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Component Selection with Fuzzy Decision Making

Johan Silvander[a]

[a] *Software Engineering Research Lab Sweden, Blekinge Institute of Technology, Karlskrona, Sweden*

Abstract

In many situations a decision maker (DM) would like to grade a component, or rank several components of the same type. Often a component type has many features, which are deemed as valuable by the DM. Other vital features are not known by the DM but are needed for the component to function. However, it should be possible to guide the DM to find the desired business solution, without putting a requirement of detailed knowledge of the component type on the DM. We propose a framework for component selection with the help of fuzzy decision making. The work is based on algorithms from fuzzy decision making, which we have adapted or extended. The framework was validated by practitioners, which found the framework useful.

Keywords: component selection; fuzzy decision making; minimization of regret; max-prod composition

1. Introduction

In many situations a decision maker (DM) would like to grade a component or rank several components based on features which are deemed as valuable by the DM. Since a component type could be viewed from different view-points, the features should be able to reflect these view-points. Different view points could be, e.g. technical, economical and environmental view-points. In many cases there are no support for matching the business use case the DM would like to obtain. Instead, the DM is faced with low level information. Even in these cases, many available tools do not support the DM with appropriate selection criteria. The DM is not permitted to weight the importance of the selected features, the limits used on the feature values are sharp, and the support for comparing the different view-points is often absent. In order to mitigate these short comings we are using fuzzy decision making [1, 3, 18].

There exist many examples of applications in the area of fuzzy decision making [13]. Mardani et al. [6] are providing a systematically review of the applications and methodologies used in fuzzy multi decision-making. Xu and Zhao [16] presents an overview on the existing theories and methods, which we can use to improve our ranking functionality.

E-mail address: johan.silvander@bth.se

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In order to propose a framework, we have combined or extended existing methods. The framework is supporting the guidance of a DM based on the DM's business use case, it gives the DM freedom to impose its own preferences, and make it possible to view the results from different view-points. The component selection functionality in our framework can be extended with, supplier selection functionality [5], and integration effort estimations [15].

In the remaining of the paper we are using the following definition of a fuzzy-set:
If X is here a set of non-negative real numbers, denoted generically by x, then a fuzzy set A in X is a set of ordered pairs $A = \{(x, \mu_A(x)) : x \in X\}$, where $\mu_A(x) \in [0, 1]$ [20]. Each element x gets a membership degree $\mu_A(x)$, which expresses the strength of the relationship between x and A. Membership degrees equal to 1 inform about the total relation between the element and the set. The function $\mu_A : X \rightarrow [0, 1]$ is called "the membership function" of A. The support of a fuzzy set A, supp(A), is a non-fuzzy (crisp) set of all $x \in X$ such that $\mu_A(x) > 0$.

The remaining of the paper is organized as follows. How the understanding of a DM's needs are constructed is described in Section 2. The construction of the membership functions is described in Section 3, and the construction of different weights are described in Section 4, which is followed by a discussion in Section 5. We end the paper with the conclusions and future work (Section 6).

2. Constructing an Understanding of Decision Maker Needs

Since we would like to propose a solution to a DM's business use case, the understanding of the needs of the DM is crucial. In this paper we are matching the needs of a DM with a set of preferences. The preferences are connected to a set of component types. How these component types, and their features, are used to give a proposed solution to a DM are described in Section 3 and Section 4. We deliberately made this choice in order to be able to introduce new components in an easy way, and have the possibility to find a use for a component which it was not intended for.

We start to introduce a set of DMs, $A = \{A_1\}$, a set of p preferences, $P = \{P_1, \ldots, P_p\}$, and a set of n needs, $N = \{N_1, \ldots, N_n\}$.

In order to capture the needs a DM has, we are constructing a questionnaire. We base our implementation of the questionnaire on work done by Rakus-Andersson [9]. Based on the knowledge of experts, we use fuzzy sets in order to describe how much a need supports a preference.

The process of determining a preference for a specific DM in A, can use different types of composition operations [20, 19, 4, 12, 21]. We decide to implement it with the help of the max-prod composition operation. Let $R_1(x, y), (x, y) \in X \times Y$ and $R_2(y, z), (y, z) \in Y \times Z$ be two fuzzy relations. Then the max-prod composition is defined as follows: $R_1 \overset{\circ}{\bullet} R_2(x, z) = max[\mu_{R_1}(x, y) * \mu_{R_2}(y, z)$, where $x \in X, y \in Y, z \in Z$ [21].

