Advances in Fuzzy Mathematics (AFM).
ISSN 0973-533X Volume 12, Number 5 (2017), pp. 1111–1122

http://www.ripublication.com/afm.htm

Fuzzy Possibilistic Optimistic Criterion-A New Approach

Dr. Tutu M. John
Department of Mathematics,
Marthoma College,
Tiruvalla, Kerala, India.

Abstract

In this paper we consider decision making under uncertainty when the probability of the states of nature is not known a priori and the outcomes of each alternative are characterized only approximately. The fuzzy approach is very useful to handle such situations. Here we take into consideration both the best and the worst consequences of a decision problem. An optimist expects the best to occur and the worst not to occur. Based on this attitude of the decision maker a new fuzzy optimistic criterion (3-FOC) is constructed. This criterion is more realistic and it has been proved that when clear ranking of alternatives is not possible using the existing criterion it is always possible to clearly rank the alternatives using 3-FOC. Example is given to illustrate the same.

AMS subject classification:
Keywords: Decision Maker (DM), 1-Fuzzy Optimistic Criterion (1-FOC) Fuzzy Aspiration degree (α_D), Fuzzy Reservation Degree (β_D), Fuzzy Aspirations Class w.r.t 'α_D' (FAC[α_D]), Fuzzy Non-Aspiration Class w. r. t 'α_D' (FNAC[α_D]), 3-Fuzzy Optimistic Criterion (3-FOC).

1. Introduction

In the field of decision making under uncertainty in the crisp environment, there are many criteria in the literature for ranking of alternatives. The most commonly used criterion is the expected utility criterion axiomatized by Savage [10], despite early criticisms by Allais [1], Ellsberg [8] and later by Kahneman and Tversky [9]. Here the subjective values attached to each consequence as well as the degree of confidence of the possible outcomes commensurate and are specifically quantified. However, in most problems which generally deal with practical life situations, this may not be always possible. Thus, there are many models designed for preference modeling in the presence of poor information. The most famous decision rule of this kind is the max–min rule by Wald [15] axiomatized by Arrow and Hurcwicz [2]. If possibility ordering on states is available, then the above criterion can be redefined [4, 4]. Another refinement of the Wald Criterion is the Possibilistic Criterion[5, 6, 7] based on a utility function 'u' on X and a possibility distribution π on S representing the relative plausibility of states both mapping on the same totally ordered scale and which can be compared.

In this paper, we use the fuzzy approach, which is very useful in real life situation, when the probability of the states of nature is not known aprori and the outcomes of each alternative are characterized only approximately.

2. Important Results

Definition 2.1. [16] Let X be the universal set. A **fuzzy set** A in X is defined as,

$$A = \{(x, \mu_A(x)) : x \in X\}$$

where $\mu_A : X \to [0, 1]$ is called the membership function of A in X and $[0, 1]$ is called the membership set or valuation set.

Definition 2.2. The **Principle of Strict Pareto Domiance** in the crisp case states that, if $u(d_1(s)) \geq u(d_2(s))$, for all $s \in S$ and if for $s^* \in S, \pi(s^*) > 0$

$$u(d_1(s^*)) > u(d_2(s^*)), \text{ then } d_1 > d_2.$$

Definition 2.3. The Possibilistic Optimistic Criterion (POC) [5, 6, 7] is given by

$$d_i \geq d_j \Leftrightarrow V^+(d_i) \geq V^+(d_j), \text{ where } V^+(d_i) = \vee_{s_j \in S}\{\pi(s_j) \wedge u(d_i(s_j))\}$$

Here $u(d_i(s_j))$ is the utility of the consequence x_{ij}, where $d_i(s_j) = x_{ij} \in X$, and $\pi(s_j)$ is the plausibility of the state s_j.

Note 2.4. In this criterion the alternatives are ranked on the merits of best consequences restricted to most plausible states.

Drawbacks of POC: Through the criterion POC is the refinement of many criteria in the crisp case, it has many drawbacks. One major drawback being that it fails to satisfy the Principle of Strict Pareto Dominance.

That is, an alternative d_1 can be ranked equal to another alternative d_2 even if d_1 is at least as satisfying as d_2 in all states and better in some states (including most plausible ones), which is absurd.

