APPLICATION OF VERBAL METHODS TO MULTI-ATTRIBUTE COMPARATIVE ANALYSIS OF INVESTMENTS RISK ALTERNATIVES IN CONSTRUCTION

Edmundas Kazimieras Zavadskas, Leonas Ustinovichius, Zenonas Turskis, Galina Shevchenko

Vilnius Gediminas Technical University
Civil Engineering Faculty
Department of Construction Technology and Management
Sauletekio av. 11, Vilnius, LT-2040, Lithuania
E-mail: Galina.Sevcenko@st.vgtu.lt

Management of investment risk is a usual practice of any investment project. The estimation of risk must be carried out at various project stages. Management of investments risk means presence of the all procedures control in any phase of the project. Quite reliable estimations of investments quality are a challenge because the uniform parameter of probability of means return does not exist yet. There is a set of attributes (parameters, factors, criteria) necessary for considering. The investor works conditions changes continuously due to an economic situation changes. The rules of an estimation of investment projects quality really can be based only on the politician of a management of the investor and lean on its intuition and experience. During decision-making becomes classification essential a role, i.e. the attitude of objects to classes of decisions. The classification subject objects can be described by means of various attributes estimations. The attributes can have both qualitative and quantitative character. At competent statement of investment process is in parallel used a method. There are known various methods of such problems decision. Verbal methods are applying in the given work for definition of investments risk in construction. The offered method of the best of building investment projects variants selection is tested in the decision of actual problem.

Keywords: *investment, project, risk, the qualifier of attributes, multi-attribute analysis*

1. Introduction

Environmental risk assessment and decision-making strategies in construction over the last several decades have become increasingly more sophisticated, information-intensive, and complex, including such approaches as expert judgment, cost-benefit analysis, and investment risk assessment. One tool that has been used to support environmental decision-making is comparative risk assessment (CRA). CRA lacks a structured method for arriving at an optimal project alternative. Multi-attribute decision analysis (MADA) provides better-supported techniques for the comparison of project alternatives based on decision matrices, and it provides structured methods for the incorporation of project stakeholders' opinions in the ranking of alternatives. Decision-making in projects is a complex and confusing problem, characterized by trade-offs between socio-political, environmental, and economic impacts. Cost-benefit analysis is often used, occasionally in concept with comparative risk assessment, to choose between competing project's alternatives. The selection of appropriate policies involves multiple attributes such as cost, benefit, environmental impact, safety, and risk. Some of these attributes cannot be condensed into a monetary value, which complicates the integration problem inherent to making comparisons and trade-offs. Even if it were possible to convert attributes rankings into a common unit this approach would not always be desirable since stakeholder preferences might be lost in the process. Furthermore, projects often involve ethics and moral principles, which are not related to any economic use or value. Moreover, decisions typically draw upon *multidisciplinary* knowledge bases, incorporating natural, physical, and social sciences, medicine, politics, and ethics.

2. Multi-Attribute Decision-Making (Madm) Methods and Tools

In recent years, multi-criteria evaluation methods have been widely used in solving both theoretical and practical problems. Actually, these methods are universal. They allow us quantitatively evaluate any complicated object described by a set of criteria. Another advantage of these methods is their ability to combine both maximizing and minimizing attributes expressed in various dimensions into one integrated criterion. The maximizing attributes imply that, if their values are growing, the situation is getting better, while for minimizing attributes this means a worsening situation. The integration is achieving by normalization. Normalization helps to convert all the attribute values into no dimensional, i.e. comparable quantities [1].

MADM methods evolved as a response to the observed inability of people. They effectively analyse multiple streams of dissimilar information. There are *many* different MADM methods [2; 3; 4; 5; 6; 7; 8; 9; 10; 11]. They based on different theoretical foundations such as optimisation, goal aspiration, or outranking, or a combination of these:

- **Optimisation models** employ numerical scores to communicate the merit of one option in comparison to others on a single scale.
- **Goal aspiration,** reference level, or threshold models rely on establishing desirable or satisfactory levels of achievement for each attribute.
- **Outranking models** compare the performance of two (or more) alternatives at a time, initially in terms of each attribute, identifies the extent to which a preference for one over the other can be asserted. Like most MADM methods, outranking models are *partially* compensatory [2].

