A New Model for Best Customer Segment Selection Using Fuzzy TOPSIS Based on Shannon Entropy

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Abstract

In today's competitive market, for a business firm to win higher profit among its rivals, it is of necessity to evaluate, and rank its potential customer segments to improve its Customer Relationship Management (CRM). This brings the importance of having more efficient decision making methods considering the current fast growing information era. These decisions usually involve several criteria, and it is often necessary to compromise among possibly conflicting factors. In this paper a new extension of fuzzy Techniques for Order Preferences by Similarity to Ideal Solution (TOPSIS) based on Shannon entropy concept for customer segment selection is proposed. Fuzzy set theories are also employed due to the presence of vagueness and imprecision of information. The contribution of this paper is that it provides a framework for MCDM which considers vagueness and ambiguity as well as allowing to set multiple aspiration levels for customer segment selection problems in which ''the more/higher is better'' (e.g., benefit criteria) or ''the less/lower is better'' (e.g., cost criteria).At the end, a numerical example of this approach is shown to illustrate its effectiveness.

Keywords: Fuzzy set theories, CRM, Customer Segment selection, MCDM, TOPSIS, Shannon entropy.

1. Introduction

Nowadays, to remain in competitive environment and to earn higher profit, companies are putting their attention on Customer Relationship Management (CRM). A company's CRM key objective is identifying and satisfying its most profitable customers [1]. For this purpose, customers are segmented based on their demands and characters [2, 3].

It is well-known that not all customers have the same importance when considering the company's profit. Identifying and applying CRM strategies on the most profitable customers will help the company to increase its revenue. In marketing, activity-based costing sometimes justifies management's confidence in the Pareto principle, otherwise known as the 80:20 rule. This rule suggests that 80 per cent of profits come from 20 per cent of customers. Companies should segment and rank their customer base according to their importance in order to choose efficient marketing planning on the targeted valuable customers [3, 4].

The two main factors of firstly, customer specifications such as income level, geographic area, family background, career information, and education level and secondly, the multiplicity of groups, themore the number of groups results in the more careful analysis, make the customer segment selection a rather complex MCDM problem [5,6].

Customer Segment selection is based on customer's demands and characteristics which cannot be categorized in an absolute or specific way as there is fuzziness in both customers' personal and requirements characteristics. All of these factors cause the lack of accuracy and ambiguity in the decision process [7].

In these cases, the fuzzy theory is one of the best tools for modelling uncertainty and increasing the accuracy of customer segment selection [8]. Fuzzy set is a class of objects with some degree of membership range between 0 and 1. It is proven that models with fuzzy sets are effective for formulating MCDM problems when the given information is not precise [8].

In fact, customer segment selection problem is a MCDM problem. A wide range of mathematical programming methods are proposed and applied to provide adequate and more accurate solutions in this area [9]. As among them are data envelopment analysis [10], linear programming [11], AHP and nonlinear programming [12], MCDM and GMCDM methods such as AHP [13], ANP [14], TOPSIS [8, 15-17], and Vikor [18]. They can also be used inartificial intelligence and knowledge discovery such as genetic algorithm [19], artificial neural networks [20], and

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data mining [21] fields; these techniques also can be used for suppliers selection problems in the field of SCM [15-17, 22].

In this work, we treated best customer segment selection as a MCDM problem. We are proposing an extension of fuzzy TOPSIS solution with weights being determined based on Shannon entropy in order to define relative importance of proposed frame work. Using this approach, we define the MCDM of customer segment selection through the estimation obtained from the fuzzy rates by a set of appropriate linguistic variables. These linguistic terms are converted to trapezoidal fuzzy numbers and then the best customer segment with respect to criteria is selected through many numerical equations. Shannon entropy concept is also used to regulate weights in order to determine relative importance of proposed framework.

In the following sections we are going to briefly describe the concepts and approaches we have done for best customer segment selection using fuzzy TOPSIS based on Shannon entropy. Finally, we show a numerical example to illustrate our proposed method.