Thus we see whether we can modify POC such that this drawback is rectified.

3. Possibilistic Decision Making in a Fuzzy Environment

This section presents the basic setting of possibilistic decision making in a fuzzy environment as follows

Definition 3.1. The possibilistic decision problem in a fuzzy environment is given by (S, D, I, μ_A), where
S-the non-empty set of states the nature
D-the non-empty set of feasible alternatives
I-information about the states represented by the possibility degree and
$\mu_A : X \to [0, 1]$ is the membership function on the set of consequences X in the fuzzy set 'satisfaction' A.

Note 3.2. Here the membership value $\mu_A(x_{ij}) \in [0, 1]$ that is assigned to the consequence $x_{ij} \in X$ in the fuzzy set 'satisfaction', is the preference measure of the consequence that is ordinally ranked, based on the preference of the decision maker.

Definition 3.3. The **Principle of Strict Pareto Dominance** in the fuzzy environment states that, if $\mu_A(d_1(s)) \geq \mu_A(d_2(s))$, for all $s \in S$ and if for $s^* \in S$, $\pi(s^*) > 0$, $\mu_A(d_1(s^*)) > \mu_A(d_2(s^*))$, then $d_1 > d_2$.

Note 3.4. Here $\mu_A(d_1(s))$ represents the membership of the consequence $d_1(s)$ in the fuzzy set 'satisfaction'.

We now construct 1-Fuzzy Optimistic Criterion (1-FOC) as follows.

4. 1-Fuzzy Optimistic Criterion (1-FOC)

This criterion is based on a membership function μ_A on X, where $\mu_A(x_{ij})$ represents the fuzzy set membership of a consequence $x_{ij} \in X$ in the fuzzy set 'satisfaction' and the possibility distribution π on S representing the possibility of states, both mapping on the totally ordered scale and can be compared.

Definition 4.1. Let (S, D, I, μ_A) be a decision problem. Then, **1-Fuzzy Optimistic Criterion (1-FOC)** is given by,

$$d_i \geq d_j \Leftrightarrow S_1^+(d_i) \geq S_1^+(d_j), \text{ for all } d_i, d_j \in D$$

where,

$$S_1^+(d_i) = \vee_{s_j \in S}[J_{1,i}^+(s_j, x_{ij})];\ J_{1,i}^+(s_j, x_{ij}) = \wedge[\pi(s_j), \mu_A(x_{ij})].$$

Remark 4.2. 1-FOC is the fuzzy version of POC. But, the drawbacks of POC are seen in 1-FOC also. Hence the need of construction of a new fuzzy optimistic criterion with the drawbacks rectified.

An optimist always expects the best to occur and the worst not to occur. Thus based on this attitude of the decision maker a new fuzzy optimistic criterion is constructed. For this we introduce certain definitions as follows.

5. Fuzzy Aspiration and Reservation Degree

An optimist always expects the best to occur. Thus in this section we first introduce the Fuzzy Aspiration Degree, which specifies the 'best' consequences as follows

Definition 5.1. Let (S, D, I, μ_A) be a decision problem, and let a consequence $x_{ij} \in X$ be totally satisfying to the DM. Then the membership of âŁ˜x_{ij} âŁ™ in the fuzzy set 'satisfaction' is 1, i.e., $\mu_A(x_{ij}) = 1$. Such consequences $x_{ij} \in X$ are called **efficient consequences**.

Definition 5.2. Let (S, D, I, μ_A) be a decision problem, and let a consequence $x_{ij} \in X$ be highly satisfying (includes totally satisfying also) to the DM. Then the membership of x_{ij} in the fuzzy set 'satisfaction' is very close or equal to 1. Such consequences $x_{ij} \in X$ are called **highly satisfying consequences**.

Definition 5.3. Let (S, D, I, μ_A) be a decision problem. Define

$$\alpha_D = \min\{\mu_A(x_{ij}) : x_{ij} \in X \text{ is 'highly satisfying'}\}.$$

Then α_D is called the Fuzzy Aspiration Degree of the decision problem for the decision maker.

