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INTEGRATED FUZZY MULTIPLE CRITERIA DECISION MAKING MODEL FOR ARCHITECT SELECTION

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Abstract. The philosophy of decision making in economics is to assess and select the most preferable solution, implement it and to gain the biggest profit. Important issues such as competitive market, changing technical, political and social environment have a key role in personnel selection. It is the crucial task which determines the company's present and future. Many decisions made cannot be accurately forecast or assessed. Understanding of the multiple criteria method and knowledge to calculate the algorithm of the method allows a decision maker to trust solutions offered by solution support systems to a greater extent. Many individual attributes considered for personnel selection such as organizing ability, creativity, personality, and leadership exhibit vagueness and imprecision. The fuzzy set theory appears as an essential tool to provide a decision framework that incorporates imprecise judgments inherent in the personnel selection process. In this paper, a fuzzy multi-criteria decision making (MCDM) algorithm using the principles of fusion of fuzzy information, additive ratio assessment (ARAS) method with fuzzy numbers (ARAS-F) and step-wise weight assessment ratio analysis (SWARA) technique are integrated. The proposed method is apt to manage information assessed using both linguistic and numerical scales in a decision making problem with a group of information sources. The aggregation process is based on the unification of information by means of fuzzy sets on a basic linguistic term set. The computational procedure of the proposed framework is illustrated through an architect's selection problem.

Keywords: personnel selection, architect, linguistic representation, ARAS, ARAS-F, SWARA, MCDM, decision making, multiple criteria.

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1. Introduction

The quality of human capital is crucial for high-tech companies to maintain competitive advantages in era of knowledge economy (Chien, Chen 2008). Human resources are one of the core competences for an organization to enhance its competitive advantage in the knowledge economy (Lin 2010). Personnel selection is the process of choosing among candidates who match the qualifications required to perform a defined job the best way (Dursun, Karsak 2010). It is one of the most important fields in human resources management, which directs company's present and future.

Among the functions of human resource management, personnel selection significantly affects the character of employees and quality of administration (Lin 2010). The personnel selection problem generally concerns with important and complex issues such as (Lin 2010):

- how to properly set the importance weights of criteria;
- how to use linguistic and numerical scales to evaluate the applicants under multiple criteria;
- and how to aggregate the evaluation results and then rank the applicants.

An effective personnel selection method should be able to assist the organization in selecting an appropriate person for a given work. The fuzzy set appears as an essential tool to provide a decision framework that incorporates imprecise judgements inherit in the personnel selection process (Dursun, Karsak 2010).

Many studies have been conducted to help organizations make effective selection decisions. Further applications of effective techniques in the personnel selection field are being developed. Kelemenis *et al.* (2011) presented an overview of recent studies on the personnel selection problem (from 1992 till 2009 year). They pointed that different techniques and conceptual models are used. For instance, fuzzy numbers, OWA operators, AHP, fuzzy analytic hierarchy process (AHP), analytic network process (ANP), fuzzy TOPSIS, fuzzy multiples objective programming, discriminant analysis, decision trees, analytic neural networks, total sum (TS) method, simple additive weighting (SAW), weighted product (WP) method, expert systems, neuro-fuzzy techniques, group TOPSIS, nominal group technique etc. are used.

Data mining involves various techniques including statistics, neural networks, decision tree, genetic algorithm, and visualization techniques that have been developed over the years. In the literature, there are a number of studies that have been conducted on resumes, interviews, assessment centers, job knowledge tests, work sample tests, cognitive tests, and personality tests in human resource management to help organizations make better personnel selection decisions, while only a few of them use MCDM techniques (Dursun, Karsak 2010).

Liang and Wang (1994) developed an algorithm for personnel selection. They presented a decision support tool for personnel selection using an integrated ANP and fuzzy DEA approach to effectively deal with the personnel selection problem. The method first aggregates decision-makers' linguistic assessments about subjective criteria weightings and ratings to obtain the fuzzy suitability index and its ranking value. Further, combining the subjective and objective ranking values, the final ranking values for personnel suitability evaluation are obtained.

Ling (2003) developed the model for the selection of architects from four theories: Theory of Job Performance, Theory of Contextual Performance, Network Theory of Embeddedness, and Theory of Firm. He described a problem by 40 attributes.

Chen and Cheng (2005) proposed an approach to rank fuzzy numbers by metric distance. The paper also developed a fuzzy computer-based group decision support system.

Chien and Chen (2008) developed a data mining framework based on decision tree and association rules to generate relationships between personnel profile data and their work behavior.

Huang *et al.* (2009) proposed a systematic approach with a feedback mechanism in which interrelations among positions and the differences among the selected employees are considered simultaneously. A fuzzy bi-objective binary integer programming model is formulated to solve a bi-objective personnel assignment problem.

Celik *et al.* (2009) proposed a fuzzy integrated multi-stage evaluation model under multiple criteria in order to manage the academic personnel selection and development processes. The model is based on Fuzzy AHP, Buckley's algorithm, fuzzy TOPSIS and SWOT.

Chen *et al.* (2010) presented a mechanism for partner selection that emphasizes the relation of criteria and motivation. AHP with fuzzy weighting and linguistic measurement is applied.

Dursun and Karsak (2010) applied fuzzy TOPSIS method with 2-tuple linguistic representation of criteria values.

Lin (2010) developed a decision support tool using an integrated analytic network process (ANP) and fuzzy data envelopment analysis (DEA) approach.

Kelemenis and Askounis (2010) presented a TOPSIS-based multi-criteria approach to personnel selection. This is based on the veto threshold, a critical characteristic of the main outranking methods. The ultimate decision criterion is not the similarity to the ideal solution but the distance of the alternatives from the veto set by the decision makers.

Lin *et al.* (2010) presented a hybrid particle swarm optimization model which utilizes random-key encoding and individual enhancement schemes.

Azadeh *et al.* (2011) applied an integrated Data Envelopment Analysis–Artificial Neural Network–Rough Set Algorithm for assessment of personnel efficiency.

Greco *et al.* (2011) introduced the concept of a representative value function in robust ordinal regression applied to multiple criteria sorting problems. The proposed approach can be seen as an extension of $\text{UTADIS}^{\text{GMS}}$, a new multiple criteria sorting method that aims at assigning actions to p pre-defined and ordered classes. This approach is applied to assess managers.

Shahhosseini and Sebt (2011) presented a fuzzy adaptive model to select the most competent construction personnel. The model is based on fuzzy AHP method.

Van Iddekinge *et al.* (2011) reconsidered some widely held beliefs concerning the (low) validity of interests for predicting criteria important to selection personnel, and reviewed theory and empirical evidence that challenge such beliefs. Then they described the development and validation of an interest-based selection measure.

