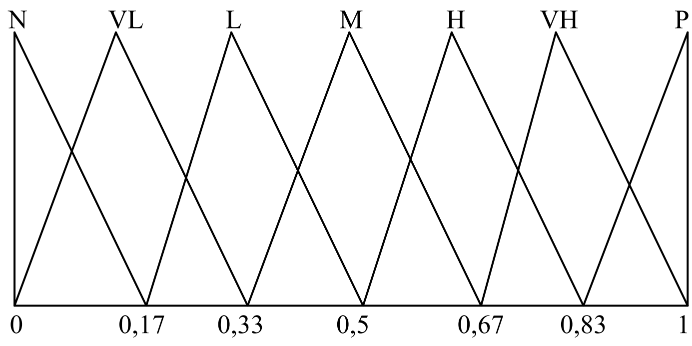


Figure 2.1 The set of seven terms with their meanings

The fuzzy numbers denoted by the letters mapped and their meanings are as below:

N=None=(0, 0, 0.17)
VL=Very Low =(0, 0.17, 0.33)
L=Low =(0.17, 0.33, 0.5)
M=Medium =(0.33, 0.5, 0.67)
H=High =(0.5, 0.67, 0.83)
VH=Very High =(0.67, 0.83, 1)
P=Perfect =(0.83, 1, 1)

2.3.3.2 Semantic Depending on the Ordered Structure of the Linguistic Term Set

This approach can be implemented when the users make their evaluations using an ordered linguistic term set. In this approach, the distribution of the linguistic terms set on the [0,1] scale may give symmetrical or unsymmetrical information. This semantic approach predicates meaning via the structure designated in the linguistic term set which does not use fuzzy sets. Here two different situations may occur:

- *Assuming that the Terms Distribute Symmetrically.*

It is assumed that the linguistic terms distributed on a scale, as with only one element number, and with the median term that shows the “approximately 0.5” value of the evaluation in the middle and other terms distributed around it symmetrically. Later, it can be said that, the meaning of the linguistic term set will be generated with equal information, with reference to Torra (1996), from the ordered structure of the term set by designating each linguistic term for each (s_i, s_{T-i}) pair. We can define this proposal by assigning a sub domain of the [0, 1] domain to each term set.

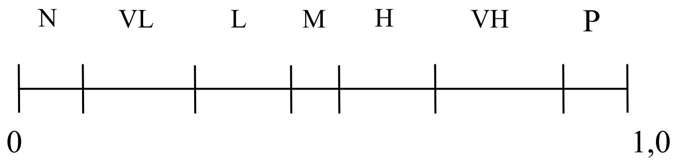


Figure 2.2 The symmetrical distributed ordered set of seven linguistic terms

- *Assuming that the Terms do not Distribute Symmetrically***.**

It can be said that the subset of the reference domain is more informative than the rest of the domain. This can be observed in Torra (1996) which scrutinizes the situations where the terms are not symmetrical. In these kinds of situations, the density of the linguistic letters in the designated definition subset can be greater than the density in the rest of the reference domain, for instance, the ordered linguistic terms set may be distributed non-symmetrically. According to the example given by Torra (1996), if we assume that we certainly need a heat control system when the temperature is “low”, the reference domain would have the distribution given in 2.3.

(AN= Almost none, QL= Quite Low)

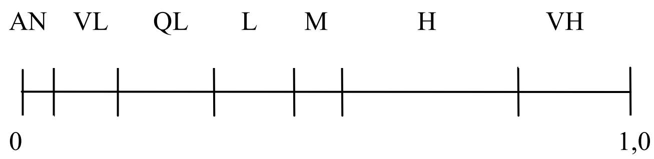


Figure 2.3 The non-symmetrical distributed ordered set of seven linguistic terms

In these situations, Torra (1996) presents a method that reduces the meaning (sub-domain) using a negation function defined through a part of the linguistic term set.

This method is efficient for generating meaning in the linguistic term set, in case the user gives the negation function values for each linguistic term. For instance, as it is expressed in Herrera and Herrera-Viedma (2000), the negation function for the linguistic term set given in Figure 2.3 may be defined as below:

$$\begin{aligned}
&\text{Neg(AN)} = \text{Neg (VL)} = \{\text{VH}\} \\
&\text{Neg(QL)} = \text{Neg (L)} = \{\text{H}\} \\
&\text{Neg(M)} = \{\text{M}\} \\
&\text{Neg(H)} = \{\text{QL},\text{L}\} \\
&\text{Neg(VH)} = \{\text{AN},\text{VL}\}
\end{aligned}$$

2.3.3.3 Mixed Semantic

In this approach, it is assumed that the elements of the ordered linguistic term set are distributed on a scale, as with only one element number, and with the median term that shows the “approximately 0.5” value of the evaluation in the middle and other terms distributed around it symmetrically, and it is thought that each linguistic term is equally informative for each (s_i, s_{T-i}) pair. The fuzzy sets shown by isosceles trapezoidal and triangular functions and the meanings for the main linguistic terms are defined.

Shortly, as in meaning depending on fuzzy sets and meaning rule, this approach defines the fuzzy sets and the meaning of the main linguistic terms. At the same time, in this meaning approach, all the linguistic terms are assumed main, and they have an ordered structure (Figure 2.4).

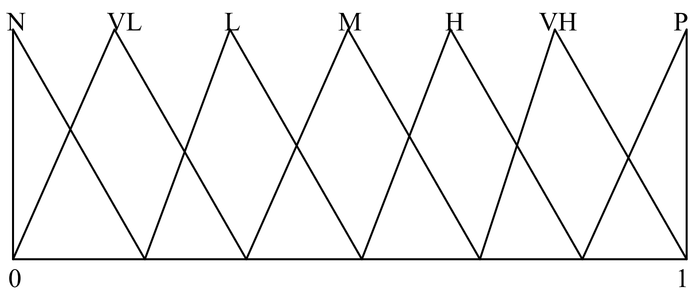


Figure 2.4 The uniform symmetrical distributed ordered set of seven linguistic terms with their meanings

2.4 Aggregation Operators of Linguistic Information

In problems with fuzzy information the processes of aggregation and defuzzification are of crucial importance (Nasibov, 2003; Nasibov and Mert, 2007). One may find four types of aggregation operators for unifying linguistic information to use in computational models. Xu (2008) touches upon these operator types as below:

(i) *Linguistic Aggregation Operators based on Linear Ordering*
(ii) *Linguistic Aggregation Operators based on Extension Principle*
(iii) *Linguistic Aggregation Operators based on Symbols*
(iv) *Linguistic Aggregation Operators based on Linguistic 2-tuples*
(v) *Linguistic Aggregation Operators making direct computations with words*

The types of aggregation of operators are distributed according to their characteristics in the computational models. The operators i, ii and iii cause loss of information during expressing the initial set of the approach. iv and v types enables us to define the linguistic information in the domain infinitely, and completes the computation process without causing any loss of information. The most widely used aggregation operators will be discussed in 2.5 while addressing computational models.

2.5 Linguistic Computational Models

We have mentioned that linguistic information is used in various areas in decision analysis. In decision analysis, during modeling the experts' views via linguistic modeling, computing with words gains importance. Therefore, computing with word processes are used to make calculations on words. In a meta-analysis by Herrera et al. (2009) mentions four basic types of computational models for operating on words during aggregation of linguistic information for decision analysis.

(i) Linguistic Computational Model Depending on Membership Functions (Computational model Depending on Extension Principle)-(Linguistic Meaning Computational model)
(ii) Computational Model Depending on Type 2 Fuzzy Sets.
(iii) Symbolic Computational Model Depending on Ordered Scales (Computational model Depending on Symbolic Transformation)
(iv) 2-tuple Linguistic Computational Model

2.5.1 Linguistic Computational Model Depending on Membership Functions (Computational model Depending on Extension Principle)

This model uses fuzzy arithmetic depending on the extension principle in order to perform calculations on linguistic variables. The Extension Principle is a basic concept, in the Fuzzy Set Theory, to generate the elements defined in classic set into fuzzy sets.

Using the fuzzy arithmetic depending on the extension principle in the process of computing with words, increases the ambiguity of the results, since the fuzzy numbers are not matched with any linguistic term in the initial term set *S*. Since the fuzzy numbers obtained do not match the linguistic terms in the initial set, a need for a linguistic approach occurs to explain the results in the initial explanation set.

In the literature there are many linguistic approach operators. When *S* is the linguistic term set, in $S^n \xrightarrow{\tilde{\tilde{F}}} F(R) \xrightarrow{app(.)} S$, S^n is the *n* Cartesian product of S', $\tilde{\tilde{F}}$ is the aggregation operator depending on extension principle, *F(R)* is the whole fuzzy numbers set on the real numbers set *R*, while in $app_1 : F(R) \rightarrow S$ S is the initial term set, S denotes to the linguistic approach function that transform the unlettered fuzzy number in the linguistic term set into the nearest letter. Herrera and Martínez (2001b) emphasize that the function of this linguistic approach causes information loss during obtaining results.

In this model, aggregation is obtained by linking linguistic letters directly to the membership functions, using classical fuzzy logic. According to Herrera et al. (2008), as it is seen in Fu (2008), Anagnostopoulos et al. (2008) this approach is used as an ordering function to align fuzzy numbers and to find a numerical evaluation.

Chen (1997) who uses this approach offered a method to be used in solving problems about tool steel material selection, with basic arithmetic operators based on the extension principle. In this method the important weights of different criteria and various alternatives under different criteria evaluated by linguistic information expressed as fuzzy numbers.

2.5.2 Computational Model Depending on Type 2 Fuzzy Sets

This approach uses Type 2 fuzzy sets while making linguistic evaluations. Türkşen (2002) argues that using Type 1 fuzzy sets is not a good approach in expressing words and they do not comprise a rich platform for computing with words. Following this, he proposes the use of Type 2 fuzzy sets.

Mendel (2007) also argues that words have different meanings for different individuals, and there is an ambiguity, thus proposes to use Type 2 fuzzy sets, that incorporates fuzziness, to model the words.

Dongrui and Mendel (2007) presented the Linguistic Weighted Avarege operator which can be expressed as the extended version of the Fuzzy Weighted Average operator. The weights and the variables used in this operator are linguistic words modeled by interval type-2 fuzzy sets.

However, in this model, the Type 2 fuzzy set obtained after the aggregation operator during the decision process should be transformed into linguistic evaluation. And this causes an information loss.

2.5.3 Symbolic Computational Model Depending on Ordered Scales

Another model used in operations with words is the linguistic computational symbolic model. This model performs computations using the indices of the linguistic letters. When the literature is examined, one can see three different symbolic computational models depending on ordered scales.

2.5.3.1 Computational Model Depending on Ordered Scales and Max-Min Operators.

Yager (1981) proposes this model to be used in multi-object decisions depending on fuzzy sets. In this model an ordered linguistic set $S = \{s_0, s_1, ..., s_g\}$ is used to perform the computations.

The operators used in this model are listed under "Linguistic Aggreation Operators based on Linear Order". In order to unify the information, the classical aggregation operators, Max, Min and Neg are used. These operators are expressed as below:

$\mathrm{Max}(s_i, s_j) = s_i$, If $s_i \geq s_j$,

$\mathrm{Min}(s_i, s_j) = s_i$, If $s_i \leq s_j$,

$\mathrm{Neg}(s_i) = s_{g-i+1}$, If *g* is the number of the elements of *S*.

Also, Yager (2007) emphasized aggregation operators and model selection based on information defined ordinal scales. In the literature there are many studies on various operators.

2.5.3.2 Linguistic Symbolic Computational Model Depending on Indices.

In this model, an ordered linguistic term set $S = \{s_0, s_1, ..., s_g\}$ is used to perform the computations when $s_i \langle s_j$ as $i \langle j$.

An intermediate value in the range $\alpha \in [0, g]$ is obtained from this set using the operator C. From this intermediate value an index $app_2(\alpha) \in \{0,1,.....g\}$ is found using $app_2(.)$ approach. This index is aggregated with a value in the range [0,g] in order to unify with a term in the terms set $S = \{s_0, s_1, ..., s_g\}$. Symbolic Aggregation is predicated as below. C is the symbolic aggregation operator, and $app_2(.)$ is an approach operation:

$$S^n \xrightarrow{C} [0, g] \xrightarrow{app_2} \{0, ..., g\} \rightarrow S$$

This model is explained in Delgado et al. (1993). If one examines this model as in Herrera et al. (2009), it is seen that aggregation directly affects the letter indices of the term sets using the convex aggregation of the linguistic letters. Generally, the number of the elements in the term set is an odd number and the elements are distributes symmetrically.

In this computational model, Linguistic Weighted Disjunction (LWD) operator, Linguistic Weighted Conjuction operator (LWC) among "Linguistics Aggregation Operators based Linear Ordering" as mentioned in Herrera and Herrera-Viedma (1997); and Linguistic Ordered Weighted Average operator (LOWA) and Linguistic Weighted Average operator (LWA) operator among "Linguistic Aggregation Operators based on Symbols" as mentioned in Herrera et al. (1995) are used.

This computational model too, causes information loss, if the result is predicated as in the initial set, since it uses an approximation operator.

2.5.3.3 Linguistic Symbolic Computational Model Depending on Virtual Linguistic Terms.

In this model seen in Xu (2004b), $S = \left\{ s_{-\frac{g}{2}}, ..., s_0, ..., s_{\frac{g}{2}} \right\}$ an intermittent term set with *g+1* number of elements is expanded to $\overline{S} = \{s_\alpha \mid \alpha \in [-t, t]\}$ a continuous term set, and t, $(t > q/2)$ be an integer great enough.

If $s_\alpha \in S$ then, s_α is predicated as the original linguistic term. This approach preserves all the information in the problem. This symbolic computational model uses altering terms during decision process, like the new virtual terms obtained during aggregation process.

In this computation, although the initial domain is intermittent, it is expanded continuously into the term set using C operator in order to prevent information loss. Also the elements of the term set obtained by using the C operator are called virtual linguistic terms. While decision makers evaluate real linguistic terms, the virtual term are used only in operations. This model can be implemented in appropriate situations.

