A fuzzy multi-criteria decision-making method for purchasing life insurance in India

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Article Info

Article history:

Received Feb 17, 2020
Revised Mar 28, 2020
Accepted May 15, 2020

Keywords:

Fuzzy MCDM
Life insurance
Multi criterion decision-making approach
TOPSIS

ABSTRACT

Life insurance is an agreement between an insured and an insurer, where the insurer pays out a sum of money either on a specific period or the death of the insured. Now a day, People can buy a policy through an online platform. There are a lot of insurance companies available in the market, and each company has various policies. Selecting the best insurance company for purchasing an online term plan is a very complex problem. People may confuse to choose the best insurance company for buying an online term. It is a multi-criteria decision making (MCDM) problem, and the problem consists of different criteria and various alternatives. Here in this paper, a model has been proposed to solve this decision-making problem. In this model, a fuzzy multi-criteria decision-making approach combined with technique for order preference by similarity to ideal solution (TOPSIS) and it has been applied to rank the different insurance companies based on online term plans. The experimental results show that the life insurance corporation of India (LIC) gets the top rank out of 12 companies for purchasing an online term plan. A sensitivity analysis has been performed to validate the proposed model.

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1. INTRODUCTION

Future is rather unpredictable and uncertain. So, in this sea of uncertainties, due to imprecise activity in day to day life. As a result, financial loss and failure of desired event may occur. LI policy provides us with assurance that our family gets financial support and security even when one of us is not around anymore [1]. Those who avail LI are ensuring the safety of their loved dependent ones. In this case the company is at a risk of compensating the deceased as they are bounded by the contract [2, 3].

In this study, we are focusing on MCDM approach for selecting the best LI company for purchasing an online term policy [4]. MCDM is helps to select the best alternative among the set of alternatives and the methods of MCDM can be used in various field [5]. To define the decision-making parameters, we used fuzzy set theory. Fuzzy set theory was introduced by [6] and it support to vagueness and uncertainty in decision-making. In fuzzy set theory parameters are specified using linguistic terms such as very low, low, medium, high, very high, very poor, poor, fare good, very good instead of exact numerical values.

Fuzzy logic may be useful to attempt at mechanization or formalization human capacities. First the capacity to converse, reason and settle on level headed choices in a domain having of imprecision, vulnerability, strife, and deficiency data. Second, the ability to play out a wide assortment of physical and mental assignments with no psychical estimation and calculation. There have some criteria for selecting the best insurance company among a set of companies. Criteria have some weighted values that are independent from each other. We evaluate the best insurance company alternative against the set of weighted criteria. We have chosen the company alternative for final implementation which is evaluating the best with respect to (w.r.t) all other criteria.

In 1997, [7] have discussed about the unfavourable selection in the purchase of insurance. In 1999, [8] has investigated after analyzed different decision-making strategies in different financial sectors problem related to insurance, banks, and financial firms, acquisition of firms, risk like bankruptcy risk, country risk and financial planning related problems. In this study, we suggested the different contributions of MCDM [9] in various financial problems and enlightened with possibility of structuring complex evaluation problems and have given different possible solutions. In 2011, [10] characterize the distance & correlation measures for hesitant fuzzy information & after that examined their characteristics in detail. In 2012, [11] have done the risk analysis and return analysis with the help of analytical hierarchy process (AHP) and ELECTRE III method in insurance linked securities (ILS) portfolios in portfolio management. Xu et al. [12] presented the ideas of entropy and cross-entropy for hesitant fuzzy information and investigated their attractive properties. In 2013, [13] have analyzed present and past status of LI sector and also discusses about the future strategies of the Indian insurance sector. In [14] presented another score function for positioning hesitant fuzzy elements (HFEs), which are the essential units of HFSs. In 2014, [15] have ranked Insurance companies especially in money back insurance policies domain with the help of classical AHP process. Khodamoradi et al. [16] have studied different insurance companies in Iran and have proposed a new hybrid method consisting DEMATEL and PROMETHEE II method using sample data from insurance companies listed in Tehran stock exchange for a period of 2010-2012 and applying the combined method, it was observed that Alborz Company has the highest and Dana Company has the lowest rate. In 2016, [17] introduced another aggregation method, to be specific, generalized Pythagorean fuzzy Einstein weighted averaging (GPFEWA) administrator and generalized Pythagorean fuzzy Einstein ordered weighted averaging (GPFEOWA) method under the Pythagorean fuzzy condition. In 2017, [18] studied the utilization of rough intelligence improvement methods and fuzzy ways for understanding the cooperative effects on financial performance. In 2018, [19] tried to present a fuzzy expert system for investigating the performance of insurance sector in Iran. Chiclana et al. [20] proposed another mining calculation dependent on animal migration optimization (AMO), called ARM–AMO, to diminish the quantity of association rules. Chatterjee et al. [21] give a best in class study over Bitcoin related advances and summarize different difficulties.

In 2019, [22] suggested a novice hybrid MCDM way to investigate service innovation methodologies for enhancing the tolerability of China’s banking sector throughout the Fintech revolution. Jha et al. [23] audit the most recent advances on IoT with IoC from a class survey of distributed articles from 2009 to 2017. Jha et al. [24] call attention to a significant issue of stock market in regard to inclining situation of exchanges where data precision, exactness of communicating data & vulnerability of qualities (shutting purpose of the day) are needed. Authors [25] expect to build up a system for MVNO in developing countries' telecommunication showcase as pursues: first, to do an intensive investigation of market and draft a possibility study for MVNOs in the telecommunications (“telecom”) advertises in developing countries; and second, to create required guidelines for upgraded development openings in the telecom. Authors in [26] focus on the latest advancement over investigates concerning machine learning for big data analytic and various procedures with regards to modern computing for different applications. Authors [27] talk about the different utilizations of IoT in social insurance and related fields. Authors [28] were proposing an advanced system for phishing detection utilizing feature extraction & classification of the mails utilizing SVM. Abbas and Chergui [29] have discussed about the impact of Pareto optimality concept on revised TOPSIS. Fahmi et al. [30] proposed a new variant of fuzzy TOPSIS based on triangular cubic hesitant fuzzy number (TCHFN). Several modified variants of fuzzy TOPSIS are used to solve the group decision making problem [31, 32]. A system for Social Media Analytics dependent on MCDM (TOPSIS) model is suggested in [33] for social media information.

This paper is presented as follows. We have discussed about the fuzzy set theory in section 2. We have discussed the propose model for ranking the insurance companies for purchasing online term policy in section 3. Numerical representation and sensitivity analysis (SA) have implemented in section 4. At last, we finish up the paper in section 5.

