Afrika Matematika (2020) 31:557–564
https://doi.org/10.1007/s13370-019-00741-9

A case study for medical decision making with the fuzzy soft sets

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Received: 29 December 2018 / Accepted: 3 November 2019 / Published online: 13 November 2019

Abstract
Molodtsov proposed a completely new approach to modelling uncertainty. This approach is called the soft set theory. Many applications of soft set theory have been developed by combining with a fuzzy set idea. In the present study, for the medical decision-making, the proposed technique related to the fuzzy soft set by Celik–Yamak through Sanchez's method was used. The real dataset which is called Cleveland heart disease dataset was used in this problem.

Keywords Cleveland dataset · Decision making · Defuzzification · Fuzzy soft set · Triangular fuzzy number · Trapezoidal fuzzy number

Mathematics Subject Classification Primary 03E75; Secondary 03E72 · 68T37 · 94D05

1 Introduction

Many terms that are used randomly in daily life often have a vagueness structure. Verbal or numerical expressions include vagueness while describing something, explaining an event, commanding and in many other cases. People use terms that do not express certainty when explaining an event or deciding on a situation. According to the age, the person can be called old, middle, young, very old or very young. Depending on the slope and ramp condition of the road, gas or brake pedal of the car is depressed slightly slower or slightly faster. All these, are examples of how the human brain behaves in uncertain and vagueness situations, and how it evaluates, identifies, and commands events.

After the fuzzy set theory which developed by Zadeh and published in 1965 [12], the analysis of uncertainty systems was acquired a new dimension. The exact solutions of many complicated problems that cannot be solved by classical mathematical methods were revealed with well-known theories such as fuzzy set theory defining uncertainty. In fuzzy sets, the tool used to identify and resolve uncertainty is membership functions. That is, the fuzzy sets are

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characterized by a membership function which assigns to each target a membership value ranging between 0 and 1.

Molodtsov proposed the concept of the soft set (SS), a completely new approach to modelling uncertainty. The SST has a generous application potential. Some of these applications have been shown by Molodtsov in his pioneering work. This theory was implemented in many areas of uncertainty such as mathematical analysis, algebraic structures, optimization theory, information systems, decision-making problems. Maji et al. [6] investigated the SST for decision making problems. In [7], the authors defined operations "AND", "OR", union-intersection of two SSs and also gave some examples. The same authors established a hybrid model known as fuzzy soft set (FSS), which is a combination of SS and FS [5]. Actually, the concept of FSS is an extension of crisp SS. In [1], some new operations related to the fuzzy soft matrix are studied and examples are given. Broumi et al. [2] given new operations based on intuitionistic FSSs.

In this study, we will consider the approach of Çelik–Yamak [3], obtained from the Sanchez's model [10] and we will use real dataset, which is called Cleveland heart disease dataset [11], for the problem of medical decision-making.

2 Decision making for imprecision

The problems faced in real-life are often not clear and precise. Therefore, various decision-making mechanisms are used to solve problems. These mechanisms are used to reduce uncertainties and make an accurate decision. Therefore, improved mathematical tools for uncertainty and imprecision are needed. The FS theory has been used quite extensively to deal with such imprecisions. In this section, we will give some definitions of the theories of SSs and FSSs.

The FS has emerged as a generalization of the classical set concept. If we choose a non-empty set X, then a function $f_A(x) : X \to [0, 1]$ is called FS on X and represented by

$$A = \{(x_i, f_A(x_i)) : f_A(x_i) \in [0, 1]; \forall x_i \in X\}.$$

FS A on X can be expressed by, set of ordered pair as follows:

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

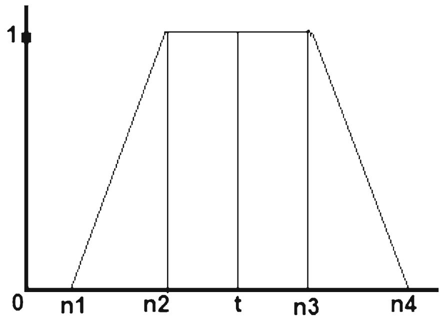
The fuzzy subset of X is a non-empty subset $\{(x, f(x)) : x \in X\}$ for some function $f : X \to [0, 1]$ [4]. Consider the function $f : \mathbb{R} \to [0, 1]$ as a subset of a non-empty base space $\mathbb{R}$. Suppose that the function f satisfies the following properties:

(i) f is a normal, that is, there exist $x_i \in \mathbb{R}$ such that $f(x_i) = 1$,

(ii) f is a fuzzy convex, that is, $f[kx + (1-k)y] \geq \min\{f(x), f(y)\}$, where $x, y \in \mathbb{R}$ and $k \in [0, 1]$,
(iii) f is upper semi-continuous,
(iv) The closure of the set C is compact, where the set $C = \{x \in \mathbb{R} : f(x) \geq 0\}$.

Therefore, the function f is called a *fuzzy number* [4].

Fig. 1 A trapezoidal FN



A triangular FN $\widehat{m}$ is represented by a triplet (m_1, m_2, m_3) and its the membership function is

$$f(x) = \begin{cases} 0, & x < m_1 \\ \frac{x-m_1}{m_2-m_1}, & m_1 \le x \le m_2 \\ \frac{x-m_3}{n_2-n_3}, & n_2 \le x \le n_3 \\ 0, & x > n_3 \end{cases}$$

A trapezoidal FN $\widehat{n}$ is a piecewise function, parameterized by a quadruplet (n_1, n_2, n_3, n_4) (Fig. 1). The membership function of a trapezoidal FN is given by

$$f(x) = \begin{cases} 0, & x < n_1 \\ \frac{x-n_1}{n_2-n_1}, & n_1 \le x \le n_2 \\ 1, & n_2 \le x \le n_3 \\ \frac{x-n_4}{n_3-n_4}, & n_3 \le x \le n_4 \\ 0, & x > n_4 \end{cases}$$

SS theory developed by Molodtsov [8] is a suitable tool for solving uncertainties in non parametric situations and is a natural generalization of FS theory. Since SS Theory is a natural generalization of FS theory, it has been applied in a wide range of fields ranging up to from mathematics to engineering from economics to optimization.

In the approximate description, there are two value sets which are called predicate and approximate. Initially, the object description has an approximate by nature and so there is no requirement to present the concept of the exact solution. The SS theory is very convenient and simply effective in performance due to the nonentity of any limitations on the approximate descriptions. With the aid of words and sentences, real sentences, real number, function, mapping and so on; any parameter can operate that we desire.

Now, we will give definitions of Soft Set and Soft Subset.

Definition 2.1 Consider X, E as initial universe and parameters sets. Take $\mathcal{P}(X)$ as a power set of X. Let $R \subset E$. Give the mapping $\mathcal{F} : R \to \mathcal{P}(X)$. Then, the pair $(\mathcal{F}, R)$ is called a soft set (SS) on X.

This definition can be also expressed as:

A SS on X is a parameterized family of subsets of the universe X. $\mathcal{F}(\alpha)$ may be considered as the set of α-approximate elements of the SS $(\mathcal{F}, R)$, for $\alpha \in R$.

Definition 2.2 Let $(\mathcal{F}, R)$ and $(\mathcal{G}, S)$ be two SSs on X. If the following conditions are hold, then it is said that $(\mathcal{F}, R)$ is a soft subset (SSS) of $(\mathcal{G}, S)$:

(i) $R \subset S$,
(ii) $\mathcal{F}(\alpha)$ and $\mathcal{G}(\alpha)$ are identical approximations, for all $\alpha \in R$.

We will denote the SSS by $(\mathcal{F}, R)\hat{\subset}(\mathcal{G}, S)$.