Definition 5.4. Let (S, D, I, μ_A) be a decision problem with Fuzzy Aspiration Degree 'α_D'. Then a consequence $x_{ij} \in X$ is a **best consequence**, if $\mu_A(x_{ij}) \geq \alpha_D$.

Example 5.5. If $\alpha_D = .9$, then the best consequences of the decision problem are all consequences whose membership values are ≥ 0.9.

5.1. Properties of α_D

1. The 'Fuzzy Aspiration Degree', varies according to the decision maker and the decision problem, since 'highly satisfying' is a fuzzy concept.
2. The Fuzzy Aspiration Degree specifies the best consequences of the decision problem.
3. When $\alpha_D = 1$, the best consequences becomes the efficient consequences.
4. We can assume $\alpha_D \in (.5, 1]$ (even though in most cases its value is higher than 0.5 and close to 1)

An Optimist also expects that the worst will not occur. Thus we introduce the Fuzzy Reservation Degree, which specifies the 'worst consequences' as follows.

Definition 5.6. Let (S, D, I, μ_A) be a decision problem and let $x_{ij} \in X$ be totally dissatisfying to the DM. Then the membership of x_{ij} in the fuzzy set 'satisfaction' is 0, i.e., $\mu_A(x_{ij}) = 0$. Such consequences $x_{ij} \in X$ are called **inefficient consequences**.

Definition 5.7. Let (S, D, I, μ_A) be a decision problem, and let a consequence $x_{ij} \in X$ be highly dissatisfying (includes totally dissatisfying also) to the DM. Then the membership of x_{ij} in the fuzzy set satisfaction is very close or equal to 0. Such consequences $x_{ij} \in X$ are called **highly dissatisfying** consequences.

Note 5.8.

(1) In the crisp case, 'inefficient' consequences are called 'worst' consequences, since for such consequences the DM is totally dissatisfied.

(2) 'Inefficient' consequences are always 'highly dissatisfying' consequences, but the converse need not be true.

Definition 5.9. Let (S, D, I, μ_A) be a decision problem. Define,

$$\beta_D = \max\{\mu_A(x_{ij}) : x_{ij} \in X \text{ is 'highly dissatisfying'}\}.$$

Then 'β_D' is called the **Fuzzy Reservation Degree** of the decision problem for the DM.

Definition 5.10. Let (S, D, I, μ_A) be a decision problem with fuzzy reservation degree âĽ˜β_DâĽ™. Then a consequence $x_{ij} \in X$ is a **worst consequence**, if

$$\mu_A(x_{ij}) \leq \beta_D.$$

Example 5.11. If $\beta_D = 0.2$, then the worst consequences of the decision problem are all consequences whose membership values are less than or equal to 0.2.

5.2. Properties of β_D

1. The 'Fuzzy Reservation Degree' varies according to the decision maker and the decision problem, since highly dissatisfying is a fuzzy concept.

2. When $\beta_D = 0$, the worst consequence becomes the inefficient consequence.

3. Clearly $\beta_D < 0.5$ (though in most cases its value is even less than 0.5 and close to 0).

For the Construction of **3-Fuzzy Optimistic Criterion (3-FOC)**, which is based on the attitude of the decision maker that the best will occur and the worst will not occur we now introduce certain definitions are follows.

6. Fuzzy Aspiration and Non-Aspiration classes

Definition 6.1. Let (S, D, I, μ_A) be a decision problem with fuzzy aspiration degree 'α_D'. Then the **Fuzzy Aspiration Class** w.r.t. α_D denoted by $FAC[\alpha_D]$, is defined as

$$FAC[\alpha_D] = \{x_{ij} \in X : \mu_A(x_{ij}) \geq \alpha_D\}.$$

Here $FAC[\alpha_D]$ is the set of best consequences of the decision problem.

