

Research Paper

A Class of Generalized best Approximation Problems in a Fuzzy Normed Linear Space

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Abstract: *In this paper, a class of generalised best approximation problems is formulated in a fuzzy normed linear space.*

Keywords: Best approximation, fuzzy normed linear-space, semi-reflexive, proximal set, continuous operators.

Introduction:

The best approximation problem in normed linear spaces were considered by several authors including Burbu [1], singer [2]. Also in locally convex spaces some results were obtained by singer [3], Samanta [4]. The principal objective of this paper is to generalise the idea of best approximation problem in a fuzzy normed linear space setting and apply to optimal control.

Some Fundamental Definitions

Definition 1: Let X be any non empty set and $F(X)$ be the set of all Fuzzy sets on X . For $U, V \in F(X)$ and $k \in K$ the field of real numbers, define $U+V=\{(x + y, \lambda \wedge \mu)|(x, \lambda) \in U, (y, \mu) \in V\}$ and $kU=\{(k x, \lambda)|(x, \lambda) \in U\}$.

Definition 2: Let X be a linear space over K (field of real or complex numbers) then a fuzzy linear space $\tilde{X} = X \times (0, 1]$ over the field K where the addition on \tilde{X} are defined by $(x, \lambda)+(y, \mu) = (x + y, \lambda \wedge \mu)$ $k(x, \lambda) = (kx, \lambda)$ is a fuzzy normed linear space if to every $(x, \lambda) \in \tilde{X}$ there is corresponds a non-negative real number $\|(x, \lambda)\|$, called fuzzy normed of (x, λ) in such a way that

(1) $\|(x, \lambda)\|=0$ iff $x = 0$ the zero element of X , $\lambda \in (0, 1]$,

- (2) $\|k(x, \lambda)\| = |k| \|(x, \lambda)\|$ for $(x, \lambda) \in \tilde{X}$ and all $k \in K$,
- (3) $\|(x, \lambda) + (y, \mu)\| \leq \|(x, \lambda \wedge \mu)\| + \|(y, \lambda \wedge \mu)\|$ for all $(x, \lambda), (y, \mu) \in \tilde{X}$,
- (4) $\|(x, \bigvee_t \lambda_t)\| = \bigwedge_t \|(x, \lambda_t)\|$ for $\lambda_t \in (0, 1]$.

Definition 3: Let X be a linear space over the field of real or complex numbers say K , then a fuzzy subset N of $X \times R$ (R is the set of real numbers) is called a fuzzy norm on X if and only if for all $x \in X$ and $c \in K$,

(N₁) for all $t \in R$ with $t < 0$, $N(x, t) = 0$,

(N₂) for all $t \in R$ with $t > 0$, $N(x, t) = 1$ if and only if $x = 0$.

(N₃) for all $t \in R$ with $t > 0$, $N(cx, t) = N(x, t/|c|)$, if $c \neq 0$.

(N₄) for all $s, t \in R$, $x, u \in X$, $N(x+u, s+t) \geq \min\{N(x, s), N(u, t)\}$

(N₅) $N(x, \cdot)$ is a non-decreasing function of R and $\lim_{t \rightarrow \infty} N(x, t) = 1$, then the pair (x, N) is called fuzzy normed linear space.

Definition 4: Let (X, N) be a fuzzy normed linear space. we define $\|x\|_\alpha = \inf \{t: N(x, t) \geq \alpha\}$, $\alpha \in (0, 1)$. Then $\{\|\cdot\|_\alpha: \alpha \in (0, 1)\}$ is an ascending family of norms on X (or) α -norms on X corresponding to the fuzzy norm on X .

Definition 5: Let X be a non-empty set and $F(X)$ be the set of all fuzzy sets in X . If $f \in F(X)$, then $f = \{(x, \mu)/x \in X \text{ and } \mu \in (0, 1]\}$. Clearly f is a bounded function for $|F(X)| \leq 1$. Let K be the space of real numbers then $F(X)$ is a linear space over the field K where the addition and scalar multiplication are defined by $f + g = \{(x, \mu) + (y, \eta)\} = \{(x+y, \mu \wedge \eta) / (x, \mu) \in f \text{ and } (y, \eta) \in g\}$

And $kf = \{(kf, \mu) / (x, \mu) \in f\}$, where $k \in K$.

The linear space $F(X)$ is said to be normed space if for every $f \in F(X)$, there is associated a non-negative real number $\|f\|$ called the norm of f in such a way that

- (1) $\|f\| = 0$ if and only if $f = 0$. For $\|f\| = 0$ if and only if $\{(x, \mu) \in f\} = 0, x = 0, \mu \in (0, 1]$ if and only if $f = 0$.
- (2) $\|kf\| = |k| \|f\|, k \in K$. For $\|kf\| = \{\|k(x, \mu)\| / (x, \mu) \in f, k \in K\} = \{|k| \|x, \mu\| / (x, \mu) \in f\} = |k| \|f\|$.
- (3) $\|f + g\| \leq \|f\| + \|g\|$ for every $f, g \in F(X)$.