Zhang and Liu (2011) proposed an intuitionistic fuzzy multi-criteria group decision making method with grey relational analysis. Intuitionistic fuzzy entropy is used to obtain the entropy weights of the criteria.

Each of aforementioned models does not present parity between each of considered alternatives with optimum alternative. The majority of the existing approaches require involved complex computations. The objective of this study is to develop a decision making approach to a multiple information sources problem, which enables to incorporate both crisp data and fuzzy data represented as linguistic variables or triangular fuzzy numbers into the analysis.

ARAS, which is a newly developed multi-attribute decision making technique, is based on the intuitive principle that the preferred alternative should have the biggest ratio to the optimal solution (Zavadskas, Turskis 2010).

The significance of the model is that it reduces the time taken by project managers to accumulate experience in architect selection, further increasing the efficiency of the construction industry.

2. Selection algorithm based on the fuzzy sets and multiple criteria decision making methods

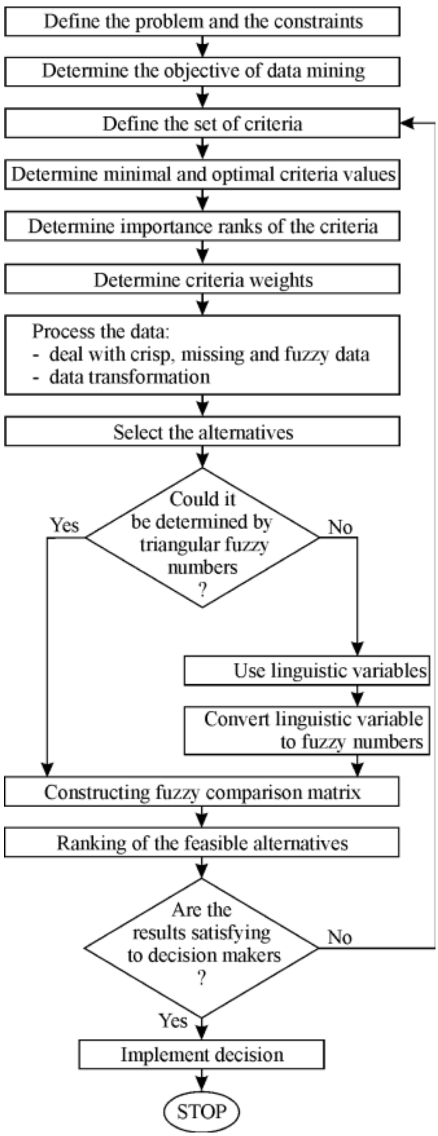


Fig. 1. The multiple criteria expert system for personnel selection

There are a lot of different multiple criteria decision making methods. The selection of appropriate decision method depends on the aim of the problem, available information, costs of decision and actors' (persons which are making decisions) qualification. A wider overview of multiple criteria decision making methods, classification and applications are presented by Zavadskas and Turskis (2011). In this research two of them are applied: ARAS-F and SWARA. The multiple criteria expert system for problem solution can be described as shown in Fig. 1.

In marketing research and particularly in the context of customer satisfaction measurement it is often attempted to measure attitudes and human perceptions. This raises a number of questions regarding appropriate scales to use, such as the number of response alternatives.

The type of information collected can directly influence scale construction. Different types of information could be measured in different ways:

a) At the nominal level. That is, any numbers used are mere labels: they express no mathematical properties.
b) At the ordinal level. Numbers indicate the relative position of items, but not the magnitude of difference. An example is a preference ranking.
c) At the interval level. Numbers indicate the magnitude of difference between items, but there is no absolute zero point. Examples are attitude scales and opinion scales.
d) At the ratio level. Numbers indicate magnitude of difference and there is a fixed

zero point. Examples include: age, income, price, costs, sales revenue, sales volume, and market share.

2.1. Basic definitions

Fuzzy multiple criteria analysis concerns about selecting or prioritizing alternatives with respect to multiple, usually conflicting criteria in a fuzzy environment (Deng 2009). There are many misconceptions about fuzzy logic. To begin with, fuzzy logic is not fuzzy. Basically, fuzzy logic is a precise logic of imprecision and approximate reasoning (Zadeh 1975d, 1979). The real-world is pervaded with fuzziness. Fuzzy logic is needed to deal effectively with fuzzy reality. More specifically, fuzzy logic may be viewed as an attempt at formalization/mechanization of two remarkable human capabilities (Zadeh 2008). By decision-making in a fuzzy environment a decision process is meant, in which the goals and/or the constraints, but not necessarily the system under control, are fuzzy in nature. This means that the goals and/or the constraints constitute classes of alternatives whose boundaries are not sharply defined. The task of developing a general theory of decision making in a fuzzy environment is one of very considerable magnitude and complexity (Bellman, Zadeh 1970). Fuzzy goals and fuzzy constraints can be defined precisely as fuzzy sets in the space of alternatives. Fuzzy set theory, which was introduced by Zadeh (1975a, b, c) to deal with problems in which a source of vagueness is involved, has been utilized for incorporating imprecise data into the decision framework. Deng (2009) presented an overview of the development in fuzzy multiple criteria analysis. Zavadskas and Turskis (2011) presented an overview of multiple criteria decision making methods in economics.

Classification of the most of fuzzy multiple criteria decision making methods in the literature is presented by Ölçer and Odabaşi (2005).

A fuzzy set can be defined mathematically by a membership function, which assigns each element x in the universe of discourse X a real number in the interval [0, 1].

A triangular fuzzy number can be defined by a triplet (α, γ, β) as illustrated in Fig. 2.

In most cases, the classes of objects encountered in the real physical world do not have precisely defined criteria of membership. A fuzzy set is a class of objects with a continuum of membership grades. Such set is characterized by a membership function which assigns to each object a grade of membership ranging between zero and one (Zadeh 1975a, b, c). A fuzzy set A defined in space X is a set of pairs:

$$A = \left\{ \left(x, \mu_A(x) \right), x \in X \right\}, \forall x \in X, \tag{1}$$

where the fuzzy set A is characterized by its membership function $\mu_A : X \to [0;1]$ which associates with each element $x \in X$, a real number $\mu_A(x) \in [0;1]$. The value $\mu_A(x)$ at x represents the grade of membership of x in A and is interpreted as the membership degree to which x belongs to A. So the closer the value $\mu_A(x)$ is to 1, the more x belongs to A.

A crisp or ordinary subset A of X can also be viewed as a fuzzy set in X with membership function as its characteristic function, i.e.

$$\mu_A(x) = \begin{cases} 1, x \in A; \\ 0, x \notin A. \end{cases} \tag{2}$$

The set X is called a universe of discourse and can be written $\subseteq X$. Sometimes a fuzzy set A in X is denoted by the list of ordered pairs $\left(x, \mu_a(x)\right)$, where the elements with zero degree are usually not listed. Thus a fuzzy set A in X can be represented as $A = \left\{\left(x, \mu_A(x)\right)\right\}$, where $x \in X$ and $\mu_A : X \to [0;1]$.