Definition 6.2. Let (S, D, I, μ_A) be a decision problem with fuzzy aspiration degree 'α_D'. Then the **Fuzzy Non-Aspiration Class-1 w.r.t. α_D** denoted by $FNAC_1[\alpha_D]$, is defined as

$$FNAC_1[\alpha_D] = \{x_{ij} \in X : \mu_A(x_{ij}) > \pi(s_j), \mu_A(x_{ij}) < \alpha_D, \mu_A(x_{ij}) \geq \beta_D\}.$$

Definition 6.3. Let (S, D, I, μ_A) be a decision problem with fuzzy aspiration degree 'α_D'. Then the **Fuzzy Non-Aspiration Class-2 w.r.t. α_D** denoted by $FNAC_2[\alpha_D]$, is defined as

$$FNAC_2[\alpha_D] = \{x_{ij} \in X : \mu_A(x_{ij}) \geq \pi(s_j), \mu_A(x_{ij}) < \alpha_D, \mu_A(x_{ij}) < \beta_D\}.$$

Definition 6.4. Let (S, D, I, μ_A) be a decision problem with fuzzy aspiration degree 'α_D'. Then the **Fuzzy Non-Aspiration Class-3 w.r.t. α_D** denoted by $FNAC_3[\alpha_D]$, is defined as

$$FNAC_3[\alpha_D] = \{x_{ij} \in X : \mu_A(x_{ij}) \leq \pi(s_j), \beta_D \leq \mu_A(x_{ij}) < \alpha_D\}.$$

Definition 6.5. Let (S, D, I, μ_A) be a decision problem with fuzzy aspiration degree 'α_D'. Then the **Fuzzy Non-Aspiration Class-4 w.r.t. α_D** denoted by $FNAC_4[\alpha_D]$, is defined as

$$FNAC_4[\alpha_D] = \{x_{ij} \in X : \mu_A(x_{ij}) < \pi(s_j), \mu_A(x_{ij}) < \alpha_D, \mu_A(x_{ij}) < \beta_D\}.$$

The construction of 3-Fuzzy Optimistic Criterion (3-FOC) is as follows.

Definition 6.6. Let (S, D, I, μ_A) be a decision problem with fuzzy aspiration degree 'α_D'.

Define,

$$J_{3,i}^{+}(s_j, x_{ij}) = \begin{cases} \frac{1}{2}[1 + \alpha_D(\mu_A(x_{ij}) \wedge \pi(s_j))] + (1-\alpha_D) \\ \qquad (\mu_A(x_{ij}) \vee \pi(s_j)) \text{ if } x_{ij} \in FAC[\alpha_D] \\ \left(\frac{\alpha_D}{2}\right)[\pi(s_j)] \wedge \mu_A(x_{ij})) + \left(1 - \frac{\alpha_D}{2}\right)[\pi(s_j) \vee \mu_A(x_{ij})], \\ \qquad \text{if } x_{ij} \in FNAC_1[\alpha_D] \\ \left(\frac{\alpha_D + 1}{2}\right)[\pi(s_j) \vee \mu_A(x_{ij})] + \left(\frac{1-\alpha_D}{2}\right)[(1-\pi(s_j)) \vee \mu_A(x_{ij})], \\ \qquad \text{if } x_{ij} \in FNAC_2[\alpha_D] \\ \alpha_D[\pi(s_j) \wedge \mu_A(x_{ij})] + (1-\alpha_D)[\pi(s_j) \vee \mu_A(x_{ij})], \\ \qquad \text{if } x_{ij} \in FNAC_3[\alpha_D] \\ \left(\frac{\alpha_D + 1}{2}\right)[\pi(s_j) \wedge \mu_A(x_{ij})] + \left(\frac{1-\alpha_D}{2}\right)[(1-\pi(s_j)) \vee \mu_A(x_{ij})], \\ \qquad \text{if } x_{ij} \in FNAC_4[\alpha_D] \end{cases}$$

Here $J_{3,i}^{+}(s_j, x_{ij}) \in [0, 1]$ is the score of the alternative $d_i \in D$ corresponding to the pair (s_j, x_{ij}). Then the **3-Fuzzy Optimistic Criterion (3-FOC)** is given by $d_i \geq d_j \Leftrightarrow S_3^{+}(d_i) \geq S_3^{+}(d_j) \forall d_i, d_j \in D$ where $S_3^{+}(d_i) = \frac{1}{n}\sum_{s_j \in S} J_{3,i}^{+}(s_i, x_{ij})$ is the 'degree of satisfaction' of the alternative d_i for the DM.