The AND and OR operator of SSs are defined as:

Definition 2.3 Let $(\mathcal{F}, R)$ and $(\mathcal{G}, S)$ be two SSs. Define $\mathcal{H}(\lambda, \mu) = \mathcal{F}(\lambda) \cap \mathcal{G}(\mu)$, $((\lambda, \mu) \in R \times S)$. Then, $(\mathcal{F}, R) \wedge (\mathcal{G}, S) = (\mathcal{H}, R \times S)$ is called $(\mathcal{F}, R)$ AND $(\mathcal{G}, S)$.

Define $\mathcal{K}(\lambda, \mu) = \mathcal{F}(\lambda) \cup \mathcal{G}(\mu)$, $((\lambda, \mu) \in R \times S)$. Then, $(\mathcal{F}, R) \vee (\mathcal{G}, S) = (\mathcal{K}, R \times S)$ is called $(\mathcal{F}, R)$ OR $(\mathcal{G}, S)$.

Choose set of k objects and set of parameters as $X = \{a_1, a_2, \ldots a_n\}$ and $\{R_1, R_2, \ldots, R_i\}$, respectively. Let $E \supseteq \{R_1 \cup R_2 \cup \cdots, R_i\}$ and each parameter set R_i represent the ith class of parameters and the elements of R_i represents a specific property set. Assumed that the property sets can be shown as FSs.

Definition 2.4 Let $\mathcal{P}(X)$ denotes the set of all FSs of X and $R_i \subset E$. Give $\mathcal{F}_i : R_i \to \mathcal{P}(X)$ be a mapping. Then, $(\mathcal{F}_i, R_i)$ is called a fuzzy soft set (FSS) over X.

Definition 2.5 Let $(\mathcal{F}, R)$ and $(\mathcal{G}, S)$ be two FSSs on X. If the following conditions are hold, then it is said that $(\mathcal{F}, R)$ is a fuzzy soft subset (FSSS) of $(\mathcal{G}, S)$:

(i) $R \subset S$,
(ii) $\mathcal{F}(\alpha)$ is a FSS of $\mathcal{G}(\alpha)$, for all $\alpha \in R$.

We write $(\mathcal{F}, R)\hat{\subset}(\mathcal{G}, S)$.

3 Method

3.1 FSS method

In this study, we will use a technique developed with FSS theory [3]. We build a patient-attributes$(m \times n)$ matrix P_A using the FSS. The entries of this matrix are FNs $\widehat{s}$ parameterized by a triplet $(s-1, s, s+1)$. Later on, the attributes-disease degrees$(n \times k)$ matrix A_D which is also called weighted matrix is built. In this matrix, each entry represents the weight of the attributes for a disease degree. Generally, these matrices are given as below:

$$P_A = \begin{bmatrix} \widehat{u_{11}} & \widehat{u_{12}} & \widehat{u_{13}} & \cdots & \widehat{u_{1n}} \\ \widehat{u_{21}} & \widehat{u_{22}} & \widehat{u_{23}} & \cdots & \widehat{u_{2n}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \widehat{u_{m1}} & \widehat{u_{m2}} & \widehat{u_{m3}} & \cdots & \widehat{u_{mn}} \end{bmatrix} \quad \text{and} \quad A_D = \begin{bmatrix} \widehat{v_{11}} & \widehat{v_{12}} & \widehat{v_{13}} & \cdots & \widehat{v_{1k}} \\ \widehat{v_{21}} & \widehat{v_{22}} & \widehat{v_{23}} & \cdots & \widehat{v_{2k}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \widehat{v_{n1}} & \widehat{v_{n2}} & \widehat{v_{n3}} & \cdots & \widehat{v_{nk}}. \end{bmatrix}$$

The patient-disease degrees matrix$(m \times k)$ P_D can be obtained from transformation operation $P_A \otimes A_D$. The general form of the matrix P_D as follows:

$$P_D = \begin{bmatrix} \widehat{w_{11}} & \widehat{w_{12}} & \widehat{w_{13}} & \cdots & \widehat{w_{1k}} \\ \widehat{w_{21}} & \widehat{w_{22}} & \widehat{w_{23}} & \cdots & \widehat{w_{2k}} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \widehat{w_{m1}} & \widehat{w_{m2}} & \widehat{w_{m3}} & \cdots & \widehat{w_{mk}} \end{bmatrix}$$

where $w_{ij} = (A, B, C)$ such that $A = \sum_{k=1}^{n}(a_{ik} - 1)(b_{kj} - 1)$, $B = \sum_{k=1}^{n} a_{ik}b_{kj}$ and $C = \sum_{k=1}^{n}(a_{ik} + 1)(b_{kj} + 1)$.