2. FUZZY SET THEORY

The fuzzy sets are represented by linguistic terms that consist one or more linguistic variables, i.e. the linguistic variables have their possible states defined in a universe of discourse, represented by these linguistic terms. A fuzzy set 'F 'can be represented as,

$$F=\{(x, \mu_{F(x)}) \mid x \in X\} \tag{1}$$

where $\mu_{F(x)}$ is the membership function (MF) for the fuzzy set F. X is called as Universe of Discourse that is represented as linguistic values. Each element of X has membership grade among 0 & 1. MF are different types i.e. triangular, trapezoidal, sigmoid, Gaussian etc.

2.1. Triangular MF

A triangular MF shown in Figure 1 is represented by the three parameters (a, b, c);

$$trimf(x: a, b, c) = \begin{cases} 0, & x \le a, \\ \frac{x-a}{b-a}, & a \le x \le b, \\ \frac{c-x}{c-b}, & b \le x \le c, \\ 0, & c \le x \end{cases} \tag{2}$$

Parameters (a, b, c) are the real number and the value of these parameters specifies the x coordinates of the three corners of the triangular MF.

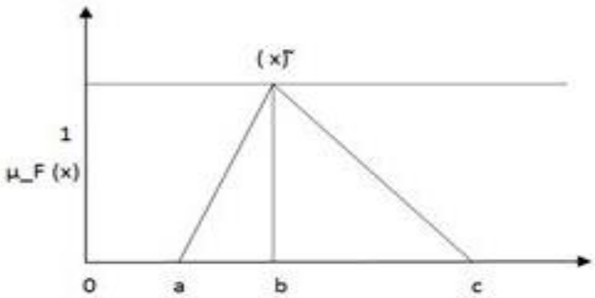

Figure 1. Triangular fuzzy number

2.2. Distance between fuzzy triangular numbers

Let $\tilde{x}=(x_1, x_2, x_3)$ and $\tilde{y}=(y_1, y_2, y_3)$ are triangular fuzzy numbers. The distance among two triangular fuzzy numbers computed by utilizing vertex method is given below.

$$d(\tilde{x}, \tilde{y}) = \sqrt{\frac{1}{3}\left[(x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_3 - y_3)^2\right]} \tag{3}$$

2.3. Linguistic variables

Linguistic variable is described by a quintuple, which is consist a variable name, term set, universe of discourse, syntactic rule and semantic rule. In fuzzy set theory, transformation scale is needed to convert the fuzzy numbers from linguistic variable [15, 34-36]. Here we will apply a 1-9 transformation scale for rating the alternatives & criteria. Linguistic variable for criteria ratings are represented in Table 1 and linguistic term for alternatives ratings are represented in Table 2.

Table 1. Linguistic variables to define the criteria ratings

Linguistic variable	Membership function
Very low (VL)	(1,1,3)
Low (L)	(1,3,5)
Medium (M)	(3,5,7)
High (H)	(5,7,9)
Very high (VH)	(7,9,9)

Table 2. Linguistic variable to define the ratings of alternatives

Linguistic variable	Membership function
Very poor (VP)	(1,1,3)
Poor (P)	(1,3,5)
Fair (F)	(3,5,7)
Good (G)	(5,7,9)
Very good (VG)	(7,9,9)

3. PROPOSED MODEL FOR RANKING OF INSURANCE COMPANIES

The proposed model for ranking of insurance companies consists of five different steps and these are depicted below.

3.1. Process for election of insurance policy

There are several types insurance policy is available in market such as term insurance plans, pension plan, health plan, endowment plan, child plan, money back plan. One of the popular plans is term insurance plan. Online term policy is a combine application of e-commerce and financial market. Now-a-days it is combined to the insurance sector and produces a new insurance product that is online term plan. There are lot of attractive facilities are available under this plan, where we can buy this type of plan directly without any help of an agent. In this paper we have chosen only the online term plan and finally ranking the insurance companies for purchasing an online term plan [13].

3.2. Process for selection of criteria

There are lot of criteria exist for recommending an insurance policy. We have chosen the 10 criteria that is described in Table 3. These criteria are taken from literature survey and consult with some experience person of this field. Criteria's are categorized in to two types i.e. cost criteria and benefit criteria. In cost criteria, lower value is preferable for alternative selection and for benefit criteria; higher value is more preferable for alternative selection [37]. In Table 3, the criteria are denoted by C_1-C_{10}, here C_4 and C_6 are the cost criteria & all other criteria are the benefit criteria.

Table 3. Criteria for recommendation of an insurance policy

Criteria	Definition	Criteria type
Average claim ratio	Total number of death claim settled	Benefit
Entry age	Age of insured person at the beginning of policy	Benefit
Policy term	The benefit amount that is received by the policy holder or nominee either death or contract stipulation	Benefit
Maturity	Period of coverage provided by a policy	Cost
Sum assured	Financial cost of a policy that is paid by the insured	Benefit
Premium	Pre-decide amount, that insurer pay to the insured	Cost
Premium payment term	Duration for the policy holder to pay the premium	Benefit
Premium payment frequency	Number of times to pay the premium	Benefit
Rebate on large sum assured	Discount on large sum assured	Benefit
Riders	Additional benefit that can be enhance the coverage	Benefit

3.3. Process for selection of alternatives

There are 24 LI companies in India under the IRDA [38]. At first, we have chosen some companies which has better claim ratio. It is an important criterion for an insurance company. It refers to the ratio of total number of death claim received & the total number of death claim settled. For an example, if a LI company receives 1000 death claim and settles 970, then the claim ratio of this company would be 97%. After that the claim ratio of each company has been evaluated for last 4 years (2011-2014) and then the average claim ratio has been calculated. Those companies which has more than 70% claim ratio have been considered. Finally, we have chosen 12 insurance companies which have online term plan facility. The alternatives of 12 insurance companies are ICICI (A_1), LIC(A_2), HDFC(A_3), SBI(A_4), MAX(A_5), BAJAJ ALLIANZ(A_6), BHARTI AXA(A_7), AEGON RELIGARE(A_8), RELIANCE(A_9). KOTAK MAHINDRA (A_{10}), CANARA HSBC(A_{11}) and AVIVA(A_{12}).

3.4. Ranking Insurance companies using fuzzy TOPSIS

We used a MCDM technique, called Fuzzy TOPSIS for choosing the best insurance company against some selected weighted criteria. TOPSIS helps to find the ideal possibility that is farthest from the negative ideal solution (NIS) and very near to the positive ideal solution (PIS). A NIS is consisting of the minimum values of each alternative and PIS is consisting of the maximum values of each alternative. The several steps of fuzzy TOPSIS are discussed as follows [35, 39-40].