In the literature, there are many operators defined for unifying linguistic information. Xu (2004a, 2004b, 2006) developed operators such as Linguistic Geometric Averaging operator (LGA), Linguistic Weighted Geometric Averaging operator (LWGA), Linguistic Ordered Weighted Geometric Averaging operator (LOWGA), Linguistic Hybrid Geometric Averaging operator (LHGA), Extended Geometric Mean operator (EGM), Extended Ordered Weighted Averaging operator (EOWA), and Extended Ordered Geometric Averaging operator (EOGWA).

In this model the virtual terms have the possibility to be ordered after selecting best alternatives. But, if the results of the operations in this model are virtual linguistic terms, the final results should be expressed using the original term set. Therefore a conversion issue emerges. However this model can be applied to linguistic decision analysis in appropriate situations.

2.5.4 2-tuple Linguistic Computational model

Herrera and Martínez (2000) propose a 2-tuple representation model. This 2-tuple linguistic computational model depends on the 2-tuple representation model which is a continuous linguistic representation model.

2.5.4.1 2-tuple Fuzzy Linguistic Representation Model Depending on Symbolic Conversion.

In defining 2-tuple linguistic representation model, the 2-tuple linguistic representation predicated with s and α as (s,α), as the symbolic conversion. Therefore, the definition of symbolic conversion should be given first to understand this model:

Definition 2: Take "β" as a result of the aggregation of the indices of a letter set valued in the linguistic term set, $S = \{s_0, s_1, ..., s_g\}$. β can be thought as a result of a symbolic aggregation operation (Herrera and Martínez (2000)).

$\beta \in [0,g]$, g+1 give the number of elements in S. It is thought that there are two values as $i = round(\beta)$ and $\alpha = \beta - i$. So much so that, they are $i \in [0,g]$ and $\alpha \in [-0.5,0.5)$'. "α" is called the symbolic conversion.

As it is understood, the symbolic conversion of the linguistic term "s_i" is a numerical value that predicates the information difference between the value of the information $\beta \in [0,g]$ in the range of $[-0.5,0.5)$ and the index of the nearest linguistic term $(i = round(\beta))$ in the range of $\{0,.....g\}$ in the term set S, after a symbolic aggregation operation.

$s_i \in S$ being the linguistic letter center of the information and $\alpha_i \in [-0.5,0.5)$ representing the difference between the original result β and the index i of the nearest linguistic term s_i to this result, the linguistic representation model is developed by the 2-tuple order (s_i, α).

Definition 3: As Herrera and Martínez (2000) put forth in their study $S = \{s_0, s_1, ..., s_g\}$ be a linguistic term set, and $\beta \in [0,g]$ is a value that shows the result of the symbolic aggregation and the 2-tuple that explains the co-information for β obtained by a following function.

$$\Delta : [0, g] \rightarrow S \times [-0.5, 0.5]$$

$$\Delta(\beta) = (s_i, \alpha), \begin{cases} s_i, i = round(\beta) \\ \alpha = \beta - i, \alpha \in [-0.5, 0.5] \end{cases} \tag{2.1}$$

round is the general rounding operator, s_i is the nearest letter index to β and α is the value of the symbolic conversion.

Annex: $S = \{s_0, s_1, \ldots.., s_g\}$ be a linguistic term set and (s_i, α) be a 2-tuple. There is always a function Δ^{-1} from the 2-tuple to the numerical value $\beta \in [0, g] \subset R$.

Proof: $\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, g]$

$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$$

A linguistic term may be converted to 2-tuple representation by adding a 0 value. $s_i \in S \Rightarrow (s_i, 0)$.

2.5.4.2 2-tuple Fuzzy Linguistic Computational Model Depending on Symbolic Conversion.

In this computational model, the symbolic model is taken as a basis. In this model, in addition to the symbolic model, a linguistic transformation concept is defined and linguistic 2-tuple representation is used. While expressing the linguistic transformation, *s* representing the linguistic terms and α representing the numerical value, the (s, α) pair represents the linguistic information. Herrera et al. (2009) argues in favor of this model that it has various advantages than the classical computational models used:

(i) The linguistic term set is handled continuously; however, in classical models the domain is intermittent.

(ii) The computational model depending on linguistic 2-tuple performs the "computing with words" process easily and without loss of information.

(iii) The results of the "Computing with Words" process are explained with the initial linguistic domain.

While the computational models used in Fuzzy Linguistic are generally continuous, the linguistic representation model (symbolic linguistic terms) used by this approach is intermittent. Therefore, the results do not match exactly to any of the terms in the initial term set. An approximation operation should be developed in order to explain the result in the source domain. But, this situation causes information loss. However, the 2-tuple computational model depending on the linguistic transformation concept in the 2-tuple linguistic representation prevents information loss. This model gives more accurate and coherent results.

Herrera and Martínez (2001b) argue that this model gives more accurate and coherent results.

- *Comparison of 2-tuples.*

The comparison of the linguistic information represented by 2-tuples is implemented according to an ordered lexical array. (s_k, α_1) and (s_l, α_2) be two 2-tuples, each of them is represented by the number of the information:

**If k<l (s_k, α_1) is smaller than (s_l, α_2).

**If k=l

1. If $\alpha_1 = \alpha_2$ (s_k, α_1) and (s_l, α_2) represent the same information.
2. If $\alpha_1 < \alpha_2$ (s_k, α_1) is smaller than (s_l, α_2).

3. If $\alpha_1 > \alpha_2$ (s_k, α_1) is greater than (s_l, α_2).

- *Negation Operator of the 2-tuples.*

The negation operator for the 2-tuples is as follows:

$$Neg((s_i, \alpha)) = \Delta(g - (\Delta^{-1}(s_i, \alpha))).$$

g+1 shows the element number of the set $S = \{s_0, s_1, \ldots s_g\}$.

- *Aggregation of the 2-tuples*

The aggregation information comprises of finding the value that summarizes the value set; thus, the result of the aggregation of 2-tuples should be a 2-tuple.

2.5.4.3 Aggregation Operators

There is more than one operator for linguistic 2-tuples that depend on classical aggregation operators. These operators enable the aggregation of information related to different criteria. The 2-tuple fuzzy linguistic representation defines the functions Δ and Δ^{-1} that convert the numerical values to 2-tuple representation without information loss. Any numerical aggregation operator can easily be implemented to 2-tuple representation. This feature confirms the applicability of the model.

- *2-tuple Arithmetic Mean (TAM)*

The classical aggregation operator, arithmetic mean is defined as below for 2-tuple representation:

Definition 4: $x = \{(r_1, \alpha_1), (r_2, \alpha_2), \ldots, (r_n, \alpha_n)\}$ be a 2-tuple set. The 2-tuple arithmetic mean $\bar{x}^e$ is calculated as below:

$$TAM\left((r_1,\alpha_1),(r_2,\alpha_2),...,(r_n,\alpha_n)\right)=\bar{x}^e=\Delta\left(\sum_{i=1}^{n}\frac{1}{n}\Delta^{-1}(r_i,\alpha_i)\right)=\Delta\left(\frac{1}{n}\sum_{i=1}^{n}\beta_i\right)$$

The arithmetic means of linguistic values can be obtained without information loss.

- *2-tuple Weighted Averaging (TWA)*

In situations where different x_i values have different effects on variable X, it has a weight represented by w_i that expresses the importance of each x_i value for the variable.

Definition 5: $x=\{(r_1,\alpha_1),(r_2,\alpha_2),....,(r_n,\alpha_n)\}$ be a 2-tuple set. $w=\{w_1,w_2,.....,w_n\}$ represents the set of weights based on the expressions $w_i\in[0,1]$ and $\sum_{i=1}^{n}w_i=1$. The 2-tuple weighted averaging $\bar{x}^e$ is calculated as below:

$$TWA\left((r_1,\alpha_1),(r_2,\alpha_2),...,(r_n,\alpha_n)\right)=\bar{x}^e=\Delta\left(\sum_{i=1}^{n}\Delta^{-1}(r_i,\alpha_i).w_i\right)=\Delta\left(\sum_{i=1}^{n}\beta_i.w_i\right)$$

- *2-tuple Ordered Weighted Averaging (TOWA)*

Martínez et al. (2005) studied on multi-granular linguistic information model for design evaluation based on security and cost analysis. In this model, the 2-tuple Ordered Averaging is used for unifying the information obtained from the experts.

Definition 6: Let $x=\{(r_1,\alpha_1),(r_2,\alpha_2),....,(r_n,\alpha_n)\}$ be a 2-tuple set. And let $w=\{w_1,w_2,.....,w_n\}$ express the set of weights based on the expressions $w_i\in[0,1]$ and $\sum_{i=1}^{n}w_i=1$. The 2-tuple ordered weighted mean $\bar{x}^e$ is calculated as below:

$$TOWA\big((r_1,\alpha_1),\ (r_2,\alpha_2),\ \ldots,\ (r_n,\alpha_n)\big) = \bar{x}^e = \Delta\left(\sum_{j=1}^{n} \Delta^{-1}(r_j,\alpha_j).w_j\right) = \Delta\left(\sum_{j=1}^{n} \beta_j^{*}.w_j\right)$$

β_j^*, expressed the greatest of values of β_i.

2.6 Linguistic Hierarchical Structures

2.6.1 Linguistic Hierarchical Structure

In studies by Kbir et al. (2000) and Cordón et al. (2002) on linguistic hierarchical structure, one can come across with systems depending on fuzzy rules. This linguistic hierarchical structure, at the same time, is used in decision models as argued by Herrera and Martínez (2001a). It is a structure that supports better results by increasing precision in aggregation processes of multi-granular linguistic information.

Linguistic hierarchy is a degree set, in which each set is a linguistic term set with different granularity than other degrees of the hierarchy.
Each degree belongs to a linguistic hierarchy represented as $l(t, h(t))$.

1) *t*, is a number that show the degree of the hierarchy.
2) *n(t)*, is the granularity of the term set of the degree *t*.

The degrees belonging to a linguistic hierarchy are ordered according to their granularity. For example, when consecutive degrees are *t* and *t+1*, they are represented as $n(t+1)\rangle n(t)$. This enables a detailed difference with the previous degree. In addition to this, linguistic term sets has the single granularity value which shows the center letter as the value of impartiality.

A linguistic hierarchy is defined as the union of all t degrees as below.

$$LH = \bigcup_{t} l(t, n(t))$$

2.6.2 Structuring Linguistic Hierarchies

In order to form a linguistic hierarchy one should take into consideration the hierarchical order formed by the increase in the granularity of the linguistic terms set in each degree. For this purpose, s_k is defined as the linguistic term of the set $(k = 0,....,n(t)-1)$ *S* in the set $S = \{s_0, s_1, ..., s_{n(t)-1}\}$ which is defined in the universal set *U* in the degree of *t*.

The definition of the set *S* is expanded into the set of $S^{n(t)}$ linguistic terms sets. In this set each term belongs to a *t* degree of the hierarchy and has the granularity of the fuzziness represented by *n(t)*. The set of $S^{n(t)}$ linguistic terms sets are represented as $S^{n(t)} = \{s_0^{n(t)}, ..., s_{n(t)-1}^{n(t)}\}$.

There are some basic rules that the linguistic hierarchy has. These rules are presented as below:

1) To preserve the previous model points of each terms' membership functions from one degree to another.
2) Making smooth modulations between successful degrees.

Here, the purpose is to form a new linguistic term set $S^{(n+1)}$. The new linguistic term is added among the term pairs belonging to the term set of the previous *t* degree. In order to apply this addition, the support of the linguistic letters should be decreased to give place to the new one between them.

In the following table the granularity number necessary for each term set in the *t* degree related to n(t).

Table 2.1 Linguistic hierarchy of letters 3, 5 and 9

	L(t,n(t))	L(t,n(t))
Level 1	L(1,3)	L(1,7)
Level 2	L(2,5)	L(2,13)
Level 3	L(3,9)	

In general, the linguistic term set of the degree *t+1* is obtained depending on the previous t degree as below.

$$L(t,n(t)) \rightarrow L(t+1,2.n(t)-1)$$

In the following figures, the linguistic hierarchies are represented graphically. As it seen in the figures, uniform and symmetrical triangular shaped fuzzy numbers in the range of [0,1] are used to predicate the linguistic terms. In this study, the triangular shaped fuzzy numbers are preferred in implementing the linguistic decision analysis approach.

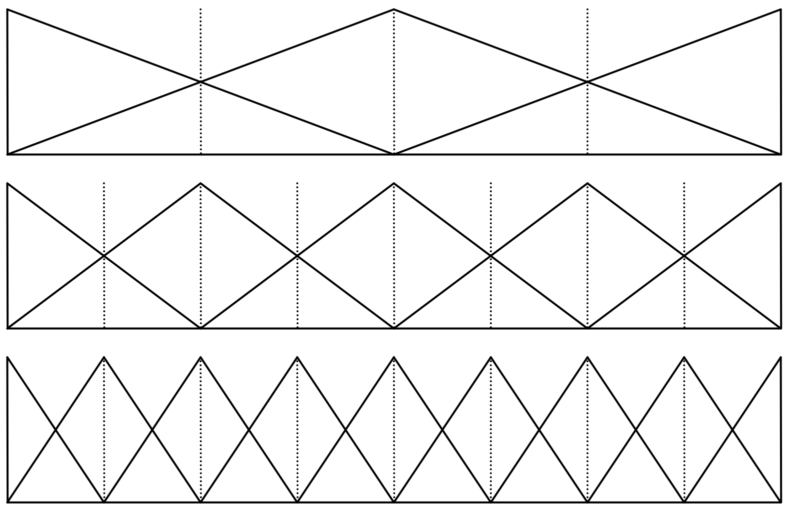


Figure 2.5 Linguistic hierarchy of letters 3, 5 and 9 (Martínez et al., 2008)

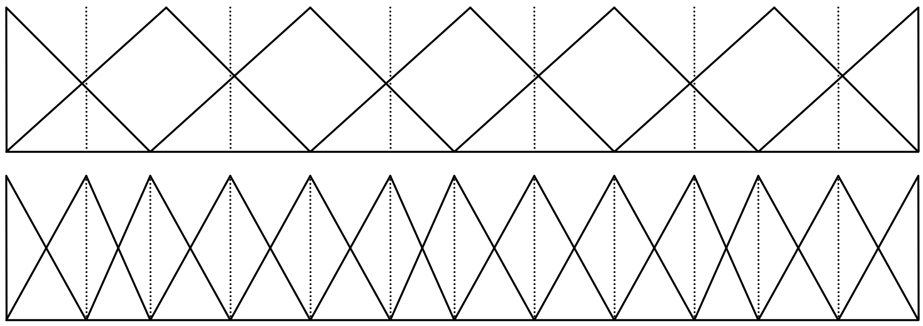


Figure 2.6 Linguistic hierarchy of letters 7 and 13 (Martínez et al., 2008)

2.6.3 Transformation Functions between the Degrees of Linguistic Hierarchy

In the normalization process for the aggregation of multi-granular information, there occurs an information loss. To prevent this basic problem, linguistic hierarchies are used. Herrera and Martínez (2001a) scrutinized this issue in their study. In order to define the transformation processes between the linguistic terms in a linguistic hierarchy term set without an information loss, transformation functions are used. In these transformation functions the 2-tuple representation is used.