An overview of principal MADM approaches is provided in the remainder of this section.
Elementary methods intended to reduce complex problems to a singular basis for selection of a preferred alternative. Competing decision attributes may be presented, but inter-attributes weightings are not required.

Pros and Cons Analysis. A Pros and Cons Analysis is a qualitative comparison method in which experts identify the qualities and defects of each alternative [12]. Other methods are based on the Pros and Cons concept, including SWOT Analysis and Force Field Analysis

Maximin and Maximax Methods.The maximin method is based upon a strategy that seeks to avoid the worst possible performance – or "maximizing" the poorest ("minimal") performing attribute.

Conjunctive and Disjunctive Methods.The conjunctive and disjunctive methods are non-compensatory, goal aspiration screening methods. They do not require attributes to be measured in commensurate units. These methods require satisfactory (in comparison with a predefined threshold) rather than best possible performance in each attribute -- i.e. if an alternative passes the screening, it's acceptable.

Lexicographic (verbal) Method. A lexicographic analysis of any problem involves a sequential elimination process that is continued until either a unique solution is found or all the problems are solved. In the lexicographic decision-making method attributes are first rank-ordered in terms of importance [13].

Decision Tree Analysis. Decision trees are useful tools for making decisions where a lot of complex quantitative information needs to be taken into account (e.g. deciding whether to take immediate action or to postpone action in treating a contaminated groundwater problem [14]). The principle behind decision tree analysis is link specific outcomes (or consequences) to specific decision nodes.

Influence Diagrams. An Influence Diagram is a graphic representation of a decision problem. This representation provides a framework for building decision analysis problems but does not provide a framework for quantitative evaluation [15].

Multi-attribute utility/value theory **(MAUT/MAVT).** Multi-Attribute Utility Theory (MAUT/MAVT) is a technique for formally drawing multiple perspectives and evaluations into a decision-making process. The goal of MAUT/MAVT is to find a simple expression for the decision-maker's preferences. Concerns for the practical implementation of MAUT/MAVT led to the development of the Simple Multi Attribute Rating Technique (SMART). SMART is a simplified multi-attribute rating approach, which utilizes *simple* utility relationships.

Similar to MAUT, AHP completely aggregates various facets of the decision problem into a single objective function. The goal is to select the alternative that results in the greatest value of the objective function. Like MAUT, AHP is a compensatory optimisation approach. The AHP technique thus relies on the supposition that humans are more capable of making relative judgments than absolute judgments. The rationality assumption in AHP is more relaxed than in MAUT. Unlike MAUT and AHP, outranking is based on the principle that one alternative may have a degree of *dominance* over another [16].

3. Common Algorithm of Weight Establishment

To determine the significances of the attributes, the expert judgment method proposed by Kendall is used [3]. Zavadskas et al. discussed the application of this method in the construction field [17; 18]. This expert judgement method has been implemented at the following stages:
Calculation of values t → • Calculation of weights q → Calculation of values S → Calculation of values T_k; → Calculation of values W → Calculation of values χ^2 → Testing the statement $\chi^2 > \chi^2_{tbl}$.
The values t_{jk} for statistical processing have been obtained by interviewing the respondents. The average attribute value $\overline{t_j}$ is calculated by the following formula:

$$\overline{t_j} = \frac{\sum_{k=1}^{r} t_{jk}}{r}, \qquad (1)$$

where t_{jk} is the ranking of the j attribute by the k respondent and r is number of respondents.

The weights of the attributes are calculated by dividing the sum of the attributes average values by the average value of each attribute:

$$q = \frac{\sum_{j=1}^{n} \overline{t_j}}{t_j}. \quad (2)$$

The total weight of the attributes must be equal to one:

$$\sum_{j=1}^{n} \frac{\sum_{j=1}^{n} \overline{t_j}}{\overline{t_j}} = 1. \quad (3)$$

Reliability of the data can be expressed by the coefficient of concordance (agreement) of the respondents' opinions by describing the extent to proximity of individual views. In cases with reiterated ranks for the same parameters, as in our case, the coefficient of concordance is

$$W = \frac{125}{r^2\left(n^3 - n\right) - r\sum_{k=1}^{r} T_k}, \quad W \in [0;1], \quad (4)$$

where S is the total square deviation of the rankings of each attribute, T_k the index of reiterated ranks in the r rank, r the number of respondents and n the number of evaluation attributes.

