

Applied Multi-Expert Decision Making Issue Based on Linguistic Models for Prostate Cancer Patients

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Abstract—In this paper, two models, one is called the probabilistic model and the other is known as the model of 2-tuple fuzzy linguistic representations, are applied to solve multi-expert decision making issues (MEDM). A MEDM problem is considered, in which a group of physicians are independently asked about assessing the effectiveness of a set of treatment therapies for a prostate cancer patient. The objective of this paper is to find the most common judgment by means of these two models. Moreover, fuzzy linguistic terms are used to express the experts' opinions and s-parametric membership functions are designed to depict the fuzzy linguistic terms.

Keywords—multi-expert decision making; group decision making; fuzzy group decision making; linguistic modeling; linguistic choice function; 2-tuple fuzzy linguistic representation model; computing with words (CW).

I. INTRODUCTION

Multidisciplinary team conferences or multidisciplinary cancer conferences play a very important role in decision-making process in modern treatment of cancer patients. In the Urology Department of Blekinge County Hospital, Karlskrona, the Multidisciplinary Team Conference (MDT) is a forum of health care providers including medical oncologists, urologists, urology sub-specialized nurses, radiologists and pathologists. The aim of the conference is to establish assessments and treatment decisions for particular patients with a spectrum of problematic urological conditions that cannot be easily solved by the means of available resources. Our long term aim is also to discuss the best and available treatment modalities of all newly diagnosed cases of prostate cancer. Quite often the decision making process is very clear and straight forward, but some cases lay outside the frames of guidelines and recommendations. Obviously the final choice of a treatment is also on discretion of the patient. This approach has two pitfalls. One of them is when there is a discrepancy between forum members and the other one is when the patient is not interested in the treatment modality chosen by the panel. The best solution is to obtain a method for solving discrepancy and simultaneously to find a method that shows the panel's results as a treatment

recommendation grade range between strongly recommended and contraindicated. Such approach should be very helpful in such diseases as a prostate cancer, which has a broad spectrum of treatment methods that can be tailored to the particular patient's needs and requirements.

In real life, we often are in such situations that we need to evaluate some information by means of numerical values. But when the numerical values are no longer available, then the linguistic approach [1] can be seen as a good alternative. Especially, in medical community, the information often is characterized vaguely and imprecisely, which makes it hard to be evaluated by numerical values. For example, the expressions such as "very painful", "slightly painful", "medium" and "not very painful" are just some examples of the linguistic evaluations of ache degrees of postoperative pain. Also in group decision making cases, when the experts assess the effectiveness of treatment therapies for prostate cancer patients, the semantic terms such as "contraindicated", "doubtful", "acceptable", "possible", "suitable", "recommended" and "strongly recommended" can be used. Comparing to the numerical quantity, the linguistic approach is regarded by [2-3] as a more realistic, intuitionistic and natural method. Due to the advantages of the linguistic approach, an extensive application has been presented in the references [4-6].

By applying two models, namely, the probabilistic model and the 2-tuple fuzzy linguistic representations [7] we wish to select the most consensual treatment therapy for a prostate cancer patient in a multi-expert decision making (MEDM) problem. Thus, the entire process will be defined in the linguistic framework.

The construction of this paper is organized as follows. In Section II the preliminaries are presented. In Section III a practical study about how these methods are applied for a prostate cancer patient is provided and the results are presented. Finally, conclusions and discussion are given in Section IV and V, respectively.

II. PRELIMINARIES

In this section, some preliminary items are presented. We start with the detailed description of the probabilistic model.

In reference [7], a general property of a MEDM problem is considered as the introduction of a finite set of experts denoted by $E = \{e_1, \dots, e_p\}$ who are asked for selecting assessments stated in another finite set of alternatives $A = \{a_1, \dots, a_n\}$. The assessments are expressed by semantic words in an order structured linguistic term set $S = \{s_0, \dots, s_g\}$, such that $s_k < s_l$ if and only if $k < l$. An example of the ordered structured linguistic term set S is given below.