Definition 7: $LH = \bigcup_t l(t, n(t))$ linguistic terms are a linguistic hierarchy represented in the term set $S^{n(t)} = \{s_0^{n(t)}, s_1^{n(t)}, \ldots\ldots, s_{n(t)-1}^{n(t)}\}$. Let there be a linguistic letter with its degree represented by t and a linguistic letter with its degree represented by $t^{'} = t + a$, $a \in Z$. Conversion from one degree to another is defined as below:

$$TF_{t'}^{t} : l(t, n(t)) \rightarrow l(t^{'}, n(t^{'})).$$

The formula,

If, $|a| \rangle 1$ then;

$$TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = TF_{t'}^{t+[(t-t^{'})/(|t-t^{'}|)]}.(TF_{t+[(t-t')/(|t-t'|)]}^{t}(s_i^{n(t)}, \alpha^{n(t)}))$$

is used.

Using the formula,

If, $|a| = 1$ then;

$$TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = TF_{t+[(t-t')/(|t-t'|)]}^{t}(s_i^{n(t)}, \alpha^{n(t)})$$

the operation is performed.

This iterative conversion function can be represented as below:

$$TF_{t'}^{t} : l(t, n(t)) \rightarrow l(t', n(t'))$$

$$TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = \Delta\left(\frac{\Delta^{-1}(s_i^{n(t)}, \alpha^{n(t)}).(n(t')-1)}{n(t)-1}\right) \tag{2.2}$$

Annex: In the different degrees of linguistic hierarchy, the conversion functions between linguistic terms

$$TF_{t}^{t'}\left(TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)})\right) = (s_i^{n(t)}, \alpha^{n(t)})$$

Proof:

$$TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = \Delta\left(\frac{\Delta^{-1}(s_i^{n(t)}, \alpha^{n(t)}).(n(t')-1)}{n(t)-1}\right)$$

The result of this operation ensures that the conversion function between the linguistic hierarchies obtains results without information loss. To give an example (Herrera and Martinez, 2001a);

$$LH = \bigcup_{t} l(1,3)$$

Term sets;

$l(1,3) = \{s_0^3, s_1^3, s_2^3\}$

$l(2,5) = \{s_0^5, s_1^5, s_2^5, s_3^5, s_4^5\}$

$l(3,5) = \{s_0^9, s_1^9, s_2^9, s_3^9, s_4^9, s_5^9, s_6^9, s_7^9, s_8^9\}$

are predicated as such.

The conversions (2.2) between different degrees are performed as below.

$$TF_1^3(s_5^9,0) = \Delta^{-1}\left(\frac{\Delta(s_5^9,0)(3-1)}{9-1}\right) = \Delta^{-1}(1,25) = (s_1^3,0.25)$$

$$TF_5^9\left(s_1^3,0.25\right) = \Delta^{-1}\left(\frac{\Delta(s_1^3,0.25).(8-1)}{3-1}\right) = \Delta^{-1}\left(5\right) = (s_5^9,0.0)$$

In this chapter we have elaborated the computing with words approach and the aggregation operators in this approach. In the next chapter we will discuss in detail the the Linguistic Decision Analysis Approach which in the scope of Decision Analysis Approach.

CHAPTER THREE

MULTI-EXPERT DECISION ANALYSIS DEPENDING ON LINGUISTIC INFORMATION

3.1 Introduction

In this chapter the Decision Analysis Approach and the phases of this approach will be discussed. Later on, the Linguistic Decision Analysis Approach, which is the main approach used in this study will be elaborated.

3.2 Decision Analysis Approach

Decision approaches are frequently used in solving the problems to be evaluated in evaluation processes. Decision analysis is a discipline that helps the experts in making coherent decisions in decision making problems, and is a convenient approach for solving the problems in the evaluation processes. This approach, during the process of evaluation at hand, enables the analysis of the alternatives, criteria and the indicators of the elements in the study to be performed easily.

Baker et al. (2002) published a book to help the decision-makers, emphasizing that a decision making process should be well-defined in order the decisions made by the decision-makers to be agreeable. In this guide book, the authors lay stress on the decision-making steps to help the decision-makers to choose the best alternative.

As it is mentioned in Herrera et al. (2009), in the literature the classical decision analysis is conducted according to the stages listed below:

(i) The decision, the aims and the alternatives of the problem is defined.
(ii) The Model: The evaluation design suitable for the problem's structure is defined.
(iii) Gathering Information: Decision-makers acquire their knowledge.

(iv) Rating Alternatives: In this stage a combined-value is calculated for each alternative

(v) Choosing Best Alternatives: The best alternative is chosen among the alternative sets by applying a selection value to the combined values calculated in the previous stage.

(vi) Sensitivity Analysis: An analysis is conducted in order to observe whether the calculated solution is appropriate enough to make decisions; if it is decided that the calculated solution is not appropriate enough to make decisions, the process returns back to the beginning stage of the solution to increase the quality of the results.

(vii) The decision is made.

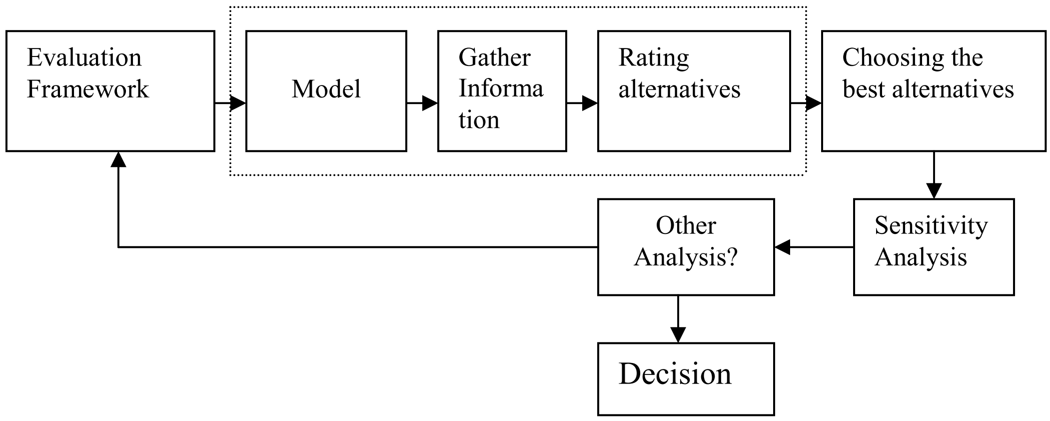


Figure 3.1 Decision analysis schema

3.3 Linguistic Decision Analysis

In the previous section on Linguistic Approach, it has been mentioned that some qualitative information in our daily lives cannot be expressed qualitatively; hence we should use linguistic approaches that can make calculations using quantitative expressions in these situations where decision making is a hard task.

The basis of linguistic decision analysis lies upon the linguistic approaches and it is applied in solving decision making problems using linguistic information. Linguistic decision analysis forms a more beneficial approach presenting flexible solutions where we cannot express information precisely; because, it enables us to use the information straight-forwardly.

Linguistic approach embeds the fuzzy sets into decision analysis. Dubois and Prade (1997) analyze the meanings of the fuzzy sets and assert that "In the literature, there are three main meanings for the membership functions: similarity, preference and ambiguity. The meaning *preference* among these is used in decision analysis.

Any choice of the expert is done using linguistic letters or fuzzy preferences. As it is seen, the embedding of fuzzy sets into decision analysis is rendered possible via "preference", one of the meanings of the fuzzy sets.

Roubens (1997) designates the process for the group to decide in classical fuzzy decision analyses into two phases given below:

(i) Aggregation Process for performance values in order to find the aggregated performance value of the decision-makers for evaluating alternatives based on the experts or the criteria.

(ii) Exploitation process of the performance values in order to find an ordering or to choose alternatives.

However, Herrera and Herrera-Viedma (2000) published a study where they inspected how linguistic decision analysis should be and explained the steps in it. In this study, they added two new phases before the aggregation and exploitation processes in addition to the classical fuzzy decision-analysis. The phases of linguistic decision analysis, after adding the aforementioned phases are as below:

(i) Choosing the linguistic term sets with their meanings

(ii) Choosing the aggregation operator for linguistic information (iii)Choosing the best alternatives

a. Aggregation process for linguistic information
b. Exploitation process

Martínez et al. (2007) uses the schema below that comprises of modeling, gathering information and rating alternatives phases as decision analysis schema. In sensory evaluation based on linguistic information to be conducted in the following chapters of this study the decision analysis schema in 3.2.

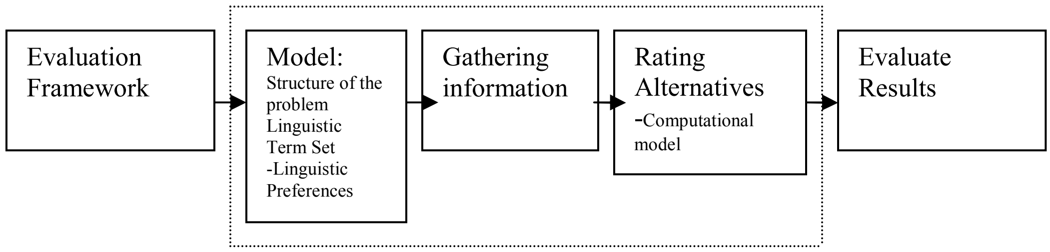


Figure 3.2 Updated decision analysis schema

When the relation of the linguistic decision analysis phases designated in Herrera and Herrera-Viedma (2000) to the linguistic decision analysis schema is examined, it is seen that the evaluation design part expresses the first phase of the linguistic decision analysis, namely, the phase in which the evaluation design for problem structure is defined and the selection linguistic term sets is done.

Different problem structures can be used to arrive at a correct decision in Decision analysis. In literature, there are studies on various models such as Multi-Expert Decision-making problem by Rahman and Fairhust (2000), on Multi Criteria Decision-making problem by Bayazıt (2002), and on Multi-expert Multi-Criteria Decision-making problem by Tsiporkova and Boeva (2006).

In problems of evaluating the opinions when the information sources are great in number, the "Multi-expert Decision-making Problem" is preferred which explains the interpretations of the decision-makers using a utility vector and set alternatives.

In the “gathering information” phase, the information about the problem is obtained from the experts. As for the “choosing alternatives” phase, it incorporates the second step of the decision analysis steps. In addition to the computational model chosen in accordance with the presentation of the linguistic terms, the aggregation operators for the solution of the problem, which are appropriate for the linguistic information, are defined.

For the aggregation of the linguistic preference variables, in the literature, four types of linguistic computational models, mentioned in 2.4, are used.

(i) Linguistic Computational model Depending on Membership Functions (Computational model Depending on Extension Principle)-(Linguistic Meaning Computational model)
(ii) Computational model Depending on Type 2 Fuzzy Sets.
(iii) Symbolic Computational model Depending on Ordered Scales (Computational model Depending on Symbolic Transformation)
(iv) 2-tuple Linguistic Computational model

Following this step, the aggregation process is conducted. The phase called the “exploitation process”, which follows the aggregation process, denotes to the phase in which the results are evaluated, in the Decision Analysis Schema. The exploitation process, then, divides into two and estimates the ordering of the alternatives and just after that, the selection of alternatives.

After the structure of the problem is determined in the evaluation design, the linguistic analysis steps are formed accordingly. When the linguistic domains are defined, the linguistic preferences are determined and the information is gathered. In the “choosing alternatives” phase, following the “gathering information” phase, the model, formed in accordance with the previous phases is analyzed.

As we mentioned in the previous chapter, 2-tuple Linguistic Computational model enables the researcher to conduct linguistic computations without loss of information. Thus, the 2-tuple Linguistic Computational model is preferred in this study.

In this way, the multi-expert decision problem is concluded through the aforementioned phases of the decision analysis using 2-tuple computational model.

3.4 Multi-granular Linguistic Information

When the recent literature is checked, it can be seen that there emerged new approaches in accordance with the structure of the linguistic information in linguistic decision analysis. Herrera et al. (2009) takes nine new approaches into consideration. As in Multi-granular linguistic modeling, one of the new approaches, forming different linguistic domains to present the options in linguistic decision analysis, enables the experts to present their preferences in a flexible way. Forming non-symmetrical domains as in unbalanced linguistic modeling can be seen in Herrera et al. (2008). Delgado et al. (1998) studied on forming the options by aggregating the numerical and linguistic representations. Herrera-Viedma et al. (2004) investigated forming the linguistic preference relations in a consistent way. Dongrui and Mendel (2007) developed a computational model based on Type 2 fuzzy sets.

In decision analysis, since the opinions of the experts vary with respect to their cultural background, their intelligence and their perception habits, it seems not logical to constrain them to only one linguistic term set. In line with this idea, it is possible define linguistic term sets with different number of elements and with different meanings in order to enable the experts to express their opinions with different domains using multi-granular linguistic information structure.

In the literature, there are various studies on this topic. Herrera et al. (2000) presented a new approach on evaluating multi-granular linguistic information based on the linguistic preference relations. This approach selects a basic linguistic term set and defines a conversion function that indicates each linguistic performance value which is expressed as a fuzzy value in this linguistic term set.

Herrera and Martínez (2001a) developed a new model based on multi-granular hierarchical linguistic information by enhancing the aforementioned model. Martínez et al. (2005) adapted this model into the field of engineering. Herrera et al. (2006) used this multi-granular hierarchical structure to evaluate the quality of the web sites' services.