2. Fuzzy Topsis

Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) is one of the most classical methods for solving MCDM problem [23]. It is based on a principle where the chosen alternative should have the longest distance from the negative-ideal solution, i.e. the solution that maximizes the cost criteria and minimizes the benefits criteria; and the shortest distance from the positive-ideal solution, i.e., the solution that maximizes the benefit criteria and minimizes the cost criteria. In classical TOPSIS, the ratings and weight soft he criteria are known precisely [17].In fuzzy TOPSIS, all the ratings and weights are defined by means of linguistic variables. A number of fuzzy TOPSIS methods and their applications have been developed and studied in recent years [17]. The following steps are performed in the fuzzy TOPSIS approach.

1. Constructing the fuzzy decision matrix.

Assumption is there are m alternatives to be evaluated against n selection criteria. This can be concisely expressed in a matrix format as shown below.

$$X = [X_{ij}]m*n \qquad (1)$$

2. Normalizing the fuzzy decision matrix.

The raw data are normalized to eliminate the anomalies with different measurement units and scales. The purpose of this linear scale transformation and normalization is to keep the data within the range of [0, 1]. If R denotes for the normalized fuzzy decision matrix, then:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} . R = [r_{ij}]m*n \qquad (2)$$

3. Constructing weighted normalized fuzzy decision matrix.

Considering the weight of each criterion, the weighted normalized decision matrix is computed by multiplying the importance weights of evaluated criteria and the values in the normalized fuzzy decision matrix. The weighted normalized decision matrix V is defined as:

$$V = [v_{ij}]_{m \times n} \quad i = 1,2,\ldots,m \quad j = 1,2,\ldots,n \quad v_{ij} = r_{ij} \cdot w_j$$

4. Determining the positive ideal solution and the negative ideal solution.

Because the positive trapezoidal fuzzy numbers are included in the interval [0, 1], the fuzzy positive ideal reference point denoted by A^+ and fuzzy negative ideal reference point denoted by $A^-$is defined as:

$$A^+ = \{(\max_i v_{ij} \mid j \in J), (\min_i v_{ij} \mid j \in J') \mid i = 1,2,\ldots m\}$$
$$= \{v_1^+, v_2^+, \ldots, v_j^+, \ldots, v_n^+\}$$

$$A^- = \{(\min_i v_{ij} \mid j \in J), (\max_i v_{ij} \mid j \in J') \mid i = 1,2,\ldots m\}$$
$$= \{v_1^-, v_2^-, \ldots, v_j^-, \ldots, v_n^-\}$$

$$where \quad J = \left\{ j = 1,2,\ldots,n \mid j \quad associated \quad with \quad benefit \quad criteria \right\}$$
$$J' = \left\{ j = 1,2,\ldots,n \mid j \quad associated \quad with \quad cost \quad criteria \right\}$$

5. Calculating the distances of each initial alternative from A^+ and A^-.

The distance of each alternative from A^+ and A^- is found respectively as shown below.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \qquad i = 1,2,\ldots,m$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \qquad i = 1,2,\ldots,m$$

6. Obtaining the closeness coefficient and rank the alternatives.

The closeness coefficient (C_i) of each alternative is calculated as:

$$c_i^* = \frac{S_i^-}{(S_i^+ + S_i^-)}, \quad 0 < c_i^+ < 1, \quad i = 1,2,\ldots, m$$

$$c_i^* = 1 \quad if \quad A_i = A^+$$

$$c_i^* = 0 \quad if \quad A_i = A^-$$

When C_i approaches to 1, this indicates that the alternative is close to the A^+ and far from A^-. So, the alternative with the highest C_i value is the best choice.

In the next section, we are showing a thorough study on trapezoidal fuzzy number and Shannon entropy where we are going to apply in our proposed fuzzy TOPSIS method.