− Step 1. Evaluation of performance assignment to the criteria and the alternatives

Let n is a set alternatives, where $A = (A_1, A_2, A_3, \dots, A_n)$, m is a set of criteria, where $C = (C_1, C_2, C_3, \dots, C_m)$ and k is number of decision maker, where $D_k (k = 1,2,..,K)$. The value of alternatives is calculated against criteria. The weights for each criterion are represented by cw_i $(i = 1,2,3, \dots, m)$. The performance assignment of each decision maker for each alterative w.r.t each criterion is represented by $\tilde{P}_k = \tilde{y}_{ijk}$ $(i = 1,2,3,..,m; j = 1,2,3,..,n; k = 1,2,3,..,K)$ with membership function $\mu_{\tilde{P}_k}(x)$.

− Step 2. Calculate the aggregate fuzzy assignment for criteria and alternatives

Triangular fuzzy number is utilized to express the fuzzy assignment of all decision makers$\tilde{P}_k = (x_k, y_k, z_k), k = 1,2,..,K$. The aggregated fuzzy rating is calculated as $\tilde{P} = (x, y, z)$, where;

$$x =_k^{min} \{x_k\}, \qquad y = \frac{1}{K}\sum_{k=1}^{K} y_k, z =_k^{max} \{z_k\} \tag{4}$$

If the effective weight of the k_{th} decision maker and fuzzy assignment are $\widetilde{cw}_{ijk} = (cw_{jk1}, cw_{jk2}, cw_{jk3})$ and $\tilde{y}_{ijk} = (x_{ijk}, y_{ijk}, z_{ijk})$ respectively, then the aggregated fuzzy ratings $(\tilde{y}_{ij})$ of alternatives w.r.t each criterion are given by where $\tilde{y}_{ij} = (x_{ij}, y_{ij}, z_{ij})$, where

$$x_{ij} =_k^{min} \{x_{ijk}\}, \quad y_{ij} = \frac{1}{K}\sum_{k=1}^{K} y_{ijk}, z_{ij} =_k^{max} \{z_{ijk}\} \tag{5}$$

The aggregated fuzzy weights $(\widetilde{cw}_{ij})$ of each criterion are calculated as $\widetilde{cw}_j = (cw_{j1}, cw_{j2}, cw_{j3})$ where,

$$cw_{j1} =_k^{min} \{cw\}, \ cw_{j3} =_k^{max} \{cw_{jk3}\} \tag{6}$$

− Step 3. Calculate the fuzzy decision matrix

Fuzzy decision matrix for the criteria and the alternatives is formed as bellows:

$$\widetilde{DM} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix} \end{array}$$

$$\widetilde{CW} = [\widetilde{cw}_1 \quad \widetilde{cw}_2 \quad \dots \quad \widetilde{cw}_n]$$

− Step 4. Fuzzy decision matrix should be normalized

Normalization should be required for transforming the raw data into normalized data. We normalized the fuzzy decision matrix is denoted by $\tilde{P}$, which is given by $\tilde{P} = [\tilde{p}_{ij}]_{m\times n}$, $i = 1,2,\dots,m$; $j = 1.2.\dots n$, for cost criteria

$$\tilde{p}_{ij} = \left(\frac{x_j^-}{z_{ij}}, \frac{x_j^-}{y_{ij}}, \frac{x^-}{x_{ij}}\right), \quad x_j^- =_i^{min} (x_{ij}) \tag{7}$$

and for benefit criteria,

$$\tilde{p}_{ij} = \left(\frac{x_{ij}}{z_j^*}, \frac{y_{ij}}{z^*}, \frac{z_{ij}}{z_j^*}\right), \quad z_j^* =_i^{max} (z_{ij}) \tag{8}$$

− Step 5. Calculate the weighted normalized fuzzy decision matrix

The weighted normalized fuzzy decision matrix(WC) is calculated by multiplying the weights $(cw_j)$of criteria with the normalized fuzzy decision matrix $\tilde{p}_{ij}$.

$$\widetilde{WC} = [\widetilde{wc}_{ij}]_{m\times n}, \ i = 1,2,\dots,m; \ j = 1.2.\dots..n, \text{ where } \widetilde{wc}_{ij} = \tilde{p}_{ij}(.)cw_j \tag{9}$$

− Step 6. Calculate the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS)

The FNIS and FPIS of the alternatives are calculated as follows,

$$F^+ = (wc_1^+, wc^+, \dots, wc_n^+) \text{ where } wc_j^+ =_i^{max} (wc_{ij3}), i = 1,2,\dots,m; \ j = 1,2,\dots,n \tag{10}$$

$$F^- = (wc_1^-, wc^-, \dots, wc_n^-) \text{ where } wc_j^- =_i^{min} (wc_{ij1}), i = 1,2,\dots,m; \ j = 1,2,\dots,n \tag{11}$$

− Step 7. Calculate the distance from FNIS and FPIS for each alternative

The distance (v_i^+, v_i^-) of each alternative $i = 1,2,\dots,m$ from the FPIS and the FNIS is calculated as follows:

$$v_i^+ = \sum_{j=1}^{n} v_t\left(\tilde{t}_{ij}, t_j^+\right), \ i = 1,2,..,m \tag{12}$$

$$v_i^- = \sum_{j=1}^{n} v_t\left(\tilde{t}_{ij}, t_j^-\right), \ i = 1,2,..,m \tag{13}$$

where $v_t(\tilde{x}, \tilde{y})$ is the distance between two fuzzy numbers$\tilde{x} and \tilde{y}$.

− Step 8. Calculate the closeness coefficient of each alternative

The closeness coefficient (S_i) denoted the distances to the FPIS (F^+) and the FNIS (F^-)simultaneously. The $S_i$of each alternative is computed as;

$$S_i = \frac{v_i^-}{v_i^- + v^+} \ , i = 1,2,..,m \tag{14}$$

− Step 9. Ranking of the alternatives

Ranking of alternatives are made according the value of closeness coefficient (S_i) in decreasing order. Choose the best alternative which has heights S_i value.

3.5. Sensitivity analysis

SA is a technique and it is used to determine the sensitiveness of the overall decision if we make changes in the input values. In this paper we have consider the assessment values of criteria as input [41]. It is also used to test the robustness of the model where uncertainties exist for different factors. We observe that how much effect on the decision if we slightly change the values of the weights of criteria? We used the SA on our model in the order to notice that the effectiveness of weights of the criteria in resolving the best insurance company for purchasing an online term.

4. RESULTS AND DISCUSSION

Let us consider that someone is interested to buy an online term policy. There are so many companies available. So problem is that how to determine the best company for buying a policy. A committee is formed which consist of three decision makers D_1, D_2, D_3 for choosing the best choice. The alternatives available for purchasing an online term policy is defined in Table 4.

There are several criteria used for purchasing an online term policy which is define in Table 3, that is Average claim ratio (C_1), Entry age (C_2), Policy term (C_3), Maturity (C_4), Sum assured (C_5), Premium (C_6), Premium payment term (C_7), Premium payment frequency (C_8), Rebate on large sum assured (C_9), Riders (C_{10}). Criteria C_4 and C_6 are the cost criteria & rest of the criteria are benefit criteria.