For $\|f + g\| = \{\|(x, \mu) + (y, \eta)\| / x, y \in X, \mu, \eta \in (0, 1]\}$

$= \{\|(x+y), (\mu \wedge \eta)\| / x, y \in X, \mu, \eta \in (0, 1]\} \leq \{\|(x, \mu \wedge \eta)\| + \|(y, \mu \wedge \eta)\| / (x, \mu) \in f \text{ and } (y, \eta) \in g\} = \|f\| + \|g\|$.

Then $(F(X), \|\cdot\|)$ is a normed linear space.

Definition 6: A 2-fuzzy set on X is a fuzzy set on $F(X)$.

Definition 7: Let $F(X)$ be a linear space over the real field K . A fuzzy subset N of $F(X) \times F(X) \times R$ (R , the set of real numbers) is called a 2-fuzzy 2-norm on X (or fuzzy 2-norm on $F(X)$) if and only if,

(N₁) for all $t \in R$ with $t \leq 0$, $N(f_1, f_2, t) = 0$,

(N₂) for all $t \in R$ with $t \geq 0$, $N(f_1, f_2, t) = 1$, if and only if f_1 and f_2 are linearly dependent,

- (N₃) $N(f_1, f_2, t)$ is invariant under any permutation of f_1 and f_2 ,
- (N₄) for all $t \in R$, with $t \geq 0$, $N(f_1, cf_2, t) = N(f_1, f_2, t / |c|)$ if $c \neq 0$, $c \in K$ (field),
- (N₅) for all $s, t \in R$, $N(f_1, f_2 + f_3, s + t) \geq \min \{N(f_1, f_2, s), N(f_1, f_3, t)\}$,
- (N₆) $N(f_1, f_2, \cdot): (0, \infty) \rightarrow [0, 1]$ is continuous,
- (N₇) $\lim_{t \rightarrow \infty} N(f_1, f_2, t) = 1$.

Then $(F(X), N)$ is a fuzzy 2-normed linear space or (X, N) is a 2-fuzzy 2-normed linear space.

Let X be a linear space. Then $(\tilde{X}, \|\cdot\|)$ is a fuzzy normed linear space. Let \tilde{X}^* denote the class of all continuous convex function defined on X .

Definition 8: Let $F(X)$ be the set of all maps from X to I , where $I = [0, 1]$. Then λ is a fuzzy point in X , x its support and α its value, λ may be denoted by λ_x^α .

Let $\gamma \in F(X)$, then $\lambda_{x_0}^{\alpha_0} \in \gamma$ iff $\gamma(x_0) > \alpha_0$, [9].

Fuzzy point $\lambda_x^\alpha, \lambda_x^{\alpha'}$ will be denoted by $\lambda, \lambda_i, i = 0, 1, 2, \dots, \lambda$ respectively.

Let X be a reference set, $I = [0, 1]$ and let $F(\alpha)$ be the set of all maps from X to I . The partial order in $F(X)$ is defined as follows $\gamma < \mu$

where $\gamma, \mu \in F(X)$ if and only if $\gamma(x) \leq \mu(x)$ for all $x \in X$.

Then $(F(X), <)$ is a complete lattice. The supremum and infimum are denoted by \vee, \wedge respectively.

Definition 9:

- (1) μ is a fuzzy set in $X \Leftrightarrow \mu \in F(X)$,
- (2) $\mu_1 < \mu_2 \Rightarrow \mu_1(x) \leq \mu_2(x), \forall x \in X$.
- (3) $(\vee_\alpha \mu_\alpha)(x) = \sup_\alpha \{\mu_\alpha(x)\}, \forall x \in X$.
- (4) $(\wedge_\alpha \mu_\alpha)(x) = \inf_\alpha \{\mu_\alpha(x)\}, \forall x \in X$.
- (5) $\mu^c(x) = 1 - \mu(x), \forall x \in X$.
- (6) $\tilde{1}(x) = 1, \tilde{0}(x) = 0, \forall x \in X$.

Definition 10: Let $f : X \rightarrow Y, \mu \in F(X), \gamma \in F(Y)$

$$\begin{aligned}
 f(\mu)(y) &= \sup_{x \in f^{-1}(y)} \{\mu(x)\}, f(y) \neq \phi \\
 &= 0, \quad f^{-1}(y) = \phi \\
 f^{-1}(\gamma)(x) &= \gamma(f(x)), \forall x \in X.
 \end{aligned}$$

Definition 11: $S \subset F(X)$ satisfies the following conditions:

- (1) $\tilde{I} \in S, \tilde{O} \in S.$
- (2) $\mu \in S, \gamma \in S \Rightarrow \mu \wedge \gamma \in S.$
- (3) $\mu_\alpha \in S \Rightarrow \bigvee_\alpha \mu_\alpha \in S.$

Then S is called a fuzzy topology on X and (X,S) a fuzzy topological space.

