Multi-Criteria Decision-Making in Ranking of Life Insurance Companies in India by using fuzzy TOPSIS

3.1 Introduction

Future is rather unpredictable and uncertain. So in this sea of uncertainties, due to imprecise activity in the day to day life. As results, financial loss and failure of the desired event may occur. Death is inevitable, it comes sooner or later, with that comes great sufferings to dependants in most of the cases where there is only one earning person in a family. So there comes the most important of all types of life insurance. Life insurance policy provides us with the assurance that our family gets financial support and security even when one of us is not around anymore [37]. The theory of insurance can be expressed as “the good fortune of the many" compensates for “the misfortune of the few". So insurance companies prepare themselves to take this burden on their shoulders in exchange for an assessed payment. Those who avail life insurance are actually ensuring the safety of their loved dependant ones. In this case, the company is at a risk of compensating the deceased as they are bounded by the contract [38]. Life insurance actually has no competition from other financial products as the there are many terms and conditions applied to the other products where it is totally different and secure. No common man wants his family to suffer from the financial crisis, that is the pillar of success for Life Insurance and as long as the humanity will be there it will exist.

Life insurance business in India started with the establishment of the Oriental life insurance company in Kolkata, West Bengal India in the year 1818 and the company failed in in1834. This business is reincarnated in the Madras Presidency 1829 by the Madras Equitable. With the enactment of the British Insurance Act in 1870, the last three decades of the nineteenth century saw the dominance of foreign insurances such as Bombay Mutual, Oriental, Empire of India, Liverpool, London Globe Insurance, Albert life assurance and Royal Insurance in the Bombay Residency [39]. But with the enactment of the Indian life assurance companies

Act in 1912, India government got the chance of investigating all statistical information about all the transactions happening around India.

The main objective is focusing on an MCDM approach for selecting the best life insurance company for purchasing an online term policy [40]. MCDM is helping to select the best alternative among the set of alternatives and the methods of MCDM can be used in the various field [1]. Fuzzy set theory is used to define the decision-making parameters. Fuzzy set theory was introduced by Zadeh [2] and it supports 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 capabilities. First, the capability to converse, reason and make rational decisions in an environment having of imprecision, uncertainty, conflict, incompleteness information. Second, the capability to perform a wide variety of physical and mental tasks without any psychical measurement and computation.

There have some criteria for selecting the best insurance company among a set of companies. Criteria have some weighted values that are independent of each other. The best insurance company alternative is evaluated against the set of weighted criteria. The alternatives of insurance companies are considered for final implementation which is evaluating the best with respect to all other criteria.

Jagdal et al. [39] have ranked Insurance companies specially in money back insurance policies domain with the help of classical AHP process and also took advice from the specialists in this field and Life Insurance Corporation, State Bank of India, Max Life Insurance, Bajaj Allianz Life Insurance and Aviva Life Insurance as their set of alternatives between which they found LIC to be the best among them using the above-mentioned method.

Zopounidis [41] has investigated after analysed different decision-making strategies in different financial sectors problem related to insurance, banks, and financial firms, acquisition of firms, risks like bankruptcy risk, country risk, and financial planning related problems. In this study, it suggested the different contributions of MCDM in various financial problems and enlightened with the possibility of structuring complex evaluation problems and has given different possible solutions.

Khodamoradi et al [42] have studied different insurance companies in Iran and have proposed new hybrid methods consisting DEMATEL and PROMETHEE II method using sample data from insurance companies listed in Tehran Stock Exchange (2010–2012) financial year and have suggested that Alborz company has the highest and DANA company has the lowest rate.

DominikHo and Michael Sherris [43] 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.

Jain Yogesh[44] have analyzed the present and past status oflife insurance sector and also discusses the future strategies of the Indian insurance sector.

Hurd and Mc Garrys[40] have discussed the unfavourable selection in the purchase of insurance.

3.2 Problem definition

Insurance is one of the most developed activities in the world today, with remarkable financial capacities and funds. By issuing life insurance policies as financial instruments and through the long-term placement of free funds, insurance companies occupy a significant place in developed financial markets as institutional investors. Life insurance growth, i.e. the transfer of insured risks to an insurance company by means of life insurance premiums, increases total available funds insurance companies can place on a financial market. The goal of insurance funds placement is protecting insurance policyholders from the risk insured against and generating maximum profit on placed funds.

After Literature study it can be concluded that methods of MCDM can be applied on Insurance purchasing where the problem consists of multiple criteria and alternatives. There are several criteria is related to purchase an Insurance that is described as below

3.3 Triangular Membership Function(MF)

A triangular MF (fig.1) is represented by the three parameters (a, b, c)

$$trimf(x\colon a,b,c) = \begin{cases} 0\,, & x \le a, \\ \frac{x-a}{b-a}\,, & a \le x \le b\,, \\ \frac{c-x}{c-b}\,, & b \le x \le c\,, \\ 0\,, & c \le x \end{cases} \tag{3.1}$$