The determined preferences will result in a selection of component types. The outcome of the selection will be used in the next section.

3. Construction of the Component Objectives

In order to grade and compare a certain type of components, we introduce three sets:

- A set of c components, $C = \{C_1, \ldots, C_c\}$, of a specific component type.
- A set of f features, $F = \{F_1, \ldots, F_f\}$, which are present in the component type.
- A set of g grades, $G = \{G_1, \ldots, G_g\}$, indicating how valuable a value of a feature is.

Examples of features are; price, energy consumption, weight and processing capacity. The value of a feature F_i is denoted as $v_{F_i}, i \in \{1, ..., f\}$. The different grades are placed in order of how valuable a value of a feature is, $G_1 > G_2 > \ldots > G_g$. The symbol ">" is used for the description "more valuable then". For each combination of F_i and G_j a value denoted as $v_{FG_{ij}}$ is given, where $i \in \{1, ..., f\}$ and $j \in \{1, ..., g\}$. This is the crisp value a feature should have to achieve a certain grade.

A specific preference is connected to a set of component types. For a specific component type, an expert is constructing a feature-grade matrix called FG_P^E. The feature-grade matrix is a $f \times g$ matrix. The matrix consists of the values for the most valuable grade and the least valuable grade, for each feature of the specific component type. Since a component type could be viewed from different view-points, a feature should indicate which view-point it belongs to.

Different view points could be, e.g. technical, economical and environmental view-points. The view-point information can be seen as a characteristics of a feature. The characteristics and their values are available in a characteristic table called T_P^E. This table is constructed by experts. The default number of grades g, is another important characteristics. Other important feature characteristics are described below.

If a higher feature value has a lower grade index than a lower feature value ($v_{FG_{i1}} > v_{FG_{ig}}$), we use the term decreasing feature-grading. When a lower feature value has a lower grade index than a higher feature value ($v_{FG_{i1}} < v_{FG_{ig}}$), we use the term increasing feature-grading. For each feature, this is indicated in the characteristic table, T_P^E.

In the literature there exist many different ways of creating the membership functions, for example, LR-representation [2], parametric s-function [11], and simple linear functions [7]. We are using simple linear functions, which are extended to support the characteristic of a feature value. The base is to treat $v_{FG_{ij}}$ as a triangular fuzzy number (Equation 1), which is described as a triple (a,b,c), where $b = v_{FG_{ij}}$. Since Equation 1 is valid for some $a < b < c$, we have to define how increasing and decreasing feature-grading should be mapped to the equation. If it is an increasing feature-grading, $a = v_{FG_{ij-1}}$ and $c = v_{FG_{ij+1}}$. If it is a decreasing feature-grading, $a = v_{FG_{ij+1}}$ and $c = v_{FG_{ij-1}}$.

$$\mu_{ij}(x) = \begin{cases} 0 & \text{if } x < a \\ \frac{x-a}{b-a} & \text{if } a \leq x \leq b \\ \frac{x-c}{b-c} & \text{if } b < x \leq c \\ 0 & \text{if } c < x \end{cases} \tag{1}$$

If a triangular form to the left of $v_{FG_{i1}}$ or to the right of $v_{FG_{ig}}$ is desired, the distances of the known values are used, in order to calculate $v_{FG_{i0}}$ or $v_{FG_{ig+1}}$. The distances can be calculated with the help of Equation 2, by using $y = 1$ or $y = g$.

$$|v_{FG_{iy-1}} - v_{FG_{iy}}| = |v_{FG_{iy}} - v_{FG_{iy+1}}| \tag{2}$$

If a membership with the value of one is desired to the left of $v_{FG_{i1}}$ or to the right of $v_{FG_{ig}}$, Equation 3 or Equation 4 can be used. Since these equations are valid for some $a < b < c$, we have to define how increasing and decreasing feature-grading should be mapped to the equation. If it is an increasing feature-grading, $a = v_{FG_{ij-1}}$ and $c = v_{FG_{ij+1}}$. If it is a decreasing feature-grading, $a = v_{FG_{ij+1}}$ and $c = v_{FG_{ij-1}}$. This is equal to using an expression to define $v_{FG_{ij}}$, i.e. $x \geq v_{FG_{ij}}$ or $x \leq v_{FG_{ij}}$ where $j = 1$ or $j = g$.