Definition 12: A fuzzy set $\lambda \in F(X)$ such that $\alpha \in (0,1)$ and

$$\begin{aligned} \lambda(x^1) &= \alpha, \text{ if } x^1 = x \\ \lambda(x^1) &= 0, \text{ if } x^1 \neq x \end{aligned}$$

is called a fuzzy point in X (written λ), x its support and α its value, λ may be denoted by λ_x^α .

Definition 13: $\lambda_{x_0}^{\alpha_0}$ is said to belong to γ (written $\lambda_{x_0}^{\alpha_0} \in \gamma$) if and only if $\gamma(x_0) > \alpha_0$.

Definition 14[9]: Let $\mu \in F(X)$. Then μ is called a neighbourhood of p if $\exists \nu \in S$ such that $p \in \nu < \mu$ where $S \subset F(X)$.

Let N_p denote the system of all neighbourhoods of p . If $\mu \in F(x)$, then $\mu = \bigvee_{x \in X} \lambda_x$ where λ_x is a fuzzy point. From now on fuzzy point $\lambda_x^\alpha, \lambda_x^{\alpha'}, i = 1, 2, \dots, \lambda_x^{\alpha'}$, will be denoted by $\lambda, \lambda_i, i = 0, 1, \dots, \lambda$ respectively.

Definition 15[11]: A fuzzy linear space $\tilde{X} = X \times (0,1]$ over the number field K where the addition and scalar multiplication on \tilde{X} are defined by

$$\begin{aligned} (x, \lambda) + (y, \mu) &= (x + y, \lambda \wedge \mu), \\ \kappa(x, \lambda) &= (\kappa x, \lambda) \end{aligned}$$

Then \tilde{X} is a fuzzy linear space if to every $(x, \lambda) \in \tilde{X}$ there corresponds a non-negative real number, $\|(x, \lambda)\|$, called the fuzzy norm of (x, λ) , such that

- (1) $\|(x, \lambda)\| = 0$ iff $x = 0$ the zero element of $X, \lambda \in (0,1]$,
- (2) $\|\kappa(x, \lambda)\| = |\kappa| \|(x, \lambda)\|, \forall (x, \lambda) \in \tilde{X}$ and all $\kappa \in K$,
- (3) $\|(x, \lambda) + (y, \mu)\| \leq \|(x, \lambda \wedge \mu)\| + \|(y, \lambda \wedge \mu)\|, \forall (x, \lambda), (y, \mu) \in \tilde{X}$,
- (4) $\|(x, \bigvee_i \lambda_i)\| = \bigwedge_i \|(x, \lambda_i)\|$ for $\lambda_i \in (0,1]$.

Then \tilde{X} will be defined as fuzzy normed linear space.

Definition 16[11]: Let X be a any non-empty set and $F(X)$ be the set of all fuzzy sets on X . For $U, V \in F(X)$ and $k \in K$ the field of real numbers, define

$$U, V = \{(x = y, \lambda \wedge \mu) \mid (x, \lambda) \in U, (y, \mu) \in V\},$$

$$\text{and } \kappa U = \{(\kappa x, \lambda) \mid (x, \lambda) \in U\}$$

Definition 17[11]: The fuzzy subset $\mu_1 + \mu_2$ is defined by

$$(\mu_1 + \mu_2)(x) = \vee \{\mu_1(x) + \mu_2(x) : x = x_1 + x_2\}.$$

And for a scalar t of K and a fuzzy subset μ of X , the fuzzy subset $t\mu$ is defined by

$$(t\mu)(x) = \begin{cases} \mu(x/t) & \text{if } t \neq 0 \\ 0 & \text{if } t = 0 \text{ and } x \neq 0 \\ \vee \{\mu(y) \mid y \in X\} & \text{if } t = 0 \text{ and } x = 0 \end{cases}$$

Definition 18[11]: $\mu \in I^X$ is said to be

- (1) convex if $tf + (1-t)f \subseteq f$ for each $t \in (0,1]$,
- (2) balanced if $tf \subseteq f$ for each $t \in K$ with $|t| \leq 1$,
- (3) absorbing if $\vee \{tf(x) \mid t > 0\} = 1$ for all $x \in X$.