The committee of 3 decision makers provide the linguistic judgment for the 10 criteria using the rating scale that is define in Table 1 and the 12 alternatives of insurance companies for each of the 10 criteria that is defined in Table 2. Linguistic judgment for the criteria and alternatives is defined in Tables 4-5.

By using (6), we calculate the aggregated fuzzy weight for each criterion. Let us take an example, the aggregated fuzzy weight for Average claim ratio (C_1) is given by ($\widetilde{cw}_j = cw_{j1}, cw_{j2}, cw_{j3}$) where;

$$cw_{j1} =_k^{min} \{7,7,7\},\ cw_{j2} = \frac{1}{3}\sum_{k=1}^{3}(9+9+9),\ cw_{j3} =_k^{max} \{9,9,9\}\widetilde{cw}_j = (7,9,9) \tag{15}$$

This way we calculate the aggregated fuzzy weight for rest of all criteria and that is define in Table 4.

Table 4. Linguistic Judgment for the criteria and aggregated fuzzy weight for criteria

Criteria	Weight of the Linguistic variable			Aggregated fuzzy weight
Average claim ratio	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)
Entry age	(5,7,9)	(5,7,9)	(7,9,9)	(5,7.66,9)
Policy term	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)
Maturity	(7,9,9)	(5,7,9)	(7,9,9)	(5,8.33,9)
Sum assured	(5,7,9)	(7,9,9)	(7,9,9)	(5,8.33,9)
Premium	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)
Premium payment term	(5,7,9)	(5,7,9)	(7,9,9)	(5,7.66,9)
Premium payment frequency	(3,5,7)	(5,7,9)	(5,7,9)	(3,6.33,9)
Riders	(3,5,7)	(5,7,9)	(3,5,7)	(3,5.66,9)
Rebate on large sum (3,5,7) assured ()	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)

we also calculate the aggregated fuzzy weight (AFW) for each alternative by using (6). Let us take an example, the aggregated fuzzy weight for alternative A_1 for criterionC_1 is

$$\tilde{y}_{ij} = (x_{ij}, y_{ij}, z_{ij}) \tag{16}$$

$$x_{ij} =_k^{min} \{7,7,7\}, \quad y_{ij} = \frac{1}{3}\sum_{k=1}^{3}(9+9+9)\ , \quad z_{ij} =_k^{max} \{9,9,9\} \tag{17}$$

Similarly, we calculate the aggregated fuzzy weight for all the possibilities w.r.t the ten criteria and that is shown in Table 5. In Table 5, the *AR* denotes the aggregated fuzzy ratings.

Table 5. Linguistic judgment for the alternatives and aggregated fuzzy weight for alternatives

		A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
	D_1	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(7,9,9)	(3,5,7)	(1,3,5)	(1,3,5)
C_1	D_2	(7,9,9)	(7,9,9)	(7,9,9)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(1,3,5)
	D_3	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)
	AR	(7,9,9)	(7,9,9)	(7,9,9)	(5,8.3,9)	(5,7.6,9)	(5,7.6,9)	(3,5.6,9)	(3,6.3,9)	(5,7.6,9)	(3,5.6,9)	(1,4.3,7)	(1,3.6,7)
	D_1	(7,9,9)	(7,9,9)	(3,5,7)	(7,9,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(7,9,9)
C_2	D_2	(7,9,9)	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)
	D_3	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,9)	(5,7,9)	(7,9,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)
	AR	(5,8.3,9)	(5,7.6,9)	(3,6.3,9)	(5,8.3,9)	(5,7.6,9)	(5,8.3,9)	(5,7.6,9)	(5,7.6,9)	(5,7,9)	(3,6.3,9)	(3,6.3,9)	(5,7.6,9)
	D_1	(5,7,9)	(5,7,9)	(1,3,5)	(5,7,9)	(3,5,7)	(5,7,9)	(7,9,9)	(1,3,5)	(5,7,9)	(5,7,9)	(1,3,5)	(3,5,7)
C_3	D_2	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(1,3,5)	(3,5,7)	(5,7,9)	(1,3,5)	(5,7,9)
	D_3	(5,7,9)	(5,7,9)	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,9)	(1,3,5)	(5,7,9)	(7,9,9)	(1,1,3)	(5,7,9)
	AR	(5,7,9)	(5,7,9)	(1,3.6,7)	(3,6.3,9)	(3,6.3,9)	(3,6.3,9)	(5,8.3,9)	(1,3,5)	(3,6.3,9)	(5,7.6,9)	(1,2.3,5)	(3,6.3,9)
	D_1	(7,9,9)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(7,9,9)
C_4	D_2	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,9)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(1,3,5)	(7,9,9)	(5,7,9)
	D_3	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,9)	(3,5,7)	(5,7,9)	(7,9,9)
	AR	(5,7.6,9)	(3,5.6,9)	(3,6.3,9)	(3,5.6,9)	(5,7.6,9)	(3.5.6,9)	(3,6.3,9)	(3,6.3,9)	(5,7.6,9)	(1,4.3,7)	(5,7.6,9)	(5,8.3,9)
	D_1	(5,7,9)	(7,9,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)
C_5	D_2	(7,9,9)	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,9)	(7,9,9)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)
	D_3	(7,9,9)	(5,7,9)	(7,9,9)	(3,5,7)	(7,9,9)	(7,9,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)
	AR	(5,8.3,9)	(5,7.6,9)	(5,7.6,9)	(3,6.3,9)	(5,8.3,9)	(5,8.3,9)	(3,6.3,9)	(3,6.3,9)	(3,5,7)	(3,6.3,9)	(3,6.3,9)	(3,5.6,9)
	D_1	(7,9,9)	(7,9,9)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,9)	(5,7,9)	(7,9,9)	(5,7,9)
C_6	D_2	(7,9,9)	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)
	D_3	(7,9,9)	(7,9,9)	(5,7,9)	(5,7,9)	(7,9,9)	(7,9,9)	(7,9,9)	(5,7,9)	(7,9,9)	(3,5,7)	(7,9,9)	(7,9,9)
	AR	(7,9,9)	(5,8.3,9)	(3,6.3,9)	(3,6.3,9)	(5,8.3,9)	(5,8.3,9)	(5,8.3,9)	(5,7.6,9)	(5,8.3,9)	(3,6.3,9)	(5,8.3,9)	(5,7.6,9)
	D_1	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)
C_7	D_2	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)
	D_3	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)
	AR	(3,6.3,9)	(3,6.3,9)	(3,6.3,9)	(3,6.3,9)	(3,5.6,9)	(3,5.6,9)	(3,5.6,9)	(3,5.6,9)	(3,5,7)	(3,5.6,9)	(3,5.6,9)	(3,5.6,9)
	D_1	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,9)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)
C_8	D_2	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)
	D_3	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)
	AR	(3,6.3,9)	(3,6.3,9)	(3,5.6,9)	(3,5.6,9)	(3,5.6,9)	(3,6.3,9)	(3,6.3,9)	(5,7.6,9)	(3,5.6,9)	(3,6.3,9)	(3,5.6,9)	(3,5.6,9)
	D_1	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(1,1,3)	(1,1,3)	(7,9,9)
C_9	D_2	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(1,1,3)	(1,1,3)	(5,7,9)
	D_3	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(1,1,3)	(1,1,3)	(5,7,9)
	AR	(5,7,9)	(5,7,9)	(3,6.3,9)	(5,7,9)	(3,6.3,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(1,1,3)	(1,1,3)	(5,7.6,9)
	D_1	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)
C_{10}	D_2	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)
	D_3	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,9)
	AR	(3,5,7)	(3,5,7)	(3,6.3,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7.6,9)