We can calculate the defuzzification of t of triangular FN (m_1, m_2, m_3) as

$$t = \frac{m_1 + m_2 + m_2 + m_3}{4} \tag{1}$$

[3]. Thus, we will obtain crisp diagnosis matrix D_F. The matrix D_F as below:

$$D_F = \begin{bmatrix} z_{11} & z_{12} & z_{13} & \cdots & z_{1k} \\ z_{21} & z_{22} & z_{23} & \cdots & z_{2k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ z_{m1} & z_{m2} & z_{m3} & \cdots & z_{mk} \end{bmatrix}$$

It will be decided according to the crisp values of the matrix D_F. If $\max z_{ij} = z_{ik}$ $(0 \leq j \leq k)$, then the disease degree of patient p_i is k $k = 1, 2, 3, 4$ or 0(absence).

3.2 Dataset

Input variables are taken from Cleveland dataset [11]. This data set contains 303 patients, 11 attributes and 5 outcomes.

This database contains 76 attributes. However, it is understood that 11 of these attributes can be used because of the analysis. The outcomes are given as degree of disease. It is integer valued from 0 (no presence) to 4. Tests with the Cleveland database have intensively on simply attempting to distinguish presence (values 1,2,3,4) from absence (value 0).

Let's choose patient sets $U = \{p_1, p_2, p_{24}, p_{25}, p_{75}, p_{303}\}$ from the Cleveland dataset.

The attributes of Cleveland dataset is given in Table 1. The outcomes are disease degrees as 1, 2, 3, 4 and 0 (absence).

According to the membership function, the age attribute is taken into account as follows: 0–20 (0.0–0.2), 21–40 (0.3–0.5), 41–60 (0.6–0.8); 61 + (0.9–1.0). In this data set, the attributes trestbps, chol, thalach, oldpeak are measured as lowest 94.0 highest 200.0; lowest 126.0 highest 564.0; lowest 71 highest 195; lowest 0.0 highest 5.6, respectively. We will give values between 0.0 and 1.0 to these measurements.

Table 1 Attributes of Cleveland dataset

Attributes	Fullname
a_1	Age in years
a_2	Chest pain type
a_3	Resting blood pressure (in mmHg)
a_4	Serum cholesterol in mg/dl
a_5	Fasting blood sugar > 120 mg/dl
a_6	Resting electrocardiographic results
a_7	Maximum heart rate achieved
a_8	ST depression induced by exercise relative to rest
a_9	The slope of the peak exercise ST segment
a_{10}	Number of major vessels (0–3) colored by fluoroscopy
a_{11}	3: normal; 6: fixed defect; 7: reversible defect

3.3 Algorithm

(i) Input the SS $(\mathcal{F}, R)$ to get the patient-attribute matrix,
(ii) Input the SS $(\mathcal{G}, S)$ to get the attribute-disease degree matrix,
(iii) Compute the transformation operation $P_A \otimes A_D$ to make the patient-disease degree matrix,
(iv) Defuzzify all the elements of the patient-disease degree matrix by Eq. 1 and to obtain the defuzzify matrix,
(v) Find k for which $z_{ik} = \max z_{ij}$.

4 Application

In this section, using the Celik–Yamak approach obtained by Sanchez's method, we give an application of FSS theory [9] for medical decision making. For this application, it will be used the Cleveland Dataset. This data set contains 303 patients.