In addition to all these studies, different models have been offered recently for decision problems that are to be resolved by a group. Jiang et al. (2008) developed a multi-granular model to evaluate the preferences expressed via fuzzy numbers. Halouani et al. (2009) defined a multi-granular linguistic Promethee Model for solving a multi-criteria problem. Andrés et al. (2010) proposed a new model based on multi-granular information for performance assessment in the field of management.

The most important point that our study puts emphasis on, is the structure of the linguistic term set defined. In situation where the linguistic term set is not structured in a multi-granular mode, loss of information may occur during aggregation process. Thus, linguistic term sets formed with respect to the structure, called linguistic hierarchy, explained in 2.6 with reference to Herrera and Martínez (2001a) are preferred to avoid loss of information during normalization process. Therefore, the aggregation process should be examined as two different processes, normalization and aggregation, using the linguistic hierarchical representation method based on multi-granular structure.

By this way, in the normalization process it is possible to explain the linguistic information in one domain, it is also possible to analyze easily the linguistic information with multi-granular structure using 2-tuple Computational model without loss of information. In this study, in Chapter 5, the specification of the domains of different degrees used in the Sensation Analysis of Olive Oil into one domain via a normalization process using linguistic hierarchies will be provided.

3.5 Linguistic Decision Analysis Phases

The phases of linguistic decision analysis are given under the headlines given below with reference to Herrera and Herrera-Viedma (2000):

(i) Choosing the Linguistic Term Sets with Their Meanings: In this phase, linguistic definitions sets are formed in order the experts to evaluate the alternatives according to different criteria. The granularity, letters and meanings of the linguistic term sets are determined in this phase.

(ii) Choosing the Operator to Aggregate the Linguistic Information: This phase involves the selection of an aggregation operator that is appropriate for the linguistic information needed to aggregate the values obtained from the experts.

(iii)Choosing Best Alternatives: This phase involves choosing the best alternative in accordance with the values obtained from the experts.

   a. Aggregation Process for Linguistic Information: This process involves obtaining a new aggregated value by applying the chosen aggregation operator on the linguistic values previously obtained from the experts.
   b. Exploitation Process: This process involves the ordering the alternatives to chose the best alternative with respect to linguistic performance values.

During the analysis, these phases are followed taking the type of the problem into consideration.

3.5.1 Choosing the Linguistic Term Sets with Their Semantics

The linguistic terms, which form the basis of the linguistic approach, should be well-formed, because proper expression of the answers to the problem to be solved is crucial for the consistency of the analysis. Thus, expressing the semantics of linguistic term sets illustratively and the term sets' having a structure that can express the required information with minimum words are demanding issues.

The formation of linguistic term sets was mentioned in detail in Chapter 2. In this section, the issue of the important points of linguistic term set formation will be dealt with shortly for reminding.

Firstly, the intended number of the elements for the linguistic term sets is determined. After choosing the linguistic term set and determining the number of its elements, appropriate linguistic descriptors are generated using either Context-Free Grammar Approach or the Approach Based on the Order of Linguistic Terms.

After generating the descriptors definitively, the semantic of the linguistic term set should be explained. As it was mentioned in Chapter 2, there are three main approaches in the literature, for explaining the semantic of the linguistic term sets. These are called, Semantic Depending on Membership Functions and A Semantic Rule, Semantic Depending on the Ordered Structure of the Linguistic Term Set and Mixed Semantic.

For instance, Mixed Semantic approach will appear in the following chapters, during the assertion of the meaning of linguistic terms sets formed for sensory evaluation of Olive Oil.

3.5.2 Choosing the Operator to Aggregate the Linguistic Information

There are two approaches in the literature for the aggregation of linguistic information. One of these is called "Approximation Approach" and the other is called "Symbolic Approach".

3.5.2.1 Approximation Approach

Linguistic computational models were defined in 2.4 in order to perform computations using linguistic terms. Also, there are aggregation operators that these models use in accordance with the structure of the linguistic information. One of the approaches that play a crucial role for the functionality of these operators is the "Approximation Approach".

"Approximation Approach" is based on linguistic operators depending on fuzzy membership functions. This approach is used to structure the linguistic model with the extension principle that offers mathematical means to realise any arithmetic operation.

However, performing operations using the arithmetic operations which are extended with fuzzy sets increase the ambiguity of the results exponentially. The final results of these are obtained as fuzzy sets which do not connect with any letter in the original linguistic term set. Should the result be expressed with a letter, it is necessary to use the linguistic approach.

This linguistic approach involves finding a letter with a meaning which is same with or similar to the meaning of the fuzzy set generated by the linguistic computational model. There is not a general method that aggregates a fuzzy set with linguistic letters; thus, special problems involve enhanced methods.

3.5.2.2 Symbolic Approach

Computations using this approach are easier and faster. In this approach operations are performed based on a linguistic term set that has a structure which is a sequential order distributed in a scale with a uniform order. Thus, it proceeds by performing direct operations on letters, taking the linguistic features and meanings of some linguistic evaluations into consideration.

For the decision analysis, the approach which is appropriate for the problem at hand is selected together with one of the computational models consistent with the approach and the aggregation operator, among the ones explained in 2.4, is determined in accordance with the structure of the linguistic information. In the decision analysis, generally, the symbolic approach is used.

3.5.3 Choosing Best Alternatives

When a multi-criteria problem is considered, according to a group of criteria $\{p_1, p_2, ..., p_m\}$, the performance values $\{v_1, v_2, ..., v_m\}$ are present for the alternatives set $X = \{x_1, x_2, x_3, ..., x_m\}$.

The result of the problem is obtained by choosing the best alternative from among the performance values. The selection process for choosing the best one from among the alternatives comprises of two phases. Of these two selection processes, called Direct and Indirect approaches, our preference should be to obtain an aggregated performance value V^c from among performance values, which is also the preference of a group of criteria.

$$\{v_1, v_2, ..., v_m\} \rightarrow V^c$$

We can speak of two phases when this approach is at issue:

(i) Aggregation Phase for Linguistic Information
(ii) Exploitation Phase of the Aggregated Linguistic Information

3.5.3.1 Aggregation Phase

When a multi-criteria decision analysis problem is taken into consideration, in order to obtain an aggregated performance value V^c over an individual performance value set $\{v_1, v_2, ..., v_m\}$ provided for the criteria, one of the aggregation operators, selected in the previous phase, is used.

First of all, the most important matter to be thought before starting the linguistic decision analysis is the issue of which representation to use in forming the linguistic performance values. Therefore, in which way the linguistic preference would be represented should be planned at the beginning of the study.

Representation of linguistic preferences can be done in two ways. One of the representations is called “Linguistic Preference Relation” and the other one “Linguistic Utility Function”. This study will focus on a sensory evaluation model based on the linguistic utility function.

In linguistic utility function approach, a utility function $V_k = \left[V_1^{\ k}, V_2^{\ k}, ..., V_n^{\ k}\right]$ for each criterion is represented with aggregation of the linguistic value $v_j^{\ k}$ which indicates the performance of these alternatives and each x_j alternative. In this situation, if the linguistic performance values $\{v_1, v_2, ..., v_m\}$ are expressed using the linguistic utility functions, then V^c is the aggregated linguistic utility function.

In situations, where linguistic information is represented as multi-granular, there are different approaches in Aggregation phase as mentioned in Herrera et al. (2000, 2001). These approaches examine the aggregation process in two phases as normalization and aggregation.

- Normalization phase: The multi-granular linguistic information is explained in one linguistic explanation set.
- Aggregation phase: The information expressed in one linguistic explanation set is aggregated.

3.5.3.2 Exploitation Phase

Exploitation phase is based on choosing the best alternative from among the values V^c. This phase uses preference functions to characterize the alternative and to choose the best alternative.

This phase comprises of two headings:

- The alternatives defined from among the V^c performance values are sorted using the linguistic preference function. For instance;

Let $X_c = \{(x_j, \mu_{X^c}(x_j)), j = 1,....,n\}$ and $\mu_{X^c} : X \rightarrow S$.

- The best one from among the ordered alternatives is chosen.

$$X^s = \{x_i \in X \mid \mu_{X^c}(x_i) = \max_{x_j \in X} \{\mu_{X^c}(x_j)\}\}.$$

The result set of the alternatives is represented as above. The definition of the linguistic preference function depends on the representation of the linguistic performance values in the beginning of the problem. If, as in our preference, the linguistic performance values are represented as linguistic utility function, the aggregated linguistic performance value obtained is given as linguistic utility function. V^c appears as a linguistic preference function when performing a direct ordering. For instance, $V^c = X^c$.

Hence, the result set of the alternatives is represented as below.

$$X^s = \{x_i, X_i \in X \mid V^c(x_i) = \max_{x_j \in X} \{V^c(x_i)\}\}$$

In this chapter of the study we have addressed the Decision Analysis Approach in general and the Linguistic Decision Analysis Approach in particular. In the next chapter we will scrutinize the Sensory Evaluation approach.

CHAPTER FOUR

SENSORY EVALUATION
BASED ON LINGUISTIC DECISION ANALYSIS

4.1 Introduction

In this chapter, the main analysis method of the study, namely Sensory Evaluation will be defined and the phases of this method will be explained in detail.

4.2 What is Sensory Evaluation?

Evaluation is a complex process frequently referred, in order to achieve various goals in different areas of daily life. This process aims at defining the goal-oriented factors, preparing the evaluation design, gathering necessary information and obtaining the appropriate evaluation results to make a conclusive evaluation.

The purpose of any evaluation is to get information about any element (goods, services, materials, etc.) and to develop different perspectives, indicators, and criteria for this element, or to find an exact definition of the element in order to make comparison with other elements to designate the best ones.

Generally, experienced people on the issue at hand, called experts, take part in analyzing different viewpoints based on different criteria to gather information about any good, element, etc. These experts perform the evaluation through their perception using their visual, olfactory, gustatory or tactile senses. The process, in which the experts use their senses to obtain information, is called Sensory Evaluation.

Sensory evaluation is commonly used in quality control processes of food products, as stated in Allison and Work (2004); in marketing studies researching the customer behaviors, as stated in Lee and O'Mahony (2005); and in engineering processes used to aggregate the information obtained from individuals.

As for the decision analysis, it contributes in obtaining more efficient results from the evaluation process by incorporating the stages of decision-making. Martínez (2007) argues that psychological studies show that individuals make decision consistent with the decision analysis approach. In this respect, decision analysis approach plays a crucial role in the evaluation process. Martínez (2007) also shows that, decision analysis approach can be customized appropriately for use in evaluation process.

In this chapter, the structure of sensory analysis will be elaborated with correspondence to the phases of decision analysis. In Chapter 5, explanation and application on how the sensory analysis regarding the classification of virgin olive oil tasted by the experts is applied to the linguistic decision analysis will throw light on the sensory evaluation process.

Since the information gathered from the experts, in sensory analysis, is obtained through senses, it is difficult to represent this information mathematically. Human senses being in question, asserts the necessity of the notion of linguistic variable.

At the beginning, the computational methods used in sensory analysis were of the statistical computational models such as factor analysis. However, the ambiguity of the information, which varies from individual to individual with respect to their senses, is very high. The existence of ambiguity implies the existence of fuzziness and thus the information at issue has a non-probability character. In these situations, obtaining information directly from the experts is aimed, using linguistic descriptors.

In order to examine ambiguity, linguistic fuzzy approach is used as a tool. Linguistic fuzzy approach incorporates the process of computation with words into sensory evaluation process. Thus, evaluation process, which is a kind of decision analysis problem, can be based on linguistic information. By incorporating linguistic information into the analysis, the linguistic computational process plays a crucial role in modeling the system.

Aggregation of linguistic words, as mention in Chapter 2, is provided by using operators appropriate for linguistic computational models. In this chapter, too, it will be seen how linguistic information bears an important role in sensory evaluation, through examining the sensory evaluation process in terms of the phases of linguistic decision analysis.

4.3 Sensory Evaluation Process Depending on Linguistic Information

Sensory evaluation, as mentioned before, poses a kind of decision analysis. The sensory evaluation problem, as decision analysis performed in terms of linguistic information obtained from the experts and thus linguistic fuzzy approach is included in the problem itself, is resulted by applying the phases of linguistic decision analysis, in accordance with the phases the classical decision analysis follows.

In Martínez (2007) sensory evaluation model depending on decision analysis, of the eight phases of classical decision analysis, only modeling, information gathering and rating alternatives phases of the appear as most important ones. Phases of decision analysis, provides an appropriate context for the decision-makers to determine their decisions through a more consistent process. The phases we see important are shown in a dotted rectangle in the schema below:

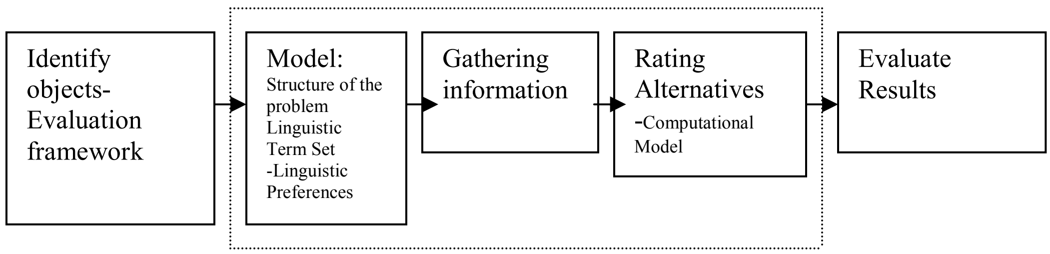


Figure 4.1 Sensory evaluation decision analysis schema.

In the following section we will look into how the phases of linguistic decision analysis for the sensory evaluation will operate using the phases of decision analysis mentioned above.

4.3.1 Modeling (Evaluating the Design)

In this phase, the structure of the problem is presented. Later, some preliminary tasks on how linguistic fuzzy approach may appear in the problem are performed. In this step, first the linguistic term set is formed. Detailed explanations on how linguistic descriptors are formed and how their meanings are selected can be found in Chapter 2 and its subsections. It was also mentioned in 3.5.3.2 that performing linguistic preferences using the utility function provided convenience of operation.