Statement of the Problem

Let E be a convex subset of \tilde{X} and \tilde{X}^* be the fuzzy conjugate space of all continuous linear functionals defined on \tilde{X} consider the problem

$$\min_{m \in \tilde{X}} \left\{ \frac{1}{2} \|m - x\|^2 + I_E(m) \right\}$$

where x is the given element of \tilde{X} and I_E is the indicator function such that

$$I_E(m) = \begin{cases} 0 & \text{if } m \in E \\ +\infty & \text{if } m \notin E \end{cases}$$

To solve this problem let us consider the following definitions and theorem.

Definition 19: An element $l \in E$ is called a best approximation to $x \in \tilde{X}$ from E if $\|x - l\| \leq \|x - m\|$, for all $x \in E$. (1)

Is the best approximation to x from E if and only if there exists $x_0^* \in \tilde{X}^*$ subject to $\|l\| + \|x_0^*\| \leq \|m\|, \forall m \in E$

$$\Rightarrow f(l) + f^*(x_0^*) \leq f^*(x_0^*), \forall m \in E \tag{2}$$

Where $f(m) = \frac{1}{2} \sup_{f \in x^*} |(m - x, f)|^2, m \in X$, where $f(m) = \frac{1}{2} \|m - x\|^2, m \in \tilde{X}$.

Theorem 1: An element $l \in E$ is the best approximation to $x \in \tilde{X}$ from element of the convex set E if and only if there exists $x_0^* \in \tilde{X}^*$ such that

- (i) $\|x_0^*\| = \|l - x\|$
- (ii) $(x_0^*, m - x) \geq \|l - x\|, \forall m \in E$

Proof: We have

$$f^*(x_0^*) = \sup_{m \in \tilde{X}} \{ (x_0^*, m) - \frac{1}{2} \|m - x\|^2 \} = (x_0^*, x) + \sup_{m \in \tilde{X}} \{ (x_0^*, m) - \frac{1}{2} \|m\|^2 \} = (x_0^*, x) + \frac{1}{2} \|x_0^*\|^2$$

and the optimality condition (2) becomes

$$\frac{1}{2} \|l - x\|^2 + \frac{1}{2} \|x_0^*\|^2 \leq (x_0^*, m - x), \forall m \in E \tag{3}$$

In particular, for $m=l$, we obtain $(\|l - x\| - \|x_0^*\|)^2 \leq 0$.

which implies condition(1).Consequently from inequality (3) condition (ii) follows.

Conversely, it is clear that condition (1) and (2) imply that l is a best approximation, because we have

$$\begin{aligned} \|l - x\|^2 &\leq (x_0^*, m - x) \\ &\leq \|x_0^*\| \cdot \|m - x\| \\ &\leq \|l - x\| \cdot \|m - x\|, \forall m \in E \end{aligned}$$

and so, we must have (1)

Corollary 1: If $l \in E$ is a best approximation of $x \in \tilde{X}$ by elements of the convex set E , then the following minimax relation

$$\begin{aligned} \|x - l\| &= \min_{m \in E} \max_{\|x^*\|=1} (x^*, m - x) \\ &= \max_{\|x^*\|=1} \min_{m \in E} (x^*, m - x) \end{aligned} \tag{4}$$

holds where $x^* \in X^*$

Proof: This follows clearly if we use the relationship between the solutions to the problem and the existence of the saddle point.

Remark 1: Let $d = \|x - m\|, m \in E$ be the distance between the point x and the convex set E . Then we obtain a weak minimax relation by replacing “min” by “inf” because in such a case only the dual problem has solutions.

If E is a convex cone vertex in the origin, then the condition (ii) of Theorem 1 is equivalent to the following pair of conditions:

$$(ii') (x_0^*, m) \leq 0, \forall m \in E$$

$$(ii'') (x_0^*, x) \leq \|x - l\|^2$$

Here is the argument, from condition (ii) replacing

$$x_0^* \text{ by } x_0^* - mn \text{ we obtain } (x_0^*, x - mn) \geq \|x - l\|^2, \forall m \in E, \forall n \in N$$

Because E is a cone.

Therefore we cannot have $(x_0^*, m) > 0$ for some element $m \in E$, that is (ii') holds. Moreover from properties (ii) and (ii') it follows that

$$\|x - l\|^2 \leq (x_0^*, x - l) \leq \|x_0^*\| \|x - l\|$$

$$\text{hence } (x_0^*, x - l) = \|x - l\|^2. \text{ Thus we have } 0 \geq (x_0^*, l) = (x_0^*, x) = (x_0^*, x - l)(x_0^*, x) - \|x - l\|^2$$

$$\text{and from (ii) if } m=0, (x_0^*, x) \geq \|x - l\|^2$$

which implies property (ii'). The reciprocal is obvious.

When E is a linear space condition (ii') is equivalent to $(x_0^*, m) = 0, \forall m \in E$,

Because in this case $E = -E$.