$$\mu_{ij}(x) = \begin{cases} 1 & \text{if } x < b \\ \frac{c-x}{c-b} & \text{if } b \leq x \leq c \\ 0 & \text{if } x > c \end{cases} \tag{3}$$

$$\mu_{ij}(x) = \begin{cases} 0 & \text{if } x < a \\ \frac{x-a}{b-a} & \text{if } a \leq x \leq b \\ 1 & \text{if } x > b \end{cases} \tag{4}$$

In some cases, a feature is said to have an infinite value (part of the information in T_P^E). An example of this is a mobile plan with unlimited amount of data usage. The b-value of $v_{FG_{i1}}$ and $v_{FG_{ig}}$ can be calculated with Equation 2 using $y = 2$ or $y = g - 1$. The calculated b-values can be used in Equation 3 or Equation 4, using the same reasoning as above.

If a DM has the authority, it can personalize the values proposed in FG_P^E and T_P^E. Whether or not a DM make any changes, it will result in a DM feature-grade matrix called FG_P^A, and a DM characteristic table called T_P^A. With in the range of the defined $v_{FG_{i1}}$ and $v_{FG_{ig}}$, the DM can change the values of $v_{FG_{i1}}$ and $v_{FG_{ig}}$, extend the the number of grades, and define $v_{FG_{i1}}$ and $v_{FG_{ig}}$ as expressions. The changes are performed with a linear scaling of the $v_{FG_{ij}}$ values.

For each component C_i, $i \in \{1, ..., c\}$, which is part of the evaluation, a membership matrix called FG_{C_i} will constructed with the help of Equation 1, Equation 2, Equation 3, and Equation 4.

3.1. Example 1

In this example the component type has four significant features, two from a technical view-point (named F_1 and F_2), and two from an economical view-point (named F_3 and F_4). By basing on experience, an expert decides the mapping between feature values and gradings. The mapping of feature F_1, is 50 to G_1 and 10 to G_g. While F_2 is mapped as 30 to G_1 and 10 to G_g. This means that a higher value is seemed to be better for these features. The mapping of feature F_3, is 200 to G_1 and 1000 to G_g. While F_4 is mapped as 10 to G_1 and 50 to G_g. This means that a lower value is seemed to be better for these two features. The expert suggests the use of Equation 2 to complete the feature-grade membership. The expert matrix (FG_P^E) for this type of components, is given below.

$$FG_P^E = \begin{array}{c} \begin{matrix} G_1 & G_g \end{matrix} \\ \begin{bmatrix} 50 & 10 \\ 30 & 10 \\ 200 & 1000 \\ 10 & 50 \end{bmatrix} \end{array} \begin{matrix} F_1 \\ F_2 \\ F_3 \\ F_4 \end{matrix}$$

The DM includes five grades using linear scaling, and keep the rest of the feature characteristics. The DM matrix (FG_P^A) for these decisions is given below.

$$FG_P^A = \begin{array}{c} \begin{matrix} G_1 & G_2 & G_3 & G_4 & G_5 \end{matrix} \\ \begin{bmatrix} 50 & 40 & 30 & 20 & 10 \\ 30 & 25 & 20 & 15 & 10 \\ 200 & 400 & 600 & 800 & 1000 \\ 10 & 20 & 30 & 40 & 50 \end{bmatrix} \end{array} \begin{matrix} F_1 \\ F_2 \\ F_3 \\ F_4 \end{matrix}$$

Two components will be compared. Component one (C_1) has the following feature values: $v_{F_1} = 30$, $v_{F_2} = 20$, $v_{F_3} = 400$ and $v_{F_4} = 30$. The feature values of component two (C_2) are $v_{F_1} = 35$, $v_{F_2} = 15$, $v_{F_3} = 600$ and $v_{F_4} = 30$. For example, when using Equation 1 to calculate the membership for $F_1 - G_3$ the DM matrix (FG_P^A) gives the values of (a, b, c) as (20, 30, 40). Since C_1 has $v_{F_1} = 30$, its membership is 1 for $F_1 - G_3$, and since C_2 has $v_{F_1} = 35$, its membership is 0.5 for $F_1 - G_3$. The membership matrices for component one (FG_{C_1}) and for component two (FG_{C_2}), are shown below.

$$FG_{C_1} = \begin{array}{c} \\ \end{array}\begin{matrix} G_1 & G_2 & G_3 & G_4 & G_5 & \\ \end{matrix}$$

$$FG_{C_1} = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{matrix} F_1 \\ F_2 \\ F_3 \\ F_4 \end{matrix} \quad (\text{columns } G_1, G_2, G_3, G_4, G_5)$$

$$FG_{C_2} = \begin{bmatrix} 0 & 0.5 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \begin{matrix} F_1 \\ F_2 \\ F_3 \\ F_4 \end{matrix} \quad (\text{columns } G_1, G_2, G_3, G_4, G_5)$$

The two matrices above, will be used in Section 4.1.