Then we calculate the normalized fuzzy decision matrix for the alternatives by using (7) and (8). Let us take an example, the normalized fuzzy rating of alternative A_1 for Average claim ratio (C_1) (benefit criteria) is calculated as:

$$z_j{}^* =_i^{max} (9,9,9)$$
$$\tilde{p}_{ij} = \left(\frac{7}{9}, \frac{9}{9}, \frac{9}{9}\right) = (0.778, 1, 1)$$

The normalized fuzzy rating of alternative for Maturity (C_4) (cost criteria) is calculated as:

$$x_j{}^- =_i^{min} (1,1,1)$$
$$\tilde{p}_{ij} = \left(\frac{1}{9}, \frac{1}{7.66}, \frac{1}{5}\right) = (0.11, 0.1304, 0.2)$$

Minimum value for cost criteria and maximum value for benefit criteria is presented in Table 6 that is used for calculating the normalized fuzzy decision matrix. The normalized fuzzy decision matrix is computed for all the possibilities w.r.t every criterion and is presented in Table 7.

Table 6. Minimum value for cost criteria and maximum value for benefit criteria

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
$x_j{}^-$	1	3	1	1	3	3	3	3	1	3
$z_j{}^*$	9	9	9	9	9	9	9	9	9	9

Table 7. Normalized fuzzy decision matrix

	C_1	C_2	C_3	C_4	C_5
A_1	(0.78,1,1)	(0.56,0.99,1)	(0.56,0.78,1)	(0.11,0.13,0.20)	(0.56,0.9259,1)
A_2	(0.78,1,1)	(0.56,0.89,1)	(0.56,0.78,1)	(0.11,0.1765,0.33)	(0.56,0.8519,1)
A_3	(0.78,1,1)	(0.33,0.70,1)	(0.11,0.74,0.78)	(0.11,0.1579,0.33)	(0.56,0.89,1)
A_4	(0.56,0.92,1)	(0.56,0.92,1)	(0.33,0.70,1)	(0.11,0.17,0.33)	(0.33,0.70,1)
A_5	(0.56,0.85,1)	(0.56,0.85,1)	(0.33,0.7037,1)	(0.11,0.13,0.20)	(0.56,0.92,1)
A_6	(0.56,0.8519,1)	(0.56,0.92,1)	(0.33,0.7037,1)	(0.11,0.17,0.33)	(0.56,0.92,1)
A_7	(0.33,0.62,1)	(0.56,0.85,1)	(0.56,0.92,1)	(0.11,0.15,0.33)	(0.33,0.70,1)
A_8	(0.33,0.7037,1)	(0.56,0.85,1)	(0.11,0.33,0.55)	(0.11,0.19,0.33)	(0.33,0.37,1)
A_9	(0.56,0.85,1)	(0.56,0.77,1)	(0.33,0.70,1)	(0.11,0.13,0.20)	(0.33,0.55,0.77)
A_{10}	(0.33,0.62,1)	(0.33,0.70,1)	(0.56,0.85,1)	(0.14,0.23,1)	(0.33,0.70,1)
A_{11}	(0.11,0.48,0.77)	(0.33,0.7,1)	(0.11,0.23,0.55)	(0.11,0.13,0.20)	(0.33,0.70,1)
A_{12}	(0.11,0.40,0.77)	(0.56,0.85,1)	(0.33,0.70,1)	(0.11,0.12,0.20)	(0.33,0.66,1)
	C_6	C_7	C_8	C_9	C_{10}
A_1	(0.33,0.33,0.42)	(0.33,0.70,1)	(0.33,0.70,1)	(0.56,0.77,1)	(0.33,0.55,0.77)
A_2	(0.33,0.36,0.60)	(0.33,0.7037,1)	(0.33,0.70,1)	(0.56,0.77,1)	(0.33,0.55,0.77)
A_3	(0.33,0.47,1)	(0.33,0.70,1)	(0.33,0.62,1)	(0.33,0.70,1)	(0.33,0.70,1)
A_4	(0.33,0.47,1)	(0.33,0.7037,1)	(0.33,0.62,1)	(0.56,0.77,1)	(0.33,0.55,0.78)
A_5	(0.33,0.36,0.60)	(0.33,0.62,1)	(0.33,0.62,1)	(0.33,0.70,1)	(0.56,0.77,1)
A_6	(0.33,0.36,0.60)	(0.33,0.62,1)	(0.33,0.70,1)	(0.56,0.78,1)	(0.33,0.55,0.77)
A_7	(0.33,0.30,0.60)	(0.33,0.62,1)	(0.33,0.70,1)	(0.56,0.77,1)	(0.33,0.56,0.78)
A_8	(0.33,0.39,0.60)	(0.33,0.62,1)	(0.56,0.85,1)	(0.56,0.77,1)	(0.33,0.56,0.77)
A_9	(0.33,0.36,0.60)	(0.33,0.56,0.77)	(0.33,0.62,1)	(0.56,0.77,1)	(0.33,0.56,0.77)
A_{10}	(0.33,0.47,1)	(0.33,0.62,1)	(0.33,0.70,1)	(0.11,0.11,0.33)	(0.56,0.78,1)
A_{11}	(0.33,0.36,0.60)	(0.33,0.62,1)	(0.33,0.62,1)	(0.11,0.33)	(0.56,0.78,1)
A_{12}	(0.33,0.39,0.60)	(0.33,0.62,1)	(0.33,0.62,1)	(0.56,0.85,1)	(0.56,0.85,1)

The next step is computing the normalized fuzzy decision matrix for all the alternatives by using (9). The values of that are present in Table 4 and the values of that is present in Table 5 are required to compute the weighted normalized fuzzy decision matrix. Let us take an example, the weighted normalized fuzzy assessment of alternative A_1 for Average claim ratio (C_1) is given by:

$$\widetilde{WC}_{ij} = (0.778, 1, 1)(7{,}9{,}9) = (5.4444{,}9{,}9)$$

Similarly, we computed the weighted normalized fuzzy decision matrix for all the alternatives w.r.t each criterion and that is presented in Table 8.