3. Trapezoidal Fuzzy Number and Shannon Entropy

A trapezoidal fuzzy number (Fig. 1)can be denoted as a tuple $\{(n_1,n_2,n_3,n_4)|\ n_1,n_2,n_3,n_4 \in R;\ n_1 \leq n_2 \leq n_3 \leq n_4\}$ which respectively, indicate the smallest possible, the most promising, and the largest possible values that would describe a fuzzy term [18]. Here, we define the membership function as following:

$$\mu_N(x) = \begin{cases} (x-n_1)/(n_2-n_1), & x \in [n_1, n_2] \\ 1 & x \in [n_2, n_3] \\ (n_4-x)/(n_4-n_3), & x \in [n_3, n_4] \\ 0 & \text{otherwise} \end{cases}$$

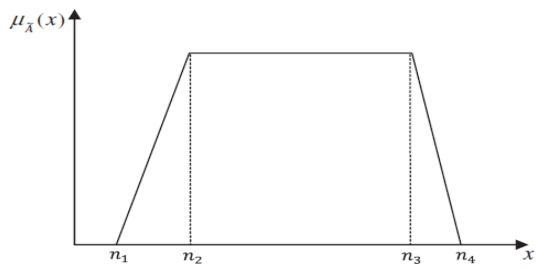

Fig. 1. Trapezoidal fuzzy number

Shannon et al. [24]has proposed the entropy concept, which is a measurement of information uncertainty based on probability theorem.

Shannon's concept is deployed as a weighting calculation method [25], through the following steps:

Step 1: Normalizing the evaluation index as:

$$P_{ij} = \frac{x_{ij}}{\sum_j x_{ij}}$$

Step 2: Calculating entropy measurement of every index using the following equation:

$$e_j = -k \sum_{j=1}^{n} P_{ij} \ln(P_{ij})$$

where $k = (\ln(m))^{-1}$

Step 3: Defining the divergence through:

$$div_j = 1 - e_j$$

The more the $div_j$is, the more important the criterion *jth* is!

Step 4: Obtaining the normalized weights of index as:

$$w_j = \frac{div_j}{\sum_j div_j}$$

4. The Proposed Method for Best Customer Segment Selection

We have combined the above approaches to define a MCDM solution for best customer segment selection using following sets and steps:

1. A set of m possible alternatives called $A = \{A_1,A_2,\ldots,A_m\}$;
2. A set of n decision criteria called $C = \{C_1,C_2,\ldots,C_n\}$;
3. A set of utility ratings of A_i $(i = 1,2,\ldots,m)$ with respect to criteria C_j $(j = 1,2,\ldots,n)$ called $X = \{x_{ij},\ i = 1,2,\ldots,m;\ j = 1,2,\ldots,n\}$.

Step 1: Identifying and defining linguistic terms and relevant member ship functions.

A set of appropriate linguistic variable is used to estimate the fuzzy rates of alternatives (Fig. 2).

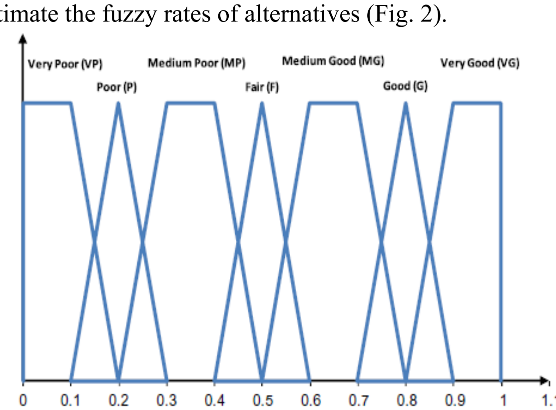

Fig. 2. Linguistic variables for the fuzzy rates of alternatives

Step 2: Constructing a decision and weighting matrix.

Thus, the decision matrix *D* and the weighting matrix *W*are concisely expressed as:

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix},\quad W = [\, w^s_1, w^s_2, \ldots, w^s_n] \qquad (4\text{-}1)$$

Step 3: Defuzzifying the decision matrix and fuzzy weights of each criterion and deriving their crisp values.

To derive the crisp values of arrays of decision matrix and fuzzy weights we may use the following equations:

$$Defuzzy(x_{ij}) = \frac{\int \mu(x).xd_x}{\int \mu(x)d_x}$$

$$= \frac{-x_{ij1}.x_{ij2} + x_{ij3}.x_{ij4} + \frac{1}{3}\left(x_{ij4} - x_{ij3}\right)^2 - \frac{1}{3}\left(x_{ij2} - x_{ij1}\right)^2}{-x_{ij1} - x_{ij2} + -x_{ij3}x_{ij4}} \qquad (4\text{-}2)$$

Step 4: Deploying the entropy concept to derive objective weights.