Example 1: Suppose that we determine a linguistic term set $S = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6\}$ consisting of $s_0 =$ “contraindicated” = CI, $s_1 =$ “doubtful” = D, $s_2 =$ “acceptable” = A, $s_3 =$ “possible” = P, $s_4 =$ “suitable” = S, $s_5 =$ “recommended” = R and $s_6 =$ “strongly recommended” = SR.

A. The Probabilistic Model

According to [7], the probability model mainly contains four steps:

- In the first step all the assessments are collected in a judgment table as shown in TABLE I. Here each judgment $L_{ij}, i = 1, \dots, n$ and $j = 1, \dots, p$ is expressed by the linguistic term selected from the linguistic term set S .

We should emphasize that each linguistic term is associated with a general s-parametric membership function [8-10] given by

$$\mu_{s_l}(z) = \begin{cases} 2 \left(\frac{z - ((z_{\min} - h_z) + h_z l)}{h_z} \right)^2 & \text{for} \\ (z_{\min} - h_z) + h_z l \leq z \leq (z_{\min} - \frac{h_z}{2}) + h_z l, \\ 1 - 2 \left(\frac{z - (z_{\min} + h_z l)}{h_z} \right)^2 & \text{for} \\ (z_{\min} - \frac{h_z}{2}) + h_z l \leq z \leq z_{\min} + h_z, \\ 1 - 2 \left(\frac{z - (z_{\min} + h_z l)}{h_z} \right)^2 & \text{for} \\ z_{\min} + h_z l \leq z \leq (z_{\min} + \frac{h_z}{2}) + h_z l, \\ 2 \left(\frac{z - ((z_{\min} + h_z) + h_z l)}{h_z} \right)^2 & \text{for} \\ (z_{\min} + \frac{h_z}{2}) + h_z l \leq z \leq (z_{\min} + h_z) + h_z l, \end{cases} \quad (1)$$

where $z \in [0,1]$ is a symbolic reference set of effectiveness, $z_{\min} = 0$, and h_z is defined as the distance of the peaks between two adjacent fuzzy sets. If we set $z_{\min}$ and h_z as fixed values when

TABLE I. THE JUDGMENT TABLE

Alternatives	Experts		
	e_1	$\dots$	e_p
a_1	L_{11}	$\dots$	L_{1p}
a_2	L_{21}	$\dots$	L_{2p}
$\dots$	$\dots$	$\dots$	$\dots$
a_n	L_{n1}	$\dots$	L_{np}

choosing $l = 0, \dots, g$, then we will obtain the membership functions for $s_0, \dots, s_g$.

- X_{a_i} is assumed as a random preference value for each alternative $a_i, i = 1, \dots, n$, with associated probability distribution P defined by [11] as

$$P(X_{a_i} = s_l) = P_E(\{e_j \in E | z_{ij} = s_l\}). \quad (2)$$

It is worth highlighting that the statement of random preference X_{a_i} is a crucial procedure in the approach of probability. Since each X_{a_i} is stochastically independent of each other, it will make the comparisons of any two random preferences to be possible.

- The choice value $V(a_i)$ for each alternative $a_i, i = 1, \dots, n$, is computed by the choice function implemented by

$$\begin{aligned} V(a_i) &= \sum_{i \neq j} P(X_{a_i} \geq X_{a_j}) \\ &= \sum_{i \neq j} \sum_{s_l \in S} \left[P(X_{a_i} = s_l) \sum_{\substack{z_{ij} \in S \\ s_l \geq z_{ij}}} P(X_{a_j} = z_{ij}) \right], \end{aligned} \quad (3)$$

where the quantity $P(X_{a_i} \geq X_{a_j})$ could be interpreted as the probability of “the performance of a_i is as least as good as that of a_j ”.