The deviation of the attribute ranking:

$$S = \sum_{j=1}^{n}\left[\sum_{k=1}^{r} t_{jk} - \frac{1}{n}\sum_{j=1}^{n}\sum_{k=1}^{r} t_{jk}\right]^2, \quad (5)$$

where t_{jk} is the rank conferred by the k respondent to the j attribute.

However, the calculated value W is stochastic; and therefore, the significance of the concordance coefficient has to be calculated.

Kendall [3] has shown that, when n>7, the value $\chi^2 = WR(N-1)$ has a distribution with degrees of freedom v=n–1, where n is the number of attributes considered and r the number of experts. It has been proved that if the calculated value χ^2 is larger than the critical tabular value χ^2_{tbl} for the pre-selected level of significance (e.g. α=0.05), then the hypothesis about the agreement of independent experts 'judgements' is not rejected. In our case, we have n=36, v=35 and the pre-selected level of significance is α=0.05, therefore, the above-mentioned conditions should be satisfied.

The significance $\chi^2$of the concordance coefficient has been calculated as follows:

$$\chi^2_{\alpha,\nu} = W \cdot r \cdot (n-1) = \frac{125}{rn(n+1) - \frac{1}{n-1}\sum_{k=1}^{r} T_k}. \quad (6)$$

If the $\chi^2_{\alpha,\nu} > \chi^2_{tbl}$ the significance of concordance coefficient exists on α level, then the agreement of experts' opinions is satisfactory and group opinion is established. Otherwise, when $\chi^2_{\alpha,\nu} > \chi^2_{tbl}$ .is obtained, the respondents' opinions are not in agreement, which implies that they differ substantially and the hypothesis on the rank's correlation cannot be accepted.

4. Proposed Algorithm

In the engineering environment, the data is almost always a sample that has been selected from some population. An effective data collection procedure can greatly simplify the analysis and lead to improved understanding of the population or process that is being studied. Decisions often need to be based on measurements from only a subset of objects selected in a sample. This process of reasoning from a sample of objects to conclusions for a population of objects is referred to as statistical inference.

To make good decisions, an analysis of how well a sample represents a population is clearly necessary. Furthermore, how should samples can be selected to provide good decisions – ones with acceptable risks? **Probability** models help quantify the risks involved in statistical inference, that is, the risks involved in decisions made every day. Probability Density functions are commonly used in engineering to describe physical systems. Undoubtedly, the most widely used model for the distribution of a random variable is a **normal distribution.** Whenever a random experiment is replicated, the random variable that equals the average (or total) result over the replicates tends to have a normal distribution as the number of replicates becomes large.

4.1. Definition

Some useful results concerning a normal distribution are summarized below and on Figure 1. For any normal random variable:

$P(\mu-\sigma<X<\mu+\sigma)=0.6827$;

$P(\mu-2\sigma<X<\mu+2\sigma)=0.9545$:

$P(\mu-3\sigma<X<\mu+3\sigma)=0.9973$.

From the symmetry of $f(x), P(X>\mu)=P(X<\mu)=0.5$. Because $f(x)$ is positive for all x, this model assigns some probability to each interval of the real line. However, the probability density function decreases as x moves farther from μ. Consequently, the probability that a measurement falls far from μ is small, and at some distance from μ the probability of an interval can be approximated as zero. The area under a normal probability density function beyond 3σ from the mean is quite small. This fact is convenient for quick, rough sketches of a normal probability density function.

The sketches help us determine probabilities. Because more than 0.9973 of the probability of a normal distribution is within the interval, 6σ is often referred to as the **width** of a normal distribution. Advanced integration methods can be used to show that the area under the normal probability density function from $-\infty \le x \le \infty$ is 1.