It should be noted that $E \cap \{x \in \tilde{X} : \|x\| \leq d\}$ and it exists if and only if there exist separating hyperplanes which meet E . Moreover, the set of all best approximations is convex and coincides with the intersection of the set with any separating hyperplanes. When this intersection non-empty the separating hyperplane is a supporting hyperplane and is given the equation

$$(x^0, m - x) = \|x - l\|^2, m \in X.$$

Now, let us study the existence of the best approximation. Let

$$d = \inf_{m \in E} \|(m - x, f)\|^2.$$

$$\text{We easily see that } \inf_{m \in E} \|m - x\| = \inf_{m \in E \cap \tilde{S}(x; d + \varepsilon)} \|m - x\|, \tag{5}$$

where $\tilde{S}(x; d + \varepsilon) = \{y \in X : \|y - x\| \leq d + \varepsilon\}, \varepsilon \geq 0$.

Theorem 2: A proper convex function $f : \tilde{X} \rightarrow]-\infty, +\infty]$ is lower-semicontinuous on X if and only if it is lower-semicontinuous with respect to the weak topology on X .

Proof: A fuzzy normed linear space is (strongly) closed if and only if it is closed in the corresponding weak topology on \tilde{X} . In particular $\text{epi } f$ is (strongly) closed if it is weakly closed. This establish the theorem.

Theorem 3: If the convex set E is such that $\exists \varepsilon > 0$ for which the set $E \cap \bar{S}(x; d + \varepsilon)$ is weakly compact, then x has a best approximation in E .

Proof: According to relation (11) it is sufficient to recall that a lower-semi-continuous (by theorem 2) on the weakly compact set $E \cap \bar{S}(x; d + \varepsilon)$.

Corollary 2: In a semi-reflexive fuzzy normed linear space every element possesses at least one best approximation with respect to every closed convex set.

Proof: The set $E \cap \bar{S}(x; d + 1)$ is convex closed and bounded and hence it is weakly compact by virtue of Alaoglu theorem ([5], p. 15).

Corollary 3: In a fuzzy normed linear space every element possesses at least one best approximation with respect to every closed, convex and finite dimensional set.

Proof: In a finite dimensional space the bounded closed convex set are compact and hence weakly compact.

Definition 20: Let \tilde{X}, \tilde{Y} be fuzzy normed linear spaces of the same nature. A linear operator $T: \tilde{X} \rightarrow \tilde{Y}$ is continuous if and only if it is bounded. In other words there exists $k > 0$ such that $\|Tl\| \leq k\|l\|, \forall l \in \tilde{X}$.

The set $L(\tilde{X}, \tilde{Y})$ of all linear continuous operators defined on \tilde{X} with values in \tilde{Y} becomes a fuzzy normed linear space by

$$\begin{aligned} \|T\| &= \sup\{\|Tl\| : \|l\| \leq 1\} \\ &= \inf\{k : \|Tl\| \leq k\|l\|, \forall l \in \tilde{X}\}. \end{aligned} \tag{6}$$

If $\tilde{Y} = R$, we find that $\tilde{X}^* = L(\tilde{X}, R)$, called the dual of \tilde{X} , is fuzzy normed linear space defined by

$$\|l^*\| = \sup\{l^*(l) : \|l\| \leq 1\} \tag{7}$$

Theorem 4: Let f_0 be a continuous linear functional on a linear subspace A of a fuzzy normed linear space \tilde{X} . Then there exists a linear functional f on the whole of \tilde{X} , i.e., $f \in \tilde{X}^*$, such that

- (i) $f|_A = f_0$,
- (ii) $\|f\| = \|f_0\|$

Proof: Since f_0 is continuous on A , by relation (7) we have

$$f_0(m) \leq \|f_0\| \cdot \|m\|, \forall m \in A$$

By the Hahn-Banach Theorem for f_0 and for the convex function

$$P(x) = \{\|f_0\| \cdot \|l\|\}$$

A specialization of this theorem yields a whole class of existence results. In this context we shall present a general and classical theorem concerning the existence of continuous linear functionals with important consequence in the duality theory of fuzzy normed linear spaces.

Theorem 5: Let m be a nonnegative number and let $h: B \rightarrow R$ be a given real function, where B is a non-empty set of fuzzy normed linear space \tilde{X} . Then, h has a continuous linear extension f on all of \tilde{X} such that $\|f\| \leq m$ if and only if the following condition holds:

$$\left| \sum_{i=1}^n \chi_i h(a_i) \right| \leq m \left\| \sum_{i=1}^n \chi_i a_i \right\|, \forall n \in N, \chi_i \in R, a_i \in B. \tag{8}$$

Proof: From relation (6) and (7) it is clear that condition (8) is necessary. To prove the sufficiency we consider $A = \text{span } B$ and we define f_0 on A by

$$f_0(m) = \sum_{i=1}^n \lambda_i h(a_i), \text{ if } m = \sum_{i=1}^n \lambda_i a_i \in A, a_i \in B.$$

First, using condition (8) we observed that f_0 is well defined on A . Moreover from condition (8) the continuity of f_0 on A follows and $\|f_0\| \leq m$. Thus any extension given under theorem 4 has all the required properties.