- Finally, by ranking the choice values obtained by the former step, we can select the optimal one by (4)

$$a_{\text{optimal}} = \max_{a_i \in A} (V(a_i)). \quad (4)$$

B. The Model of 2-tuple Fuzzy Linguistic Representation

In this model, the physicians' judgments of the treatments are represented by 2-tuples of the form of (s_l, α) , where $s_l \in S$ is a fuzzy semantic term and $\alpha \in [-0.5, 0.5]$ is defined as a numerical value.

A 2-tuple fuzzy linguistic representation model presented in [11] composes the following steps:

- Each judgment which is expressed by a fuzzy semantic word in TABLE I is changed into a 2-tuple fuzzy linguistic representation as (s_l, α) . If $s_l \in S$, then $(s_l, 0)$ will reflect s_l . Next, $x_{a_i} = \{(s_l, \alpha)\}$ is defined as a finite set that consists of judgments of the 2-tuple fuzzy linguistic representations for each alternative $a_i, i = 1, \dots, n$.
- Two transformations are used in this model.

The first transform Δ^1 maps a 2-tuple fuzzy representation (s_l, α) , which belongs to the space of $S \times [-0.5, 0.5]$, into a numerical value $\beta \in [0, g]$. Here s_l has the closest index label to β , and $[0, g]$ represents the interval consisting of the semantic label indices in the linguistic term set $S = \{s_l\}, l = 0, \dots, g$. The action of Δ^1 is formalized by

$$\Delta^1: S \times [-0.5, 0.5] \rightarrow [0, g] \\ (s_l, \alpha) \rightarrow \beta = l + \alpha.$$

Example 2: Let $S = \{s_0, \dots, s_6\}$ and $\beta \in [0, 6]$. In TABLE II the assessment of a_1 , given by expert e_3 , is expressed by the fuzzy semantic term s_2 = "acceptable" = A. By the 2-tuple fuzzy representation we can employ the judgment $(A, 0)$ for s_2 = "acceptable" = A and $\alpha = 0$.

Due to the first transformation, the 2-tuple fuzzy representation of $(A, 0)$ can be performed as a numerical value $\beta = l + \alpha = 2 + 0 = 2$, which belongs to the interval $[0, 6]$.

TABLE II. THE DECISION TABLE OF THE JUDGMENTS

Alternatives	Experts			
	e_1	e_2	e_3	e_4
a_1	s_0	s_1	s_2	s_3
a_2	s_2	s_0	s_1	s_4
a_3	s_3	s_4	s_5	s_1
a_4	s_2	s_1	s_2	s_0

The second transformation Δ^2 can be regarded as an inverse of the first one, i.e., it maps a numerical value $\beta \in [0, g]$ into a 2-tuple (s_l, α) by

$$\Delta^2: [0, g] \rightarrow S \times [-0.5, 0.5] \\ \beta \rightarrow (s_l, \alpha).$$

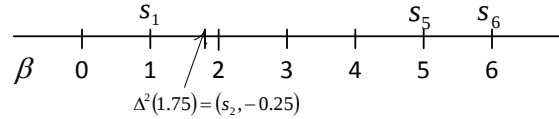


Figure 1. The 2-tuple fuzzy linguistic representation of $\beta = 1.75$

Example 3: Let $S = \{s_0, \dots, s_6\}$ and $\beta \in [0, 6]$. Suppose that $\beta = 1.75 \in [0, 6]$. Since 1.75 is closer to s_2 than to s_1 , then we choose s_2 as the semantic word. The difference between 1.75 and 2 is 0.25, and 1.75 lies to the left of 2. Therefore, we choose -0.25 to be the value of α . By means of the second transformation, $\Delta^2(1.75) = (s_2, -0.25)$, which is depicted in Fig 1.