The expressions selected for the linguistic preferences also affect the result of the problem. For instance, if the individual linguistic performance values are expressed as utility function, the aggregated performance value obtained as a result of the problem, too, is expressed as utility function. Thus, the structure of the linguistic preference should be planned at the outset, with respect to the question of the problem.

We mentioned, in the previous chapters, that Herrera and Herrera-Viedma (2000) studied on the phases of decision analysis with linguistic information the subject. They incorporated the phase of forming linguistic information to the process by adding two more phases into the model. Here, it is crucial that the information is formed in accordance with the multi-granular linguistic hierarchy. This enables the information to be processes more efficiently.

Modeling phase, also, enables the configuration of the basis of decision analysis. Using utility function in order to define the linguistic variables properly and in order to present the performance evaluation for the evaluation of the criteria; at the same time using multiple hierarchies in configuring linguistic terms enables the researchers to achieve more consistent results towards making the decision.

In this phase, at the same time, we decide which model, among the ones in the literature, to use for performing the linguistic computations. In this study, we prefer the 2-tuple representation model, as it does not cause loss of information as mentioned in Martínez (2007).

4.3.2 Information Gathering

Information gathering requires obtaining information from the experts. The information obtained from the experts comprises of linguistic evaluations for the features of the objects evaluated, when the representation is done using the utility function.

A group of experts are represented as $\{e_1, e_2, e_3, ..., e_n\}$. The object to be evaluated by the experts are represented as $O = \{o_1, ..., o_m\}$, and the evaluated features of each object as $F = \{f_1, ..., f_n\}$, and the linguistic term set formed with respect to the evaluation as $S = \{s_0, ..., s_g\}$.

The preferences of the expert in the linguistic term set are represented as a utility vector as below:

$$U_i = \{u_{11}^i, ..., u_{1n}^i, u_{21}^i, ..., u_{2n}^i, ..., u_{m1}^i, ..., u_{mn}^i\}$$

This vector represents the utility vector formed according to the *n* features of *m* objects that are evaluated by *i* experts. Thus, each expert represents their own utility vector using the linguistic letters in the linguistic term set.

Since the multi-granular hierarchical structure will be used, while conducting sensory evaluation, the information should have the same hierarchical order. Therefore, the hierarchical order is set in accordance with the information obtained from the experts.

In order to provide the hierarchical order, the conversion formula of the 2-tuple representation model is used. The process in which this operation takes place is the normalization phase, which is the first phase suggested for the aggregation process for multi-granular structures.

4.3.3 Rating Alternatives

The evaluation of the information obtained from the experts is done in this phase. The information normalized in the information gathering phase are aggregated in this phase via aggregation operators.

As for the computational model proposed by Martínez (2007) for sensory analysis, it is the 2-tuple computational model. This model produces more consistent results compared to other models. There are various aggregation operators, developed on this model. The detailed explanation on the operators of this model was given in Chapter 2. The appropriate aggregation operator is selected with respect to the structure of the problem at hand.

This phase, also, can be expressed as the aggregation process. This aggregation process comprises of two phases:

(i). Computing collective evaluations for each feature.
(ii).Computing a collective evaluation for each object.

4.3.3.1 Computing collective evaluations for each feature.

After the information for each f_k feature of each j. o_j objects, gathered from each e_i expert is expressed using u^i_{jk} utility vector, the aggregated value is calculated using the aggregation operators determined in the previous phases in the model represented as the related model AG_1 .

$$u_{jk} = AG_1\{u^1_{jk},...,u^n_{jk}\}.$$

4.3.3.2 Computing a collective evaluation for each object.

In this phase, finding a global u_j value is the purpose. For each object, a value that represents the aggregated form of the features using the aggregation operation AG_2 and aggregation operators determined before.

$$u_j = AG_2\left(u_{j1},\ldots,u_{jk}\right).$$

4.3.4 Evaluating the Results

In order to complete the evaluation process, the values obtained, for use in the analysis of the evaluated objects, in the previous section are used. In sensory analysis problems, the aggregated evaluation obtained from the objects evaluated is put as the result.

The results can be obtained toward different aims. It is possible to indicate which object is the best one among the objects evaluated by the experts; it is possible to rate the value of the object, in any area, with respect to its quality on a scale; or it is possible that one may want to know which feature is much better for the object evaluated. Sensory analysis aiming at these results ends in this phase. The last evaluation criterion of the phase result may vary according to the aim of the problem.

The enhancing phase mentioned in Chapter 3 may differ at this point. In some cases, the result may be wanted to be indicated with its expression in the initial domain. In such cases, if the model implemented is the 2-tuple computational model, the result value is converted to its value in the initial domain using the conversion function. However, in other computational models, loss of information may occur during conversion.

CHAPTER FIVE

SENSORY EVALUATION MODEL OF OLIVE OIL BASED ON LINGUISTIC INFORMATION AND ITS APPLICATION

5.1 Introduction

In this chapter, the phases of decision analysis with respect to the Sensory Evaluation (Martínez, 2008) of the class of natural olive oil, as the basic investigation method, will be scrutinized and will be elaborated through an application.

5.2 Information about National and International Olive Council

International Olive Council is the world's only international and inter-governmental organization for olive oil and table olive. It was founded with the initiative of UN in 1959 in Madrid, Spain. It was named the International Olive and Olive Oil Council (COOI) until 2006, before taking its current name (International Olive Council).

The council supports the international technical cooperation on research, project development, training and technology transfer. It also favours the distribution of international brands in olive oil and table oil, and the making the production of olive and olive oil widespread. The council provides the information in the international olive and olive oil markets to be reliable by encouraging the consumption of olive oil.

Turkey, in 1998, was separated from COI by the exercise of the government of that time. This issue was a matter of debate for the sector. In 21 May 2007, as part of the national agricultural policies determined in the Agriculture Law no 5488, the first product council possessing a legal entity, National Olive and Olive Oil Council was established by merchants and industrialists, who trade the main and by products of olive; and the associations, unions, cooperatives, and institutions comprised of these merchants and industrialists. With the practices of this council, the accession to COI was realized.

5.3 Information on the Standards of International Olive Council

In order to conduct the sensory analysis of olive oil correctly and regularly, documents, accepted as standard by COI, were published. The definitions were standardized in order the tasters to speak a common language and to find the common ground.

Standard COI/T.20/ Doc. No. 4 “Sensory Analysis: General Basic Vocabulary” document provides information on the general basic vocabulary for the sensory analysis. This document designates the basic concepts the tasters use during the taste (International Olive Council).

Standard COI/T.20/ Doc. No.5 “Glass for Oil Tasting” document depicts the properties of glasses to be used in taste (International Olive Council).

Standard COI/T.20/ Doc. No.6 “Guide for the Installation of a Test Room” is a guide for setting up a test room. The room in which the taste is performed should have the qualities determined in the document (International Olive Council).

Standard COI/T.20/Doc. No.14 “Guide for The Selection, Training and Monitoring of Skilled Virgin Olive Oil Tasters” document provides guidance for selecting, training and observing the capabilities of the tasters (International Olive Council).

Standard COI/T.20/Doc. No.15 “Sensory Analysis of Olive Oil Method for the Organoleptic Assessment of Virgin Olive Oil” document explains the sensory analysis method of olive oil for the organoleptic assessment of virgin olive oil (International Olive Council).

5.4 The Sensory Analysis Method of Olive Oil for the Organoleptic Assessment of Virgin Olive Oil

Since the effect of sensory features are considered important in assessing the quality of olive oil, COI developed a method for determining the class of virgin olive oil, keeping the sensory features of virgin olive oil in mind.

The purpose of this method, well accepted internationally, is the assessment of the organoleptic characteristics of natural olive oil, and to provide a new method for classification in terms of these basic characteristics.

The method aims at providing the consumer unflawed oil, and also providing information to the manufacturer about the defect, if there is any, and in which phase of production it might have been occurred with regard of the type of the defect. Thus, it enables sorting out the man-induced errors and increasing high-quality production.

This method is only applicable to virgin olive oil. The classification of olive oil in terms of their defects and fruitiness is performed by a taster in a taste panel. Therefore the sensory analysis of olive oil is a job that requires training and experience.

The taste panel is carried out by the panel leader. A. S. Kantarcı (personal communication, July 2008), a board member of National Olive and Olive Oil Council and one of the most experienced oil tasters in Turkey, argues that the leader who is responsible for carrying out the taste panel should be one who was trained suitably for the olive oil types to be analyzed.

Panel leader is responsible for the organization and operation of the panel. The leader should invite the tasters on a date before the panel and answer all their questions about the panel to be carried out. However, the leader should avoid giving information on the oil samples.

The panel leader is also responsible for taking in inventory and cleaning of appliances; preparing and coding the oil samples; presenting the samples to the tasters in an appropriate order for the experiment; unifying and processing statistically the data obtained. The tastes giving consistent results, first, require the panel to be prepared objectively. Therefore, the panel leader should be objective. The tasters as well as the leader have important role in carrying out the panel appropriately.

The leader of the panel group comprising of the National Olive and Olive Council members is Mrs. Ümmühan Tibet.

In order the color of the olive oil to be tasted not to affect the decisions of tasters it should be kept in coloured glass containers. The properties of the taste glass are determined in Standard COI/T.20/Doc. No.5. There should be 15 ml of oil in each container. A glass cap should be put on the glasses in order the oil not to lose its aroma. The room, in which the taste will be performed, should be organized with regard to Standard COI/T.20/ Doc. No.6. The ideal environment is then the room temperature is 28 $^{o}C \pm 2^{o}C$ and relative humidity is between 60% and 70%. With this temperature, observing the sensory differences of samples and perceiving easily the aromatic elements peculiar to different samples are aimed at.

The best time for taste of oil is the morning. It is recommended that the tastes are performed between 10 am and 12 am in the morning. The precision of olfaction and gustation increases before meals. However, the capacities of tasters in differentiating between similar samples are important and these capacities develop through training.

The rules, the tasters should obey, are determined in chapter 9.4 of COI/T.20/Doc.No.15. According to the standards adopted, the number of tasters for each panel may vary between 8 and 12.

After the appropriate conditions are ensured for the organoleptic assessment of virgin olive oil, the samples coded by the panel leader are presented to the tasters.

After the sample is put in the oil glasses, the tasters, after covering the glass with glass cap, twirl the glass one or two turns or they heat the samples on special heaters; thus the volatile elements in the oil evaporates and the required excitatives for the olfaction of the tasters arise.

Later, the glass cap is removed. The tasters smell the oil by slowly taking deep breaths. Olfaction should not exceed 30 seconds. If the tasters cannot reach any decision after this period, they should rest a short time before repeating the taste.

After the olfactory test, other restronasal, gustatory and tactile tests are performed. The taster takes a sip, approximately 3 ml, of oil and passes it all over his oral cavity, especially the front and back of the tongue to feel the density of its flavor near his throat.

The Palate and the throat are among important indicators for the taster along with the tongue. Sweet, salty, sour and bitter flavors show differences according to the areas of the tongue, the palate and the throat.

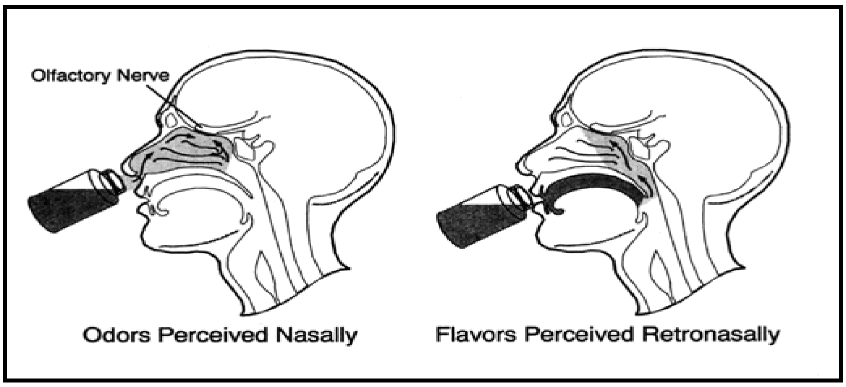


Figure 5.1 The sensory areas of the taster

The taster, after passing the oil in his mouth, takes consecutive short breaths from his mouth and provides the volatile elements in the oil to reach the back parts of the nasal cavity. While the bitter taste is felt in the front areas of the tongue, the pungent taste is felt in the throat.

When passing of oil towards palate and throat by the tongue is not done slowly, either the pungent and bitter features of the oil are not noticed or the pungent feature inhibits the bitter feature.

It is emphasized that the passing of sufficient oil towards the palate from the back of the tongue is of great importance, while the taster concentrates on bitter and pungent excitatives by Ü.Tibet (Personal communication, July 2008).

When virgin olive oil is assessed organoleptically, in order to avoid the interference effect due to taste of different samples, it is recommended to perform at most 3 pass of taste, with 4 samples in each pass.

Between tasting samples, the tongue can be cleansed of the effects of the oil by eating a slice of apple. Later the mouth is gargled with some water in room temperature. It is recommended that the period between two passes of taste is at least 15 minutes.

The organoleptic features of olive oil are categorized as positive features and negative features. The taster should know about the positive and negative features while determining and assessing the organoleptic features of the oil. Olive oil which has the highest quality, known as extra virgin olive oil should not have any negative features.

The perceptions of the tasters, with regard to the intensity of the features after the organoleptic assessment performed in trust of the panel leader and in appropriate conditions taking positive and negative features into consideration, are recorded on a form called profile sheet.

In the standard published by COI, the opinions of the tasters on the features the olive oil, are manifested by the tasters' marking the point, corresponding the intensity of the feature, on an arrow going to infinite, on the profile sheet. The tasters fill in the profile sheets as such. At the end of the panel, the profile sheets are delivered to the panel leader.