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

$\widetilde{x}$

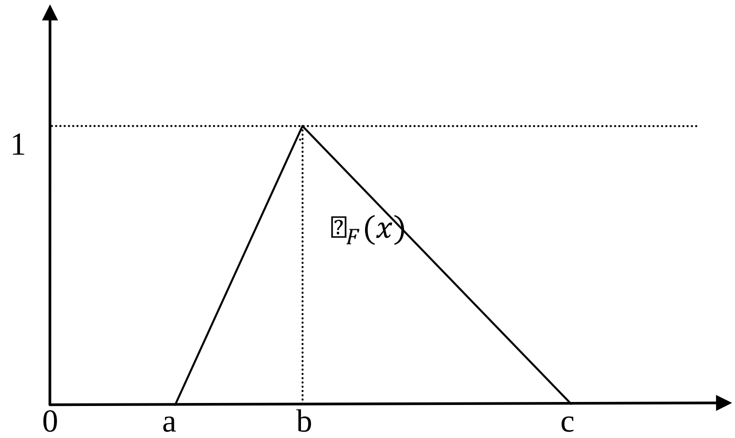

Figure.3.1. Triangular fuzzy number

$\widetilde{x}\,\widetilde{y}$

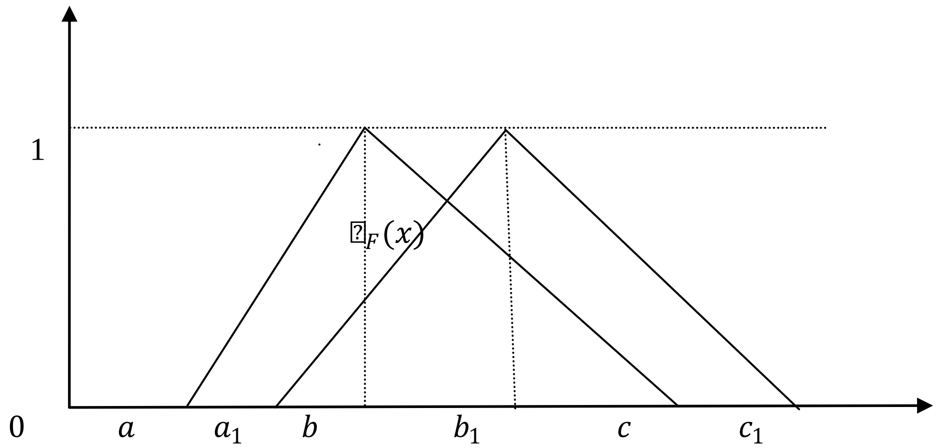

Figure.3.2. Two different triangular fuzzy numbers

3.3.1Distance 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 between two triangular fuzzy numbers calculated by using vertex method is given bellow[45] [3].

$$d(\tilde{x}, \tilde{y}) = \sqrt{\frac{1}{3}\,[(x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_3 - y_3)^2\,]} \qquad (3.2)$$

3.4 Linguistic variables

A linguistic variable is described by a quintuple, which consists a variable name, term set, the universe of discourse, syntactic rule, and semantic rule. In fuzzy set theory, transformation scale is needed to convert the fuzzy numbers from linguistic variable[45] [46][47]. Apply a 1-9 transformation scale for rating the alternatives and criteria. Linguistic variable for criteria ratings are represented in Table.3.1 and linguistic term for alternatives ratings are represented in Table. 3.2.

Table 3.1: 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 3.2: 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)

3.5 Proposed model for ranking of insurance companies

The proposed model for ranking of insurance companies consist five different steps and these are described as bellows.

3.5.1 Process for selection of insurance policy

There is several types insurance policy are available in the market such as term insurance plans, pension plan, health plan, endowment plan, child plan, money back plan [48]. One of the popular plans is term insurance plan. An online term policy is a combine application of e-commerce and financial market [49] [23]. Nowadays it is combined with the insurance sector and produce a new insurance product, that is online term plan. There are a lot of attractive facilities are available under this plan, where people can buy this type of plan directly without any help of an agent. Here only the online term plans considered and finally ranking the insurance companies for purchasing an online term plan.

3.5.2 Process for selection of criteria

There are a lot of criteria are exist for purchasing an insurance policy. 10 criteria have been chosen, that is described in table 3. These criteria are taking from literature survey and consult with some experienced person of this field. Criteria are categorized into two types ie. Cost criteria and benefit criteria. In cost criteria, the lower value is more preferable for alternative selection and for benefit criteria, a higher value is more preferable for alternative selection [3].

In table 3.3, the criteria are denoted by $C_1 - C_{10}$, here $C_4$and C_6 are the cost criteria and all other criteria are the benefit criteria.

Table 3.3: Criteria for purchasing an insurance policy

Criteria	Definition	Criteriatype
Average claim ratio (C_1)	Total number of death claim settled	Benefit
Entry age (C_2)	Age of insured person at the beginning of policy	Benefit
Policy term (C_3)	The benefit amount that is received by the policyholder or nominee either death or contract stipulation	Benefit
Maturity (C_4)	Period of coverage provided by a policy	Cost
Sum assured (C_5)	Financial cost of a policy that is paid by the insured	Benefit
Premium (C_6)	The pre-decide amount, that insurer pay to the insured.	Cost
Premium payment term (C_7)	Duration for the policyholder to pay the premium	Benefit
Premium payment frequency (C_8)	Number of times to pay the premium	Benefit
Rebate on large sum assured (C_9)	Discount on large sum assured	Benefit
Riders (C_{10})	Additional benefit that can enhance the coverage	Benefit

3.5.3 Process for selection of alternatives

There are 24 Life insurance companies in India under the IRDA (Insurance Regulatory and Development Authority of India) [50] [51] [52].

At first, some of the companies have had chosen which has better claim ratio. It is an important criteria for an insurance company. It refers to the ratio of a total number of death claim received and the total number of death claim settled. For an example, if a life insurance 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 calculate the average claim ratio. Consider those companies which have more than 70% claim ratio.

Finally, 12 insurance companies have chosen which has online term plan facility. In table 3.4, the alternatives of insurance companies are denoted by $A_1 - A_{12}$.

Table 3.4.Name 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}
ICICI	LIC	HDFC	SBI	MAX	BAJAJ ALLIANZ	BHARTI AXA	AEGON RELIGARE	RELIANCE	KOTAK MAHINDRA	CANARA HSBC	AVIVA

3.5.4 Ranking life insurance companies using fuzzy TOPSIS

MCDM technique is used, called Fuzzy TOPSIS for choosing the best insurance company against some selected weighted criteria. TOPSIS helps to find the best alternative which is farthest from the Negative Ideal Solution (NIS) and very near to the Positive Ideal Solution(PIS). An NIS is consists of the minimum values of each alternative and PIS is consist of the maximum values of each alternative. The several steps of fuzzy TOPSIS are discussed as follows [3]:

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 are to calculated against criteria. The weight for each criteria are represented by cw_i $(i = 1,2,3,\dots,m)$. The performance assignment of each decision maker for each alterative with respect to each criteria is represents 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 used 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

$$x = \min_k \{x_k\}, \qquad y = \frac{1}{K}\sum_{k=1}^{K} y_k, z = \max_k \{z_k\} \tag{3.3}$$

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 with respect to each criteria on are given by where $\tilde{y}_{ij} = (x_{ij}, y_{ij}, z_{ij})$ where,

$$x_{ij} = \min_k \{x_{ijk}\}, \quad y_{ij} = \frac{1}{K}\sum_{k=1}^{K} y_{ijk}, z_{ij} = \max_k \{z_{ijk}\} \tag{3.4}$$

The aggregated fuzzy weights $(\widetilde{cw}_{ij})$ of each criterion are calculated as $\widetilde{cw}_j = (cw_{j1}, cw_{j2}, cw_{j3})$where,$cw_{j1} = \min_k \{cw\}$,$cw_{j2} = \frac{1}{K}\sum_{k=1}^{K} cw_{jk2}$,

$$cw_{j3} = \max_k \{cw_{jk3}\} \tag{3.5}$$

Step 3: Calculate the fuzzy decision matrix.