When the universe of discourse is discrete and finite with cardinality n, that is $X = \{x_1, x_1, \ldots, x_n\}$, the fuzzy set A can be represented as

$$A = \sum_{i=1}^{n} \frac{\mu_A(x_i)}{x_i} = \frac{\mu_A(x_1)}{x_1} + \frac{\mu_A(x_2)}{x_2} + \cdots + \frac{\mu_A(x_n)}{x_n}. \tag{3}$$

When the universe of discourse X is an interval of real numbers, the fuzzy set A can be expressed as

$$A = \int_X \frac{\mu_A(x)}{x}. \tag{4}$$

A fuzzy number is defined to be a fuzzy triangular number (a, β, γ) if its membership function is fully described by three parameters (a < β < γ).

$$\mu_A(x) = \begin{cases} \dfrac{1}{\beta-\alpha}x - \dfrac{\alpha}{\beta-\alpha}, & \mathit{if}\ x \in [\alpha, \beta]; \\ \dfrac{1}{\beta-\gamma}x - \dfrac{\alpha}{\beta-\gamma} & , \mathit{if}\ x \in [\beta, \gamma]; \\ 0 & , \mathit{otherwise}. \end{cases} \tag{5}$$

The most typical fuzzy set membership function is triangular membership function (Fig. 2).

The basic operations of fuzzy triangular numbers $\tilde{n}_1$ and $\tilde{n}_2$ (van Laarhoven, Pedrycz 1983) are defined as follows:

$$\tilde{n}_1 \oplus \tilde{n}_2 = \left(n_{1\alpha} + n_{2\alpha}, n_{1\gamma} + n_{2\gamma}, n_{1\beta} + n_{2\beta}\right) \text{ addition,} \tag{6}$$

$$\tilde{n}_1 (-) \tilde{n}_2 = \left(n_{1\alpha} - n_{2\beta}, n_{1\gamma} - n_{2\gamma}, n_{1\beta} - n_{2\alpha}\right) \text{ substraction,} \tag{7}$$

$$\tilde{n}_1 \otimes \tilde{n}_2 = \left(n_{1\alpha} \otimes n_{2\alpha}, n_{1\gamma} \otimes n_{2\gamma}, n_{1\beta} \otimes n_{2\beta}\right) \text{ multiplication,} \tag{8}$$

$$\tilde{n}_1 (\div) \tilde{n}_2 = \left(\frac{n_{1\alpha}}{n_{2\beta}}, \frac{n_{1\gamma}}{n_{2\gamma}}, \frac{n_{1\beta}}{n_{2\alpha}}\right) \text{ division,} \tag{9}$$

$$k\tilde{n}_1 = \left(kn_{1\alpha}, kn_{1\beta}, kn_{1\gamma}\right) \text{ multiplication of any real number } k \text{ and a fuzzy number,} \tag{10}$$

$$\left(\tilde{n}_1\right)^{-1} = \left(\frac{1}{n_{1\beta}}, \frac{1}{n_{1\gamma}}, \frac{1}{n_{1\alpha}}\right) \text{ inverse of triangular fuzzy number.} \tag{11}$$

Suppose $\tilde{W} = \left[\overline{\tilde{w}_1, \tilde{w}_n}\right] = \left[\tilde{w}_j\right]$ is fuzzy group weight for n criteria and $\tilde{w}_j$ is fuzzy triangular number

$$\tilde{w}_j = \left(w_{j\alpha}, w_{j\gamma}, w_{j\beta}\right), \tag{12}$$

where $w_{j\alpha} = \min\limits_k y_{jk},\ j = \overline{1,n},\ k = \overline{1,p}$ is minimum possible value,

$w_{j\gamma} = \left(\prod\limits_{k=1}^{p} y_{jk}\right)^{\frac{1}{p}},\ j = \overline{1,n},\ k = \overline{1,p}$ is the most possible value, and

$w_{j\beta} = \max\limits_k y_{jk},\ j = \overline{1,n},\ k = \overline{1,p}$ is the maximal possible value of j-th criterion.

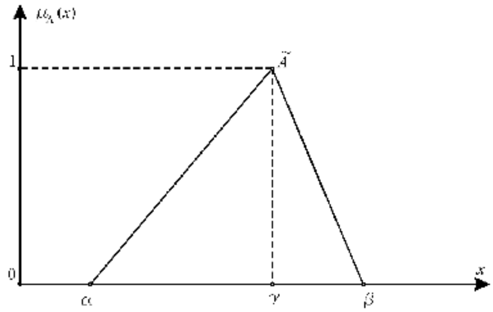


Fig. 2. Triangular membership function

In order to obtain a crisp output, a defuzzification process is needed to be applied. Defuzzification is the process of producing a quantifiable result in fuzzy logic, given fuzzy sets and corresponding membership degrees. The output of the defuzzification process is a single number. Many defuzzification techniques have been proposed in the literature.

2.2. Additive Ratio Assessment method (ARAS) with fuzzy criteria values (ARAS-F)

This section outlines the fuzzy MCDM approach, which is based on ARAS with fuzzy criteria values method (Zavadskas, Turskis 2010).

Aras method was developed by Zavadskas and Turskis (2010). Later, modifications of ARAS method, such as ARAS-G (grey relations are applied) and ARAS-F, were published (Turskis, Zavadskas 2010a, b). There are only a few applications of ARAS method (Tupenaite *et al.* 2010; Zavadskas *et al.* 2010b; Bakshi, Sarkar 2011).

ARAS method (Zavadskas, Turskis 2010) is based on the argument that the phenomena of complicated world could be understood by using simple relative comparisons. It is argued that the ratio of the sum of normalized and weighted criteria scores, which describe alternative under consideration, to the sum of the values of normalized and weighted criteria, which describes the optimal alternative, is degree of optimality, which is reached by the alternative under comparison.

According to the ARAS method (Zavadskas, Turskis 2010), a utility function value determining the complex relative efficiency of a reasonable alternative is directly proportional to the relative effect of values and weights of the main criteria considered in a project.

The first stage is fuzzy decision-making matrix (FDMM) forming. In the FMCDM of the discrete optimization problem any problem which has to be solved is represented by the following DMM of preferences for m reasonable alternatives (rows) rated on n criteria (columns):

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{01} & \cdots & \tilde{x}_{0j} & \cdots & \tilde{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{i1} & \cdots & \tilde{x}_{ij} & \cdots & \tilde{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mj} & \cdots & \tilde{x}_{mn} \end{bmatrix}; \tag{13}$$

$$i = \overline{0, m}; \; j = \overline{1, n},$$

where m – number of alternatives, n – number of criteria describing each alternative, $\tilde{x}_{ij}$ – fuzzy value representing the performance value of the i alternative in terms of the j criterion, $\tilde{x}_{0j}$ – optimal value of j criterion. A tilde "~" will be placed above a symbol if the symbol represents a fuzzy set.