In order to determine the weights by entropy measure, we normalized the decision matrix for each criterion C_j *(j = 1,2,...,n)* and then calculated the projection value of each criterion called P_{ij}.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \qquad (4\text{-}3)$$

Afterward, the entropy value (e_j), divergence (div_j) and weight for each criterion C_j (w_j^0) is calculated.

$$e_j = -k\sum_{i=1}^{m} p_{ij}.\ln(p_{ij}) \qquad ,k = \frac{-1}{\ln(m)} \qquad (4\text{-}4)$$

$$div_j = 1 - e_j \qquad (4\text{-}5)$$

$$w_j^0 = \frac{div_j}{\sum_{j=1}^{n} div_j} \qquad (4\text{-}6)$$

Step 5: Obtaining the decision matrix to identify the jth criterion with respect to it hand normalize it so that each criterion value is limited between 0 and 1 to be comparable.

$$V = [v_{ij}]_{m*n} \quad i = 1,2,...,m \qquad j = 1,2,...,n \qquad (4\text{-}7)$$

$$A^* = \left\{(\max_i v_{ij} \middle| j \in J), (\min_i v_{ij} \middle| j \in J^{'}\right\}$$
$$A^* = \left\{v_1^*, v_2^*, ..., v_n^*\right\} \qquad (4\text{-}8)$$

$$A^- = \left\{(\min_i v_{ij} \middle| j \in J), (\max_i v_{ij} \middle| j \in J^{'}\right\}$$
$$A^- = \left\{v_1^-, v_2^-, ..., v_n^-\right\} \qquad (4\text{-}9)$$

$$S_i^* = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^*)^2} \quad , \quad S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \qquad (4\text{-}10)$$

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*} \qquad (4\text{-}11)$$

At last, to choose the best alternative, they are ranked according to C_i values.

5. A Numerical Example

In this section an applied example is explained to illustrate the proposed method effectiveness. This is done in an electronics company to evaluate, rank and select its customers segments. The problem is that the company wants to identify its best customer segment among four customer segment candidates (*m*=4) based on its following six criteria (*n*=6):

- C_1: The cultural level
- C_2: More on the availability of the customer
- C_3:Occupational and social level
- C_4: Level of education
- C_5: The age group
- C_6:Financial ability

The followings are used for this purpose:

Firstly, linguistic terms and their corresponding fuzzy numbers are obtained from Fig.2 and are tabulated in TABLE1.

Next, the ratings of customer segments (A_i) with respect to criteria (C_i) are done using the linguistic terms as shown in TABLE 2. This is further expanded to equivalent fuzzy values (TABLE 3)

TABLE 4 shows the defuzzifying of the fuzzy values of customer segment rates using (4-2).

Afterwards, Projection value of each criterion is calculated using (4-3) as shown in TABLE 5.Next, e_j, div_jandw_j^0 are calculated based on (4-4), (4-5) and (4-6) equations (TABLE 6).

The V_{ij} matrix is determined according to (4-7) and the results are presented in TABLE 7.

At the same time, the values of A^+ and $A^-$are determined according to (4-8) and (4-9) equations (TABLE 8).

Next, the values of S^+ and S^- are determined according to (4-10) equation as shown in TABLE 9.

TABLE 10 shows C_i values based on equation (4-11).

At last, the best customer segment is selected based on C_i values; results is shown in TABLE 11.

Table 1

Linguistic terms and corresponding fuzzy numbers

Rate		Fuzzy number
Very poor	VP	(0,0,0.1,0.2)
Poor	P	(0.1,0.2,0.2,0.3)
Medium poor	MP	(0.2,0.3,0.4,0.5)
Fair	F	(0.4,0.5,0.5,0.6)
Medium good	MG	(0.5,0.6,0.7,0.8)
Good	G	(0.7,0.8,0.8,0.9)
Very good	VG	(0.8,0.9,1,1)

Table 2

Rating of customer segments with respect to criteria

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	VG	F	MG	G	G	VG
A_2	MG	MG	G	MG	VG	G
A_3	MG	MG	F	MG	G	F
A_4	VG	G	G	MG	VG	F