Now, we construct the matrices for medical decision making by algorithm in previous section:

The patient-attributes matrix P_A is given by

$$P_A = \begin{bmatrix} \widehat{9} & \widehat{2} & \widehat{5} & \widehat{3} & \widehat{7} & \widehat{8} & \widehat{6} & \widehat{2} & \widehat{9} & \widehat{1} & \widehat{5} \\ \widehat{9} & \widehat{7} & \widehat{5} & \widehat{3} & \widehat{1} & \widehat{8} & \widehat{4} & \widehat{3} & \widehat{5} & \widehat{8} & \widehat{1} \\ \widehat{7} & \widehat{6} & \widehat{4} & \widehat{3} & \widehat{1} & \widehat{9} & \widehat{5} & \widehat{6} & \widehat{1} & \widehat{6} & \widehat{8} \\ \widehat{8} & \widehat{7} & \widehat{4} & \widehat{4} & \widehat{2} & \widehat{9} & \widehat{4} & \widehat{5} & \widehat{5} & \widehat{6} & \widehat{9} \\ \widehat{5} & \widehat{8} & \widehat{3} & \widehat{4} & \widehat{2} & \widehat{5} & \widehat{8} & \widehat{1} & \widehat{7} & \widehat{3} & \widehat{2} \\ \widehat{4} & \widehat{6} & \widehat{4} & \widehat{3} & \widehat{1} & \widehat{2} & \widehat{7} & \widehat{1} & \widehat{2} & \widehat{5} & \widehat{3} \end{bmatrix}.$$

In this matrix, rows are shown in patients $\{p_1, p_2, p_{24}, p_{25}, p_{75}, p_{303}\}$ and columns are shown attributes $\{a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9, a_{10}, a_{11}\}$. For example, $\mathcal{F}(p_1) = \{a_1/\widehat{9}, a_2/\widehat{2}, a_3/\widehat{5}, a_4/\widehat{3}, a_5/\widehat{7}, a_6/\widehat{8}, a_7/\widehat{6}, a_8/\widehat{2}, a_9/\widehat{9}, a_{10}/\widehat{1}, a_{11}/\widehat{5}\}$.

The attributes-disease degrees matrix A_D consist of the rows and columns which are attributes $\{a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9, a_{10}, a_{11}\}$ and disease degrees $1 = d_1, 2 = d_2, 3 = d_3, 4 = d_4, 0 = d_0$, respectively. For example, $\mathcal{G}(a_1) = \{d_1/\widehat{4}, d_2/\widehat{3}, d_3/\widehat{1}, d_4/\widehat{2}, d_5/\widehat{9}\}$.

$$A_D = \begin{bmatrix} \widehat{4} & \widehat{3} & \widehat{1} & \widehat{2} & \widehat{9} \\ \widehat{8} & \widehat{9} & \widehat{7} & \widehat{5} & \widehat{1} \\ \widehat{7} & \widehat{8} & \widehat{9} & \widehat{8} & \widehat{1} \\ \widehat{3} & \widehat{5} & \widehat{8} & \widehat{9} & \widehat{2} \\ \widehat{9} & \widehat{8} & \widehat{4} & \widehat{2} & \widehat{5} \\ \widehat{3} & \widehat{2} & \widehat{2} & \widehat{1} & \widehat{9} \\ \widehat{3} & \widehat{1} & \widehat{4} & \widehat{9} & \widehat{2} \\ \widehat{9} & \widehat{7} & \widehat{8} & \widehat{1} & \widehat{5} \\ \widehat{8} & \widehat{9} & \widehat{7} & \widehat{1} & \widehat{8} \\ \widehat{5} & \widehat{8} & \widehat{3} & \widehat{2} & \widehat{9} \\ \widehat{8} & \widehat{4} & \widehat{9} & \widehat{5} & \widehat{2} \end{bmatrix}$$

The patients-disease degrees matrix P_D is obtained from the matrices P_A and A_D. Therefore, the rows and columns of the matrix P_D are shown in patients and disease degrees, respectively.