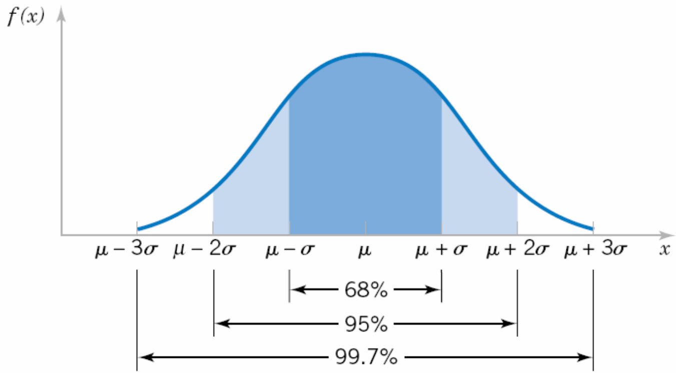

Figure 1. Probabilities associated with a normal distribution

In this research we suppose that all values, which differ from average value μ more than on 2σ, are rejected, also indicator weights are defined by applying the remained values.

To determine the significances of the attributes, the expert judgement method proposed by Kendall [3] has been used. Zavadskas *et al.* [4], Kaklauskas *et al.* [5, 6], Zavadskas and Kaklauskas [17], Vilutiene and Zavadskas [7] discuss the application of this method in the construction field. This expert judgement method is implemented at the following stages:

Calculation of values t_{jk} →Calculation of weights q_j →Calculation of values S →Calculation of values T_k →Calculation of values W →Calculation of values $\chi^2_{\alpha,v}$ → Testing the statement $\chi^2_{\alpha,v} > \chi^2_{tbl}$.

5. Case Study

Organizational and technological complexity of construction projects generates enormous risks. Investment risk managing theory allows planning investment problems. Managing the risk of investments means presence of an effective control for all procedures in any phase of the project, when varying factors are taking place, which influence the realization of the project. In most cases, any investment project possesses several parameters of efficiency. Conditions of investor works continuously change assessment. Investment projects' quality rules can be based only on the investor's leadership politics at this moment. The quality evaluation principle based on the intuition and experience of the decision maker [13]. We present investments problem to the construction in this article. The stakeholders must to select the best alternative of investments. The alternatives are as follows:

a_1 – to build nine-storey 42 flat dwelling house;
a_2 – to build five-storey building for offices;
a_3 – to build 3 storey building for offices and five-storey building with 20 apartments.

In the following case study, we highlight the analysis and explanation methods of the proposed solution algorithm that are particularly interesting for applications in construction. The problem has been described by the system of attributes. The total list of attributes has been designed after rough analysis of similar problems solution. Highly qualified specialists left five the most important attributes [13]:
Technological risk – x_1;
Period before termination construction works – x_2;
Period after termination construction works – x_3;
Financial risk – x_4;
Political and Legal risk – x_5.

The values for statistical processing t_{jk} have been obtained by interviewing the highly skilled construction specialists (Table 1).

Table 1. Attributes' weights ranks determined by the experts (the bigest is the best value)

Expert $k = 1,...,25$	Efficiency attributes ranks values, t_{jk}; $j = 1,...,n$; $n = 5$.				
	x_1	x_2	x_3	x_4	x_5
1	2	5	3	1	4
2	4	1	2	5	3
3	5	4	3	2	1
4	5	3	4	2	1
5	5	4	3	1	2
6	5	3	4	1	2
7	5	4	2	3	1
8	4	5	1	3	2
9	5	3	4	1	2
10	5	4	1	2	3
11	5	4	1	3	2
12	3	5	4	1	2
13	4	2	1	3	5
14	5	3	4	1	2
15	5	4	2	3	1
16	5	4	3	2	1
17	2	4	3	5	1
18	4	3	5	2	1
19	5	3	4	1	2
20	4	5	1	2	3
21	5	4	2	3	1
22	1	4	3	2	5
23	5	4	3	2	1
24	3	5	1	5	2
25	1	4	3	5	2

The algorithm of attributes weight establishment and process of calculation [10] is presented in Table 2. After performed calculations, we have established attributes weights.