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

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

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

Step 4: Fuzzy decision matrix should be normalized

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

for cost criteria

$$\tilde{p}_{ij} = \left(\frac{x_j{}^-}{z_{ij}}, \frac{x_j{}^-}{y_{ij}}, \frac{x^-}{x_{ij}}\right),\ \ x_j{}^- = \underset{i}{min}\,(x_{ij})(3.6)$$

and for benefit criteria,

$$\tilde{p}_{ij} = \left(\frac{x_{ij}}{z_j{}^*}, \frac{y_{ij}}{z^*}, \frac{z_{ij}}{z_j{}^*}\right),\ \ z_j{}^* = \underset{i}{max}\,(z_{ij}) \qquad (3.7)$$

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 $\tilde{p}_{ij}$.

$\widetilde{WC} = [\widetilde{wc}_{ij}]_{m\times n},\ i = 1,2, \dots, m;\ \ j = 1,2, \dots, n$ where$\widetilde{wc}_{ij} = \tilde{p}_{ij}\,(.)cw_j$(3.8)

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,

$F^+ = (wc_1{}^+, wc^+, \dots, wc_n{}^+)$where $wc_j{}^+ = \underset{i}{max}\,(wc_{ij3})$,$i = 1,2, \dots, m;\ \ j = 1,2, \dots, n$(3.9)

$F^- = (wc_1{}^-, wc^-, \dots, wc_n{}^-)$where $wc_j{}^- = \underset{i}{min}\,(wc_{ij1})$,$i = 1,2, \dots, m;\ \ j = 1,2, \dots, n$(3.10)

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:

$$v_i{}^+ = \sum_{j=1}^{n} v_t\left(\tilde{t}_{ij}, t_j{}^+\right),\ i = 1,2,..,m \qquad (3.11)$$

$$v_i{}^- = \sum_{j=1}^{n} v_t\left(\tilde{t}_{ij}, t_j{}^-\right),\ i = 1,2,.., \qquad (3.12)$$

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

$$S_i = \frac{v_i{}^-}{v_i{}^- + v^+}\ ,i = 1,2,..,m \qquad (3.13)$$

Step 9: Ranking of the alternatives.

Ranking of alternatives is made according to the value of closeness coefficient (S_i) in decreasing order. Choose the best alternatives which have heights S_i value.

3.6 Method

3.6.1 *Participants*

Four hundred (Male = 310, Female = 90) under graduate and post graduate students from engineering and the management streams of KIIT University, Bhubaneswar, Odisha (India) participated in the study. With the prior permission of the concerned teacher, in each class of about 40 students, the researcher briefed about the purpose of the study and informed content was sought from participants. Those who signed the informed consent and agreed to participate, they were given the questionnaire during the class hour to complete and return the questionnaire to the researcher. The participants took about 40 min to complete the questionnaire.

The socio-demographic profiles of male and female students were compared using *F* test when the data were in interval scale and Chi-square test when the data were in nominal scale. More number of male students participated in the study compared to the female students because of high enrolment ratio (>.80) of male students in engineering and management education. Most of the boys were the natives from urban areas and the girls from semi-urban areas. Very few male as well as female students were from rural areas. The female students were little older than their male counterparts and had studied more years in formal educational institutions than male students. Of the total, 79.5% of the students had no job experience and the reaming students had maximum up to four years of experience. Both male and female students were predominantly from nuclear family having minimum 1 to maximum 5 members and few were from joint/extended families. The average annual income of parents and family members of male and female students did not differ. On the average, the annual income varied from as low as 5,000 to as high as 65 lac. Indian rupees (Table 3.5).

Table 3.5 Sample profile

Characteristic	Descriptive Statistics	Male	Female	χ^2	F
Gender	*N (%)*	310 (77.50)	90 (22.50)	121.00***	
Birth Place					
Urban	*N (%)*	168(54.20)	38(42.2)	13.42***	
Semi-urban		86(27.70)	43(47.80)		
Rural		56(18.10)	9(10.00)		
Age	*M (SD)*	20.81(4.50)	23.61(3.97)		28.34***
Years studied		14.99(3.06)	17.73(3.52)		52.11***
Job experience		0.64(2.81)	1.02(1.93)		1.45
Family size		4.67(1.85)	4.69(1.34)		0.01
Income (in INR)		466399(771448)	530888(988621)		0.42

INR= Indian rupees
*p<0.05. **p<0.01. ***p<0.001.

3.7 Numerical representation

Let us consider that someone is interested in buying an online term policy. There are so many companies are available [52]. So problem is that how to determine the best company for buying a policy. A committee is formed, that is consist of three decision maker D_1, D_2, D_3 for choosing the best choice. The alternatives available for purchasing an online term policy is define in Table 3.4.

There are several criteria used for purchasing an online term policy 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 and rest of the criteria are benefit criteria.

The committee of 3 decision makers provide the linguistic judgement 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 aredefine in Table2. Linguistic judgement for the criteria and alternatives are define in Table 3.5 and Table 3.6.

Table 3.6. Linguistic assessments for the criteria

Criteria	(D_1)	(D_2)	(D_3)
Average claim ratio (C_1)	VH	VH	VH
Entry age (C_2)	H	H	VH
Policy term (C_3)	VH	VH	VH
Maturity (C_4)	VH	H	VH
Sum assured (C_5)	H	VH	VH
Premium (C_6)	VH	VH	VH
Premium payment term (C_7)	H	H	VH
Premium payment frequency (C_8)	M	H	H
Riders (C_9)	M	H	M
Rebate on large sum assured (C_{10})	M	M	M