$$P_D = \begin{bmatrix} \widehat{336} & \widehat{301} & \widehat{287} & \widehat{217} & \widehat{314} \\ \widehat{296} & \widehat{307} & \widehat{255} & \widehat{231} & \widehat{313} \\ \widehat{320} & \widehat{284} & \widehat{296} & \widehat{218} & \widehat{283} \\ \widehat{372} & \widehat{341} & \widehat{341} & \widehat{235} & \widehat{327} \\ \widehat{270} & \widehat{267} & \widehat{254} & \widehat{215} & \widehat{227} \\ \widehat{211} & \widehat{209} & \widehat{206} & \widehat{192} & \widehat{161} \end{bmatrix}$$

where

$$\begin{aligned} &\widehat{336} = (223, 336, 454), \quad \widehat{301} = (191, 301, 433), \quad \widehat{287} = (179, 287, 417), \\ &\widehat{217} = (122, 217, 322), \quad \widehat{314} = (215, 314, 432), \\ &\widehat{296} = (186, 296, 428), \\ &\widehat{307} = (200, 307, 436), \quad \widehat{255} = (150, 255, 382), \\ &\widehat{231} = (107, 231, 305), \quad \widehat{313} = (267, 313, 431), \end{aligned}$$

$$\begin{aligned} &\widehat{320} = (208, 320, 454), \quad \widehat{284} = (175, 284, 415), \\ &\widehat{296} = (196, 296, 425), \quad \widehat{218} = (128, 218, 330), \quad \widehat{283} = (185, 283, 403), \end{aligned}$$

$$\begin{aligned} &\widehat{372} = (253, 372, 513), \quad \widehat{341} = (225, 341, 479), \\ &\widehat{341} = (228, 341, 477), \quad \widehat{235} = (138, 235, 354), \quad \widehat{327} = (222, 327, 454), \end{aligned}$$

$$\begin{aligned} &\widehat{270} = (166, 270, 396), \quad \widehat{267} = (232, 267, 390), \quad \widehat{254} = (164, 254, 375), \\ &\widehat{215} = (133, 215, 319), \quad \widehat{227} = (137, 227, 339), \end{aligned}$$

$$\begin{aligned} &\widehat{211} = (124, 211, 318), \quad \widehat{209} = (121, 209, 317), \quad \widehat{206} = (125, 206, 307), \\ &\widehat{192} = (124, 192, 280), \quad \widehat{161} = (82, 161, 256). \end{aligned}$$

The defuzzifying matrix D_F constructed from Eq. (1):

$$D_F = \begin{bmatrix} 674,5 & 306,5 & 292,5 & 219,5 & 318,75 \\ 301,5 & 312,5 & 260,5 & 218,5 & 331 \\ 325,5 & 289,5 & 323,25 & 223,5 & 288,5 \\ 377,5 & 346,5 & 316,75 & 220,5 & 332,5 \\ 275,5 & 289 & 261,75 & 240,5 & 232,5 \\ 216 & 214 & 211 & 197 & 165 \end{bmatrix}$$

Decision It is seen that in the matrix D_F, heart disease degree of the patient p_1 is 1. That is, the maximum score was measured in the first person. Additionally, when the available data are calculated with the FSS, the highest patient with 2 disease degrees is p_2, the highest patient with 3 disease degrees is p_{24}, the highest patient with 4 disease degrees is p_{75} and the highest measured person with no heart disease is p_{25}.

5 Conclusion

In this paper, an application of FSS theory developed by Sanchez and implemented by Celik–Yamak by fuzzy arithmetic operations has been studied. In this application, the real dataset which called Cleveland dataset is used.

The relation matrix and weighted matrix was formed according to the given algorithm and the patient diagnostic matrix was obtained by transformation operation. The fuzzifying values of the patient diagnostic matrix were defuzzifying and obtained the crisp diagnosis matrix. This study shows the contribution of FSSs in decision making problems and especially in medical diagnosis.

Acknowledgements I have benefited much from the constructive reports of the anonymous referees, and I am grateful for their valuable comments on the first draft on this paper, which improved the presentation and readability.

Compliance with ethical standards

Conflict of interest The author declares that he has no conflict of interest.

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