Kendall [3] has shown that, when $n > 7$, the value $\chi^2 = Wr(n-1)$ has a distribution with degrees of freedom $v = n-1$, where n is the number of attributes considered and r the number of experts. It has been proved that if the calculated value χ^2 is larger than the critical tabular value χ^2_{tbl} for the pre-selected level of significance is $\alpha = 0.01$, therefore, the above-mentioned conditions should be satisfied. If the $\chi^2_{\alpha,v} > \chi^2_{tbl}$ is obtained, the respondents' opinions are not in agreement, which implies that they differ substantially and the hypothesis on the rank's correlation cannot be accepted. The concordance coefficient based on the attributes weights is $W = 0.66$. In this case, the tabular value has been taken from Fisher and Yates statistical tables [19]. When the degrees of freedom is $v = n-1 = 5-1 = 4$ and pre-selected level of significance is $\alpha = 0.01$ (or error probability $P = 1\%$), in that case we have the value $\chi^2_{tbl} = 13.3$. Since $\chi^2_{\alpha,v} > \chi^2_{tbl}$, then, the assumption is made that the coefficient of concordance is significant and expert rankings are in concordance with 99% probability.

In Table 3 we have some values of attributes, which difference from the mediocre values of each attribute is significant. The values that are less than mediocre value $\bar{t}_j - 2\sigma$ are marked by bold italic font and ones which values are bigger than $\bar{t}_j + 2\sigma$ are marked by bold font. The values, which difference from mediocre values is too big, eliminated as is presented in Table 3.

Table 2. Algorithm of attributes weights establishment [10; 11]

Process of calculation	Efficiency attributes x_j ; $j = 1,...,n$; $n = 5$.				
	x_1	**x_2**	**x_3**	**x_4**	**x_5**
Sum of ranks $\bar{t}_j = \sum_{k=1}^{r=25} t_{jk}$	102	94	67	61	52
The average attribute rank value $\bar{t}_j = \frac{\sum_{k=1}^{r=25} t_{jk}}{r}$	4.08	3.76	2.68	2.44	2.08
Attribute rank	1	2	3	4	5
Attribute weight $q_j = \frac{\bar{t}_j}{\sum_{j=1}^{n=5} \bar{t}_j}$	0.27	0.25	0.18	0.16	0.14
$\sum_{k=1}^{r=25} (t_{jk} - \bar{t}_j)^2$	11.42	14.81	47.46	22.81	25.60
Dispersion of experts ranking values $\sigma^2 = \frac{1}{r-1} \sum_{k=1}^{r=25} (t_{jk} - \bar{t}_j)^2$	0.34	0.44	1.40	0.67	0.75
Variation $\beta_j = \frac{\sigma}{\bar{t}_j}$	0.12	0.17	0.44	0.32	0.48
Ranking sum average	$V = \frac{1}{r} \sum_{j=1}^{n=5} \sum_{k=1}^{r=25} t_{jk} = 0{,}2(102 + 64 + 67 + 61 + 52) = 75.2$				
The total square ranking deviation	$S = \sum_{j=1}^{n=5} \left(\sum_{k=1}^{r=25} t_{jk} - V \right)^2 = (102 - 75.2)^2 + (94 - 75.2)^2 + (67 - 75.2)^2 + (61 - 75.2)^2 + (52 - 75.2)^2 = 1879$				
The coefficient of concordance	$W = \frac{12S}{r^2(n^3 - n)} = \frac{12 \cdot 1879}{25^2(5^3 - 5)} = 0.30$				
The significance of the concordance coefficient (not related ranks) $\chi^2_{\alpha,v}$	$\chi^2_{\alpha,v} = \frac{12S}{rn(n+1) - \frac{1}{n-1} \sum_{k=1}^{r} T_k} = \frac{12 \cdot 1879}{25 \cdot 5(5+1)} = 3.01$, where $\frac{1}{n-1} \sum_{k=1}^{r} T_k = 0$				
Rank of table concordance χ^2_{tbl} when the importance equals to 1 %.	The freedom degrees value of a solved problem $v = n - 1 = 5 - 1 = 4$; $\chi^2_{tbl} = 13.3$				
Compatibility of expert judgement (Kendall [3]).	$\chi^2_{\alpha,v} = 3{,}01 \succ \chi^2_{tbl} = 13.3$ - The hypothesis about the consent of experts in rankings is not accepted				

Table 3. Attributes weights determined by the experts

Expert $k = 1,...,25$	Efficiency attributes ranks values, t_{jk} ; $j = 1,...,n$; $n = 5$.				
	x_1	*x_2*	*x_3*	*x_4*	*x_5*
1	***X***	5	3	***X***	**X**
2	4	***X***	2	**X**	3
⋮	⋮	⋮	⋮	⋮	⋮
25	***X***	4	3	**X**	2
6σ=	4	4	3	4	4
σ=	X.67	X.67	X.5X	X.67	X.67
μ-2σ=	***2.74***	***2.33***	***1.68***	***1.1X***	***X.74***
μ +2σ=	**5.42**	**5.1**	**4.02**	**3.78**	**3.42**
r=	**25-4=21**	**25-2=23**	**25-7=18**	**25-1X=15**	**25-3=22**

The calculation of attributes weights performed as shown in Table 4.