Table 3.7. Linguistic assessments for 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}
C_1	D_1	VG	VG	VG	VG	G	G	F	G	VG	F	P	P
	D_2	VG	VG	VG	G	G	G	F	G	G	F	F	P
	D_3	VG	VG	VG	VG	VG	VG	G	F	G	G	F	F
C_2	D_1	VG	VG	F	VG	G	G	G	G	G	F	G	VG
	D_2	VG	G	G	G	VG	VG	VG	VG	G	G	F	G
	D_3	G	G	G	VG	G	VG	G	G	G	G	G	G
C_3	D_1	G	G	P	G	F	G	VG	P	G	G	P	F
	D_2	G	G	F	F	G	F	G	P	F	G	P	G
	D_3	G	G	P	G	G	G	VG	P	G	VG	VP	G
C_4	D_1	VG	F	G	F	G	G	F	G	G	F	G	VG
	D_2	G	F	G	G	VG	F	G	F	G	P	VG	G
	D_3	G	G	F	F	G	F	G	G	VG	F	G	VG
C_5	D_1	G	VG	G	G	G	G	F	F	F	G	G	F
	D_2	VG	G	G	G	VG	VG	G	G	F	F	F	F
	D_3	VG	G	VG	F	VG	VG	G	G	F	G	G	G
C_6	D_1	VG	VG	M	F	G	G	G	G	VG	G	VG	G
	D_2	VG	G	G	G	VG	VG	VG	VG	G	G	G	G
	D_3	VG	VG	G	G	VG	VG	VG	G	VG	F	VG	VG
C_7	D_1	G	G	F	G	G	F	G	G	F	G	F	G
	D_2	G	F	G	F	F	F	F	F	F	F	F	F
	D_3	F	G	G	G	F	G	F	F	F	F	G	F
C_8	D_1	G	G	G	F	F	G	F	VG	G	F	F	F
	D_2	F	F	F	G	G	G	G	G	F	G	G	F
	D_3	G	G	F	F	F	F	G	G	F	G	F	G
C_9	D_1	G	G	G	G	F	G	G	G	G	VP	VP	VG
	D_2	G	G	G	G	G	G	G	G	G	VP	VP	G
	D_3	G	G	F	G	G	G	G	G	G	VP	VP	G
C_{10}	D_1	F	F	G	F	G	F	F	F	F	G	G	G
	D_2	F	F	F	F	G	F	F	F	F	G	G	G
	D_3	F	F	G	F	G	F	F	F	F	G	G	VG

By using Eqn (3.5), the aggregated fuzzy weight for each criterion is calculated. 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

$cw_{j1} = \substack{min \\ k} \ \{7,7,7\}, \ cw_{j2} = \frac{1}{3}\sum_{k=1}^{3}(9+9+9), \ cw_{j3} = \substack{max \\ k} \ \{9,9,9\}$

$\widetilde{cw}_j = (7,9,9)$

This way the aggregated fuzzy weight for rest of all criteria and that is define in Table 3.7

Table 3.8:Aggregated fuzzy weight for criteria

Criteria	(D_1)	(D_2)	(D_3)	Aggregated fuzzy weight
Average claim ratio (C_1)	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)
Entry age (C_2)	(5,7,9)	(5,7,9)	(7,9,9)	(5,7.66,9)
Policy term (C_3)	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)
Maturity (C_4)	(7,9,9)	(5,7,9)	(7,9,9)	(5,8.33,9)
Sum assured (C_5)	(5,7,9)	(7,9,9)	(7,9,9)	(5,8.33,9)
Premium (C_6)	(7,9,9)	(7,9,9)	(7,9,9)	(7,9,9)
Premium payment term (C_7)	(5,7,9)	(5,7,9)	(7,9,9)	(5,7.66,9)
Premium payment frequency (C_8)	(3,5,7)	(5,7,9)	(5,7,9)	(3,6.33,9)
Riders (C_9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5.66,9)
Rebate on large sum(3,5,7) assured (C_{10})	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)

The aggregated fuzzy weight for each alternative is also to calculateby using Eq. (3.4). Let us take an example, the aggregated fuzzy weight for alternative A_1 for criterion $C_1$is

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

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

Similarly, the aggregated fuzzy weight for all the alternatives is calculated with respect to the ten criteria and that is presented in Table 3.8

Table 3.9: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}
C_1	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)
	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)
Aggregate ratings		(7,9,9)	(7,9,9)	(7,9,9)	(5,8.33,9)	(5,7.66,9)	(5,7.6,9)	(3,5.66,9)	(3,633,9)	(5,7.66,9)	(3,5.66,9)	(1,433,7)	(1,3.66,7)
C_2	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)
	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)
Aggregate ratings		(5,8.33,9)	(5,7.66,9)	(3,6.33,9)	(5,8.33,9)	(5,7.66,9)	(5,8.33,9)	(5,7.66,9)	(5,7.66,9)	(5,7,9)	(3,6.33,9)	(3,6.33,9)	(5,7.66,9)
C_3	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)
	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)
Aggregate ratings		(5,7,9)	(5,7,9)	(1,3.66,7)	(3,6.33,9)	(3,6.33,9)	(3,6.33,9)	(5,8.33,9)	(1,3,5)	(3,6.33,9)	(5,7.66,9)	(1,2.33,5)	(3,6.33,9)
C_4	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)
	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)

Aggregate ratings		(5,7.66,9)	(3,5.66,9)	(3,6.33,9)	(3,5.66,9)	(5,7.66,9)	(3.5.66,9)	(3,6.33,9)	(3,6.33,9)	(5,7.66,9)	(1,4.33,7)	(5,7.66,9)	(5,8.33,9)
C_5	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)
	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)
Aggregate ratings		(5,8.33,9)	(5,7.66,9)	(5,7.66,9)	(3,6.33,9)	(5,8.33,9)	(5,8.33,9)	(3,6.33,9)	(3,6.33,9)	(3,5,7)	(3,6.33,9)	(3,6.33,9)	(3,5.66,9)
C_6	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)
	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)
Aggregate ratings		(7,9,9)	(5,8.33,9)	(3,6.33,9)	(3,6.33,9)	(5,8.33,9)	(5,8.33,9)	(5,8.33,9)	(5,7.66,9)	(5,8.33,9)	(3,6.33,9)	(5,8.33,9)	(5,7.66,9)
C_7	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)
	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)
Aggregate ratings		(3,6.33,9)	(3,6.33,9)	(3,6.33,9)	(3,6.33,9)	(3,5.66,9)	(3,5.66,9)	(3,5.66,9)	(3,5.66,9)	(3,5,7)	(3,5.66,9)	(3,5.66,9)	(3,5.66,9)
C_8	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)
	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)
Aggregate ratings		(3,6.33,9)	(3,6.33,9)	(3,5.66,9)	(3,5.66,9)	(3,5.66,9)	(3,6.33,9)	(3,6.33,9)	(5,7.66,9)	(3,5.66,9)	(3,6.33,9)	(3,5.66,9)	(3,5.66,9)
C_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)
	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)
Aggregate ratings		(5,7,9)	(5,7,9)	(3,6.33,9)	(5,7,9)	(3,6.33,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(1,1,3)	(1,1,3)	(5,7.66,9)
C_{10}	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)
	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)
		(3,5,7)	(3,5,7)	(3,6.33,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7.66,9)