4. Importance of the Component Objectives

Initially an expert will give an importance weight (w_j, $j \in \{1, ..., f\}$) to each feature (F_j). The importance weights will be normalized to unity (Equation 5). The feature importance weights are stored in a $1 \times f$ matrix named W_F^E. If the DM has the authority, it may change the importance weight for one or several features. The importance weights can be given in a desired scale and will be normalized to unity. The changed importance weights ($W_F^{E^c}$) and unchanged importance weights will be stored in a $1 \times f$ matrix named W_F^A. In order to keep W_F^A normalized, each changed importance weight will be scaled according to Equation 6.

$$w_{f_j} = \frac{w_j}{\sum_{k=1}^{f} w_k} \tag{5}$$

$$w_{f_j}^c = \frac{w_j^c}{\sum_{k=m}^{f} w_k^c} \sum_{k=m}^{f} w_k, \text{ if } w_k^c \in W_F^{E^c} \tag{6}$$

The process of determining a grade for a specific component (C_i, $i \in \{1, ..., c\}$) can use different types of composition operations [20, 19, 4, 12, 21]. We decide to implement it with the help of the max-prod composition operation. When we apply the max-prod composition the resulting operation is

$$M_{C_i} = W_F^A \overset{\circ}{\bullet} FG_{C_i} \tag{7}$$

where M_{C_i} is a $1 \times c$ matrix containing the membership degree for component (C_i) in each of the grades. The grade with the highest membership degree in M_{C_i}, is chosen as the grade for the component (C_i). If several grades can be selected, then the average grade is calculated. It is possible to select any features from the component in order to grade them as a subgroup. It can be valuable to grade a component based on the different view-points by creating $M_{C_{i_{vp}}}$.

Using the grade of the components to select the most desired component is possible but often to coarse grained. Instead we propose to use the minimization of regret, and the weight of the grades, to compare the different components.

Since the different grades ($G = \{G_1, \ldots, G_g\}$) are placed in order of the value a certain feature contributes with, we know that the greatest number is g. We use this knowledge when we compute the weight value w_{G_j} for grade G_j, $j \in \{1, ..., g\}$ (Equation 8). This approach do not have the same flexibility as the method proposed by Rakus-Andersson and Frey [10]. Instead we trade flexibility for calculation performance. The weight values are stored in a $g \times 1$ matrix named W_G.

$$w_{G_j} = \frac{g - j + 1}{\sum_{k=1}^{g} k} \tag{8}$$

In order to rank the different components, we will use another fuzzy decision-making technique call minimization of regret [17, 8, 9]. We form a $c \times g$ matrix named MG, where the grading result for the components (M_{C_i}) forms the rows and the associated grades are the columns ($k \in \{1, ..., g\}, i \in \{1, ..., c\}$).

$$MG = \begin{array}{c} \begin{matrix} G_1 & \ldots & G_k & \ldots G_g \end{matrix} \\ \left[\begin{matrix} & & \\ & mg_{ik} & \\ & & \end{matrix} \right] \end{array} \begin{matrix} \mathbf{M}_{C_1} \\ \vdots \\ \mathbf{M}_{C_i} \\ \vdots \\ \mathbf{M}_{C_c} \end{matrix}$$

The procedure of finding the component with best value (c_{i*}) is to follow the flow below:

1. For each G_k calculate MG_k according to Equation 9.
2. Calculate c_{ik} according to Equation 10, which forms a matrix MG_D.
3. Apply the weights on MG_D according to Equation 11, which forms a vector with c columns.
4. Select the column i with the minimum value, as the best valued component (Equation 12)

$$MG_k = \max_{1 \le i \le c} mg_{ik} \tag{9}$$

$$c_{ik} = MG_k - mg_{ik} \tag{10}$$

$$MG_D W_G \tag{11}$$

$$c_{i*} = \min_{1 \le i \le c} MG_D W_{G i} \tag{12}$$

With the help of different $M_{C_{i(vp)}}$s, it is possible to find the component (C_i) with the best value for a specific view-point. The possibility to look at the components from different view-points may affect the final decision.