Panel leader converts the intensity points marked on the arrow into quantitative expressions using a scale. Thus, the intensities are expressed numerically. Later on, the data obtained from the tasters, are processed using statistical analyses. If 50% of the tasters make mention of various information in the "Other" option, the median of the defect is calculated by the panel leader and an aggregated computation is performed. Medians of each feature are obtained statistically and confidence intervals are built up. Median is a nonparametric method that is preferred in situation where extreme values are possible. In the classical approach, the median method is used, keeping in mind that the tasters may mark extreme values due to differences in their perceptions (International Olive Council)

In the light of the information presented above, according to COI, the classification is done according to the conditions below:

(i). **Extra Virgin Olive Oil:** If the median of defects is 0, and the median of the fruity feature is greater than 0;

(ii). **Virgin Olive Oil:** If the median of defects is greater than 0 and smaller than or equal to 3.5, and the median of the fruity feature is greater than 0;

(iii). **Ordinary Virgin Olive Oil**: If the median of defects is greater than 3.5 and smaller than or equal to 6; or if the median of defects is smaller than 3.5 and the median of the fruity feature is 0;

(iv). **Lampante Virgin Oil:** If the median of defects is greater than 6.

5.5 Sensory Evaluation Model Based on Linguistic Information on Olive Oil

As it was mentioned in the previous section, the organoleptic assessment of olive oil is used in determining the quality type of virgin olive oil. Organoleptic assessment involves a sensory evaluation process. The oil sample to be classified is tasted by the tasters in the panel. As it was mentioned in 5.4, the data obtained from marking of the intensity of the feature, made by the taster on the profile sheets are converted into numerical values using a scale.

As the sensory evaluation of olive oil depends on the experience and perception of the tasters, it can be said that, instead of designating the values of the variables numerically, it is easier for the tasters in expressing their opinions when these values are determined linguistically.

Martínez et al. (2008) put forward a multi-granular sensory evaluation model. The linguistic data is obtained through multi-granular hierarchical structures set up for the features in the profile sheet, within this model. As each taster has different perception and experience, using linguistic words provide more distinct results by avoiding ambiguity caused by these differences. The linguistic values obtained from the tasters are subjected to the sensory evaluation operations developed with regard to the linguistic decision analysis phases.

5.5.1 Assessment Design

While conducting sensory evaluation, a taster may not have the same level of knowledge or tasters may have different levels of perception of one particular feature. Therefore, it would provide convenience for the tasters to prepare a multi-granular linguistic design.

As it is mentioned in the standards of COI, the number of the olive oil tasters may vary between 8 and 12. Here in this study, the assessment process is addressed in respect of a taster team of 8 tasters. The 8 person taster team $E = \{e_1,...,e_8\}$ has to come through by evaluating the designated features positive or negative. There are 5 negative features: Fusty- Muddy- Sediment, Musty-Humid, Wine- Vinegary- Acid – Sour, Metallic, Rancid; and 3 positive features, Fruity, Bitter, and Pungent:

$f = \{f_1,..., f_8\}$

The hierarchical structure for the assessment of olive oil by the tasters, composed for evaluating the features qualitatively, proposed by Martínez et al. (2008) after studies on different taste specialists, is of second level and expressed with 5 letters (Figure 5.2) for some features; and is of third level and expressed with 9 letters (Figure 5.3) for other features.

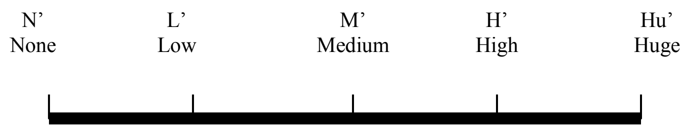


Figure 5.2 Second level scale for sensory evaluation in LH

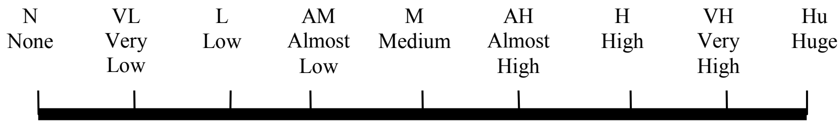


Figure 5.3 Third level scale for sensory evaluation in LH

In this stage, as it is mentioned in Martínez (2007) on sensory evaluation, first linguistic variables and linguistic domains should be composed as in the phase of assessment design.

The linguistic term sets are defined for the linguistic variables which express the positive and negative features in the organoleptic assessment. A multi-granular hierarchical structure is used while composing the linguistic term sets for olive oil. The linguistic term sets with 5 and 9 elements, in terms of the multi-granular hierarchical structure, are composed taking the multi-granular information structure into consideration. The descriptors, along with the element numbers, are generated using an approach based on the ordered structure of the linguistic terms. Later, the meanings of the linguistic descriptors should be determined. At this point, triangular fuzzy numbers and the mixed semantic, which is an approach that depends on the ordered structure of linguistic term set, are seen as option. It is also appropriate to express the linguistic choices as utility vectors.

Later, the linguistic variables and the elements of linguistic terms, and the profile sheet with which the tasters will express the linguistic values about olive oil to be evaluated are formed. The profile sheet, composed using the linguistic expressions for the tasters to express their perceptions linguistically, is presented in the Appendix Section.

5.5.2 Obtaining Information from Tasters

In Obtaining Information phase, the information on the perceptions of the tasters on virgin olive oil is collected linguistically, by giving them the profile sheets composed in the assessment design phase with respect to the standards defined by COI.

Aggregation process starts with this phase, Normalization, the first step of the aggregation process, steps in this phase and the hierarchical conversion technique mentioned in 2.6 to convert the linguistic values of different levels in the hierarchical structure into the determined level.

5.5.3 Rating Objects

In rating the object phase was expressed as "rating alternatives" in sensory evaluation. According to the phases of linguistic decision analysis, this phase corresponds to the choosing the best alternatives. Here, the aggregation operation, after the normalization of the information obtained from the tasters, should be concluded and the final result should be attained. In this phase, the aggregation operators relative to the computational model determined are used.

There are two distinct feature groups for olive oil: positive and negative. The assessments for determining the type of olive oil will be conducted by evaluating these two groups simultaneously. Therefore, in order to obtain an aggregated value for the features, the linguistic expressions collected from tasters for each feature should be aggregated. For this, the median operator relative to the 2-tuple computational model, which was determined as the computational model of this study, is used.

Definition 8: Median Operator: Let $X = \{(s_j, \alpha)_1, ..., (s_j, \alpha)_n\},\ s_j \in S = \{s_0, ..., s_g\}$ be a 2-tuple ordered set. If $(s_j, \alpha)_k$ expresses the k sized element of the set X, median of X, according to the 2-tuple median operator is calculated as below:

$$Med(X) = \begin{cases} Med(X) = (s_j, \alpha)_{\frac{n+1}{2}}, \text{if n odd} \\ Med(X) = (s_j, \alpha)_{\frac{n}{2}}, \text{if n even} \end{cases}$$

If n is an even number it is not unique.

$$Med(X) \in \left[(s_j, \alpha)_{\frac{n}{2}}, (s_j, \alpha)_{\frac{n+1}{2}} \right].$$

$$Med(X) = \Delta\left(\frac{\Delta^{-1}(s_j,\alpha)_{\frac{n}{2}} + \Delta^{-1}(s_j,\alpha)_{\frac{n+1}{2}}}{2}\right). \tag{5.1}$$

This phase consists of two steps:

(i). Computing collective evaluation for each feature.

For aggregation of the values given for each feature by the tasters, the *F=Med(X)* value is obtained using the 2-tuple Λ^F aggregation operator.

(ii).Computing a collective evaluation for each object.

In this step, an aggregated value is obtained for the oil sample at hand using the definition in 4.2.3.1.

During the assessment of the features of olive oil, two values are obtained in this phase. These are the value for the fruity feature among positive features, and the value for the aggregated form of the median values of negative features. Let us assume that p is used for positive features, and d for negative features.

While $d = \max(g_i,...,g_j)$, expresses the negative features $f_i, i \in \{1,2,3,4,5\}$ $g_i = \Lambda^F(f_i)$ defines the median values.

$p = \Lambda^F(f_6)$ defines the median value for the fruity feature.

5.5.4 Evaluating Results

In this phase, a classifier is formed by converting the classification criteria of virgin olive oil, determined in COI standards, using the 2-tuple representation.

The classifying criteria with 2-tuple representation are as below:

$$cls(d,p)=\begin{cases}\text{extra virgin} & \mathrm{d}=\left(\mathrm{s}_0^9,0\right)\text{ve } p>\left(s_0^9,0\right)\\ \text{virgin} & \left(\mathrm{s}_0^9,0\right)<d\leq\left(s_{3,5}^9,0\right)\text{ve } p>\left(s_0^9,0\right)\\ \text{ordinary virgin} & \left(\mathrm{s}_{3,5}^9,0\right)<d\leq\left(s_6^9,0\right)\text{ya da d}\leq\left(\mathrm{s}_{3,5}^9,0\right)\text{ve p}=\left(\mathrm{s}_0^9,0\right)\\ \text{lampante} & \mathrm{d}>\left(\mathrm{s}_6^9,0\right)\end{cases}\tag{5.2}$$

The result is attained by comparing the d and p values obtained in the second step of Rating Objects phase with the classifier defined above and thus the type of the olive oil is determined. The values are presented differently in the Turkish Food Codex of 2007 (T.C. Tarım ve Köyişleri Bakanlığı, 2007).

5.6 Application

In the application section of this study, a database, comprising of the linguistic information on training samples used in the taste panel organized between 8 and 10 March 2010 by National Olive and Olive Oil Council and EBSO (Aegean Region Chamber of Industry) and training samples used in the panel organized between 23-25 June 2010 by the National olive and Olive Oil Council, is established.

At the same time, a software called SAPOO (Sensory Analysis Package: Olive Oil) is developed using Borland C++ Builder environment. In this software, the sensory evaluation model based on linguistic decision analysis, which is the main analysis method in the study, is used to determine the type of virgin olive oil. The menus of the software are designed in order to facilitate the panel leader.

The database is established by taking four tables, namely the taster information, oil information, panel information and company information, as basis. These entries related to these tables are filled in by data entry from the software. These records can be accessed using the submenus of the software. The tables of the database work linked with the analysis table. The new information to be entered in the analysis table is recorded by data calling from the records in the tables.

When the software including the database is run, the following screen welcomes the user (Figure 5.4).

Figure 5.4 SAPOO introduction screen.

5.6.1 Data Entry Phases

Before starting the determining the type of any olive oil sample, the data should be entered into the database. The data entry into the databes can be performed following the steps below:

I. The information of the companies, from which the samples subject to sensory analysis are obtained, is recorded. In order to enter data in the "Company Information" field, the Data→ "Company Information" subtab is selected (Figure 5.5). The data is entered in the screen (Figure 5.6).

Figure 5.5 Company information access screen.

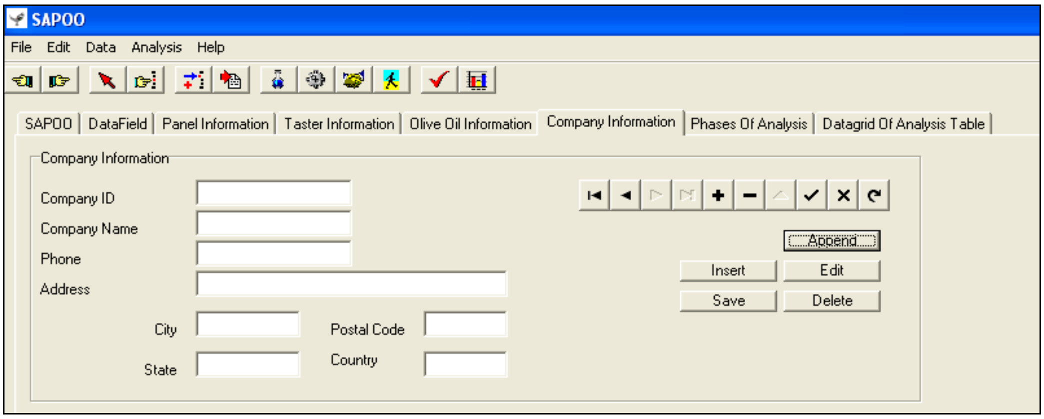


Figure 5.6 Company information data entry screen.

II. The data on the Olive Oil Samples subject to sensory analysis are entered. In order to enter data in "Olive Oil Information" field, Data → Olive Oil Information subtab is selected (Figure 5.7). The data is entered in the screen (Figure 5.8).

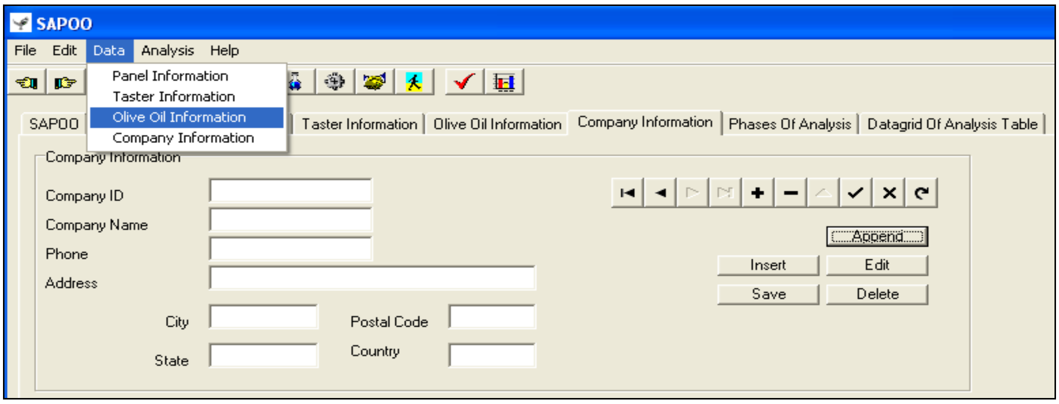


Figure 5.7 Olive oil information access screen.