Then calculate the normalized fuzzy decision matrix for the alternatives by using eq. (3.6) and (3.7). Let us take an example, the normalized fuzzy rating of alternative A_1 for Average claim ratio (C_1) (benefit criteria) is calculated as

$$z_j{}^* = \underset{i}{max}\,(9,9,9)$$

$$\tilde{p}_{ij} = \left(\frac{7}{9}, \frac{9}{9}, \frac{9}{9}\right) = (0.778, 1, 1)$$

The normalized fuzzy rating of alternative A_1 for Maturity (C_4)(cost criteria) is calculated as

$$x_j{}^- = \underset{i}{min}\,(1,1,1)$$

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

Similarly, anormalized fuzzy decision matrix is calculated for all the alternatives with respect to each criteria and that is presented in Table 3.10.

Minimum value for cost criteria and maximum value for benefit criteria is presented in Table 3.9, which is used for calculating the normalized fuzzy decision matrix.

Table 3.10: 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 3.11:Normalized fuzzy decision matrix

	C_1	C_2	C_3	C_4	C_5
A_1	(0.7778,1,1)	(0.5556,0.9259,1)	(0.5556,0.7778,1)	(0.1111,0.1304,0.20)	(0.5556,0.9259,1)
A_2	(0.7778,1,1)	(0.5556,0.8519,1)	(0.5556,0.7778,1)	(0.1111,0.1765,0.3333)	(0.5556,0.8519,1)
A_3	(0.7778,1,1)	(0.3333,0.7037,1)	(0.1111,0.4074,0.7778)	(0.1111,0.1579,0.3333)	(0.5556,0.8519,1)
A_4	(0.5556,0.9259,1)	(0.5556,0.9259,1)	(0.3333,0.7037,1)	(0.1111,0.1765,0.3333)	(0.3333,0.7037,1)
A_5	(0.5556,0.8519,1)	(0.5556,0.8519,1)	(0.3333,0.7037,1)	(0.1111,0.1304,0.20)	(0.5556,0.9259,1)
A_6	(0.5556,0.8519,1)	(0.5556,0.9259,1)	(0.3333,0.7037,1)	(0.1111,0.1765,0.3333)	(0.5556,0.9259,1)
A_7	(0.3333,0.6296,1)	(0.5556,0.8519,1)	(0.5556,0.9259,1)	(0.1111,0.1579,0.3333)	(0.3333,0.7037,1)
A_8	(0.3333,0.7037,1)	(0.5556,0.8519,1)	(0.1111,0.3333,0.5556)	(0.1111,0.1579,0.3333)	(0.3333,0.7037,1)
A_9	(0.5556,0.8519,1)	(0.5556,0.7778,1)	(0.3333,0.7037,1)	(0.1111,0.1304,0.20)	(0.3333,0.5556,0.7778)
A_{10}	(0.3333,0.6296,1)	(0.3333,0.7037,1)	(0.5556,0.8519,1)	(0.1429,0.2308,1)	(0.3333,0.7037,1)
A_{11}	(0.1111,0.4815,0.7778)	(0.3333,0.7037,1)	(0.1111,0.2593,0.5556)	(0.1111,0.1304,0.20)	(0.3333,0.7037,1)
A_{12}	(0.1111,0.4074,0.7778)	(0.5556,0.8519,1)	(0.3333,0.7037,1)	(0.1111,0.1200,0.20)	(0.3333,0.6296,1)

C_6	C_7	C_8	C_9	C_{10}
(0.3333,0.3333,0.4286)	(0.3333,0.7037,1)	(0.3333,0.7037,1)	(0.5556,0.7778,1)	(0.3333,0.5556,0.7778)
(0.3333,0.3600,0.60)	(0.3333,0.7037,1)	(0.3333,0.7037,1)	(0.5556,0.7778,1)	(0.3333,0.5556,0.7778)
(0.3333,0.4737,1)	(0.3333,0.7037,1)	(0.3333,0.6296,1)	(0.3333,0.7037,1)	(0.3333,0.7037,1)
(0.3333,0.4737,1)	(0.3333,0.7037,1)	(0.3333,0.6296,1)	(0.5556,0.7778,1)	(0.3333,0.5556,0.7778)
(0.3333,0.3600,0.60)	(0.3333,0.6296,1)	(0.3333,0.6296,1)	(0.3333,0.7037,1)	(0.5556,0.7778,1)
(0.3333,0.3600,0.60)	(0.3333,0.6296,1)	(0.3333,0.7037,1)	(0.5556,0.7778,1)	(0.3333,0.5556,0.7778)
(0.3333,0.3600,0.60)	(0.3333,0.6296,1)	(0.3333,0.7037,1)	(0.5556,0.7778,1)	(0.3333,0.5556,0.7778)
(0.3333,0.3913,0.60)	(0.3333,0.6296,1)	(0.5556,0.8519,1)	(0.5556,0.7778,1)	(0.3333,0.5556,0.7778)
(0.3333,0.3600,0.60)	(0.3333,0.5556,0.7778)	(0.3333,0.6296,1)	(0.5556,0.7778,1)	(0.3333,0.5556,0.7778)
(0.3333,0.4737,1)	(0.3333,0.6296,1)	(0.3333,0.7037,1)	(0.1111,0.1111,0.3333)	(0.5556,0.7778,1)
(0.3333,0.3600,0.60)	(0.3333,0.6296,1)	(0.3333,0.6296,1)	(0.1111,0.1111,0.3333)	(0.5556,0.7778,1)
(0.3333,0.3913,0.60)	(0.3333,0.6296,1)	(0.3333,0.6296,1)	(0.5556,0.8519,1)	(0.5556,0.8519,1)

The next step is to compute the normalized fuzzy decision matrix for all the alternatives by using Eq. (3.8). The values of $\tilde{r}_{ij}$ that is present in Table. 3.10 and the values of $\widetilde{w}_j$ that is present in

Table. 3.7 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, the weighted normalized fuzzy decision matrix is calculated for all the alternatives with respect to each criteria and that is presented in Table 3.11.