- The third step contains the computation of the arithmetic mean of $\bar{x}_{a_i}^e$ of 2-tuples for each alternative $a_i, i = 1, \dots, n$. This is based on transformations Δ^1 and Δ^2 involved in

$$\bar{x}_{a_i}^e = \Delta^2 \left(\sum_{l=0}^g \frac{1}{n} \Delta^1(s_l, \alpha) \right). \quad (5)$$

Since the arithmetic means, supplied from the previous step, are presented by 2-tuples, a computational technique to compare the arithmetic mean for each alternative proposed in [11] is given as follows.

- Let (s_k, α_1) and (s_l, α_2) be two 2-tuples fuzzy linguistic representations, with each one representing a counting of information as follows:
 - if $k < l$, then (s_k, α_1) is smaller than (s_l, α_2) .
 - if $k = l$, then
 - if $\alpha_1 = \alpha_2$, then (s_k, α_1) and (s_l, α_2) represents the same information.
 - if $\alpha_1 < \alpha_2$, then (s_k, α_1) is smaller than (s_l, α_2) .
 - if $\alpha_1 > \alpha_2$, then (s_k, α_1) is greater than (s_l, α_2) .
- At last, by comparing the arithmetic values with each other and ranking the alternatives, the optimal alternative(s) will be obtained.

III. A PRACTICAL STUDY

In this section we want to present a practical study in medical group decision making task. The members of a physician group are asked for providing the opinions on some treatment schemes for a prostate cancer patient. The methods of probabilistic model and the 2-tuple fuzzy linguistic model are applied and the results are presented.

A. The Probabilistic Model

Let us suppose that $E = \{e_1, e_2, e_3, e_4\}$ denotes a collection consisting of four physicians. And another set

$A = \{a_1, a_2, a_3, a_4, a_5, a_6\}$ contains sex types of treatment schemes for a prostate cancer patient, where a_1 = “wait and see”, a_2 = “active monitoring”, a_3 = “symptom based treatment”, a_4 = “brachytherapy”, a_5 = “external beam radiation therapy” and a_6 = “radical prostatectomy”. Also, $L = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6\}$ includes seven linguistic terms, in which s_0 = “contraindicated”, s_1 = “doubtful”, s_2 = “acceptable”, s_3 = “possible”, s_4 = “suitable”, s_5 = “recommended” and s_6 = “strongly recommended”.

By inserting $z_{\min} = 0$, $h_z = 0.167$ and $l = 0$ in (1), we obtain the function for s_0 = “contraindicated” expanded by

$$\mu_{s_0}(z) = \begin{cases} 2 \left(\frac{z+0.167}{0.167} \right)^2 & \text{for } -0.167 \leq z \leq -0.0835, \\ 1 - 2 \left(\frac{z}{0.167} \right)^2 & \text{for } -0.0835 \leq z \leq 0, \\ 1 - 2 \left(\frac{z}{0.167} \right)^2 & \text{for } 0 \leq z \leq 0.0835, \\ 2 \left(\frac{z-0.167}{0.167} \right)^2 & \text{for } 0.0835 \leq z \leq 0.167. \end{cases} \quad (6)$$

By following the same procedure for $l = 1, 2, 3, 4, 5$ and 6 we generate membership functions

$$\mu_{s_1}(z) = \begin{cases} 2 \left(\frac{z}{0.167} \right)^2 & \text{for } 0 \leq z \leq 0.0835, \\ 1 - 2 \left(\frac{z-0.167}{0.167} \right)^2 & \text{for } 0.0835 \leq z \leq 0.167, \\ 1 - 2 \left(\frac{z-0.167}{0.167} \right)^2 & \text{for } 0.167 \leq z \leq 0.2505, \\ 2 \left(\frac{z-0.334}{0.167} \right)^2 & \text{for } 0.2505 \leq z \leq 0.334, \end{cases} \quad (7)$$

$$\mu_{s_2}(z) = \begin{cases} 2 \left(\frac{z-0.167}{0.167} \right)^2 & \text{for } 0.167 \leq z \leq 0.2505, \\ 1 - 2 \left(\frac{z-0.334}{0.167} \right)^2 & \text{for } 0.2505 \leq z \leq 0.334, \\ 1 - 2 \left(\frac{z-0.334}{0.167} \right)^2 & \text{for } 0.334 \leq z \leq 0.4175, \\ 2 \left(\frac{z-0.501}{0.167} \right)^2 & \text{for } 0.4175 \leq z \leq 0.501, \end{cases} \quad (8)$$

$$\mu_{s_3}(z) = \begin{cases} 2 \left(\frac{z-0.334}{0.167} \right)^2 & \text{for } 0.334 \leq z \leq 0.4175, \\ 1 - 2 \left(\frac{z-0.501}{0.167} \right)^2 & \text{for } 0.4175 \leq z \leq 0.501, \\ 1 - 2 \left(\frac{z-0.501}{0.167} \right)^2 & \text{for } 0.501 \leq z \leq 0.5845, \\ 2 \left(\frac{z-0.668}{0.167} \right)^2 & \text{for } 0.5845 \leq z \leq 0.668, \end{cases} \quad (9)$$

$$\mu_{s_4}(z) = \begin{cases} 2 \left(\frac{z-0.501}{0.167} \right)^2 & \text{for } 0.501 \leq z \leq 0.5845, \\ 1 - 2 \left(\frac{z-0.668}{0.167} \right)^2 & \text{for } 0.5845 \leq z \leq 0.668, \\ 1 - 2 \left(\frac{z-0.668}{0.167} \right)^2 & \text{for } 0.668 \leq z \leq 0.7515, \\ 2 \left(\frac{z-0.835}{0.167} \right)^2 & \text{for } 0.7515 \leq z \leq 0.835, \end{cases} \quad (10)$$

$$\mu_{s_5}(z) = \begin{cases} 2 \left(\frac{z-0.668}{0.167} \right)^2 & \text{for } 0.668 \leq z \leq 0.7515, \\ 1 - 2 \left(\frac{z-0.835}{0.167} \right)^2 & \text{for } 0.7515 \leq z \leq 0.835, \\ 1 - 2 \left(\frac{z-0.835}{0.167} \right)^2 & \text{for } 0.835 \leq z \leq 0.9185, \\ 2 \left(\frac{z-1.002}{0.167} \right)^2 & \text{for } 0.9185 \leq z \leq 1.002, \end{cases} \quad (11)$$

and

$$\mu_{s_6}(z) = \begin{cases} 2 \left(\frac{z-0.835}{0.167} \right)^2 & \text{for } 0.835 \leq z \leq 0.9185, \\ 1 - 2 \left(\frac{z-1.002}{0.167} \right)^2 & \text{for } 0.9185 \leq z \leq 1.002, \\ 1 - 2 \left(\frac{z-1.002}{0.167} \right)^2 & \text{for } 1.002 \leq z \leq 1.0855, \\ 2 \left(\frac{z-1.169}{0.167} \right)^2 & \text{for } 1.0855 \leq z \leq 1.169. \end{cases} \quad (12)$$

We sample all functions (6)–(12) in a family of fuzzy set restrictions, which are plotted in Fig 2.

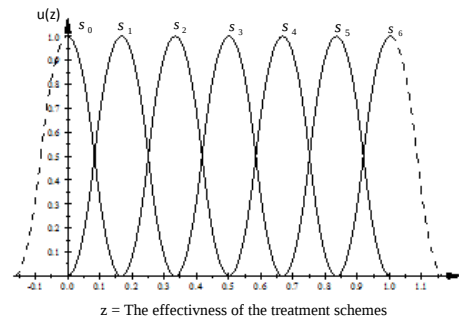


Figure 2. S-parametric membership functions for linguistic fuzzy sets

By using the probabilistic model, we collect all the experts' judgments in TABLE III, whereas the random preference value of each judgment is given in TABLE IV.

By using (3), we calculate the choice value for a_1 as the following structure

TABLE III. THE COLLECTION OF THE JUDGMENTS

Alternatives	Experts			
	e_1	e_2	e_3	e_4
a_1	s_0	s_0	s_0	s_0
a_2	s_6	s_6	s_5	s_5
a_3	s_0	s_0	s_0	s_0
a_4	s_3	s_2	s_4	s_4
a_5	s_3	s_1	s_3	s_4
a_6	s_4	s_5	s_4	s_5

TABLE IV. THE AGGREGATION OF RANDOM PREFERENCE

	Random Preference						
	s_0	s_1	s_2	s_3	s_4	s_5	s_6
X_{a_1}	1	0	0	0	0	0	0
X_{a_2}	0	0	0	0	0	0.5	0.5
X_{a_3}	1	0	0	0	0	0	0
X_{a_4}	0	0	0.25	0.25	0.5	0	0
X_{a_5}	0	0.25	0	0.5	0.25	0	0
X_{a_6}	0	0	0	0	0.5	0.5	0

$$\begin{aligned}
 V(a_1) &= \sum_{1 \neq j} P(X_{a_1} \geq X_{a_j}) \\
 &= \sum_{1 \neq j} \sum_{s_l \in S} [P(X_{a_1} = s_l) \sum_{\substack{z_{ij} \in S \\ s_l \geq z_{ij}}} P(X_{a_j} = z_{ij})] \\
 &= P(X_{a_1} \geq X_{a_2}) + \dots + P(X_{a_1} \geq X_{a_6}) \\
 &= 0 + 1 + 0 + 0 + 0 = 1.
 \end{aligned}$$

For other a_i , $i = 2, 3, 4, 5, 6$, $V(a_i)$ are calculated in the similar way as

$$\begin{aligned}
 V(a_2) &= 1 + 1 + 1 + 1 + 1 = 5, \\
 V(a_3) &= 1 + 0 + 0 + 0 + 0 = 1, \\
 V(a_4) &= 1 + 0 + 1 + 0.75 + 0.25 = 3, \\
 V(a_5) &= 1 + 0 + 1 + 0.5 + 0.125 = 2.625, \\
 \text{and} \\
 V(a_6) &= 1 + 0.25 + 1 + 1 + 1 = 4.25.
 \end{aligned}$$

The collection of choice values for each a_i , $i = 1, \dots, 6$ is aggregated in Table V.

We choose the optimal therapy alternative by means of (4) as

TABLE V. THE COLLECTION OF CHOICE VALUES

The Collection of Choice Value for Each Alternative					
$V(a_1)$	$V(a_2)$	$V(a_3)$	$V(a_4)$	$V(a_5)$	$V(a_6)$
1	5	1	3	2.625	4.25

$$\begin{aligned}
 a_{\text{optimal}} &= \max_{a_i \in A} \{V(a_i)\} = \max\{1, 5, 1, 3, 2.625, 4.25\} \\
 &= 5 = V(a_2).
 \end{aligned}$$

The value of 5 indicates the choice value of a_2 to be maximal. This means that the second therapy alternative is the most efficacious.

We want to confirm the result by applying the model of 2-tuple fuzzy linguistic representations.

B. The Model of 2-tuple Linguistic Representation

According to the algorithm for the model of 2-tuple fuzzy representation, the judgment which is transformed into 2-tuples is given in TABLE VI.

TABLE VI. THE JUDGMENTS EXPRESSED IN THE 2-TUPLES REPRESENTATION MODEL

Experts	Alternatives					
	a_1	a_2	a_3	a_4	a_5	a_6
e_1	(CI, 0)	(SR, 0)	(CI, 0)	(P, 0)	(P, 0)	(S, 0)
e_2	(CI, 0)	(SR, 0)	(CI, 0)	(A, 0)	(H, 0)	(R, 0)
e_3	(CI, 0)	(R, 0)	(CI, 0)	(S, 0)	(P, 0)	(S, 0)
e_4	(CI, 0)	(R, 0)	(CI, 0)	(S, 0)	(S, 0)	(R, 0)

We calculate the arithmetic mean for the first alternative a_1 by means of (5).

$x_{a_1} = \{(CI, 0), (CI, 0), (CI, 0), (CI, 0)\}$ is a finite set consisting of four 2-tuple linguistic representations for the alternative a_1 . By adopting (5), the arithmetic means value for a_1 is calculated as:

$$\bar{x}_{a_1}^e = \Delta^2 \left(\frac{1}{4} (0 + 0 + 0 + 0) \right) = \Delta^2(0) = (s_0, 0.5).$$

For the second alternative the arithmetic means value is given as follows:

$$\bar{x}_{a_2}^e = \Delta^2 \left(\frac{1}{4} (6 + 6 + 5 + 5) \right) = \Delta^2(5.5) = (s_5, 0.5).$$

By the same reasoning, when setting $i = 3, 4, 5, 6$ in (5), we implement

$$\bar{x}_{a_3}^e = \Delta^2 \left(\frac{1}{4} (0 + 0 + 0 + 0) \right) = \Delta^2(0) = (s_0, 0),$$

$$\bar{x}_{a_4}^e = \Delta^2 \left(\frac{1}{4} (3 + 2 + 4 + 1) \right) = \Delta^2(2.5) = (s_2, 0.5),$$

$$\bar{x}_{a_5}^e = \Delta^2 \left(\frac{1}{4} (3 + 1 + 3 + 4) \right) = \Delta^2(2.75) = (s_3, -0.25),$$

and

$$\bar{x}_{a_6}^e = \Delta^2 \left(\frac{1}{4} (4 + 5 + 4 + 5) \right) = \Delta^2 (4.5) = (s_4, 0.5).$$

We present the collection of the arithmetic values for all alternatives in TABLE VII.

TABLE VII. TABLE OF THE ARITHMETIC VALUES

The Collection of the Arithmetic Values					
$\bar{x}_{a_1}^e$	$\bar{x}_{a_2}^e$	$\bar{x}_{a_3}^e$	$\bar{x}_{a_4}^e$	$\bar{x}_{a_5}^e$	$\bar{x}_{a_6}^e$
$(s_0, 0)$	$(s_5, 0.5)$	$(s_0, 0)$	$(s_2, 0.5)$	$(s_3, -0.25)$	$(s_4, 0.5)$

According to the computational technique presented earlier, we compare the above 2-tuples which represent the arithmetic values for all the alternatives. We obtain the result presented as $a_2 > a_6 > a_5 > a_4 > a_1 = a_3$, which shows that alternative a_2 is the most efficacious treatment scheme. This result converges to the previous result from “the probabilistic model”.

IV. CONCLUSION

In this paper two models, like the probabilistic model and the model of 2-tuple fuzzy linguistic representations, have been applied in a MEDM problem to find the most consensual treatment scheme for a prostate cancer patient. The convergence results from both of the approaches verify the high reliability of adopting the linguistic approach in solving group decision making problems. Moreover, the independent assumed preferences of each alternative make the computation of comparing the probabilities easy to be performed. Especially, the use of the 2-tuple fuzzy linguistic representation model prevents the loss of information and makes the result more precise. At last but not at least, the use of s -parametric membership functions not only makes the fuzzy sets intuitionistic, but also increases the accuracy rate of the comparative analysis. Having discovered the hierarchy of therapies we also wish to utilize the formulas of membership functions to assign the group decision efficacy of each treatment to an expression from the list suggested. We treat this query as a challenge in our future research.

V. DISCUSSION

From the medical point of view, we found both methods very interesting in decision-making process when panelists were not unanimous. The results seem to be reasonable. The process of sampling the data by filling the questionnaires was easy and quickly accomplished. We hope to introduce one of the models in our clinical practice to assess the method in a real life conditions. Hopefully, this approach can allow us to find better treatment strategies and to give prostate cancer patients more flexibility concerning the treatment options. This should be a great complement to the current guidelines and scientific society recommendations.

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