Theorem 6: For any linear subspace A of a fuzzy normed linear space

\tilde{X} and $l \in \tilde{X}$ there exists $f \in \tilde{X}^*$ with the following properties :

- i) $f|_A = 0$,
- ii) $f(l) = \inf_{m \in A} \{\|l - m\|^2 = d(l, A)\}$,
- iii) $\|f\| = \inf_{m \in A} \{\|l - m\|\} = d(l, A)$.

Proof: We take $B = A \cup \{l\}$ and $h: B \rightarrow R$ defined by $h(m) = 0, m \in A$, and $h(l) = d^2(l, A)$. We observe that for any $\lambda \neq 0$ we have

$$\begin{aligned} \left| \lambda h(l) + \sum_{i=1}^n \lambda_i h(a_i) \right| &= |\lambda h(l)| = |\lambda| d^2(l, A) \leq |\lambda| d(l, A) \left\| l + \sum_{i=1}^n \frac{\lambda_i}{\lambda} a_i \right\| \\ &= d(l, A) \left\| l + \sum_{i=1}^n \frac{\lambda_i}{\lambda} a_i \right\|, \forall n \in N, \lambda_i \in R, a_i \in B, \end{aligned}$$

which is just inequality (8).The desire result then follows by applying Theorem 5. Indeed, we have properties (i) and (ii) and $\|f\| \leq d(l, A)$. Since $m = d(l, A)$. On the other hand, if we consider a sequence $\{m_n\} \subset A$ such that $\|l + m_n\| \rightarrow d(l, A)$ we obtain

$$\|f\| \geq f\left(\frac{l + m_n}{\|l + m_n\|}\right) = \frac{f(l)}{\|l + m_n\|} = \frac{d^2(l, A)}{\|l + m_n\|} \rightarrow d(l, A)$$

which implies $\|f\| \geq d(l, A)$. Hence property (iii) also holds.

Corollary 4: In a fuzzy normed linear space \tilde{X} for every $l \in \tilde{X}$ there exists a continuous linear function $f \in X^*$ such that

(i) $f(l) = \|l\|,$

(ii) $\|f\| = \|l\|,$

Moreover, if $l \neq 0$, there exists $g \in X^*$ such that

(i') $g(l) = \|l\|,$

(ii') $\|g\| = 1$

Proof: By Theorem 6, $d(l, A) = \|l\|$ where $A = \{0\}$. Then the corollary completes the proof.

Definition 21: The space \tilde{X} is strictly convex if every point of the polar set $\{l \in X : \|l\| = 1\}$ is an extreme point.

Theorem 7: A fuzzy normed linear space \tilde{X} is strictly convex if and only if the following equivalent properties hold:

(i) if $\|x + y\| = \|x\| + \|y\|$ and $x \neq 0$ there is $t > 0$ such that $y = tx$

(ii) if $\|x\| = \|y\| = 1$ and $x \neq y$, then $\|\lambda x + (1 - \lambda)y\| < 1$ for all $\lambda \in [0, 1]$,

(iii) if $\|x\| = \|y\| = 1$ and $x \neq y$, then $[\frac{1}{2}(x + y)] < 1$,

(iv) the function $x \rightarrow \|x\|^2, x \in \tilde{X}$, is strictly convex.

Proof: Let \tilde{X} be strictly convex and let $x, y \in \tilde{X} \setminus \{0\}$ be such that

$$\|x + y\| = \|x\| + \|y\|$$

By corollary 4 for $x \in \tilde{X}$, there exists a continuous functional

$x^* \in X^*$ such that $(x + y, x^*) = \|x + y\|, \leq \|x^*\| = 1$.

$(x, x^*) \leq \|x\|$ and $(y, x^*) = \|y\|$, ie.

$$\left(\frac{x}{\|x\|}, x^* \right) = \left(\frac{y}{\|y\|}, x^* \right) = 1$$

Because \tilde{X} is strictly convex it follows that $\frac{x}{\|x\|} = \frac{y}{\|y\|}$

Hence property (i) holds with $t = \frac{\|y\|}{\|x\|}$

To prove that (i) \rightarrow (ii) we assume by contradiction that there exists $x \neq y$ such that $\|x\| = \|y\| = 1$ and $\|\lambda x + (1 - \lambda)y\| = 1$.

Therefore we have $\|\lambda x + (1 - \lambda)y\| = \|\lambda x\| + \|(1 - \lambda)y\|$.

According to property (i) there exist $t \geq 0$ such that $\lambda x = t(1 - \lambda)y$.