If optimal value of j criterion is unknown, then

$$\begin{aligned} \tilde{x}_{0j} &= \max_i \tilde{x}_{ij}, && \textit{if } \max_i \tilde{x}_{ij} \textit{ is preferable, and} \\ \tilde{x}_{0j} &= \min_i \tilde{x}^*_{ij}, && \textit{if } \min_i \tilde{x}^*_{ij} \textit{ is preferable}. \end{aligned} \tag{14}$$

Usually, the performance values $\tilde{x}_{ij}$ and the criteria weights $\tilde{w}_j$ are viewed as the entries of a DMM. The system of criteria as well as the values and initial weights of criteria are determined by experts. The information can be corrected by the interested parties, taking into account their goals and opportunities.

Then the determination of the priorities of alternatives is carried out in several stages.

Usually, the criteria have different dimensions. The purpose of the next stage is to receive dimensionless weighted values from the comparative criteria. In order to avoid the difficulties caused by different dimensions of the criteria, the ratio to the optimal value is used. There are various theories describing the ratio to the optimal value. However, the values are mapped either on the interval $[0;1]$ or the interval $[0;\infty)$ by applying the normalization of a DMM.

In the second stage the initial values of all the criteria are normalized – defining values $\tilde{\bar{x}}_{ij}$ of normalised decision-making matrix $\tilde{\bar{X}}$:

$$\tilde{\bar{X}} = \begin{bmatrix} \tilde{\bar{x}}_{01} & \cdots & \tilde{\bar{x}}_{0j} & \cdots & \tilde{\bar{x}}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\bar{x}}_{i1} & \cdots & \tilde{\bar{x}}_{ij} & \cdots & \tilde{\bar{x}}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\bar{x}}_{m1} & \cdots & \tilde{\bar{x}}_{mj} & \cdots & \tilde{\bar{x}}_{mn} \end{bmatrix} \tag{15}$$
$$i = \overline{0, m};\ j = \overline{1, n}.$$

The criteria, whose preferable values are maxima, are normalized as follows:

$$\tilde{\bar{x}}_{ij} = \frac{\tilde{x}_{ij}}{\sum_{i=0}^{m} \tilde{x}_{ij}}. \tag{16}$$

The criteria, whose preferable values are minima, are normalized by applying two-stage procedure:

$$\tilde{x}_{ij} = \frac{1}{\tilde{x}^*_{ij}};\ \ \tilde{\bar{x}}_{ij} = \frac{\tilde{x}_{ij}}{\sum_{i=0}^{m} \tilde{x}_{ij}}. \tag{17}$$

When the dimensionless values of the criteria are known, all the criteria, originally having different dimensions, can be compared.

The third stage is defining normalized-weighted matrix – $\tilde{\hat{X}}$. It is possible to evaluate the criteria with weights $0 < \tilde{w}_j < 1$. Only well-founded weights should be used because weights are always subjective and influence the solution. The values of weight w_j are usually determined by the expert evaluation method. The sum of weights w_j would be limited as follows:

$$\sum_{j=1}^{n} w_j = 1. \tag{18}$$

$$\tilde{\hat{X}} = \begin{bmatrix} \tilde{\hat{x}}_{01} & \cdots & \tilde{\hat{x}}_{0j} & \cdots & \tilde{\hat{x}}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\hat{x}}_{i1} & \cdots & \tilde{\hat{x}}_{ij} & \cdots & \tilde{\hat{x}}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\hat{x}}_{m1} & \cdots & \tilde{\hat{x}}_{mj} & \cdots & \tilde{\hat{x}}_{mn} \end{bmatrix}; \tag{19}$$

$i = \overline{0, m};\ j = \overline{1, n}$.

Normalized-weighted values of all the criteria are calculated as follows:

$$\tilde{\hat{x}}_{ij} = \tilde{\overline{x}}_{ij} \tilde{w}_j; \qquad i = \overline{0, m}, \tag{20}$$

where w_j is the weight (importance) of the *j* criterion and $\overline{x}_{ij}$ is the normalized rating of the *j* criterion.

The following task is determining values of optimality function:

$$\tilde{S}_i = \sum_{j=1}^{n} \tilde{\hat{x}}_{ij}; \qquad i = \overline{0, m}, \tag{21}$$

where $\tilde{S}_i$ is the value of optimality function of *i*-th alternative.

The biggest value is the best, and the smallest one is the worst. Taking into account the calculation process, the optimality function $\tilde{S}_i$ has a direct and proportional relationship with the values $\tilde{x}_{ij}$ and weights $\tilde{w}_j$ of the investigated criteria and their relative influence on the final result. Therefore, the greater the value of the optimality function $\tilde{S}_i$, the more effective the alternative. The priorities of alternatives can be determined according to the value $\tilde{S}_i$. Consequently, it is convenient to evaluate and rank decision alternatives when this method is used.

The result of fuzzy decision making for each alternative is fuzzy number $\tilde{S}_i$. There are several methods for defuzzification. The centre-of-area is the most practical and simple to apply to:

$$S_i = \frac{1}{3}(S_{i\alpha} + S_{i\beta} + S_{i\gamma}). \tag{22}$$

The degree of the alternative utility is determined by a comparison of the variant, which is analysed, with the most ideal S_0. The equation used for the calculation of the utility degree K_i of an alternative A_i is given below:

$$K_i = \frac{S_i}{S_0}; \qquad i = \overline{0, m}, \tag{23}$$

where S_i and S_0 are the optimal criterion values, obtained from Eq. (22).

It is clear, that the calculated values K_i are in the interval [0;1] and can be ordered in an increasing sequence, which is the wanted order of precedence. The complex relative efficiency of the reasonable alternative can be determined according to the utility function values.

2.3. Criteria weights determination

Methods of utility theory based on qualitative initial measurements include two widely known groups of methods: AHP and fuzzy set theory methods (Zimmermann 1985, 2000).

There are various approaches for assessing weights (Zavadskas *et al.* 2010a, b), e.g. the eigenvector method, SWARA (Keršuliene *et al.* 2010), expert method (Zavadskas, Vilutienė 2006), analytic hierarchy process (AHP) (Saaty 1977, 1980), Entropy method, etc.

Each of experts first of all ranks criteria. The most significant criterion is given rank 1, and the least significant criterion is given rank 8. The overall ranks to the group of experts are determined according to the mediocre value of ranks.

Later, SWARA method is applied to determine fuzzy group weights of criteria.

The step-wise weight assessment ratio analysis (SWARA) (Keršuliene *et al.* 2010) methodology is developed in 2010 and applied for the selection of rational dispute resolution method. The new procedure for the criteria weights determination can be described as is presented in Fig. 2.