Table 8. Weighted normalized fuzzy decision matrix

	C_1	C_2	C_3	C_4	C_5
A_1	(5.44,9,9)	(2.778,7.0988,9)	(3.89,7,9)	(0.56,1.0870,1.80)	(2.78,7.7160,9)
A_2	(5.44,9,9)	(2.78,6.5309,9)	(3.89,7,9)	(0.56,1.4706,3)	(2.78,7.0988,9)
A_3	(5.44,9,9)	(1.67,5.3951,9)	(0.78,3.6667,7)	(0.56,1.3158,3)	(2.78,7.0988,9)
A_4	(3.89,8.3333,9)	(2.78,7.0988,9)	(2.33,6.3333,9)	(0.56,1.4706,3)	(1.67,5.8642,9)
A_5	(3.89,7.6667,9)	(2.78,6.5309,9)	(2.33,6.3333,9)	(0.56,1.0870,1.80)	(2.78,7.7160,9)
A_6	(3.89,7.6667,9)	(2.78,7.0988,9)	(2.33,6.3333,9)	(0.56,1.4706,3)	(2.78,7.7160,9)
A_7	(2.33,5.6667,9)	(2.78,6.5309,9)	(3.89,8.33,9)	(0.56,1.3158,3)	(1.67,5.862,9)
A_8	(2.33,6.3333,9)	(2.78,6.5309,9)	(0.78,3,5)	(0.56,1.3158,3)	(1.67,5.8642,9)
A_9	(3.89,7.6667,9)	(2.78,5.9630,9)	(2.33,6.3333,9)	(0.56,1.0870,1.80)	(1.67,4.6296,7)
A_{10}	(2.33,5.6667,9)	(1.67,5.3951,9)	(3.89,7.6667,9)	(0.73,1.9231,9)	(1.67,5.8642,9)
A_{11}	(0.78,4.3333,7)	(1.67,5.3951,9)	(0.78,2.3333,5)	(0.56,1.087,1.80)	(1.67,5.8642,9)
A_{12}	(0.78,3.6667,7)	(2.78,6.5309,9)	(2.33,6.3333,9)	(0.56,1,1.8000)	(1.67,5.2469,9)
	C_6	C_7	C_8	C_9	C_{10}
A_1	(2.33,3,3.8571)	(1.67,5.3951,9)	(1,4.4568,9)	(1.67,4.4074,9)	(1,2.78,5.4444)
A_2	(2.33,3.2400,5.40)	(1.67,5.3951,9)	(1,4.4568,9)	(1.67,4.4074,9)	(1,2.78,5.4444)
A_3	(2.33,4.2632,9)	(1.67,5.3951,9)	(1,3.9877,9)	(1,3.9877,9)	(1,3.5185,7)
A_4	(2.33,4.2632,9)	(1.67,5.3951,9)	(1,3.9877,9)	(1.67,4.4074,9)	(1,2.78,5.4444)
A_5	(2.33,3.2400,5.40)	(1.67,4.8272,9)	(1,3.9877,9)	(1,3.9877,9)	(1.67,3.8889,7)
A_6	(2.33,3.2400,5.40)	(1.67,4.8272,9)	(1,4.4568,9)	(1.67,4.4074,9)	(1,2.78,5.4444)
A_7	(2.33,3.2400,5.40)	(1.67,4.8272,9)	(1,4.4568,9)	(1.67,4.4074,9)	(1,2.78,5.4444)
A_8	(2.33,3.5217,5.40)	(1.67,4.8272,9)	(1.67,5.3951,9)	(1.67,4.4074,9)	(1,2.78,5.4444)
A_9	(2.33,3.2400,5.40)	(1.67,4.2593,7)	(1,3.9877,9)	(1.67,4.4074,9)	(1,2.78,5.4444)
A_{10}	(2.33,4.2632,9)	(1.67,4.8272,9)	(1,4.4568,9)	(0.33,0.6296,3)	(1.67,3.8889,7)
A_{11}	(2.33,3.2400,5.40)	(1.67,4.8272,9)	(1,3.9877,9)	(0.33,0.6296,3)	(1.67,3.8889,7)
A_{12}	(2.33,3.5217,5.40)	(1.67,4.8272,9)	(1,3.9877,9)	(1.67,4.8272,9)	(1.67,4.2593,7)

Then we compute the FPIS and FNIS by using (10) and (11). For an example, the FPIS (F^{+}) and FNIS (F^{-}) for average claim ratio (C_1)is given by: $F^{+} = (9, 9, 9)$ and $F^{-} = (0.7778, 0.7778, 0.7778)$) Similarly, we calculate the FPIS and FNIS for all the criteria that is presented in Table 9.

Table 9. FPIS (F^{+}) and FNIS (F^{-})

	$FPIS(F^{+})$	$FPIS(F^{-})$
C_1	(9,9,9)	(0.78,0.7778,0.7778)
C_2	(9,9,9)	(1.67,1.6667,1.6667)
C_3	(9,9,9)	(0.78,0.7778,0.7778)
C_4	(9,9,9)	(0.56,0.5556,0.5556)
C_5	(9,9,9)	(1.67,1.6667,1.6667)
C_6	(9,9,9)	(2.33,2.3333,2.3333)
C_7	(9,9,9)	(1.67,1.6667,1.6667)
C_8	(9,9,9)	(1,1,1)
C_9	(9,9,9)	(0.33,0.3333,0.3333)
C_{10}	(7,7,7)	(1,1,1)

Now we computed the distance $v_t(.)$ for every possibility from FPIS ( ) and FNIS ( ) by using (3), (12), and (13). For an example the distances $(v_{t}, {A_1}^{+})$ and$(v_{t}, {A_1}^{-})$ of alternative A_1 for Average claim ratio are computed as follows:

$$\left(v_{t}, {A_1}^{+}\right) = \sqrt{\frac{1}{3}[(5.4444 - 9)^2 + (9 - 9)^2 + (9 - 9)^2]} = 2.0528$$

$$\left(v_{t}, {A_1}^{-}\right) = \sqrt{\frac{1}{3}[(5.4444 - 0.7778)^2 + (9 - 0.7778)^2 + (9 - 0.7778)^2]} = 7.2338$$

This way we calculate the distances for all the criteria and all the possibilities that are depicted in Tables 10-11.