Since $\|x\| = \|y\|$, we obtain $\lambda = t(1 - \lambda)$ and so $x = y$, which is a contradiction. The implications (ii) \rightarrow (iii) and (iv) \rightarrow (ii) are obvious.

Now we assume that \tilde{X} is not strictly convex. Therefore there exist $x_0^* \in \tilde{X}^*$ and

$x_1, x_2 \in \tilde{X}$ with $\|x_1^*\| = 1, \|x_1\| = \|x_2\| = 1, x_1 \neq x_2$ such that $(x_1, x_0^*) = (x_2, x_0^*) = 1$, hence $\frac{1}{2}(x_1 + x_2, x_0^*) = 1$.

Thus $\left\| \frac{1}{2}(x_1 + x_2) \right\| = \sup\{ \frac{1}{2}(x_1 + x_2, x^*) : \|x^*\| = 1 \} \geq \frac{1}{2}(x_1 + x_2, x_0^*) = 1$, contradicts the property

(iii). Hence property (iii) implies the strict convexity of \tilde{X} . Now from the equality

$$\lambda\|x\|^2 + (1 - \lambda)\|y\|^2 = \{\lambda\|x\| + (1 - \lambda)\|y\|\}^2 = \{\lambda\|x\| + (1 - \lambda)\|y\|\}^2 + \lambda(1 - \lambda)(\|x\| + \|y\|)^2$$

It follows that

$$\|\lambda x + (1 - \lambda)y\|^2 \leq \{\lambda\|x\| + (1 - \lambda)\|y\|\}^2 \leq \lambda\|x\|^2 + (1 - \lambda)\|y\|^2, \forall x, y \in \tilde{X}$$

with $\|x\| \neq \|y\|$ and $\lambda \in]0, 1[$. If $\|x\| = \|y\|$,

We obtain the strict convexity of the function $x \rightarrow \|x\|^2, x \in \tilde{X}$, from (ii). Thus the implication (ii) \rightarrow (iv) is established and the proof is complete.

Theorem 8: If \tilde{X} is a fuzzy linear space which is strictly convex, then each element $x \in \tilde{X}$ possesses at most one best approximation with respect to a convex set $E \subset \tilde{X}$.

Proof: Assume by contradiction that there exist two distinct best approximations l_1, l_2 in E . Since the set of best approximations is convex, it follows that $\frac{1}{2}(l_1 + l_2)$ is also a best approximation.

Hence if $d = \inf\{\|m - x\| : m \in E\}$, we have $0 < d = \|x - l_1\| = \|x - l_2\| = \left\|x - \frac{1}{2}(l_1 + l_2)\right\|$

Where \tilde{X}^* is the conjugate space of \tilde{X} and $\left\|\frac{1}{d}(x - l_1)\right\| = \left\|\frac{1}{d}(x - l_2)\right\| = 1$.

In view of the strict convexity (see Theorem 7) we have

$$1 > \left\|\frac{1}{2d}(x - l_1) + \frac{1}{2d}(x - l_2)\right\| = \frac{1}{d}\left\|x - \frac{1}{2}(l_1 + l_2)\right\| = 1,$$

which is a contradiction. This completes the proof.

Remark 2: This property is characteristic of the strictly convex spaces: if in a fuzzy normed linear space \tilde{X} , every element possesses at most a best approximation with respect to every convex set (it is enough for the segments), then \tilde{X} is strictly convex.

Indeed, if we assume that \tilde{X} is not strictly convex, then there exists $x, y \in \tilde{X}, x \neq y$, with $\|x\| = \|y\| = \frac{1}{2}\|x + y\| = 1$.

Furthermore, $\|\alpha x + (1 - \alpha)y\| = 1, \forall \alpha \in [0, 1]$.

Hence the origin has at the best approximation with respect to the closed convex set $[x, y]$ every element of the set and this clearly contradicts the uniqueness.

From Corollary 2 and Theorem 3 it follows that in a semireflexive strictly fuzzy linear space, for every closed convex set E we can define the function $P_E : \tilde{X} \rightarrow \tilde{X}$ by $P_E(x) = l$, where l is the best approximation of \tilde{X} by elements of E . This function is called the projection function of the space \tilde{X} into E . We note that $P_E(x) \in E$ for every $x \in \tilde{X}$.