However, according to the above mentioned methods the attribute weights cannot be valued as one weight of attribute is higher/lower significant than the other attribute, because attributes are ranked according to preferences of expert decision- making. The SWARA procedure for the attributes weights determination which provides the opportunity to estimate the differences of their significances can be described as presented in Fig. 3.

This method allows including experts opinion about significance ratio of the criteria in the process of rational decision determination.

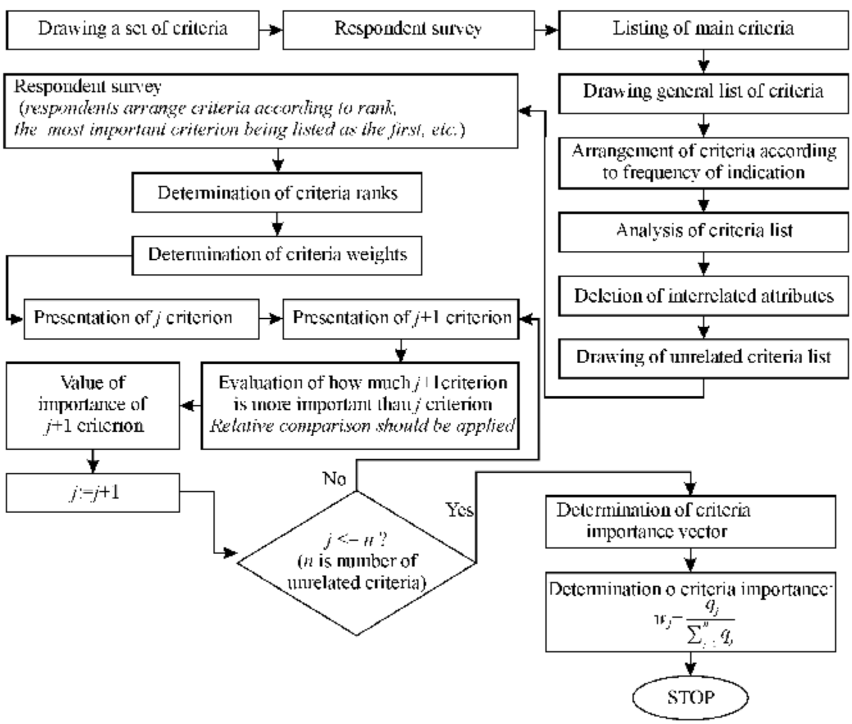


Fig. 3. Determining of the criteria weights (developed by paper's authors)

3. Architect selection using fuzzy MCDM approach

Each personnel selection problem is individual and needs own criteria set. For architect's assessment set of essential criteria consists of: education, academic level, long life learning, working knowledge, working skills, work experience, culture, competence, team player, leadership excellence, ability to work in different business units, determination of goal, problem solving ability, decision making skills, strategic thinking, ability to sell oneself and ideas, interpersonal skills, management experience, emotional steadiness, communication skills, ability of good discussion, personality assessment, computer skills, self-confidence, fluency in foreign languages, responsibility, patience, effective time using, and age.

Ling (2003) presented a conceptual model for selection of architects by project managers. He determined four main criteria groups to select an architect:

1. Task performance criterion, which includes: creativity; innovative decisions; strategic decision making; knowledge of economics; knowledge of construction and construction technologies; knowledge of design legislation system, regulations and requirements; accuracy of work and good design skills in detailing; good knowledge of contracting and job experience.
2. Contextual performance criterion includes: speed of generating and preparing drawings of a design; close attention to the essential details of the project; fair done specifications of the project; innovative ideas how to improve design; ability to satisfy clients requirements in a proper way both to the company and client; ability to follow the client's and project manager's instructions and orders; ability to work independently; ability to revise project's quality and achieving determined goals; leadership; ability to control subcontractors and staff.
3. Network criterion: reputation; ability to work in the team; prior work with consultants and clients.
4. Price criterion: low fee; architect allows the client to delay payments of professional fees.

The problem's set of criteria was determined by three decision makers (owners) of the designing firm as follows:

x_1 – Working knowledge, working skills, work experience, knowledge of design process and legislation system;

x_2 – Education, academic level, long life learning;

x_3 – Ability to revise project's quality and achieving determined goals; leadership; ability to work in team; ability to control subcontractors and staff;

x_4 – Creativity and strategic decision making;

x_5 – Ability to satisfy client's and project manager's requirements;

x_6 – Ability to work with clients, consultants and community;

x_7 – Culture and communication skills;

x_8 – Responsibility and ability in detailing of the project.

At the first stage of problem solution three decision makers determined criteria ranks by simple ranking.

The criteria ranks are determined according to the ranks as is shown in Table 1.

Table 1. Average criteria ranks

Criteria	Ranks of criteria: Expert 1	Expert 2	Expert 3	$r_j = \left(\prod_{k=1}^{p} r_{jk} \right)^{\frac{1}{p}}, j = \overline{1,n}, k = \overline{1,p}$	Group rank
x_1	1	1	4	4.04	3
x_2	2	3	3	3.96	2
x_3	3	2	1	3.30	1
x_4	6	6	5	8.23	6
x_5	5	4	2	5.82	4
x_6	7	8	8	11.10	8
x_7	8	7	7	10.62	7
x_8	4	5	6	7.40	5
n – number of criteria; k – number of experts					

At the second stage SWARA method was applied. The decision makers prepared Table 2, Table 3 and Table 4.

Calculation results are shown in tables. The experts were allowed to determine criteria weights according to the group ranks which are established in Table 1. For instance, criterion x_6 must be evaluated as the least significant, or, at least, to be equally significant as criterion x_7, criterion x_3 must be evaluated as the most significant, or at least, to be equally significant as criterion x_2.