We now give an example to show that 1-FOC fails to satisfy the Principle of Strict Pareto Dominance, but 3-FOC satisfies it.

Example 6.7. Let $D = \{d_1, d_2, d_3, d_4\}$ be the set of alternatives and $S = \{s_1, s_2, s_3, s_4\}$ be the states of nature with possibility degree of states given by $\pi(s_1) = 0.3, \pi(s_2) = 0.5, \pi(s_3) = 1$ and $\pi(s_4) = 0.6$. Let the 'satisfaction table' of the decision problem be given in Table 1.

Table 1:

$D \backslash S$	s_1	s_2	s_3	s_4
d_1	.4	.6	.7	.5
d_2	.4	.6	.7	.4
d_3	.6	.4	.2	.5
d_4	.8	.5	.6	.7

Then, by 1-FOC, $d_1 = d_2$ even though 'd_1' is as satisfying as 'd_2' in states s_1, s_2 and s_3 and better in s_4.

Thus, 1-FOC and also POC fails to satisfy the Principle of Strict Pareto Dominance, but by 3-FOC, for say $\alpha_D = 0.8$ and $\beta_D = 0.2$, we get

$$S_3^+(d_1) = .55, \quad S_3^+(d_2) = .53, \quad S_3^+(d_3) = .405, \quad S_3^+(d_4) = .643$$
$$\therefore d_4 > d_1 > d_2 > d_3.$$

$\therefore d_1 > d_2$ and thus 3-FOC satisfies the Principle of Pareto Dominance.

Next, we prove the theorem to show that 3-FOC in general satisfies the Principle of Strict Pareto Dominance.

Theorem 6.8. Let (S, D, I, μ_A) be a decision problem. For $d_1, d_2 \in D$ suppose $\mu_A(d_1(s_j)) \geq \mu_A(d_2(s_j))$, for all $s_j \in S$ and for $s_r \in S$, $\pi(s_r) > 0$, let $\mu_A(d_1(s_r)) > \mu_A(d_2(s_r))$ where $d_i(s_j) = x_{ij} \in X$, for all $d_i \in D\ \forall\ s_j \in S$. Then, if by 1-FOC, $d_1 = d_2$, by 3-FOC, $d_1 > d_2$.

Proof. For $d_1, d_2 \in D$, let $\mu_A(d_1(s_j)) = \mu_A\ (d_2\ (s_j))\ d_1 > d_2\ \forall\ s_j \in S - \{s_r\}$ and let $s_r \in S, \pi(s_r) > 0$,

$$\mu_A(d_1(s_r)) > \mu_A(d_2(s_r)), \text{ where } d_i(s_j) = x_{ij} \in X,$$

for all $d_i \in D\ \forall\ s_j \in S$. Let α_D, β_D be the aspiration degree and the reservation degree respectively of the decision maker for the given decision problem. Also, let $FAC[\alpha_D]$ denote the fuzzy aspiration class and $FNAC_1[\alpha_D]$, $FNAC_2[\alpha_D]$, $FNAC_3[\alpha_D]$ and $FNAC_4[\alpha_D]$ denote the fuzzy non-aspiration classes w.r.t. 'α_D'.

Then, $\mu_A(x_{1r}) > \mu_A(x_{2r})$ (given). For, $x_{1r}, x_{2r} \in X$, since by 1-FOC, $d_1 = d_2$, two cases arise.

Case I: If for $s_k \in S - \{s_r\}, \pi(s_k) > 0$,

$$\vee_{s_j \in S}[J^+_{1,1}(s_j, x_{ij})] = J^+_{1,1}(s_k, x_{1k})(\text{ for a fixed } k)$$

Then, since $J^+_{1,1}(s_1, x_{ij}) = J^+_{1,2}(s_j, x_{ij}) \forall j \neq r$ and

$$J^+_{1,1}(s_r, x_{1r}) \geq J^+_{1,2}(s_r, x_{2r})$$

$$\Rightarrow \vee_{s_j \in S}[J^+_{1,2}(s_j, x_{ij})] = J^+_{1,2}(s_k, x_{1k}).$$