Definition 22: Let us consider the following general family of minimization problems

$$(P_y) \min\{F(x, y) : x \in \tilde{X}, y \in \tilde{Y} \text{ where } \tilde{X}, \tilde{Y} \text{ are fuzzy linear spaces and } \tilde{X} \times \tilde{Y} \rightarrow \bar{R}\}.$$

Let us denote by

$$h(y) = \inf\{F(x, y) : x \in \tilde{X}, y \in \tilde{Y} \text{ where } \tilde{Y} = Y \times [0, 1] \text{ and } Y \text{ is a linear space over the same field } K \text{ and } H = \{(y, a) \in \tilde{Y} \times R : \text{there exists } \bar{x} \in \tilde{X} \text{ such that } F(\bar{x}, y) \leq a\}.$$

Theorem 9: Let \tilde{X}, \tilde{Y} are fuzzy linear spaces and $F: \tilde{X} \times \tilde{Y} \rightarrow]-\infty, +\infty]$ by a positively homogeneous and lower-semicontinuous function satisfying the following convexity condition

$$F(x,0) > 0 \text{ for any } x \in \tilde{X} \setminus \{0\}. \tag{9}$$

Then if $\text{epi}F$ is locally compact, every problem P_y has an optimal solution whenever its value is finite.

Proof: It is easy to observe that

$$H = P_{Y \times R}(\text{epi}F).$$

By hypothesis $\text{epi} h$ is a closed cone and so $(\text{epi}F)_\infty = \text{epi} F$. Therefore, it is sufficient to use corollary 11.13 ([1], p. 28) for $T = \text{Proj}_{Y \times R}$ and $A = \text{epi}F$, taking into account that the separation condition (1.42) of corollary 1.13 ([1], p. 28) may be written as condition (9).

Theorem 10: If E is a closed locally compact convex set of a strictly convex fuzzy linear space \tilde{X} , then the projection function is continuous on \tilde{X} .

Proof: If $x_n \rightarrow x, \forall \varepsilon > 0$, then $\exists n_0(\varepsilon) \in \mathbb{N}$ such that $\|x_n - x\| < \varepsilon, \forall n > n_0(\varepsilon)$. Denote

$$d_n = \inf_{m \in E} \{\|x_n - m\|\}, \quad d = \inf_{m \in E} \{\|x - m\|\},$$

where \tilde{X}^* is the dual space \tilde{X} . We have

$$d_n \leq \inf_{m \in E} \{\|x - m\| + \|x_n - x\|\} < d + \varepsilon, \forall n > n_0(\varepsilon).$$

$$\text{Hence } \|x - P_E x_n\| \leq \|x_n - P_E x_n\| + \|x_n - x\| < d_n + \varepsilon < d + 2\varepsilon.$$

Since the set $E \cap \bar{S}(x; d + \varepsilon)$ does not contain any half-line it follows that it is compact where $\bar{S}(x; d + \varepsilon) = \{y \in \tilde{X} : \|y - x\| \leq d + \varepsilon\}, \varepsilon > 0$. Thus $\bigcap_{\varepsilon > 0} \bar{S}(x; d + \varepsilon) \cap E \neq \emptyset$ and any subsequence of $P_E x_n$ has a cluster point which satisfies $\|x - l\| = d$. Because \tilde{X} is strictly convex, this point is unique and so $P_E x_n \rightarrow l = P_E x$ as claimed.

Definition 23: A set E is called proximal if every element of \tilde{X} has a best approximation in E . That is, the set E is proximal if the problem $\min_{m \in E} \{\|x - m\|\}$ has a solution for every $x \in \tilde{X}$.

Theorem 11: A nonempty set E of a fuzzy linear space \tilde{X} is proximal if and only if $\text{epi} \|\cdot\| + E \times \{0\}$ is closed in $X \times R$.

Moreover if E is a convex set which contains the origin we have

$$\min_{m \in M} \{\|x - m\|\} = \max_{x^* \in S^* \cap E^0} \{(x^*, x) - P_{E^0}(x^*)\} \text{ for every } x \in \tilde{X}, \text{ where } E^0 \text{ is the polar set of } E \text{ [2].}$$

Proof: Taking in Theorem 2.11 (Chap. 3[1]), $f = I_E, g = -\sup_{f \in \tilde{X}^*} |(\cdot, f)|, A = I$, we observe that

$$H = \{m + x, \sup_{f \in \tilde{X}^*} |((x, f) + r)| \in XxR; m \in E, x \in X, r > 0\} = \text{epi} \sup_{f \in \tilde{X}^*} |(\cdot, f)| + E \times \{0\}.$$

Remark 3: It is easy to see that $\text{epi} \sup_{f \in \tilde{X}^*} |(\cdot, f)| = \text{cone}(\bar{S}(0,1) \times \{1\})$ and so if E is cone, then $\text{epi} \sup_{f \in \tilde{X}^*} |(\cdot, f)| + E \times \{0\}$ is closed in $\tilde{X} \times R$ if and only if $S(0,1) + E$ is closed in \tilde{X}

In particular, If E is a linear subspace, denoting by $\phi_E : \tilde{X} \rightarrow \tilde{X}/E$ the canonical mapping, the above condition says that $\phi_E(\bar{S}(0,1))$ is closed in quotient space $\tilde{X} \setminus E$.

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