Table 3.12: Weighted Normalized fuzzy decision matrix

	C_1	C_2	C_3	C_4	C_5
A_1	(5.4444,9,9)	(2.7778,7.0988,9)	(3.8889,7,9)	(0.5556,1.0870,1.80)	(2.7778,7.7160,9)
A_2	(5.4444,9,9)	(2.7778,6.5309,9)	(3.8889,7,9)	(0.5556,1.4706,3)	(2.7778,7.0988,9)
A_3	(5.4444,9,9)	(1.6667,5.3951,9)	(0.7778,3.6667,7)	(0.5556,1.3158,3)	(2.7778,7.0988,9)
A_4	(3.8889,8.3333,9)	(2.7778,7.0988,9)	(2.3333,6.3333,9)	(0.5556,1.4706,3)	(1.6667,5.8642,9)
A_5	(3.8889,7.6667,9)	(2.7778,6.5309,9)	(2.3333,6.3333,9)	(0.5556,1.0870,1.80)	(2.7778,7.7160,9)
A_6	(3.8889,7.6667,9)	(2.7778,7.0988,9)	(2.3333,6.3333,9)	(0.5556,1.4706,3)	(2.7778,7.7160,9)
A_7	(2.3333,5.6667,9)	(2.7778,6.5309,9)	(3.8889,8.3333,9)	(0.5556,1.3158,3)	(1.6667,5.8642,9)
A_8	(2.3333,6.3333,9)	(2.7778,6.5309,9)	(0.7778,3,5)	(0.5556,1.3158,3)	(1.6667,5.8642,9)
A_9	(3.8889,7.6667,9)	(2.7778,5.9630,9)	(2.3333,6.3333,9)	(0.5556,1.0870,1.80)	(1.6667,4.6296,7)
A_{10}	(2.3333,5.6667,9)	(1.6667,5.3951,9)	(3.8889,7.6667,9)	(0.7143,1.9231,9)	(1.6667,5.8642,9)
A_{11}	(0.7778,4.3333,7)	(1.6667,5.3951,9)	(0.7778,2.3333,5)	(0.5556,1.087,1.80)	(1.6667,5.8642,9)
A_{12}	(0.7778,3.6667,7)	(2.7778,6.5309,9)	(2.3333,6.3333,9)	(0.5556,1,1.8000)	(1.6667,5.2469,9)

C_6	C_7	C_8	C_9	C_{10}
(2.3333,3,3.8571)	(1.6667,5.3951,9)	(1,4.4568,9)	(1.6667,4.4074,9)	(1,2.7778,5.4444)
(2.3333,3.2400,5.40)	(1.6667,5.3951,9)	(1,4.4568,9)	(1.6667,4.4074,9)	(1,2.7778,5.4444)
(2.3333,4.2632,9)	(1.6667,5.3951,9)	(1,3.9877,9)	(1,3.9877,9)	(1,3.5185,7)
(2.3333,4.2632,9)	(1.6667,5.3951,9)	(1,3.9877,9)	(1.6667,4.4074,9)	(1,2.7778,5.4444)
(2.3333,3.2400,5.40)	(1.6667,4.8272,9)	(1,3.9877,9)	(1,3.9877,9)	(1.6667,3.8889,7)
(2.3333,3.2400,5.40)	(1.6667,4.8272,9)	(1,4.4568,9)	(1.6667,4.4074,9)	(1,2.7778,5.4444)
(2.3333,3.2400,5.40)	(1.6667,4.8272,9)	(1,4.4568,9)	(1.6667,4.4074,9)	(1,2.7778,5.4444)
(2.3333,3.5217,5.40)	(1.6667,4.8272,9)	(1.6667,5.3951,9)	(1.6667,4.4074,9)	(1,2.7778,5.4444)
(2.3333,3.2400,5.40)	(1.6667,4.2593,7)	(1,3.9877,9)	(1.6667,4.4074,9)	(1,2.7778,5.4444)
(2.3333,4.2632,9)	(1.6667,4.8272,9)	(1,4.4568,9)	(0.3333,0.6296,3)	(1.6667,3.8889,7)
(2.3333,3.2400,5.40)	(1.6667,4.8272,9)	(1,3.9877,9)	(0.3333,0.6296,3)	(1.6667,3.8889,7)
(2.3333,3.5217,5.40)	(1.6667,4.8272,9)	(1,3.9877,9)	(1.6667,4.8272,9)	(1.6667,4.2593,7)

Then compute the FPIS and FNIS by using Eqs. (3.9) and (3.10). 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, calculate the FPIS and FNIS for all the criteria that are presented in Table. 3.12.

Table 3.13:FPIS(F^+) and FNIS (F^-)

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

Now calculate the distance $v_t(.)$ for each alternatives from FPIS(F^+) and FNIS(F^-) by using Eqs. (3.2), (3.11), and (3.12). For an example the distances $(v_{t}, A_1{}^+)$ and$(v_{t}, A_1{}^-)$ of alternative A_1 for Average claim ratio (C_1) 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, calculate the distances for all the criteria and all the alternatives that are presented in Table. 3.13 &3.14.

Table 3.14: 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	2.0528	2.0528	2.0528	2.9759	3.0497	3.0497	4.3033	4.1455	3.0497	4.3033	5.5792	5.7749
C_2	3.7564	3.8649	4.7178	3.7564	3.8649	3.7564	3.8649	3.8649	3.9975	4.7178	4.7178	3.8649
C_3	3.1688	3.1688	5.7749	4.1455	4.1455	4.1455	2.9759	6.3141	4.1455	3.0497	6.5332	4.1455
C_4	7.8690	7.3937	7.4466	7.3937	7.8690	7.3937	7.4466	7.4466	7.8690	6.2912	7.8690	7.8983
C_5	3.6681	3.7564	3.7564	4.6047	3.6681	3.6681	4.6047	4.6047	5.0622	4.6047	4.6047	4.7562
C_6	5.9692	5.4949	4.7217	4.7217	5.4949	5.4949	5.4949	5.3980	5.4949	4.7217	5.4949	5.3980
C_7	4.7178	4.7178	4.7178	4.7178	4.8714	4.8714	4.8714	4.8714	5.1721	4.8714	4.8714	4.8714
C_8	5.3116	5.3116	5.4505	5.4505	5.4505	5.3116	5.3116	4.7178	5.4505	5.3116	5.4505	5.4505
C_9	4.9957	4.9957	5.4505	4.9957	5.4505	4.9957	4.9957	4.9957	4.9957	7.7712	7.7712	4.8714
C_{10}	4.33	4.33	4.005	4.33	3.5648	4.33	4.33	4.33	4.33	3.5648	3.5648	3.462