Table 2. Criteria describing candidates and their weights determined by applying SWARA method (Expert 1)

Criteria	Comparative importance of average value s_j	Coefficient $k_j = s_j + 1$	Recalculated weight $q_j = \frac{x_{j-1}}{k_j}$	Weight $w_j = \frac{q_j}{\sum_{j=1}^{n} q_j}$
Expert 1				
Ability to revise project's quality and achieving determined goals; leadership; ability to work in team; ability to control subcontractors and staff – x_3	0.00	1	1	0.201
Education, academic level, long life learning – x_2	0.33	1	1	0.201
Working knowledge, working skills, work experience, knowledge of design process and legislation system – x_1	0.00	1.33	0.752	0.151
Creativity and strategic decision making – x_4	0.33	1	0.752	0.151

End of Table 2

Criteria	Comparative importance of average value s_j	Coefficient $k_j = s_j + 1$	Recalculated weight $q_j = \frac{x_{j-1}}{k_j}$	Weight $w_j = \frac{q_j}{\sum_{j=1}^{n} q_j}$
Ability to satisfy client's and project manager's requirements – x_5	0.40	1.33	0.565	0.114
Ability to work with clients, consultants and community – x_6	0.40	1.40	0.404	0.081
Culture and communication skills – x_7	0.40	1.40	0.288	0.058
Responsibility and ability in detailing of the project – x_8		1.40	0.206	0.041

Table 3. Criteria describing candidates and their weights determined by applying SWARA method (Expert 2)

Criteria	Comparative importance of average value s_j	Coefficient $k_j = s_j + 1$	Recalculated weight $q_j = \frac{x_{j-1}}{k_j}$	Weight $w_j = \frac{q_j}{\sum_{j=1}^{n} q_j}$
Expert 2				
Ability to revise project's quality and achieving determined goals; leadership; ability to work in team; ability to control subcontractors and staff – x_3	0.00	1	1	0.246
Education, academic level, long life learning – x_2	0.50	1	1	0.246
Working knowledge, working skills, work experience, knowledge of design process and legislation system – x_1	0.70	1.50	0.667	0.164
Creativity and strategic decision making – x_4	0.00	1.70	0.392	0.096
Ability to satisfy client's and project manager's requirements – x_5	0.70	1.00	0.392	0.096
Ability to work with clients, consultants and community – x_6	0.00	1.70	0.231	0.057
Culture and communication skills- x_7	0.50	1.00	0.231	0.057
Responsibility and ability in detailing with the project – x_8		1.50	0.154	0.038

Table 4. Criteria describing candidates and their weights determined by applying SWARA method (Expert 3)

Criteria	Comparative importance of average value s_j	Coefficient $k_j = s_j + 1$	Recalculated weight $q_j = \frac{x_{j-1}}{k_j}$	Weight $w_j = \frac{q_j}{\sum_{j=1}^{n} q_j}$
Expert 3				
Ability to revise project's quality and achieving determined goals; leadership; ability to work in team; ability to control subcontractors and staff – x_3	0.00	1	1	0.192
Education, academic level, long life learning – x_2	0.00	1	1	0.192
Work knowledge, working skills, work experience, knowledge of design process and legislation system – x_1	0.70	1	1	0.192
Creativity and strategic decision making – x_4	0.00	1.7	0.588	0.113
Ability to satisfy client's and project manager's requirements – x_5	0.70	1	0.588	0.113
Ability to work with clients, consultants and community – x_6	0.00	1.70	0.346	0.066
Culture and communication skills- x_7	0.00	1	0.346	0.066
Responsibility and ability to detail the project – x_8		1	0.346	0.066

According to the calculations by applying SWARA method, fuzzy group criteria weights were established as is shown in Table 5.

As mentioned, the main feature of SWARA method is the possibility to estimate experts or interest groups opinion about significance ratio of the criteria in the process of their weights determination.

Table 5. Fuzzy group criteria weights

	Criteria weights			Fuzzy group criteria weights		
	Expert 1	Expert 2	Expert 3	$w_{j\alpha}$	$w_{j\gamma}$	$w_{j\beta}$
x_1	0.151	0.192	0.164	0.151	0.246	0.192
x_2	0.201	0.192	0.246	0.192	0.311	0.246
x_3	0.201	0.192	0.246	0.192	0.311	0.246
x_4	0.151	0.113	0.096	0.096	0.179	0.151

End of Table 5

	Criteria weights			Fuzzy group criteria weights		
	Expert 1	**Expert 2**	**Expert 3**	$w_{j\alpha}$	$w_{j\gamma}$	$w_{j\beta}$
x_5	0.114	0.113	0.096	0.096	0.156	0.114
x_6	0.081	0.066	0.057	0.057	0.100	0.081
x_7	0.058	0.066	0.057	0.057	0.087	0.066
x_8	0.041	0.346	0.038	0.038	0.346	0.346

In this study, the eleven linguistic term set with associated semantic is considered (Table 6 and Fig. 4).

Table 6. Label set

Label set	Linguistic term	Fuzzy number		
		α	γ	β
s_0	Absent	0	0	0.1
s_1	Nothing answered, task was not completed	0	0.1	0.2
s_2	Very bad	0.1	0.2	0.3
s_3	Bad	0.2	0.3	0.4
s_4	Weak	0.3	0.4	0.5
s_5	Satisfactory enough	0.4	0.5	0.6
s_6	Satisfactory	0.5	0.6	0.7
s_7	Good enough	0.6	0.7	0.8
s_8	Good	0.7	0.8	0.9
s_9	Very good	0.8	0.9	1.0
s_{10}	Excellent	0.9	1.0	1.0

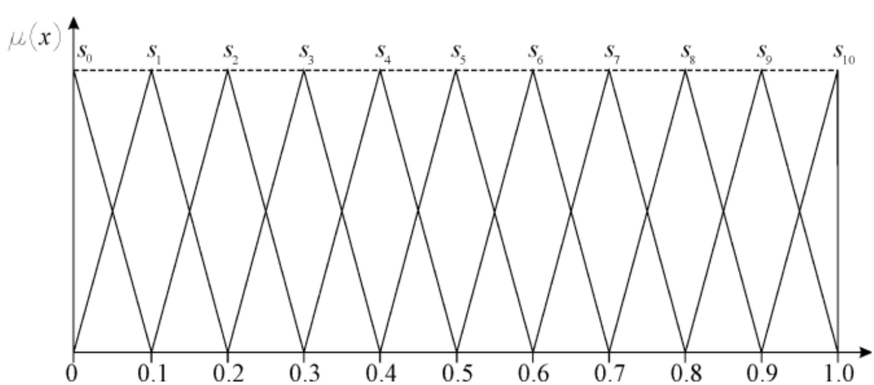


Fig. 4. Membership functions for linguistic values s_i

The candidates were rated. Data related to architect selection problem are given in Table 8.

Table 7. Rating of the candidates with respect to subjective criteria

Criteria	Candidates	Decision makers		
		D_1	D_2	D_3
x_1	A_1	s_9	s_8	s_5
	A_2	s_8	s_6	s_8
	A_3	s_8	s_9	s_5
x_2	A_1	s_6	s_7	s_7
	A_2	s_5	s_9	s_8
	A_3	s_8	s_9	s_5
x_3	A_1	s_5	s_8	s_6
	A_2	s_8	s_9	s_5
	A_3	s_9	s_8	s_8
x_4	A_1	s_8	s_9	s_6
	A_2	s_5	s_8	s_5
	A_3	s_5	s_5	s_5
x_5	A_1	s_8	s_8	s_5
	A_2	s_6	s_5	s_8
	A_3	s_8	s_6	s_8
x_6	A_1	s_9	s_9	s_5
	A_2	s_8	s_9	s_8
	A_3	s_8	s_8	s_8
x_7	A_1	s_8	s_9	s_6
	A_2	s_5	s_8	s_5
	A_3	s_5	s_5	s_5
x_8	A_1	s_8	s_8	s_5
	A_2	s_6	s_5	s_8
	A_3	s_8	s_6	s_8

According to the Table 6, Table 7 and Fig. 4, it is a prepared matrix with fuzzy group criteria values (Table 8) and fuzzy decision making matrix with fuzzy group weights (Table 9).