Table 10. Distance $v_i(A_i, F^{+})$ for alternatives

	$v_t, {A_1}^{+}$	$v_t, {A_2}^{+}$	$v_t, {A_3}^{+}$	$v_t, {A_4}^{+}$	$v_t, {A_5}^{+}$	$v_t, {A_6}^{+}$	$v_t, {A_7}^{+}$	$v_t, {A_8}^{+}$	$v_t, {A_9}^{+}$	$v_t, {A_{10}}^{+}$	$v_t, {A_{11}}^{+}$	$v_t, {A_{12}}^{+}$
C_1	2.05	2.05	2.05	2.99	3.04	3.04	4.30	4.14	3.04	4.30	5.57	5.77
C_2	3.75	3.86	4.71	3.75	3.86	3.75	3.86	3.86	3.99	4.71	4.71	3.86
C_3	3.16	3.16	5.77	4.14	4.14	4.14	2.97	6.31	4.14	3.04	6.53	4.14
C_4	7.86	7.39	7.44	7.39	7.86	7.39	7.44	7.44	7.86	6.29	7.86	7.89
C_5	3.66	3.75	3.75	4.60	3.66	3.66	4.60	4.60	5.06	4.60	4.60	4.75
C_6	5.96	5.49	4.72	4.72	5.49	5.49	5.49	5.39	5.49	4.72	5.49	5.39
C_7	4.71	4.71	4.71	4.71	4.87	4.87	4.87	4.87	5.17	4.87	4.87	4.87
C_8	5.31	5.31	5.45	5.45	5.45	5.31	5.31	4.71	5.45	5.31	5.45	5.45
C_9	4.99	4.97	5.45	4.99	5.45	4.99	4.99	4.99	4.99	7.77	7.77	4.87
C_{10}	4.33	4.33	4.05	4.33	3.56	4.33	4.33	4.33	4.33	3.56	3.56	3.46

Table 11. Distance $v_i(A_i, F^{-})$ for alternatives

	$v_t, {A_1}^{-}$	$v_t, {A_2}^{-}$	$v_t, {A_3}^{-}$	$v_t, {A_4}^{-}$	$v_t, {A_5}^{-}$	$v_t, {A_6}^{-}$	$v_t, {A_7}^{-}$	$v_t, {A_8}^{-}$	$v_t, {A_9}^{-}$	$v_t, {A_{10}}^{-}$	$v_t, {A_{11}}^{-}$	$v_t, {A_{12}}^{-}$
C_1	7.23	7.2339	7.29	6.69	6.44	6.44	5.59	5.7991	6.44	5.59	4.13	3.96
C_2	5.30	5.1210	4.74	5.30	5.12	5.30	5.12	5.1210	4.94	4.74	4.74	5.12
C_3	6.21	6.2183	3.96	5.79	5.79	5.79	6.69	2.7547	5.79	6.44	2.59	5.79
C_4	0.78	1.5069	1.47	1.50	0.78	1.50	1.47	1.4780	0.78	4.93	0.78	0.76
C_5	5.52	5.3079	5.30	4.87	5.52	5.52	4.87	4.8784	3.52	4.87	4.87	4.71
C_6	0.96	1.8463	4.00	4.00	1.84	1.84	1.84	1.8988	1.84	4.00	1.84	1.89
C_7	4.74	4.74	4.74	4.74	4.61	4.61	4.61	4.61	3.42	4.61	4.61	4.61
C_8	5.03	5.03	4.93	4.93	4.93	5.03	5.03	5.28	4.93	5.03	4.93	4.93
C_9	5.58	5.58	5.44	5.58	5.44	5.58	5.58	5.58	5.58	1.54	1.54	5.68
C_{10}	2.76	2.76	3.75	2.76	3.86	2.76	2.76	2.76	2.76	3.86	3.86	3.96

Then we calculate the distances ${v_i}^{+}$ and ${v_i}^{-}$ using (12) and (13). Let us take an example, the distances ${v_i}^{+}$and$({v_i}^{-})$ of alternative A_1 for Average claim ratio (C_1) are computed as follows:

$({v_i}^{+})$=45.839 and $({v_i}^{-})$=44.1547

We compute the closeness coefficient (S_i) buy using distances v_i^+ and v_i^- for all the alternatives that is given by (14). Let us take an example the S_i of alternative $A_1$is given by:

$$S_i = \frac{44.1547}{44.1547 + 45.8394} = 0.4906$$

Similarly, we compute for all alternatives, that is presented in Table 12.

Table 12. Closeness coefficients of the alternatives

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
v_i^-	44.15	45.36	45.61	46.21	44.37	44.42	43.59	40.17	40.0463	45.67	33.94	41.45
v_i^+	45.83	45.08	48.09	47.09	47.42	47.01	48.19	50.68	49.5671	49.20	56.45	50.49
S_i	0.49	0.50	0.48	0.49	0.48	0.48	0.47	0.44	0.4469	0.48	0.37	0.45

Finally, we rank the alternatives by comparing theCC_ivalue, that is given in Table 12. We find that LIC (A_2)>SBI(A_4)>ICICI (A_1)> HDFC(A_3)> BAJAJ ALIANZ(A_6)> MAX(A_5)>KOTAK MAHINDRA (A_{10})> BHARTI AXA (A_7)> AVIVA(A_{12})> RELIANCE(A_9)> AEGON RELIGARE (A_8)> CANARA HSBC (A_{11}). So LIC (A_2) is recommended as best insurance company for an online term plan. Ranking of all the alternatives are presented in Figure. 2.