If in this case

$$J^+_{1,1}(s_r, x_{1r}) > J^+_{1,2}(s_r, x_{2r}),$$

then it follows directly by applying 3-FOC, that

$$d_1 > d_2$$

If $J^+_{1,1}(s_r, x_{1r}) = J^+_{1,2}(s_r, x_{2r})$, then proceeding similar to proof given in Case II, by 3-FOC

$$d_1 > d_2$$

Case II: If

$$\vee_{s_j \in S}[J^{+}_{1,1}(s_j, x_{1j})] = J^{+}_{1,1}(s_r, x_{1r}),$$

and

$$\vee_{s_j \in S}[J^{+}_{1,2}(s_j, x_{2j})] = J^{+}_{1,2}(s_r, x_{2r}),$$

then since by 1-FOC

$$\begin{aligned} d_1 &= d_2 \text{ (given)} \\ &\Rightarrow S^{+}_{1}(d_1) = S^{+}_{1}(d_2) \\ &\Rightarrow J^{+}_{1,1}(s_r, x_{1r}) \ = J^{+}_{1,2}(s_r, x_{2r}) \\ &\Rightarrow \mu_A(x_{1r}) \wedge \pi(s_r) \ = \ \mu_A(x_{2r}) \wedge \pi(s_r) \end{aligned}$$

$\therefore$ Since $\mu_A(x_{1r}) > \mu_A(x_{2r})$, it follows that

$$\mu_A(x_{1r}) > \pi(s_r) \text{ and } \mu_A(x_{2r}) \geq \pi(s_r).$$

Thus, x_{1r} and x_{2r} belong to either $FAC[\alpha_D]$, $FNAC_1[\alpha_D]$ or $FNAC_2[\alpha_D]$. It then follows that, if

1. $x_{1r}, x_{2r} \in FAC[\alpha_D]$
2. $x_{1r}, x_{2r} \in FNAC_1[\alpha_D]$
3. $x_{1r}, x_{2r} \in FNAC_2[\alpha_D]$
4. $x_{1r} \in FAC[\alpha_D]$ and $x_{2r} \in FNAC_1[\alpha_D]$
5. $x_{1r} \in FAC[\alpha_D]$ and $x_{2r} \in FNAC_2[\alpha_D]$
6. $x_{1r} \in FNAC_1[\alpha_D]$ and $x_{2r} \in FNAC_2[\alpha_D]$.

In all cases, we get $J^+_{3,1}(s_r, x_{1r}) > J^+_{3,2}(s_r, x_{2r})$. Thus, by 3-FOC

$$
\begin{aligned}
S_3^+(d_1) &= \frac{1}{n}\sum_{s_j\in S} J^+_{3,1}(s_j, x_{1j}) \\
&= \frac{1}{n}\left[\sum_{s_j\in S-\{s_r\}} J^+_{3,1}(s_j, x_{1j}) + J^+_{3,1}(s_r, x_{1r})\right] \\
&= \frac{1}{n}\left[\sum_{s_j\in S-\{s_r\}} J^+_{3,2}(s_j, x_{2j}) + J^+_{3,1}(s_r, x_{1r})\right] \\
&> \frac{1}{n}\left[\sum_{s_j\in S-\{s_r\}} J^+_{3,2}(s_j, x_{2j}) + J^+_{3,2}(s_r, x_{2r})\right] \\
&= \frac{1}{n}\left[\sum_{s_j\in S} J^+_{3,2}(s_j, x_{2j})\right] \\
&= S_3^+(d_2) \\
&\therefore S_3^+(d_1) > S_3^+(d_2), \text{ and hence } d_1 > d_2
\end{aligned}
$$

If $\alpha_D = 1$, and if $x_{1r}, x_{2r} \in FAC[\alpha_D]$ or if $x_{1r}, x_{2r} \in FNAC_1[\alpha_D]$, by 3-FOC, $d_1 = d_2$. Then in such cases, we can take $\alpha_D = 0.999$ (say) which approximates to 1. Then proceedings as above, we get $J^+_{3,1}(s_r, x_{1r}) > J^+_{3,2}(s_r, x_{2r})$, and thus

$$d_1 > d_2$$

Hence clear ranking of alternatives is always possible using 3-FOC. ■

Note 6.9. Thus any number of alternatives can be clearly ranked using 3-FOC, when the decision maker is an optimist.