Table 3.15: 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	7.2339	7.2339	7.2339	6.6925	6.4483	6.4483	5.5954	5.7991	6.4483	5.5954	4.1376	3.9607
C_2	5.3079	5.1210	4.7497	5.3079	5.1210	5.3079	5.1210	5.1210	4.9488	4.7497	4.7497	5.1210
C_3	6.2183	6.2183	3.9607	5.7991	5.7991	5.7991	6.6925	2.7547	5.7991	6.4483	2.5979	5.7991
C_4	0.7812	1.5069	1.4780	1.5069	0.7812	1.5069	1.4780	1.4780	0.7812	4.9398	0.7812	0.7629
C_5	5.5259	5.3079	5.3079	4.8784	5.5259	5.5259	4.8784	4.8784	3.5225	4.8784	4.8784	4.7115
C_6	0.9603	1.8463	4.0070	4.0070	1.8463	1.8463	1.8463	1.8988	1.8463	4.0070	1.8463	1.8988
C_7	4.7497	4.7497	4.7497	4.7497	4.6104	4.6104	4.6104	4.6104	3.4237	4.6104	4.6104	4.6104
C_8	5.0315	5.0315	4.9304	4.9304	4.9304	5.0315	5.0315	5.2840	4.9304	5.0315	4.9304	4.9304
C_9	5.5823	5.5823	5.4439	5.5823	5.4439	5.5823	5.5823	5.5823	5.5823	1.5491	1.5491	5.6887
C_{10}	2.7637	2.7637	3.7569	2.7637	3.8639	2.7637	2.7637	2.7637	2.7637	3.8639	3.8639	3.9609

Then calculate the distances v_i^+ and v_i^- using Eqs. (3.11) and (3.12). 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

$$(v_i^+) = \sqrt{\frac{1}{3}[(5.4444-9)^2 + (9-9)^2 + (9-9)^2]} + \sqrt{\frac{1}{3}[(2.778-9)^2 + (7.0988-9)^2 + (9-9)^2]} + \ldots + \sqrt{\frac{1}{3}[(1-9)^2 + (2.778-9)^2 + (5.4444-9)^2]} = 45.8394$$

$$(v_i^-) = \sqrt{\frac{1}{3}[(5.4444-0.7778)^2 + (9-0.7778)^2 + (9-0.7778)^2]} + \sqrt{\frac{1}{3}[(2.778-0.7778)^2 + (7.0988-0.7778)^2 + (9-0.7778)^2]} + \ldots + \sqrt{\frac{1}{3}[(1-0.7778)^2 + (2.778-0.7778)^2 + (5.4444-0.7778)^2]} = 44.1547$$

Then compute the closeness coefficient (S_i) buy using distances v_i^+ and v_i^- for all the alternatives that is given by Eq. (3.13). 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, compute the CC_i for all alternatives, that is presented in Table. 3.15.

Table 3.16: Closeness coefficients(S_i) 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^-	44.1547	45.3614	45.6181	46.2180	44.3704	44.4223	43.5995	40.1704	40.0463	45.6735	33.9449	41.4445
v_i^+	45.8394	45.0866	48.0940	47.0918	47.4292	47.0169	48.1990	50.6888	49.5671	49.2073	56.4568	50.4930
S_i	0.4906	0.5015	0.4868	0.4953	0.4833	0.4858	0.4749	0.4421	0.4469	0.4814	0.3755	0.4508

Finally, ranking the alternatives by comparing theCC_ivalue, that is given in Table. 3.16. The respective rank of insurance companies are 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 selected as best insurance company for purchasing an online term plan. Ranking of all the alternatives are presented in figure.3.3.

Table 3.17: Final ranking of alternatives

Ranking	1	2	3	4	5	6	7	8	9	10	11	12
Alternatives	LIC	SBI	ICICI	HDFC	BAJAJ ALLIANZ	MAX	KOTAK MAHINDRA	BHARTI AXA	AVIVA	RELIANCE	AEGON RELIGARE	CANARAHSBC

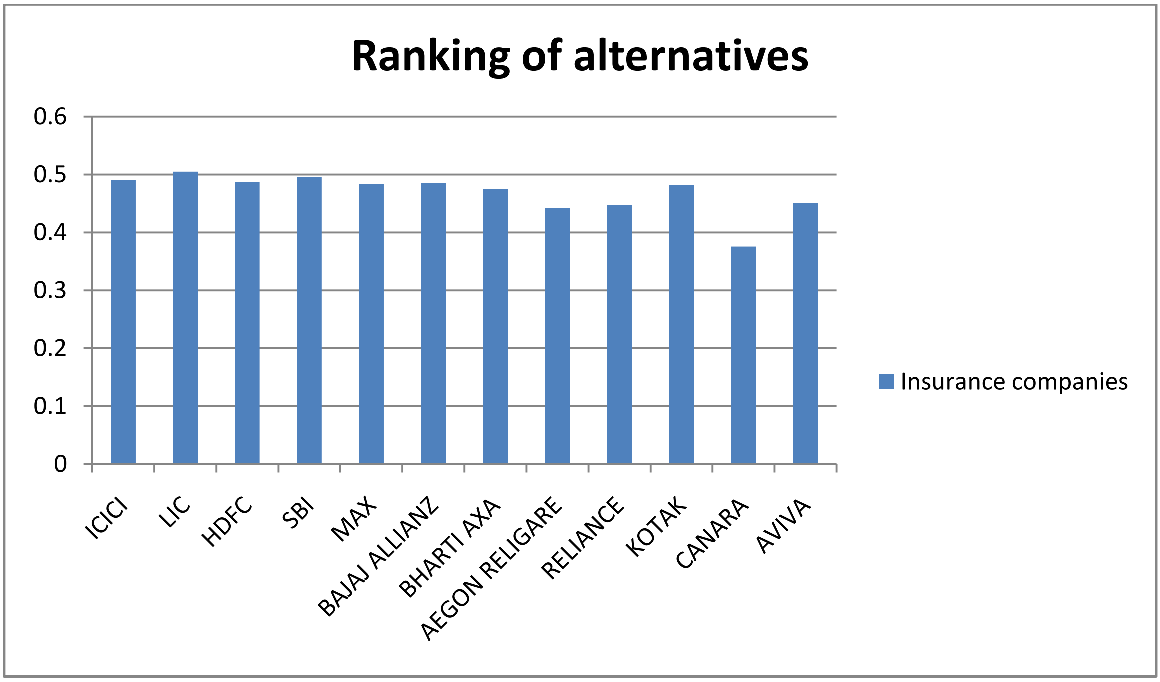

Figure3.3. Final ranking of alternatives

3.7 Sensitivity analysis

A sensitivity analysis is conducted to find the influence of weights of criteria on the best insurance company choosing for purchasing an online term policy. 25 experiments were conducted, which are presented in Table. 3.17.