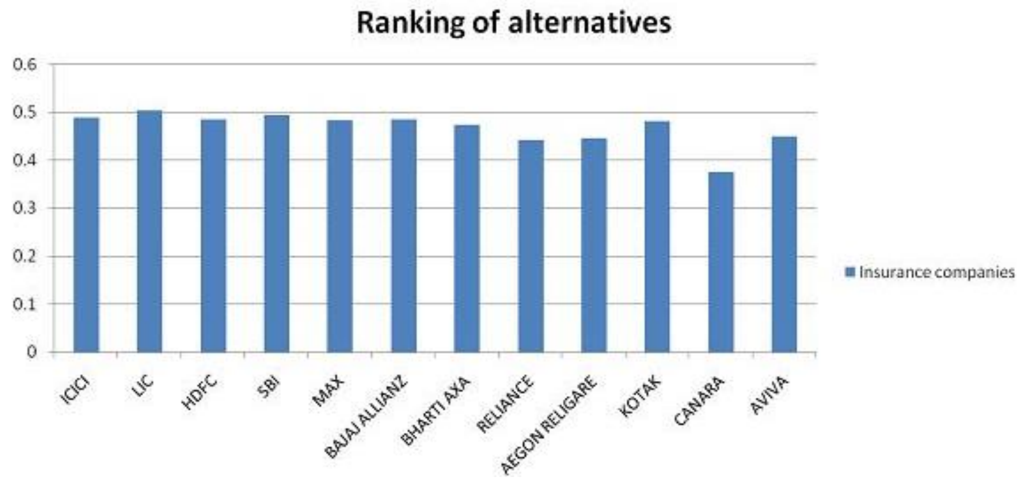

Figure 2. Ranking of insurance companies

4.1. Sensitivity analysis

We conducted a SA to find the influence of weights of criteria on the best insurance company choosing for purchasing an online term policy. The numbers of 25 experiments were conducted, which are presented in Table 13. In the first two experiments, all of the criteria weight we are assigned to (7, 9, 9) and (5,7,9), that is presented in Table 13. In third and fourth experiment, we set the weight of criterion $_1$=(7, 9, 9) and the rest of criteria have weight=(5, 7, 9) and (3, 5, 7) respectively. In fifth experiment, we set the weight of criterion C_1=(5, 7, 9) and the rest of criteria have weight=(3, 5, 7). In experiments 6-9, we set the weight of all criteria=(7, 9, 9) except the cost criteria C_4 and C_6. The weights of C_4 and C_6 for the experiments 6-9 are respectively (5, 7, 9), (3, 5, 7), (1, 3, 5) and (1, 1, 3). In experiments 10-13, we set the weight of all criteria=(5, 7, 9) except the cost criteria C_4 and C_6. The weights of C_4 and C_6 for the experiments 10-13 are respectively (7, 9, 9), (3, 5, 7), (1, 3, 5) and (1, 1, 3). In experiment 14 and 15, we set the weight of all criteria=(3, 5, 7) except the cost criteria C_4 and C_6. The weights of C_4 and C_6 for the experiments 14 and15 are respectively (1, 3, 5) and (1, 1, 3). In experiment 16, we set the weights of criteria C_1 and C_2=(7, 9, 9), and all other criteria weights=(5, 7, 9). In experiment 17, we set the weights of criteria C_1, C_2 and C_3=(7, 9, 9), and all other criteria weights=(5, 7, 9). In experiments 18-20, all criteria have weights (3, 5, 7), (1, 3, 5) and (1, 1, 3) respectively. In experiment 21 and 22, we set the weight of all criteria=(3, 5, 7) except the cost criteria C_4 and C_6. The weights of C_4 and C_6 for the experiments 21 and 22 are respectively (7, 9, 9) and (5, 7, 9). In experiment 23, we set the weight of criterion C_1=(3, 5, 7) and all other criteria weights=(1, 3, 5). In experiment 24, we set the weights of criteria C_1 and C_2=(3, 5, 7) and all other criteria weights=(1, 3, 5). In experiment 25, we set the weights of criteria C_1, C_2 and C_3=(3, 5, 7) and the rest of criteria have weight=(1, 3, 5). Out of 25 experiments, LIC (A_2) is selected as best insurance company in first 17 experiments. However, SBI (A_4) is selected as best insurance company in last 8 experiments.

Table 13. Experiment for sensitivity analysis

Exp. No.	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
1	0.51	0.52	0.50	0.51	0.51	0.51	0.49	0.46	0.46	0.49	0.38	0.47
2	0.46	0.47	0.47	0.47	0.46	0.46	0.45	0.43	0.43	0.46	0.37	0.44
3	0.47	0.49	0.48	0.48	0.47	0.47	0.46	0.43	0.43	0.46	0.37	0.44
4	0.47	0.48	0.48	0.48	0.47	0.47	0.45	0.43	0.44	0.46	0.37	0.44
5	0.46	0.47	0.47	0.47	0.46	0.46	0.45	0.43	0.43	0.46	0.37	0.43
6	0.51	0.52	0.50	0.51	0.50	0.50	0.49	0.46	0.46	0.49	0.38	0.47
7	0.53	0.54	0.512	0.52	0.52	0.52	0.50	0.47	0.47	0.49	0.39	0.49
8	0.55	0.55	0.52	0.53	0.53	0.53	0.52	0.49	0.49	0.49	0.40	0.50
9	0.57	0.57	0.53	0.54	0.55	0.55	0.53	0.50	0.50	0.49	0.41	0.52
10	0.46	0.48	0.47	0.48	0.46	0.47	0.46	0.43	0.43	0.46	0.36	0.44
11	0.48	0.49	0.47	0.48	0.48	0.48	0.47	0.44	0.44	0.46	0.37	0.45
12	0.49	0.50	0.48	0.49	0.49	0.49	0.48	0.45	0.45	0.46	0.38	0.47
13	0.51	0.51	0.49	0.50	0.50	0.50	0.49	0.46	0.46	0.46	0.39	0.48
14	0.473	0.47	0.471	0.47	0.47	0.47	0.46	0.44	0.45	0.43	0.38	0.45
15	0.49	0.49	0.48	0.48	0.48	0.48	0.47	0.45	0.45	0.45	0.39	0.46
16	0.48	0.49	0.48	0.49	0.48	0.48	0.46	0.44	0.44	0.47	0.37	0.45
17	0.49	0.50	0.48	0.49	0.48	0.48	0.47	0.44	0.44	0.47	0.37	0.45
18	0.45	0.46	0.46	0.46	0.45	0.45	0.45	0.42	0.42	0.45	0.37	0.43
19	0.43	0.44	0.44	0.45	0.44	0.44	0.43	0.41	0.41	0.44	0.37	0.42
20	0.39	0.40	0.41	0.41	0.40	0.40	0.40	0.38	0.37	0.41	0.34	0.39
21	0.44	0.45	0.45	0.46	0.44	0.44	0.43	0.41	0.41	0.45	0.36	0.42
22	0.43	0.45	0.45	0.46	0.44	0.44	0.43	0.41	0.41	0.45	0.36	0.42
23	0.44	0.45	0.46	0.46	0.45	0.45	0.44	0.42	0.42	0.45	0.37	0.42
24	0.45	0.46	0.46	0.46	0.45	0.45	0.44	0.43	0.42	0.45	0.37	0.43
25	0.46	0.47	0.46	0.47	0.46	0.46	0.45	0.42	0.43	0.46	0.37	0.43

5. CONCLUSION

Since several companies offer a wide variety of policies, a recommender system which works on multi-criteria is devised to rank the LI policies and rank them. The customers can be recommended insurance based on the ranks. Increase in data resulted in techniques to extract important data from a large amount of information. A fuzzy method is more suitable to handle a large amount of information as well as imprecise data. In this paper, a fuzzy MCDM (TOPSIS) has been applied to rank the insurance companies in India for purchasing an online policy. The experimental results showed that LIC has been selected as the best insurance company for an online term plan followed by SBI. The results of the sensitivity analysis showed LIC has been selected as the best insurance company in the first 17 experiments out of 25. Since the data are collected from the expert opinion, it may vary from expert to expert, so it can be considered as the limitation of this proposed model. In future, we will extend this work by applying other fuzzy methods or Pythagorean fuzzy method and bio-inspired methods to solve this problem of insurance selection.

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