Normalized fuzzy decision making matrix is presented in Table 10. Solution results are presented in Table 11.

Table 8. The fuzzy group criteria values

Criterion	Candi-dates	D_1			D_2			D_3			Fuzzy group value		
		α	γ	β	α	γ	β	α	γ	β	α	γ	β
x_1	A_1	0.8	0.9	1.0	0.7	0.8	0.9	0.4	0.5	0.6	0.4	0.73	1
	A_2	0.7	0.8	0.9	0.5	0.6	0.7	0.7	0.8	0.9	0.5	0.73	0.9
	A_3	0.7	0.8	0.9	0.8	0.9	1.0	0.4	0.5	0.6	0.4	0.73	1

End of Table 8

Criterion	Candidates	D1			D2			D3			Fuzzy group value		
		α	γ	β	α	γ	β	α	γ	β	α	γ	β
x_2	A_1	0.5	0.6	0.7	0.6	0.7	0.8	0.6	0.7	0.8	0.5	0.67	0.8
	A_2	0.4	0.5	0.6	0.8	0.9	1.0	0.7	0.8	0.9	0.4	0.73	1
	A_3	0.7	0.8	0.9	0.8	0.9	1.0	0.4	0.5	0.6	0.4	0.73	1
x_3	A_1	0.4	0.5	0.6	0.7	0.8	0.9	0.5	0.6	0.7	0.4	0.63	0.9
	A_2	0.7	0.8	0.9	0.8	0.9	1.0	0.4	0.5	0.6	0.4	0.73	1
	A_3	0.8	0.9	1.0	0.7	0.8	0.9	0.7	0.8	0.9	0.7	0.83	1
x_4	A_1	0.7	0.8	0.9	0.8	0.9	1.0	0.5	0.6	0.7	0.5	0.77	1
	A_2	0.4	0.5	0.6	0.7	0.8	0.9	0.4	0.5	0.6	0.4	0.60	0.9
	A_3	0.4	0.5	0.6	0.4	0.5	0.6	0.4	0.5	0.6	0.4	0.50	0.6
x_5	A_1	0.7	0.8	0.9	0.7	0.8	0.9	0.4	0.5	0.6	0.4	0.70	0.9
	A_2	0.5	0.6	0.7	0.4	0.5	0.6	0.7	0.8	0.9	0.4	0.63	0.9
	A_3	0.7	0.8	0.9	0.5	0.6	0.7	0.7	0.8	0.9	0.5	0.73	0.9
x_6	A_1	0.8	0.9	1.0	0.8	0.9	1.0	0.4	0.5	0.6	0.4	0.77	1
	A_2	0.7	0.8	0.9	0.8	0.9	1.0	0.7	0.8	0.9	0.7	0.83	1
	A_3	0.7	0.8	0.9	0.7	0.8	0.9	0.7	0.8	0.9	0.7	0.80	0.9
x_7	A_1	0.7	0.8	0.9	0.8	0.9	1.0	0.5	0.6	0.7	0.5	0.77	1
	A_2	0.4	0.5	0.6	0.7	0.8	0.9	0.4	0.5	0.6	0.4	0.60	0.9
	A_3	0.4	0.5	0.6	0.4	0.5	0.6	0.4	0.5	0.6	0.4	0.50	0.6
x_8	A_1	0.7	0.8	0.9	0.7	0.8	0.9	0.4	0.5	0.6	0.4	0.70	0.9
	A_2	0.5	0.6	0.7	0.4	0.5	0.6	0.7	0.8	0.9	0.4	0.63	0.9
	A_3	0.7	0.8	0.9	0.5	0.6	0.7	0.7	0.8	0.9	0.5	0.73	0.9

Table 9. The fuzzy decision making matrix with fuzzy group weights (all criteria should to be maximized and optimal value equals to 1.0)

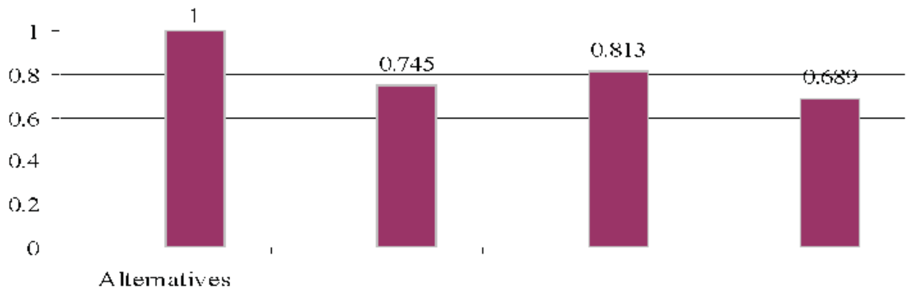
Criterion	Alternatives												Fuzzy group weight		
	A_0	A_1			A_2			A_3			Total			$\tilde{w}_j$	
	Ratings														
	α; γ; β	α	γ	β	α	γ	β	α	γ	β	α	γ	β	$w_{j\alpha}$	$w_{j\gamma}$	$w_{j\beta}$
x_1	1.0	0.7	0.8	0.9	0.5	0.6	0.7	0.7	0.8	0.9	2.9	3.2	3.5	0.151	0.246	0.192
x_2	1.0	0.7	0.8	0.9	0.8	0.9	1.0	0.4	0.5	0.6	2.9	3.2	3.5	0.192	0.311	0.246
x_3	1.0	0.5	0.6	0.7	0.6	0.7	0.8	0.6	0.7	0.8	2.7	3	3.3	0.192	0.311	0.246
x_4	1.0	0.4	0.5	0.6	0.8	0.9	1.0	0.7	0.8	0.9	2.9	3.2	3.5	0.096	0.179	0.151
x_5	1.0	0.7	0.8	0.9	0.8	0.9	1.0	0.4	0.5	0.6	2.9	3.2	3.5	0.096	0.156	0.114
x_6	1.0	0.4	0.5	0.6	0.7	0.8	0.9	0.5	0.6	0.7	2.6	2.9	3.2	0.057	0.100	0.081
x_7	1.0	0.7	0.8	0.9	0.8	0.9	1.0	0.4	0.5	0.6	2.9	3.2	3.5	0.057	0.087	0.066
x_8	1.0	0.8	0.9	1.0	0.7	0.8	0.9	0.7	0.8	0.9	3.2	3.5	3.8	0.038	0.346	0.346