4.1. Example 1, continued

The expert has given the following weight to the features, $w_1 = 80$, $w_2 = 60$, $w_3 = 60$, and $w_4 = 60$. W_F is calculated with the help of Equation 5. These values are not changed by the DM.

$$W_F^A = W_F^E = \begin{bmatrix} 0.308 \; 0.231 \; 0.231 \; 0.231 \end{bmatrix}$$

According to the result of the max-prod composition, component one is given the grade of three and component two is given the grade of three.

$$M_{C_1} = W_F^A \overset{\circ}{\bullet} FG_{C_1} = \begin{bmatrix} 0 \; 0.231 \; 0.308 \; 0 \; 0 \end{bmatrix}$$

$$M_{C_2} = W_F^A \overset{\circ}{\bullet} FG_{C_2} = \begin{bmatrix} 0 \; 0.231 \; 0.231 \; 0.231 \; 0 \end{bmatrix}$$

MG is given by M_{C_1} and M_{C_2}. MG_D is calculated with the help of Equation 9 and Equation 10.

$$MG = \begin{array}{c} \\ \end{array} \begin{array}{ccccc} G_1 & G_2 & G_3 & G_4 & G_5 \end{array} \\ MG = \begin{bmatrix} 0 & 0.231 & 0.308 & 0 & 0 \\ 0 & 0.231 & 0.231 & 0.231 & 0 \end{bmatrix} \begin{array}{c} \mathbf{M}_{C_1} \\ \mathbf{M}_{C_2} \end{array}$$

$$\begin{array}{ccccc} G_1 & G_2 & G_3 & G_4 & G_5 \end{array} \\ MG_D = \begin{bmatrix} 0 & 0 & 0 & 0.231 & 0 \\ 0 & 0 & 0.077 & 0 & 0 \end{bmatrix} \begin{array}{c} \mathbf{M}_{C_1} \\ \mathbf{M}_{C_2} \end{array}$$

The weight of the grades (W_G) are calculated with the help of Equation 8.

$$W_G = \begin{bmatrix} 0.333 \\ 0.267 \\ 0.200 \\ 0.133 \\ 0.067 \end{bmatrix}$$

With the help of Equation 11, Equation 12, and based on the decisions the DM has taken, we can conclude that component two is more valuable than component one.

$$MG_D W_G = \begin{bmatrix} 0.031 \; 0.015 \end{bmatrix}$$

5. Discussion

Without any further analyzes we can not tell if the use of a Sigmoid function [13], and the parametric s-function [11] will give us a more reliable result when we are trying to understand the DM needs. The Sigmoid function can be used to calculate the membership degree of a need, based on the answers we get from the DM. The parametric s-function can be used to derive the membership degrees between needs and preferences.

Instead of using the max-min composition, we are using the max-prod composition [21]. The max-prod composition is less sensitive to differences between the values in the compared sets, than the max-min composition. In order to get a good ranking measure we use a method named, minimization of regret [17, 8, 9]. This method gives one value for each component instead of one value for each grade.

In this paper we do not support multi-objective decision making [7, 14, 13]. This can be useful when an expert is deciding on the weights for the different features of a specific component type.

At the moment, we are not supporting grading and ranking of a feature which has a set of categorical variables. An example could be in which geographical areas a component is possible to use, and the DM are acting in more than one of these geographical areas but prefer some geographical areas better than others.

Except for the calculation of the results, a way of visualizing the results have to be proposed. At the moment we are considering several different ways to show how the different view-points, and the different feature characteristics are impacting the result.

However, the proposed framework gives the DM freedom to impose its own preferences, based on the DM's business use case. The results can be viewed from different view-points, which can be chosen based on the role the DM is acting in.

6. Conclusion and Future Work

The proposed framework for component selection is based on algorithms from fuzzy decision making, which we have adapted or extended.

The framework was validated by practitioners, which found the framework useful. The possibility to get results which would not be part of a decision making with crips sets was appreciated. This makes it possible for the DM to understand how far from a desired outcome the results are, and what criteria are constraining the results. The possibility for an expert to use linguistic variables for the matching of needs and preferences, contributes to lower the chance of "analyzes-paralyzes". Another appreciated feature was the possibility to view the results from different view-points.

The next step is to perform a small scale implementation of the framework together with practitioners. This will give us useful information about how to extend the framework, in order to support more advanced component selection use cases. Some of the missing functionality, listed in Section 5 , will be part of the extended framework.

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