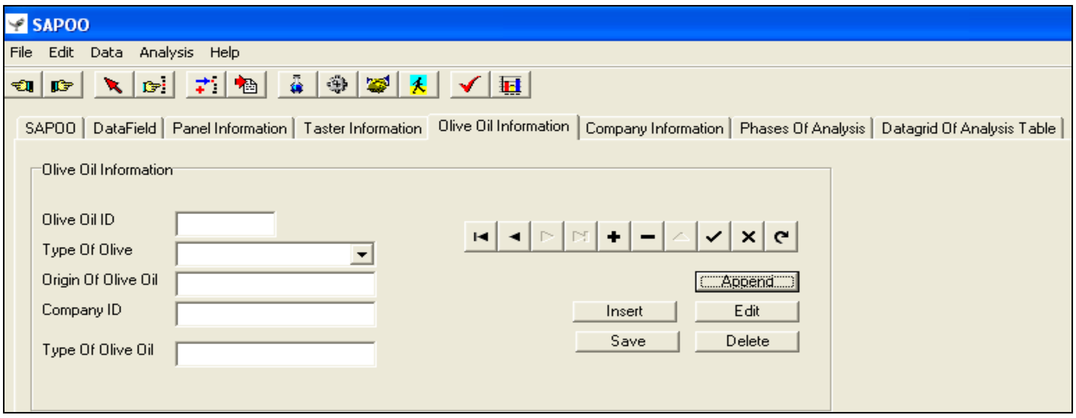


Figure 5.8 Olive oil information data entry screen.

III. The information on the tasters, who will perform the assessment depending their experience and perception on the samples subject to sensory analysis are recorded. In order to enter data into “Taster Information” field, Data→ Taster Information subtab is selected (Figure 5.9). The data is entered in the corresponding screen (Figure 5.10). Here, panel leaders are also recorded as taster by giving the corresponding number.

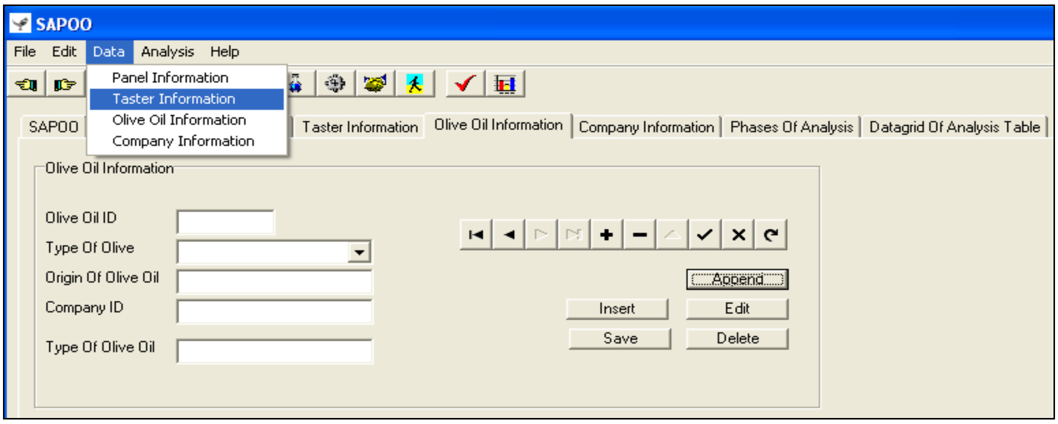


Figure 5.9 Taster information access screen.

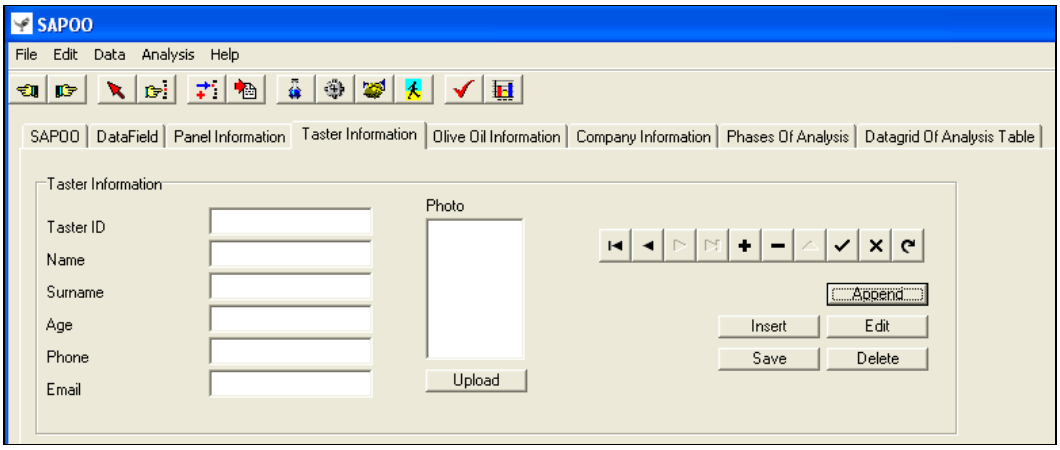


Figure 5.10 Taster information data entry screen.

IV. The information on the panels, in which the samples subject to sensory analysis are evaluated, is recorded. In order to enter data into “Panel Information” field, Data→ Panel Information subtab is selected (Figure 5.11). The data is entered in the corresponding screen (Figure 5.12).

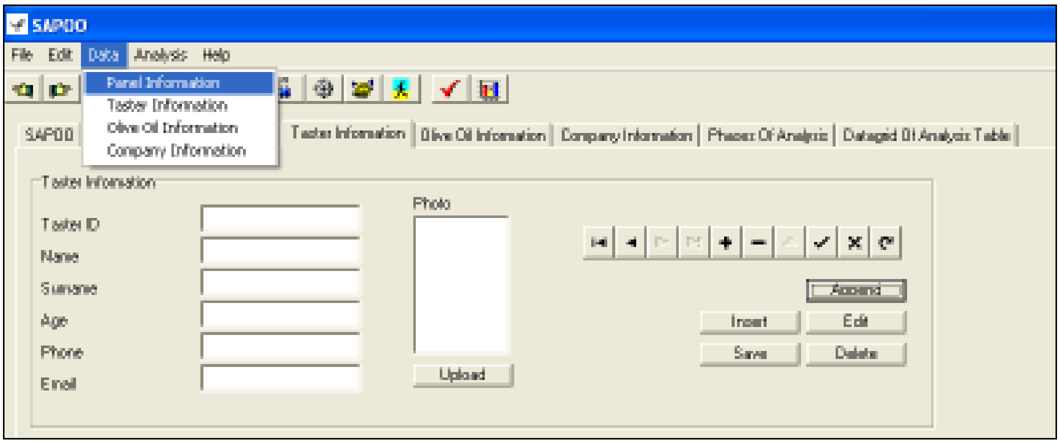


Figure 5.11 Panel information access screen.

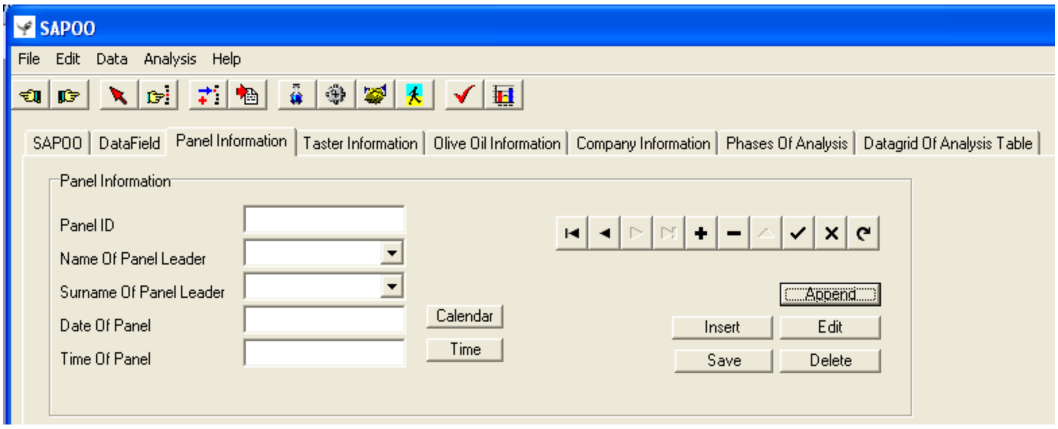


Figure 5.12 Panel information data entry screen.

By performing the phases above, the basic information required for determining the type of virgin olive oil is recorded into the database. When the data recorded in the tables of the database is required to be reported, the relative report can be accessed using the subtabs of File tab (Figure 5.13).

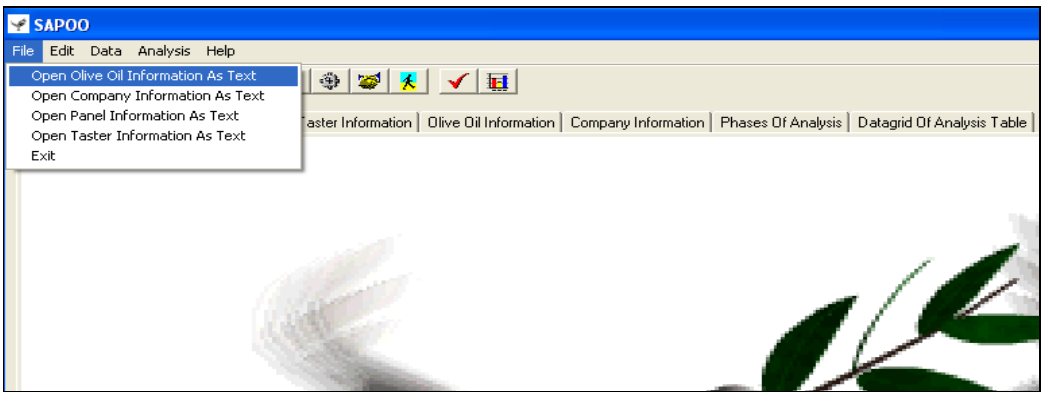
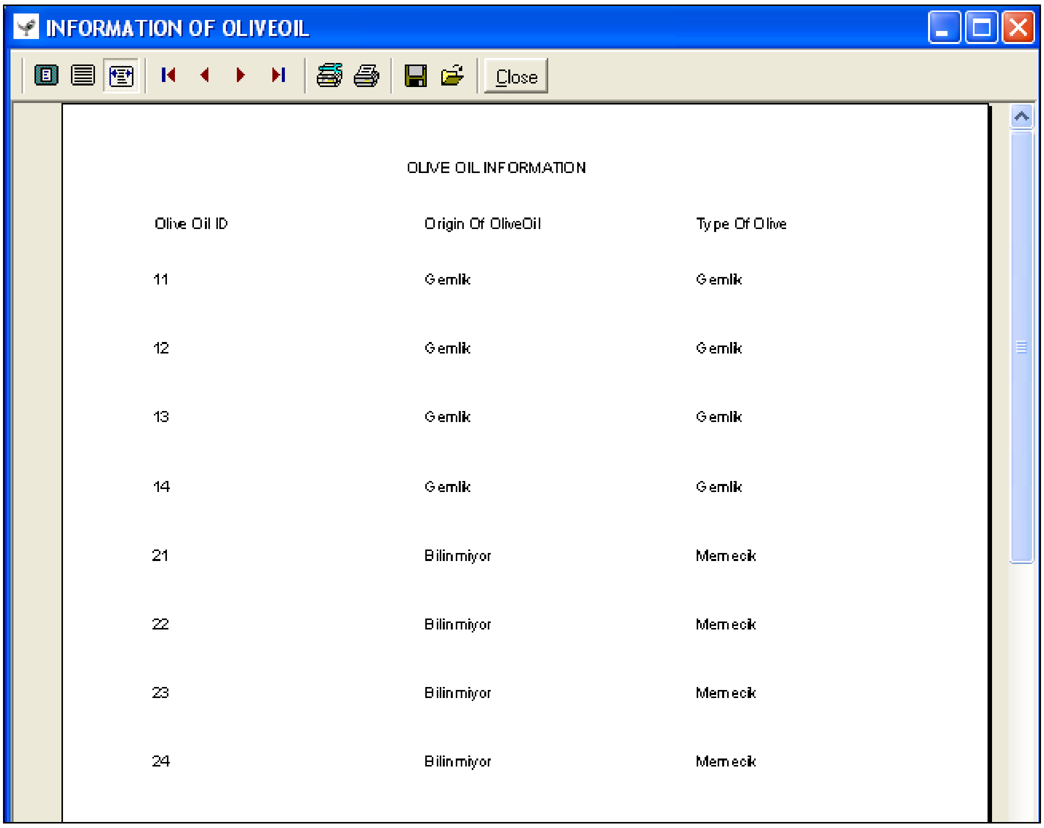


Figure 5.13 Olive oil information report access screen

Reports can be saved as file or can be printed out. The report on the olive oil information can be accessed as below (5.14). Similarly, the data in the tables “Company Information”, “Panel Information” and “Taster Information” can be reported.



Olive Oil ID	Origin Of OliveOil	Type Of Olive
11	Gemlik	Gemlik
12	Gemlik	Gemlik
13	Gemlik	Gemlik
14	Gemlik	Gemlik
21	Bilinmiyor	Memecik
22	Bilinmiyor	Memecik
23	Bilinmiyor	Memecik
24	Bilinmiyor	Memecik

Figure 5.14 Olive oil information report screen

5.6.2 Determining the Type of Virgin Olive Oil

In 5.5.1 we mentioned the assessment design. The data is obtained from the profile sheets composed to collect the linguistic information from the tasters. The 2-tuple computational model is used in the process of computing with words. 2-tuple median operator is preferred as the aggregation operator. In order to perform the analysis in the software developed, Analysis → Satisfy Type Of Natural Olive Oil route is followed.

The “panel”, “taster”, “olive oil” information and the linguistic values related to the features of the samples recorded by the tasters are entered into the Data Field (Figure 5.15).