Table 10. The fuzzy normalized decision making matrix

Criterion	Alternatives												Fuzzy group weight		
	A_0			A_1			A_2			A_3					
	Ratings												$\tilde{w}_j$		
	α	β	γ	α	β	γ	α	β	γ	α	β	γ	$w_{j\alpha}$	$w_{j\gamma}$	$w_{j\beta}$
x_1	0.2857	0.3125	0.3448	0.2000	0.2500	0.3103	0.1429	0.1875	0.2414	0.2000	0.2500	0.3103	0.151	0.246	0.192
x_2	0.2857	0.3125	0.3448	0.2000	0.2500	0.3103	0.2286	0.2813	0.3448	0.1143	0.1563	0.2069	0.192	0.311	0.246
x_3	0.3030	0.3333	0.3704	0.1515	0.2000	0.2593	0.1818	0.2333	0.2963	0.1818	0.2333	0.2963	0.192	0.311	0.246
x_4	0.2857	0.3125	0.3448	0.1143	0.1563	0.2069	0.2286	0.2813	0.3448	0.2000	0.2500	0.3103	0.096	0.179	0.151
x_5	0.2857	0.3125	0.3448	0.2000	0.2500	0.3103	0.2286	0.2813	0.3448	0.1143	0.1563	0.2069	0.096	0.156	0.114
x_6	0.3125	0.3448	0.3846	0.1250	0.1724	0.2308	0.2188	0.2759	0.3462	0.1563	0.2069	0.2692	0.057	0.100	0.081
x_7	0.2857	0.3125	0.3448	0.2000	0.2500	0.3103	0.2286	0.2813	0.3448	0.1143	0.1563	0.2069	0.057	0.087	0.066
x_8	0.2632	0.2857	0.3125	0.2105	0.2571	0.3125	0.1842	0.2286	0.2813	0.1842	0.2286	0.2813	0.038	0.346	0.346

Table 11. The normalized-weighted fuzzy decision making matrix and solution results

Criterion	Alternatives											
	A_0			A_1			A_2			A_3		
	Ratings											
	α	β	γ	α	β	γ	α	β	γ	α	β	γ
x_1	0.043	0.077	0.066	0.030	0.062	0.060	0.022	0.046	0.046	0.030	0.062	0.060
x_2	0.055	0.097	0.085	0.038	0.078	0.076	0.044	0.087	0.085	0.022	0.049	0.051
x_3	0.058	0.104	0.091	0.029	0.062	0.064	0.035	0.073	0.073	0.035	0.073	0.073
x_4	0.027	0.056	0.052	0.011	0.028	0.031	0.022	0.050	0.052	0.019	0.045	0.047
x_5	0.027	0.049	0.039	0.019	0.039	0.035	0.022	0.044	0.039	0.011	0.024	0.024
x_6	0.018	0.034	0.031	0.007	0.017	0.019	0.012	0.028	0.028	0.009	0.021	0.022
x_7	0.016	0.027	0.023	0.011	0.022	0.020	0.013	0.024	0.023	0.007	0.014	0.014
x_8	0.010	0.099	0.108	0.008	0.089	0.108	0.007	0.079	0.097	0.007	0.079	0.097
$\tilde{S}_i$	0.255	0.543	0.496	0.154	0.396	0.414	0.177	0.432	0.444	0.140	0.365	0.387
S_i		0.431			0.321			0.351			0.297	
K_i		1.000			0.745			0.813			0.689	



The best candidate from available and feasible is the second architect. He was selected by decision makers.

4. Conclusions

In the era of competitive markets, appropriate selection of personnel determines success of organizations. In this paper a sequential decision making process in group, where preferences of actors are presented by linguistic preference relations is given. The proposed model helps to overcome difficulties in personnel selection process. This allows to find consensus under a linguistic assessment approach and to cooperate in the solution finding of the group decision problem. The values of criteria set describing candidates in most cases are lexical values. The fuzzy set theory is a proper way to deal with uncertainty. It can be stated that the ratio with an optimal alternative may be used in cases when it is seeking to rank alternatives and find ways to improve them. The presented case study shows that this model successfully could help in cases when actors need to select among feasible candidates.

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INTEGRUOTAS NERAIŠKUSIS DAUGIATIKSLIS SPRENDIMŲ PRIĖMIMO MODELIS ARCHITEKTUI ATRINKTI

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Santrauka. Sprendimų priėmimas ekonomikoje pagrįstas galimų sprendinių įvertinimu, tinkamiausio sprendinio atrinkimu, įgyvendinimu ir didžiausio pelno gavimu. Tokie svarbūs klausimai, kaip užsitikrinti vietą konkurencingoje rinkoje, besikeičianti techninė, politinė ir socialinė aplinka, yra vieni svarbiausių parenkant personalą. Tai labai svarbus uždavinys, tiesiogiai veikiantis bendrovės gyvavimą dabar ir ateityje. Daug sprendinių negali būti tiksliai prognozuojami arba įvertinti. Supratimas apie daugiatikslius metodus ir skaičiavimo metodo algoritmo išmanymas yra prielaidos sprendimų priėmėjui pasitikėti sprendiniais, kuriuos pateikia sprendimų priėmimo sistemos. Yra pateikiama daug atskirų rodiklių personalui atrinkti: organizaciniai gebėjimai, kūrybiškumas, asmeninės ir lyderio savybės. Visi šie rodikliai turi vieną bendrą savybę – jie negali būti tiksliai apirėžti. Tokiems uždaviniams spręsti neraiškiųjų aibių teorija gali pateikti sprendimo būdus, kurie įvertina netikslumus, būdingus personalo atrankos procesui. Šiame straipsnyje neraiškusis daugiatikslis sprendimų priėmimo (MCDM) algoritmas, taikant neraiškiosios informacijos sintezės principus, suminį santykinių dydžių vertinimo (ARAS) metodą, kurio reikšmės aprašomos neraiškiaisiais skaičiais (ARAS-F), ir laipsnišką rodiklių svorio santykinių dydžių analizės (SWARA) metodą, yra integruotas. Siūlomas metodas tinkamas informacijai, vertinamai tiek žodžiais, tiek skaitmenimis, išreiškiamoms skalėms, uždaviniui, kurio informacija surenkama iš grupės informacijos šaltinių, apdoroti. Sujungimo procesas grindžiamas informacija, taikant neraiškiųjų aibių teoriją pagrindinėms žodžiais aprašomoms reikšmėms pakeisti. Siūlomo algoritmo taikymas pavaizduotas sprendžiant architekto parinkimo uždavinį.

Reikšminiai žodžiai: personalo atranka, architektas, žodinis rodiklių aprašymas, ARAS, ARAS-F, SWARA, MCDM, sprendimų priėmimas.

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