Table 3

Rating of customer segment candidates with respect to criteria (fuzzy values)

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	(0.8,0.9,1,1)	(0.4,0.5,0.5,0.6)	(0.5,0.6,0.7,0.8)	(0.7,0.8,0.8,0.9)	(0.7,0.8,0.8,0.9)	(0.8,0.9,1,1)
A_2	(0.5,0.6,0.7,0.8)	(0.5,0.6,0.7,0.8)	(0.7,0.8,0.8,0.9)	(0.5,0.6,0.7,0.8)	(0.8,0.9,1,1)	(0.7,0.8,0.8,0.9)
A_3	(0.5,0.6,0.7,0.8)	(0.5,0.6,0.7,0.8)	(0.4,0.5,0.5,0.6)	(0.5,0.6,0.7,0.8)	(0.7,0.8,0.8,0.9)	(0.4,0.5,0.5,0.6)
A_4	(0.8,0.9,1,1)	(0.7,0.8,0.8,0.9)	(0.7,0.8,0.8,0.9)	(0.5,0.6,0.7,0.8)	(0.8,0.9,1,1)	(0.4,0.5,0.5,0.6)

Table4

Defuzzyfied values of customer segment ratings with respect to criteria

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.92	0.50	0.65	0.80	0.80	0.92
A_2	0.65	0.65	0.80	0.65	0.92	0.80
A_3	0.65	0.65	0.50	0.65	0.80	0.50
A_4	0.92	0.80	0.80	0.65	0.92	0.50

Table 5

Shannon entropy results

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.29	0.19	0.24	0.29	0.23	0.34
A_2	0.21	0.25	0.29	0.24	0.27	0.29
A_3	0.21	0.25	0.18	0.24	0.23	0.18
A_4	0.29	0.31	0.29	0.24	0.27	0.18

Table 6

e_j, $div_j$and w_j^0results

	C_1	C_2	C_3	C_4	C_5	C_6
e_j	0.99	0.99	0.99	1.00	1.00	0.97
div_j	0.01	0.01	0.01	0.00	0.00	0.03
w_j^0	0.17	0.17	0.17	0.00	0.00	0.49

Table 7

V_{ij}results

	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.049	0.032	0.041	0.00	0.00	0.167
A_2	0.036	0.042	0.049	0.00	0.00	0.142
A_3	0.036	0.042	0.031	0.00	0.00	0.088
A_4	0.049	0.053	0.049	0.00	0.00	0.088

Table 8

A^+, A^- values

	C_1	C_2	C_3	C_4	C_5	C_6
A^+	0.049	0.053	0.049	0.00	0.00	0.167
A^-	0.036	0.032	0.031	0.00	0.00	0.088

Table 9

S^+, S^- values

S^+_1	S^+_2	S^+_3	S^+_4
0.022	0.030	0.083	0.079
S^-_1	S^-_2	S^-_3	S^-_4
0.081	0.058	0.01	0.030

Table 10

C_i values

C_1	C_2	C_3	C_4
0.79	0.66	0.11	0.28

Table 11

Ranking of customer segment candidates based on C_i

1	2	3	4
A_1	A_2	A_3	A_4

6. Conclusions

With the today's highly competitive business environment, companies have to work hard and harder to highlight their advantages against their competitors in market. Many researchers and practitioners have focused their work on this area and deployed a wide range of scientific and technical approaches. Best customer segment selection should aim get more profit through a MCDM problem. We proposed an extension of fuzzy TOPSIS while weights are regulated based on Shannon entropy for customer segment selection problem. We have also shown the results of a numerical example of the proposed method. We could confirm that TOPSIS is a helpful tool in multi-criteria decision making problem like best customer segment selection.

The contribution of this work is that it provides a framework for MCDM which considers vagueness and ambiguity as well as allowing to set multiple aspiration levels for customer segment selection problems in which ''the more/higher is better'' (e.g., benefit criteria) or ''the less/lower is better'' (e.g., cost criteria).

Furthermore, the proposed method may be suitable for different MCDM problems, such as management problems (e.g., location selection and project management) and supply chain problems (e.g., supplier selection problems) when available data are inaccurate, vague, imprecise and ambiguous by nature.

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