In the first two experiments, all of the criteria weights are assigned to (7,9,9) and (5,7,9), that is presented in Table. 17. In third and fourth experiment, set the weight of criterion $C_1 = (7,9,9)$ and the rest of criteria have weight=(5,7,9) and (3,5,7) respectively. In fifth experiment, set the weight of criterion $C_1 = (5,7,9)$ and the rest of criteria have weight=(3,5,7). In experiment 6-9, 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 experiment 10-13, 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, 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, set the weights of criteria $C_1$and $C_2 = (7,9,9)$, and all other criteria weights=(5,7,9). In experiment 17, set the weights of criteria C_1, C_2 and $C_3 = (7,9,9)$, and all other criteria weights =(5,7,9). In experiment 18-20, all criteria have weights (3,5,7), (1,3,5) and (1,1,3) respectively. In experiment 21 and 22, 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, set the weight of criterion $C_1 = (3,5,7)$ and all other criteria weights =(1,3,5). In experiment 24, set the weights of criteria C_1 and $C_2 = (3,5,7)$ and all other criteria weights =(1,3,5). In experiment 25, 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 experiment

Table 3.18: Experimental result of 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	0.5168	0.5282	0.5073	0.5183	0.5103	0.5111	0.4973	0.4672	0.4665	0.4952	0.3832	0.4797
2	0.4689	0.4796	0.4713	0.4784	0.4690	0.4691	0.4598	0.4348	0.4322	0.4649	0.3703	0.4466
3	0.4794	0.4900	0.4813	0.4862	0.4768	0.4769	0.4644	0.4397	0.4399	0.4693	0.3724	0.4484
4	0.4783	0.4883	0.4839	0.4845	0.4745	0.4744	0.4597	0.4388	0.4418	0.4666	0.3751	0.4405
5	0.4658	0.4759	0.4719	0.4751	0.4652	0.4651	0.4543	0.4328	0.4326	0.4613	0.3725	0.4384
6	0.5156	0.5263	0.5051	0.5158	0.5090	0.5095	0.4960	0.4660	0.4657	0.4926	0.3836	0.4787
7	0.5329	0.5405	0.5142	0.5253	0.5238	0.5228	0.5088	0.4776	0.4792	0.4950	0.3937	0.4922
8	0.5516	0.5558	0.5241	0.5357	0.5399	0.5372	0.5227	0.4903	0.4939	0.4977	0.4046	0.5068
9	0.5709	0.5719	0.5341	0.5463	0.5564	0.5520	0.5368	0.5024	0.5083	0.4996	0.4138	0.5213
10	0.4695	0.4808	0.4729	0.4803	0.4698	0.4702	0.4606	0.4355	0.4325	0.4670	0.3698	0.4472
11	0.4835	0.4912	0.4785	0.4859	0.4815	0.4801	0.4705	0.4445	0.4436	0.4659	0.3793	0.4581
12	0.4991	0.5036	0.4864	0.4940	0.4949	0.4920	0.4820	0.4550	0.4559	0.4671	0.3890	0.4705
13	0.5144	0.5157	0.4936	0.5015	0.5080	0.5034	0.4930	0.4645	0.4673	0.4670	0.3968	0.4821
14	0.4733	0.4799	0.4711	0.4771	0.4737	0.4717	0.4638	0.4401	0.4592	0.4388	0.3825	0.4534
15	0.4902	0.4930	0.4788	0.4851	0.4881	0.4841	0.4758	0.4505	0.4515	0.4585	0.3915	0.4665
16	0.4850	0.4955	0.4840	0.4917	0.4820	0.4824	0.4695	0.4447	0.4445	0.4719	0.3743	0.4533
17	0.4928	0.5033	0.4860	0.4969	0.4872	0.4877	0.4776	0.4462	0.4497	0.4795	0.3749	0.4584
18	0.4559	0.4663	0.4625	0.4683	0.4587	0.4585	0.4509	0.4283	0.4250	0.4582	0.3712	0.4395
19	0.4365	0.4463	0.4491	0.4529	0.4431	0.4424	0.4375	0.4186	0.4144	0.4481	0.3729	0.4287
20	0.3968	0.4079	0.4130	0.4154	0.4052	0.4040	0.4009	0.3825	0.3789	0.4152	0.3416	0.3929
21	0.4401	0.4548	0.4564	0.4622	0.4455	0.4473	0.4397	0.4180	0.4124	0.4597	0.3602	0.4270
22	0.4399	0.4538	0.4547	0.4603	0.4449	0.4464	0.4391	0.4175	0.4124	0.4574	0.3609	0.4266
23	0.4493	0.4588	0.4612	0.4619	0.4517	0.4512	0.4422	0.4247	0.4242	0.4523	0.3745	0.4277
24	0.4549	0.4634	0.4626	0.4670	0.4564	0.4566	0.4471	0.4301	0.4290	0.4538	0.3783	0.4330
25	0.4622	0.4703	0.4605	0.4710	0.4609	0.4611	0.4558	0.4258	0.4344	0.4614	0.3750	0.4382

3.8 Conclusion

We propose an MCDM model for selecting the best life insurance company for purchasing an online term policy. The proposed model consists of 5 different steps. In step 1, we select the insurance policy from different policies. Finally, we have chosen the online term policy. In step 2, we identify the criteria for selecting the best life insurance company for purchasing an online term policy. These criteria are Average claim ratio, Entry age, Policy term, Maturity, Sum assured Premium, Premium payment term, Premium payment frequency, Rebate on the large sum assured, Riders. In step 3, the alternatives of companies are determined. The decision makers provide judgement for the criteria and alternatives of companies in step. 4. We evaluate the aggregated score for all alternatives by using fuzzy TOPSIS methodology. Finally, we have chosen the highest score for implementation. In last step sensitivity analysis is performed on the decision-makingprocess to evaluate the effectiveness of criteria weights. Finally, we conclude that our propose model is the ability to deal with the MCDM problem and it can be applied to choose the best insurance company for purchasing an online term policy.