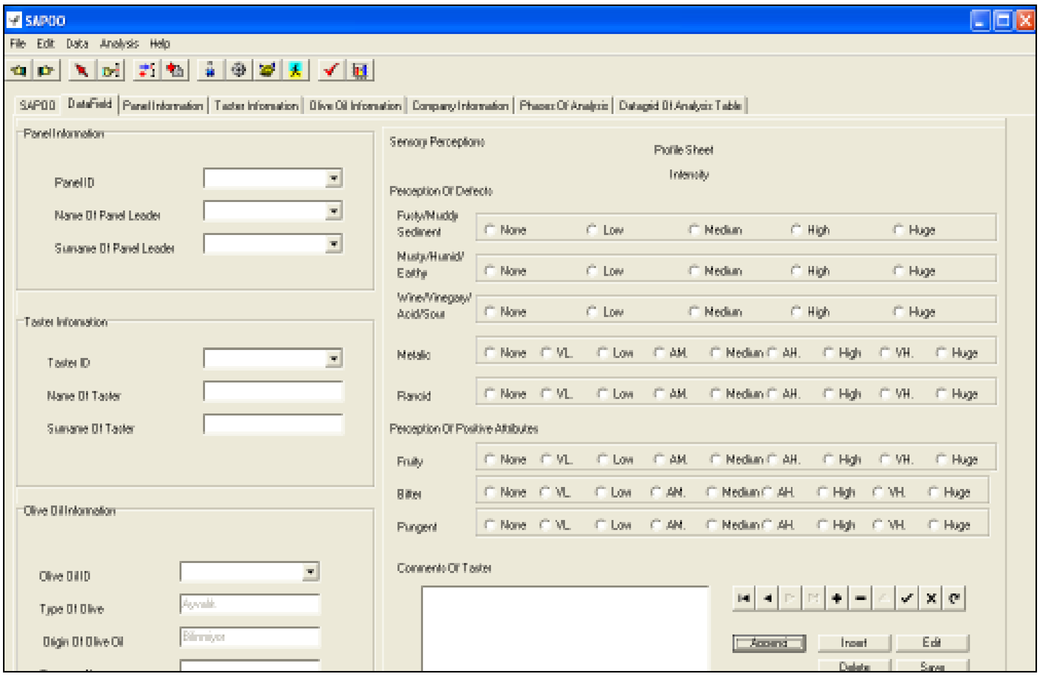


Figure 5.15 Data field, data entry screen.

After the data entry into the Data Field is completed, the analysis is performed (5.16).

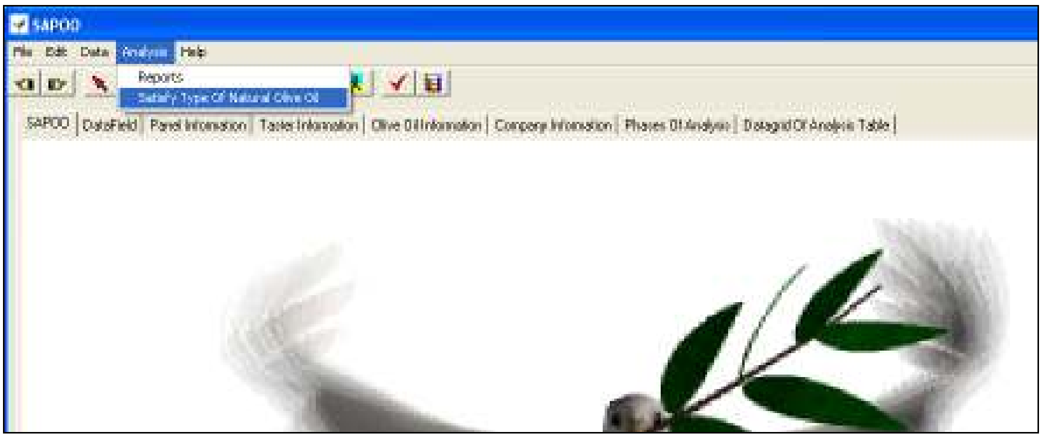


Figure 5.16 Data analysis access screen.

The result related to the type of olive oil is recorded into the database table holding the olive oil information first. Later, it is designated as the corresponding type of olive oil under the title “Type of Olive Oil” in the Olive Oil Data Entry Screen (5.17).

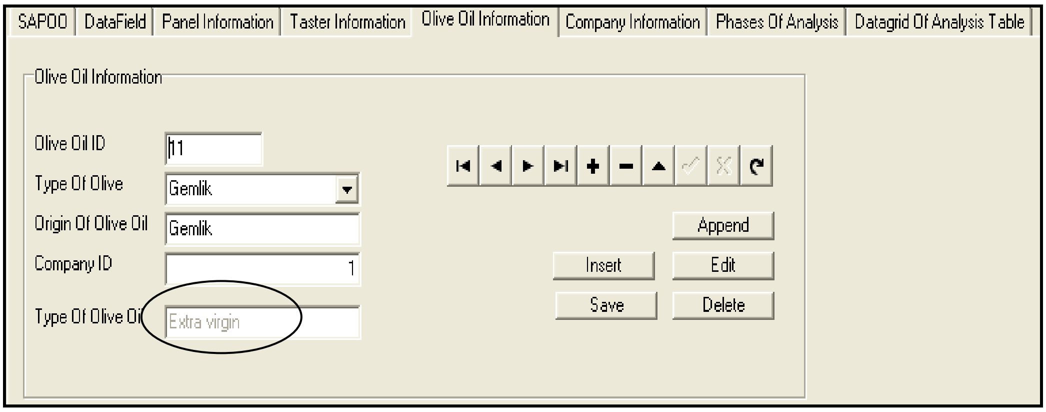


Figure 5.17 Data analysis, olive oil information subtab screen.

As the data entry is completed, the phases of decision analysis will be conducted. These phases will be conducted as below (Table 5.1), when oil sample No 11 in panel No 11 is taken into assessment with 8 person taster team.

Table 5.1 Olive oil taste panel utility vectors for each variable obtained from tasters.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
e_1	M'	N'	N'	N	L	VL	VL	N
e_2	N'	N'	N'	N	VL	AH	L	AH
e_3	N'	N'	N'	N	N	VL	N	L
e_4	N'	N'	N'	N	N	VL	N	VL
e_5	N'	N'	N'	N	N	AH	N	M
e_6	N'	N'	N'	N	N	AH	M	M
e_7	N'	N'	N'	N	N	M	L	L
e_8	N'	N'	L'	N	VL	VL	N	VL

The data obtained linguistically from the tasters are presented using 2-tuple representation model as below (Table 5.2):

Table 5.2 Olive oil taste panel utility vectors for each feature under 2-tuple representation model.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
e_1	$(s_2^5,0)$	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^9,0)$	$(s_2^5,0)$	$(s_1^9,0)$	$(s_1^9,0)$	$(s_0^9,0)$
e_2	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^9,0)$	$(s_1^9,0)$	$(s_5^9,0)$	$(s_2^9,0)$	$(s_5^9,0)$
e_3	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_1^9,0)$	$(s_0^9,0)$	$(s_2^9,0)$
e_4	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_1^9,0)$	$(s_0^9,0)$	$(s_1^9,0)$
e_5	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_5^9,0)$	$(s_0^9,0)$	$(s_4^9,0)$
e_6	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_5^9,0)$	$(s_4^9,0)$	$(s_4^9,0)$
e_7	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^5,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_4^9,0)$	$(s_2^9,0)$	$(s_2^9,0)$
e_8	$(s_0^5,0)$	$(s_0^5,0)$	$(s_1^5,0)$	$(s_0^9,0)$	$(s_1^5,0)$	$(s_1^9,0)$	$(s_0^9,0)$	$(s_1^9,0)$

The linguistic term sets are expressed on second and third levels using the multi-granular hierarchical structure for each feature. In the normalization process these expressions are converted into third level expressions using the hierarchical conversion (2.2) explained in 2.6.2 (Table 5.3).

Table 5.3 2-tuple representation of olive oil taste panel utility vectors for each feature under normalized S^9 .

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
e_1	$(s_4^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_2^9,0)$	$(s_1^9,0)$	$(s_1^9,0)$	$(s_0^9,0)$
e_2	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_1^9,0)$	$(s_5^9,0)$	$(s_2^9,0)$	$(s_5^9,0)$
e_3	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_1^9,0)$	$(s_0^9,0)$	$(s_2^9,0)$
e_4	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_1^9,0)$	$(s_0^9,0)$	$(s_1^9,0)$
e_5	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_5^9,0)$	$(s_0^9,0)$	$(s_4^9,0)$
e_6	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_5^9,0)$	$(s_4^9,0)$	$(s_4^9,0)$
e_7	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_4^9,0)$	$(s_2^9,0)$	$(s_2^9,0)$
e_8	$(s_0^9,0)$	$(s_0^9,0)$	$(s_2^9,0)$	$(s_0^9,0)$	$(s_1^9,0)$	$(s_1^9,0)$	$(s_0^9,0)$	$(s_1^9,0)$

After the data are normalized as above, in aggregation phase two steps are followed.

- Computing collective evaluation for each feature:

The linguistic information obtained from the tasters for each feature is aggregated using the 2-tuple computational model with the median operator mentioned in 5.5.3 (Table 5.4).

For instance;

$$\Lambda^F\left[(s_1^9,0),(s_5^9,0),(s_1^9,0),(s_1^9,0),(s_5^9,0),(s_5^9,0),(s_4^9,0),(s_1^9,0)\right] = (s_2^9,0.5)$$

The aggregation operator Λ^F for 2-tuples is defined as $F = \mathrm{Med}(X)$ (5.1) .

Table 5.4 Olive oil taste panel utility vectors for each feature relative to 2-tuple median.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8
$\Lambda^F(f_i)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_0^9,0)$	$(s_2^9,0.5)$	$(s_0^9,0.5)$	$(s_2^9,0)$

- Computing a collective evaluation for each object:

After the aggregated assessment is conducted for each feature, another aggregated value should be calculated in order to express the type of olive oil. In this phase, corresponding to the Aggregation-Development phase, the aggregated values for both positive features and for the fruity feature, one of the positive features, are taken into consideration.

Let *p* express the value of fruity feature and let *d* represent the negative features. These values are calculated as below:

While $d = \max(g_i, \ldots, g_j)$ $g_i = \Lambda^F(f_i)$ represents the median for negative features $f_i, i \in \{1,2,3,4,5\}$, $p = \Lambda^F(f_6)$ gives the median value for the fruity feature. The values for the example are as below:

$d = \max\{(s_0^0,0),(s_0^0,0),(s_0^0,0),(s_0^0,0),(s_0^0,0)\} = (s_0^0,0)$.

$p = (s_2^9,0.5)$.

For the comparison of *p* and *d* values, the classification rules in formula (5.2) are used.

In this study, the classification rules are used as above. The p and d values obtained for the example are compared to these classification rules. As a result of this comparison, the type of the olive oil is found extra virgin olive oil.

$cls\left((s_0^9,0),(s_2^9,0.5)\right)$: Extra Virgin Olive Oil

As a conclusion, the type of the virgin olive oil sample can be determined as above. It can be said that, this analysis method, supported by the software, yields more reliable result since it enables expressing the perceptions linguistically. The database of the study has 10 company records, 22 oil records, 22 panel records and 47 taster records. As a consequence of these analyses the type of virgin olive oil samples are determined using linguistic expressions. Besides the software enables the user to report the analysis results easily.

CHAPTER SIX

CONCLUSION

We have mentioned that in cases, where the perceptions of experts are at issue, using linguistic fuzzy approach is more appropriate. The fuzziness of this approach enables us to provide a more flexible assessment profile for the experts in expressing their opinions in order to reach meaningful results. Therefore, qualitative modeling of the fuzzy information based on human perception is more suitable for the job. In this study, the sensory evaluation model based on decision analysis for olive oil suggested by Martínez et al. (2008) is applied and results were obtained via qualitative modeling.

The linguistic expressions in the study are formed in a multi-granular structure in order the experts to reflect their opinions more flexibly. In order to obtain more consistent results a 2-tuple computational model, which does not cause any information loss, is used. By this way, the multi-expert decision analysis problem is solved using the linguistic approach as the basic method.

In this study an application is conducted on the sensory evaluation of olive oil with the linguistic values obtained from tasters. This study brings a new perspective on the analysis of sensory evaluation which is based on the experiences and perceptions of the experts. The data used in the application are collected from the taster-candidates who participated in the tasting trainings administered by Mrs. Ümmühan TİBET, the panel leader of the National Olive and Olive Oil Council, in 8-9 March 2010 and 23-25 June 2010. The perception of the candidates of various olive oil samples are indicated on the profile sheets prepared. Using these profile sheets, the type of the olive oil samples subjected to sensory analysis are determined using linguistic values.

Along with this analysis results, this study yielded two by-products. One of them is the software package implemented to determine the type of virgin olive oil, and the other one is that this study has taken the first step to build a wide data bank for olive oil in order to make use of previous and current data on olive oil for the sector to develop.

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APPENDICES

APPENDIX-1

NATÜREL ZEYTİNYAĞI İÇİN PROFİL KAĞIDI

KUSURLARIN ALGISININ YOĞUNLUĞU

Kızışmış/Çamurlu Hiç □ Düşük □ Orta□ Yüksek □ Pek Çok Yüksek □

Küflü/Nemli
/Toprak Hiç □ Düşük □ Orta□ Yüksek □ Pek Çok Yüksek □

Şarabımsı/
Sirkemsi Hiç □ Düşük □ Orta□ Yüksek □ Pek Çok Yüksek □
/Asidik/Ekşi

Metalik Hiç □ Çok Düşük □ Düşük □ Hemen hemen orta □ Orta □
Hemen Hemen Yüksek □ Yüksek □ Çok Yüksek □ Pek Çok Yüksek □

Okside Hiç □ Çok Düşük □ Düşük □ Hemen hemen orta □ Orta □
Hemen Hemen Yüksek □ Yüksek □ Çok Yüksek □ Pek Çok Yüksek □

OLUMLU DEĞİŞKENLERİN ALGISININ YOĞUNLUĞU

Meyvemsi Hiç □ Çok Düşük □ Düşük □ Hemen hemen orta □ Orta □
Hemen Hemen Yüksek □ Yüksek □ Çok Yüksek □ Pek Çok Yüksek □

Acı Hiç □ Çok Düşük □ Düşük □ Hemen hemen orta □ Orta □
Hemen Hemen Yüksek □ Yüksek □ Çok Yüksek □ Pek Çok Yüksek □

Yakıcı Hiç □ Çok Düşük □ Düşük □ Hemen hemen orta □ Orta □
Hemen Hemen Yüksek □ Yüksek □ Çok Yüksek □ Pek Çok Yükse

APPENDIX 1 – CONTINUED

TADIMCI BİLGİLERİ

Tadımcının Adı Soyadı:
Tadımcının Yaşı:
Tadımcının Telefon Numarası:

PANEL BİLGİLERİ

Panel Numarası:
Panel Tarihi:
Panel Saati:
Panel Danışmanının İsmi:

YAĞ BİLGİLERİ

Yağ Numunesinin Kodu:
Yağın Zeytin Çeşidi:
Yağın Mahreci: