Modelling Perceptive-Based Information (Words) For Decision Support System

Elissa Nadia Madi, Binyamin Yusoff

Abstract: Uncertainty analysis can be broadly classified into quantitative and qualitative types. An example of qualitative uncertainty is 'words' as a natural language in which can mean different things to different people. Hence, there is always exist an uncertainty in words or linguistic-linked assessment that need to be considered and manage wisely. Such uncertainty is commonly involve in decision-making problem as it highly dependent on human perceptions. This study explores the relationship between two variables namely the level of uncertainty to the input and the changes of output based on multi criteria decision support system. There is positive relationship between these two variables. Based on that, the novel technique of generating the interval type-2 fuzzy membership functions is proposed where it can accurately map the decision makers' perceptions to the fuzzy set model which can reduce the potential of loss information. In literature, the output ranking of the system is presented as crisp number. However, this study proposed new form of output which is in interval form based on multi criteria decision support. Overall, this study provides a new insight of how we should not ignore the uncertainty when it affects the input by provide an intelligent way to map human perceptions to the system using fuzzy set.

Index Terms: fuzzy set, membership functions, multi criteria decision support.

I. INTRODUCTION

Human life is always characterized by subjective judgments where they consist of different personal opinions which influenced by various fac tors such as personal views, experience and background. They are made using a mixture of qualitative and quantitative information. Qualitative information cannot be directly measured. For example, human perceptions, feelings, emotions and words. However, quantitative information can be directly measured or computed from direct measurement such as a mean value of temperatures, standard deviations of days, etc. Regardless of any kind of information, either they are qualitative or quantitative, there always has uncertainty about it and the amount of uncertainty can exist from small to large in size.

Qualitative uncertainty can be distinguishing with quantitative uncertainty; for example, words can be interpreted with different things to different people. Therefore, there are linguistic uncertainties related to them that need to be considered and manage wisely. Qualitative uncertainty commonly involves in decision-making problem as the problem is highly dependent on human perceptions. In this problem, for certain context, it is highly dependent on words (i.e., perceptions and words) where words are utilized as the main input to reach the desired decision. However, words are always characterized by uncertain and vague meaning, which result in increasing complexity of solving the decision-making problem. Fuzzy sets can be considered as one of the successful traditional frameworks in dealing with uncertainty where the uncertainty is presented by the degree of membership, within the range of [0, 1] (i.e., certainty degree assigned the elements to belong to the set or not). However, in [1] argued that fuzzy set (also known as Type-1 fuzzy set, T1FS) is not suitable to model words. In [2] introduced an extension of T1FS set known as Type-2 fuzzy set (T2 FSs) in 1975 wherein this set, there exist additional dimension which associated with uncertainty about the degree of membership. For example, consider the room temperature; whether the temperature of 27 degrees Celsius belongs to this set or not may have a degree of membership of 0.9 with a certainty of 0.5 and a membership of 0.8 with a certainty of 0.6. Type-2 fuzzy set (T2 FS) is known as one of successful methods to model the problem. It is useful when uncertain information is present in determining the precise and exact membership function for a set. In most cases, however, providing crisp numbers, for example, using Likert scale to assess something for either to determine level of certain or measure a degree of belonging to the set is problematic (i.e. there could exist uncertainties about them), and thus it is more meaningful to provide intervals [3]. Therefore, the theory of type-2 fuzzy set provides a useful account of how uncertainties should be handled in the decision-making process when uncertainty about words is present.

Multi-criteria decision support problems are one of the critical issues in the domain of decision science. The problem become complex when criteria and alternatives are conflicting with each other's. Commonly, a group of decision makers (DMs) give evaluation to each alternative in the predetermined set $A=\{A_1, A_2, \ldots, A_n\}$against different criteria. However, the problem arises when dealing with subjective preferences (i.e., qualitative information) as the qualitative information has dynamic characteristic as compared to quantitative information [4]. The variations in human preferences can be modelled accurately in order to design an intelligent decision-support system (DSS). In other words, the construction of the system should be aimed to mimic human reasoning in conjunction with using imprecise information to reach the decision. In general framework of fuzzy multi-criteria decision support system (MCDSS), exist an approach to assign a set of linguistic term (Bad, Moderate, Good, etc.) using fuzzy membership functions (MFs) to give rating of each alternative against a set of criteria. For example, one of the techniques, known as

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Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) [5], the performance of a set of alternative is evaluated with respect to a set of criteria using specific scale which then mapped into the fuzzy MFs with associated parameter (Table 1). The evaluation from decision maker is mapped using fuzzy set in order to perform pre-processing evaluations given by decision maker. For example, the linguistic label Good, can be approximated in a range of value, for example, 8 - 10.

Table 1: Linguistic labels for rating alternatives in decision making

Linguistic Labels	Poor (P)	Moderate (M)	Good (G)
Fuzzy Number	(0, 0, 5)	(0, 5, 10)	(5, 10, 10)

However, the conventional FTOPSIS used Type-1 fuzzy sets (T1FSs) where it characterized by precise membership functions in the range [0, 1], which resulted that the uncertainty is disappeared once they have been chosen. In addition, human as a decision maker exhibit dynamic behavior which caused dynamic variation in the decision making process [6]. Recently, a variety of fuzzy set frameworks has been suggested to model uncertainty. The main challenge in the construction of the model is the generation of the fuzzy MFs [7], [8]. In the MCDSS framework, this will affect the overall ranking result at the end of the model. Additionally, lack of investigations has been observed in the literature on how to construct the MFs and specify the parameter of MFs in MCDSS paradigm. Thus, in this study, an experiment is conducted by introducing a various level of small changes in parameter which simulate the level of uncertainty in the MFs which associated with the linguistic labels. The purpose of doing this is to explore any relationship between the amount of uncertainty (i.e., small changes level) introduced in MFs and to observe changes of overall decision support output. In addition, this experiment will lead towards a proposal of a novel and direct technique to generate Type-2 MFs for providing a better and accurate model of uncertainty based on MCDSS technique. Additionally, the output results are remains in the same form of information which is in a range of values (i.e., interval form). This type of output results is the main difference as opposed to the standard MCDSS technique wherein classical one, it provides output results in a crisp rank. Thus, this novel technique is interesting when both the input and output of the information are in the same form. Furthermore, it can minimize the potential of loss of information during the process by mapping all the information directly to fuzzy sets.

The paper is organized as follows. In Section II, the background of the study is presented. In Section III, we demonstrate the synthetic example which implements TOPSIS model. Section IV explains the proposed method to design fuzzy membership functions (MFs) as well as the implementation of the proposed model. Section V provides a discussion based on the result. Finally, we state our conclusions in Section VI.

II. RESULTS & DISCUSSIONS

This section provides a review of theoretical background used in this paper, namely fuzzy set theory, construction of fuzzy membership functions and the detail of fuzzy TOPSIS as one of the multi-criteria decision support system models.

Fuzzy Set Theory

Definition 1: A Fuzzy Set A or (Type-1 FS) in universe of discourse R is defined as:

$$A = \{(x, \mu_A(x)) | \forall x \in X\}, \quad (1)$$

where $\mu_A(x) \to [0,1]$ is the degree of membership expressed by membership functions (MFs). If $\mu_A(x)$ equals 1, x absolutely belongs to a fuzzy set A. Unlike in the conventional set theory, the degree of belonging, $\mu_A(x)$ may be a value between 0 and 1, which taking partial membership of x in the fuzzy set A [9].

Definition 2: A fuzzy number is a fuzzy set defined on R that meet the conditions of convexity and normality [10].

Definition 3: A Type-2 Fuzzy Set (T2FS), denoted $\tilde{A}$, is characterized by a Type-2 membership function$\mu_{\tilde{A}}(x, u)$, where $x \in X$ and $u \in J_x \subseteq [0,1]$ as shown in:

$$\tilde{A} = \{((x, u), \mu_{\tilde{A}}(x, u)) | \forall x \in X, \forall u \in J_x \subseteq [0,1]\}, \quad (2)$$

in which $0 \leq \mu_{\tilde{A}}(x, u) \leq 1$. $\tilde{A}$ can also be expressed as:

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{A}}(x, u)/(x, u), \ J_x \subseteq [0,1], \quad (3)$$

where $\iint denotes$ union over all admissible x and u. For discrete universes of discourse $\int is$ changed by $\sum$.

Definition 4: Let all $\mu_{\tilde{A}}(x, u) = 1$ in both (2) and (3), then $\tilde{A}$ is an interval type-2 fuzzy set (IT2FS) [11].

Definition 5: Footprint of uncertainty (FOU) is defined as the union of all primary memberships of an IT2FS, where $\tilde{A}$ consists of a bounded region [11]:

$$FOU(\tilde{A}) = \cup_{x \in X} J_x \quad (4)$$

Construction of Fuzzy Membership Functions

Linguistic variables are often vague and imprecise in nature since their meanings are based on a context-dependent. For example, the concept of cheap and expensive are not only depend on a single factor (e.g., depend on an item), but also depend on other external factors (e.g., a buyer or a host of specific circumstances). Thus, the construction of fuzzy sets involves a specific domain of interest, one or more experts in this domain and also a knowledge engineer. There exist two kinds of IT2 MFs that commonly used in the literature; fuzzy set with uncertain mean and fuzzy set with uncertain spread or standard deviation [12]. Both of them are shown in Fig. 1 and 2.

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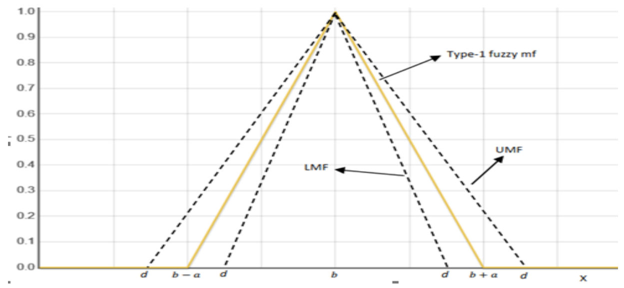

Fig. 1: Uncertain spread fuzzy triangular MF

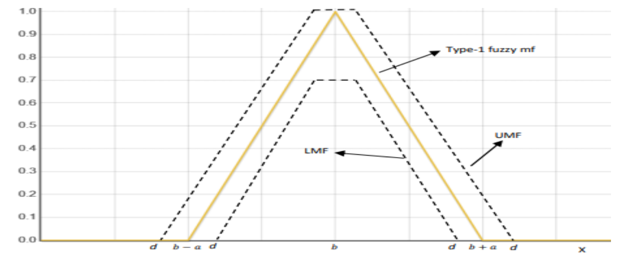

Fig. 2: Uncertain center fuzzy triangular MF

Multi-Criteria Decision Support System (MCDSS)

The Multi-Criteria Decision Support System (MCDSS) is a subset of Multi-Criteria Decision Making (MCDM) method. Since four decades ago, various MCDM methods have been proposed and introduced. Thus, the number of new methods continues to grow from past to present.

Based on the surveys conducted by [13], MCDM is one of the powerful tools for obtaining the best choice for complex decision making situations. The MCDM methods have also been successful applied in various domains.

MCDM can be classified into two main categories: 1) Multi-Objective Decision Making (MODM); 2) Multiple-Attribute Decision Making (MADM [14], [15]). MODM method is suitable for the design or planning model, which its main objective is to achieve an optimal solution by taking into account the various interactions among the given constraints. MADM is a method which makes selections among some elements in a set of actions with the presence of multiple, commonly conflicting attributes. We are particularly interested in one of MADM methods namely as Fuzzy TOPSIS.

The selection of this method to be implemented in our experiments are basically motivated by few findings provided by some studies. For example, in [16] concluded, the simulation experiment provide result that TOPSIS has the fewest rank reversals among other MADM methods. Additionally, a survey conducted by [17] conclude that, among numerous MCDM methods developed to solve real-world decision problems, the TOPSIS method continues to work satisfactorily across different application areas. More recently, in [18] claimed that TOPSIS method is suitable for cautious (risk avoider) decision maker(s), because the decision maker (s) may want to have a decision which not only makes as much profit as possible but also avoids as much risk as possible. Thus, in this study fuzzy TOPSIS method [5] is implemented in our experiment to observe changes in the overall decision support output when various uncertainty level is introduced in the membership functions. A reader is advised to refer Fig. 3 and [19] for further reference on a step-wise procedure in fuzzy TOPSIS technique.

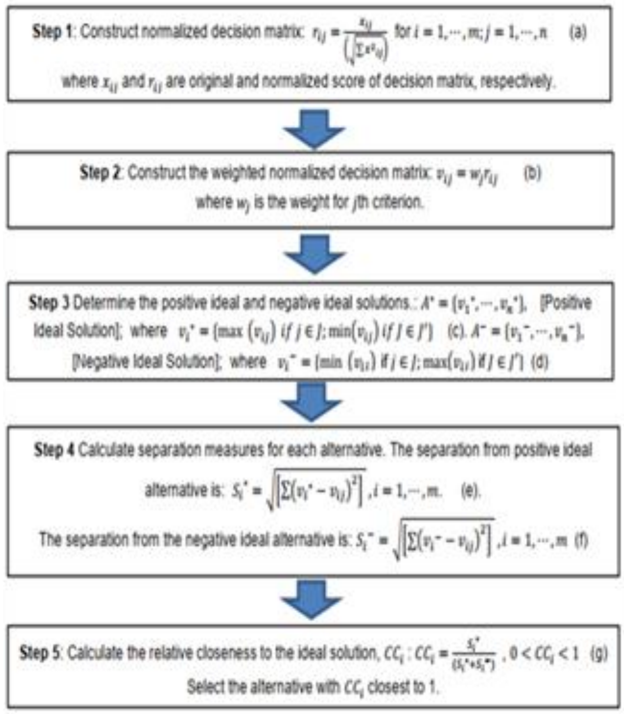

Fig. 3: Stepwise procedure of Fuzzy TOPSIS

III. INTRODUCING UNCERTAINTY INTO MEMBERSHIP FUNCTIONS

Generation Type-1 Fuzzy Membership Function

Fuzzy sets are commonly used to represent linguistic variables such as *height* or *goodness* on an everyday basis. On real-world occasions, the decision maker normally faced difficulty in providing an assessment in a certain and precise manner. Thus, it is quite natural to use words instead of numerical values to provide assessment or evaluations. In the standard fuzzy TOPSIS method, the scale is developed using TFNs. For example, as shown in Table 1. In this study, the evaluation given by a set of the decision maker to the fuzzy TOPSIS model should remain fixed and the small changes (i.e., level of uncertainty present in MFs) to overall decision support output would be explored. The effect of introducing small changes to the MFs is investigated by using type-2 fuzzy TOPSIS method. Next, the details of the overall experimental procedure are explained using the following example.

Example 1

Assume that a couple wants to buy a car. After preliminary screening, two types of car, Car 1 and Car 2 remain for further evaluation. A couple consists of two decision-makers, D1 and D2 is formed to conduct further evaluation and to select the most suitable car. Three attributes are considered; Economy (C1); Comfort (C2) and Safety (C3). The decision-makers evaluate these two types of cars with respect to the three attributes C1, C2 and C3, where the weighting vector is $w = (0.2,0.4,0.4)$. The decision-makers use the scale (Table 1) to evaluate these two types of cars. Assume that the evaluation are given by

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decision makers D1 and D2 are summarized in Table 2, where the linguistic label used in the evaluation is from Table 1.

Table 2: Rating of each alternative

		DM's Rating	
Criteria	Alternatives	DM1	DM2
C1	A1	G	F
	A2	G	F
C2	A1	G	G
	A2	F	P
C3	A1	P	P
	A2	F	G

We discuss this procedure in two different cases. The first one is using standard fuzzy TOPSIS technique where Type-1 fuzzy MFs are used to represent the label and as we mentioned previously, no uncertainty is present in Type-1 fuzzy MFs. Next, we describe the next case where a series of small changes, known as δ such that $\delta \in [0,1]$, are introduced to the standard T1 MFs and directly construct IT2 MFs.

Additionally, the output results which is index ranking remain in the interval form so that we could preserve as much information as we could and reduced the potential of loss of information. We believed by keeping it in the same form (i.e., interval) the output would be interesting because it is more realistic since in many situations, we normally depend on measures or quantities which are not exact but approximate. Case 1 is presented in the next section followed by Case 2.

Case 1: No Uncertainty Present (T1 Fuzzy TOPSIS)

We can express the evaluating values represented by the linguistic scale in Table 1 by fuzzy triangular numbers, shown as in Table 3. The weight vector is the same for both decision makers. Firstly, we follow the step-wise procedure in the standard fuzzy TOPSIS method to get the ranking output as the decision. The procedure is shown in Fig. 3 and is explained in this section.

Table 3: Rating of alternatives by two DMs

DM 1			
	C1	C2	C3
A1	(5,10,10)	(5,10,10)	(0,0,5)
A2	(5,10,10)	(0,5,10)	(0,5,10)
DM 2			
A1	(0,5,10)	(5,10,10)	(0,0,5)
A2	(0,5,10)	(0,0,5)	(5,10,10)

Following evaluation, the next step is to aggregate all the evaluations values to form a fuzzy decision matrix using (5).

$$x_{ij} = \frac{1}{K}\left[x_{ij}^{1}(+)x_{ij}^{2}(+)\ldots\, x_{ij}^{K}\right] \quad (5)$$

where x_{ij} is the evaluations of alternatives given by kth decision maker.

Next, Table 4 summarized the results for this example. Then, Step 1 (normalization) in Fig. 3 is applied, where j indicates benefit criteria and j' indicates cost criteria. In this example, only benefit criteria are considered. The normalized value is shown in Table 5.

Table 4: Fuzzy decision values

	C1	C2	C3
A1	(2.5,7.5,10)	(5,10,10)	(0,0,5)
A2	(2.5,7.5,10)	(2.5,7.5,10)	(2.5,7.5,10)

Table 5: Fuzzy Normalized Decision Values

	C1	C2	C3
A1	(0.25,0.75,1)	(0.5,1,1)	(0,0,0.5)
A2	(0.25,0.75,1)	(0.25,0.75,1)	(0.25,0.75,1)

Next step is to get the weighted normalized fuzzy decision values which implemented based on Step 2 shown in Fig. 3. In this step, values in Table 5 are multiplied by its associated weight and the result is shown in Table 6. Next, identify the ideal solution values. In this example, the perfect value are used. Both values, Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) are defined as (6) and (7) respectively. The values from Step 3 (Fig. 3) by which the definition of this ideal solution is shown as follows:

$$A^{+} = [(1\ 1\ 1), (1\ 1\ 1), (1\ 1\ 1)] \quad (6)$$

$$A^{-} = [(0\ 0\ 0), (0\ 0\ 0), (0\ 0\ 0)] \quad (7)$$

Table 6: Fuzzy weighted normalized decision values

	C1	C2	C3
A1	(0.05,0.15,0.2)	(0.2,0.4,0.4)	(0,0,0.2)
A2	(0.05,0.15,0.2)	(0,0.1,0.3)	(0.1,0.3,0.4)

Next, use Step 4 (Fig. 3) to find the distance between both ideal solutions and a set of alternatives. In this case, the distance of each alternative and output are summarized in Table 7. The output of this method is the relative Closeness Coefficient (CC) which computed using Step 5 (Fig. 3). Based on this, ranking of alternatives can be determined based on descending order of CC values. In this synthetic example, Car 2 is the best one followed by Car 1.

Table 7: Output for fuzzy TOPSIS

	$dist_i^{+}$	$dist_i^{-}$	CCi	Rank
A1 (Car 1)	0.4803	0.6091	0.1972	2
A2 (Car 2)	2.4884	0.6242	0.2005	1

IV. NOVEL METHOD IN CONSTRUCTION OF INTERVAL TYPE-2 FUZZY MEMBERSHIP FUNCTIONS

In this section, we explained how we construct IT2 MFs using T1 MFs by introducing a series of uncertainty in the MFs. Assume a T1 MFs shown as solid line in Fig. 1 is defined by:

$$\mu_l(x) = \frac{x-b}{a} + 1, \quad \mu_r(x) = \frac{b-x}{a} + 1$$

where $\mu_l(x)$ is the left function, which is strictly increasing and $\mu_r(x)$ is the right function which is strictly decreasing. This is a symmetrical case where the value of a is the same for both the left and the right functions. For a non-symmetrical case, the properties of the function can be summarized as follows:

- a in the left side (a_l) is not equal to a in the right side (a_r)
- $a_l \leq a_r$
- If $(b-a)$, then $b < b+a$

Then, assume we introduced uncertainty with level δ to the same T1 MFs in Fig. 1. The MF is now shifted to IT2 MF where the area between standard T1 MF with upper (UMF) and/or lower (LMF) bound of new MFs are now become footprint of uncertainty (FOU) (Definition 5 in Section II). This is the case where the shape is generated by the uncertain spread. The generalization of the process is summarized in Fig. 1, where this generalization further can be used to generate other type of fuzzy set (e.g., General T2 FS, z-slice based general T2 FS, etc.).

The left, μ_l and right, μ_r MFs are now has 2 functions each, where it defined for UMF and LMF respectively. The UMF and LMF for left side are defined as in (8) and (9) respectively.

$$\mu_l^{UMF}(x) = \frac{x-b}{a-d} + 1 \quad (8)$$

$$\mu_r^{LMF}(x) = \frac{x-b}{a+d} + 1 \quad (9)$$

For the right side, the UMF and LMF are defined as in (10) and (11) respectively.

$$\mu_l^{UMF}(x) = \frac{b-x}{a+d} + 1 \quad (10)$$

$$\mu_r^{LMF}(x) = \frac{b-x}{a-d} + 1 \quad (11)$$

From these definitions (i.e., in (8) to (11)), the construction of any fuzzy MFs can be done directly by specifying the center for triangular MFs and approximate level of uncertainty, δ. Next, we demonstrate the experiment procedure by using this novel fuzzy MF generation as in Example 1 (Section III) and we classified the next problem as Case 2 that is the case of uncertain spread MFs with uncertainty present.

Case 2: Uncertainty Present (Uncertain Spread in Membership Functions)

As we mentioned in Section III-A, a series of the delta is introduced in the standard T1 MFs. The delta, $\delta_i, i = 1,2,\ldots,m$, where $\forall d_i \in [0,1]$, are considered as uncertainty in the decision-making process. In this experiment, we have chosen 7 delta values:

$$\delta_7 = (0.10, 0.15, 0.17, 0.20, 0.30, 0.40, 0.50),$$

where these values are used to shift left and right of every MF according to (8) to (11). We demonstrate for the first case, $\delta_1 = 0.10$, to be implemented in our example, (i.e., Example 1) in Section III-A. The introduction of $\delta_1 = 0.10$ is done by shifted left to 0.10 and shifted right to 0.10 of standard Type-1 MF (Fig. 4).

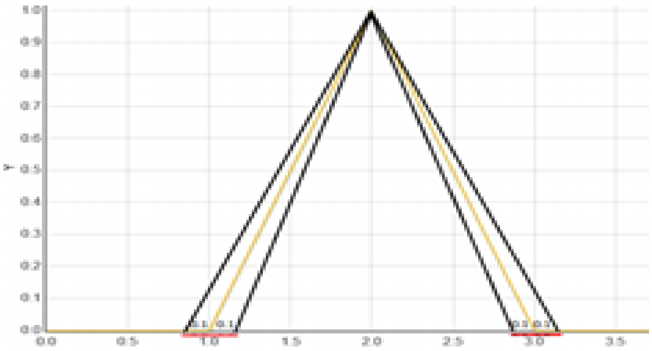

Fig. 4: Triangular fuzzy membership function

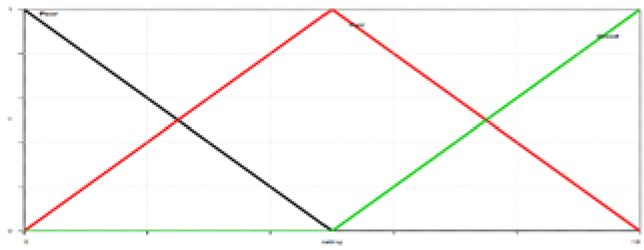

Fig. 5: Triangular fuzzy number for rating scale

Then, a fuzzy variable of `Rating', with 3 linguistic labels, `Poor', `Fair' and `Good', as shown in Fig. 5, is now become an interval Type-2 fuzzy MFs (IT2 MFs), bounded with upper membership function (UMF) and lower membership function (LMF). For example, we defined UMF and LMF of fuzzy label `Poor' as in (12) and (13) respectively.

$$\mu_{poor}^{UMF}(x) = 1 - \frac{x}{0.1} \quad (12)$$

$$\mu_{poor}^{LMF}(x) = 1 + \frac{x}{0.1} \quad (13)$$

Then, we can define fuzzy label `Poor' as an interval type-2 fuzzy number $poor = [(0,0,4.9),(0,0,5.1)]$ where the first element is indicated of lower value and the second element is indicated of upper value. Note that this generation of IT2 fuzzy MF is based on the original T1 fuzzy MF from Fig. 4 and Table 1. The same procedure is applied to generate other linguistic labels such as `Fair' and `Good'. The overall labels for linguistic variable `Rating' is now become interval Type-2 fuzzy MFs. Thus, the labels in the linguistic variable `Rating' is now can be rewritten as IT2 fuzzy linguistic scale as in Table 8.

Table 8: IT2 fuzzy parameters for the rating of alternatives

	IT2 Fuzzy Linguistic Scale
Poor	[(0,0,4.9),(0,0,5.1)]
Fair	[(0.1,5,9.9),(-0.1,5,10.1)]
Good	[(5.1,10,10)(4.9,10,10)]

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Next, the same fuzzy TOPSIS procedure as Case 1 (Section III-A) is applied to get the rank of alternative. However, since the IT2 fuzzy MFs bounded by LMF and UMF, we treated the value separately, i.e., instead of having one single ranking value for output results (CC_i) in this experiment, the result is in interval, which is a novel type of output. We present the experiment result in Table 9 and Fig. 6.

	$\delta = 0.10$	$\delta = 0.15$	$\delta = 0.20$	$\delta = 0.25$
Car 1	[0.1971508, 0.1971569]	[0.1971511,0.1971602]	[0.1971521,0.1971643]	[0.197154,0.197169]
Car 2	[0.2005143, 0.2005666]	[0.2005114,0.2005901]	[0.2005125,0.2006179]	[0.200518,0.200650]

	$\delta = 0.28$	$\delta = 0.30$	$\delta = 0.40$	$\delta = 0.50$
Car 1	[0.197155,0.197172]	[0.1971562,0.1971746]	[0.1971632,0.1971878]	[0.1971730,0.1972040]
Car 2	[0.200522,0.200671]	[0.2005264,0.2006865]	[0.2005556,0.2007729]	[0.2005556,0.2007729]

Table 9: Interval closeness coefficient for uncertain spread MFs

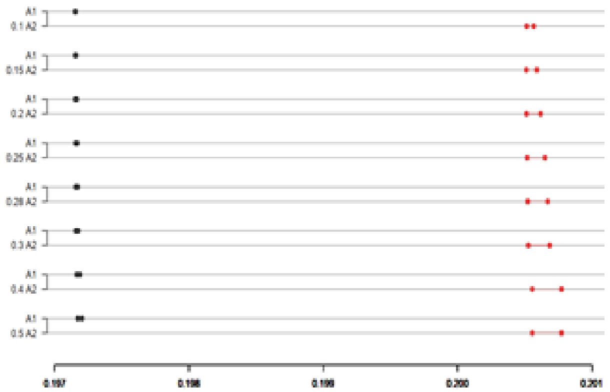

Fig. 6: Case 2 result - Interval closeness coefficient

V. DISCUSSION

For the case uncertainty present, there exist small significance difference of overall decision output. For comparison purpose, we present the result of Type-1 fuzzy TOPSIS, wherein this synthetic example, the closeness coefficient values for both cars are 0.1971524 and 0.2005322 respectively. However, when a series of delta, δ (i.e., uncertainty) is introduced to the uncertain spread MFs, the overall output result has a small difference on the output (i.e., closeness coefficient value) (Table 9). One of the reasons for having slightly different values on output is because, only `Fair' MF having shifted to the left and to the right direction, while two other MFs; `Poor' and `Good', having shifted to the right and left respectively.

Based on this, the difference among various output values should be considered when implement it with any decision-making process. As this generation of fuzzy MFs is fully straight away, there could minimize any potential of loss information when transferring the evaluation made by decision makers to any decision support system. The size of the interval corresponds to the decision makers' level of confidence and certainty. The width of the interval output denotes the decision makers' confidence about the evaluation where a small size of interval is used when they are confidence, and a wider interval is used when they are less confidence. Thus, it can be clearly seen that whenever the uncertainty affects the input, it should be considered that every step in the process has that uncertainty. Each value in interval has a specific meaning that we should not ignore especially when it is applying in a medical context as this context commonly deal with life and death of a human.

VI. CONCLUSION

In this paper, an experiment was conducted by introducing a series of delta δ values to simulate the uncertainty present in the input of the decision-making process. The purpose of doing this is to explore any relationship between the amount of uncertainty introduced in MFs and to observe changes in overall decision support output. Clearly, the presence of uncertainty causes a changing in output values. Further, this experiment successful lead towards a proposal of a novel and direct technique to generate Type-2 MFs for providing a better and accurate model of uncertainty based on MCDSS method. This method has few advantages as it is direct way of generating the MFs, thus, it can minimize the potential of loss information given by decision makers. Additionally, the output results are remains in the same form of information which is in interval-based number. This type of output results is the main difference as opposed to the standard MCDSS method wherein classical approach, it provides output results in a rank of a crisp number. Thus, this novel technique is interesting when both the input and output of the information are in the same form. Each value in the interval is considered and can support the decision maker to decide. The accurately model preference information to fuzzy MFs can reduce the potential of making any misleading decision. In future, we will explore different techniques and methods of a ranking interval. Based on this, we will develop our ranking algorithm specifically focusing on various intervals values.

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