7. Conclusion

In this paper a new Fuzzy Optimistic Criterion 3-FOC is constructed. It is based on the optimistic attitude of the decision maker that the best will occur and the worst will not occur. This criterion is the modification of 1-FOC which is the fuzzy version of the Possibilistic Optimistic Criterion in the literature. All the drawbacks of the existing models are rectified using this criterion, one major draw being that an alternative can be ranked equal to another alternative, even if it is as satisfy as the other in all states and better in some states, which is absurd. Many other models have been constructed for decision making under uncertainty in a fuzzy and intutionstic fuzzy environment in our papers [11, 12, 13, 14].

References

[1] M. Allais, ‘Le Comportment de I’homme, rationnel devant le risqué: Critique des postulates de I’ecode, americaine’, Econometrica, 21 (1953), 503–546.

[2] K. J. Arrow, L. Hurwicz, An Optimality Criterion for Decision Making under Ignorance, in J. L Ford, CF Carter (Eds.), ‘Uncertainity and Expectations in Economics’, Basil Blacwell and Mortt Ltd., 1972.

[3] C. Boutilier, ‘Toward a logic for Qualitative Decision Theory’, in P. Tarasso, J. Doyle, E. Sandewall (Eds), Proc. International Conference on Principles of Knowledge Representation and Reasoning(KR’94), Bonn, Germany, Morgan Kaufmann, San Mateo, CA, (1994), 75–86.

[4] R. Brafman and M. Tennenholtz, ‘On the Foundations of Qualitative Decision Theory’ in Proc. AAAI-96 (Portland) OR, (1996), 1291–1296.

[5] D. Dubois and H. Prade, ‘Possibility Theory as a Basis for Qualitative Decision Theory’, in Proc. IJCAI-95, Montreal, Quebec, (1995), 1924–1930.

[6] D. Dubois, H. Prade and Sabbadin, ‘Decision Theoretic Foundations of Possibility Theory’, European J. Oper. Res., 128, (2001), 459–478

[7] D. Dubois, H. Fargier and P. Perney, ‘Qualitative Decision Theory with Preference Relations and Comparative Uncertainty-An Axiomatic Approach’, Artificial Intelligence, (2003), 219–260.

[8] D. Ellsberg, ’Risk, Ambiguity and the Savage Axioms’, Quart. J. Economics 75 (1961), 643–669.

[9] D. Kahneman, A. Tversky, ‘Prospect Theory and Analysis of Decision Under Risk’, Econometrica, 47 (1979), 262–291.

[10] L. J. Savage, ‘The Foundations of Statistics’, Wiley, New York, 1954.

[11] Tutu M. John and Sunny Kuriakose, ’Decision Making A New Approach’, Journal of Science, Technology and Management, 3(3) (2000), 29–33

[12] Tutu M. John and Sunny Kuriakose, ’Possibilistic Optimistic Criteria in the Fuzzy Environment’, Advances in Fuzzy Sets and Systems, 8(1) (2011), 1–11.

[13] Tutu M. John and Sunny Kuriakose, ’Decision Making Under Uncertainty in a Fuzzy Environment’, International Journal of Fuzzy Mathematics & Systems, 1(3) (2011), 273–279.

[14] Tutu M. John and Sunny Kuriakose, ’Optimistic Criteria in a Fuzzy and Intuitionistic Fuzzy Environment’, Bulletin of Kerala Mathematical Association, 8(2), (2011), 343–349.

[15] A. Wald, ’Statistical Decision Functions’, Wiley, New York, 1950.

[16] L. A. Zadeh, Fuzzy sets, Inform. Control 8 (1965) 338–353.

Mathematical symbols used.

- Decision Maker (DM)
- 1-Fuzzy Optimistic Criterion (1-FOC)
- Fuzzy Aspiration degree (α_D)
- Fuzzy Reservation Degree (β_D)
- Fuzzy Aspirations Class w.r.t 'α_D' (FAC[α_D])
- Fuzzy Non-Aspiration Class w. r. t 'α_D' (FNAC[α_D])
- 3-Fuzzy Optimistic Criterion (3-FOC)