Table 4. New proposed algorithm of attributes weights establishment

Process of calculation	Efficiency attributes x_j ; $j = 1,...,n$; $n = 5$.				
	x_1	x_2	x_3	x_4	x_5
Sum of ranks $\bar{t}_j = \sum_{k=1}^{r=25} t_{jk}$	96	91	56	35	38
The average attribute rank value $\bar{t}_j = \frac{\sum_{k=1}^{r=25} t_{jk}}{r}$	4.57	3.96	3.11	2.33	1.73
Attribute rank	1	2	3	4	5
Attribute weight $q_j = \frac{\bar{t}_j}{\sum_{j=1}^{n=5} t_j}$	0.29	0.25	0.20	0.15	0.11
$\sum_{k=1}^{r=25} (t_{jk} - \bar{t}_j)^2$	11.42	14.81	47.46	22.81	25.60
Dispersion of experts ranking values $\sigma^2 = \frac{1}{r-1} \sum_{k=1}^{r=25} (t_{jk} - \bar{t}_j)^2$	0.34	0.44	1.40	0.67	0.75
Variation $\beta_j = \frac{\sigma}{\bar{t}_j}$	0.12	0.17	0.44	0.32	0.48
Ranking sum average	$V = \frac{1}{r} \sum_{j=1}^{n=5} \sum_{k=1}^{r=25} t_{jk} = 0,2(96 + 91 + 56 + 35 + 38) = 63,2$				
The total square ranking deviation	$S = \sum_{j=1}^{n=5} \left(\sum_{k=1}^{r=25} t_{jk} - V \right)^2 = (96-63,2)^2 + (91-63,2)^2 + (56-63,2)^2 + (35-63,2)^2 + (38-63,2)^2 = 3330,8$				
The coefficient of concordance	$W = \frac{12S}{r^2(n^3 - n)} = \frac{12 \cdot 3330,8}{19,82^2(5^3 - 5)} = 0,91$				
The significance of the concordance coefficient (not related ranks) $\chi^2_{\alpha,v}$	$\chi^2_{\alpha,v} = \frac{12S}{rn(n+1) - \frac{1}{n-1}\sum_{k=1}^{r} T_k} = \frac{12 \cdot 3330,8}{19,8 \cdot 5(5+1)} = 16,82$, where $\frac{1}{n-1}\sum_{k=1}^{r} T_k = 0$				
Rank of table concordance χ^2_{tbl} when the importance equals to 1 %.	The freedom degrees value of a solved problem $v = n - 1 = 5 - 1 = 4$; $\chi^2_{tbl} = 13.3$				
Compatibility of expert judgement (Kendall [3]).	$\chi^2_{\alpha,v} = 16,8 \succ \chi^2_{tbl} = 13.3$ - The hypothesis about the consent of experts in rankings is accepted				

The values of attribute weights established as follows:
$\boldsymbol{q}_1$=0,29; $\boldsymbol{q}_2$=0,25; $\boldsymbol{q}_3$=0,20; $\boldsymbol{q}_4$=0,15; $\boldsymbol{q}_5$=0,11.

Conclusions

Solving many multi-attribute problems, we have to identify weights of attributes. The expert inquiry method can be applied for this purpose.

Qualification, experience and knowledge of the experts generally vary and are unequal in different fields. Having not enough knowledge in a particular field of science or business is the reason why experts give most attributes prominence or, on the contrary, understate them.

Thus, divergent rating values of some attributes must be eliminated. An algorithm, presented in this article, can be used for this purpose. Attributes rating values, which differ more than per 2σ from an average value, can be eliminated.

This is the way to have a concerted experts' opinion and to get more precise calculation results.

Based on the results the most reasonable decisions can be made, without increasing the number of experts.

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