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Practical Decision Making

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Key Words: Decision making; multiple-criteria decision analysis; decision support systems; multiple choice decision; Promethee II method.

Abstract. *The purpose of this paper is to demonstrate how scientific algorithms, methodologies and software decision support systems can be easily applied to solving a typical multiple-criteria choice business problem. The Multichoice system for multiple-criteria decision analysis is considered for the demonstration, along with the well-known method Promethee II.*

1. Introduction

The business management today is a process where defined targets are accomplished through careful resource planning. Wise managing of people, materials, energy, finances etc., is a number one condition for success. Decisions made by managers define how effective these resources will be managed. For many years the skills for making right decisions was regarded as a talent and as a result of field experience through tries and errors. Main accents were on the personnel values such as talent, insight, and non-standard thinking, rather than the use of mathematical quantitative methods. In time, along with technologies development and market evolution, it was more and more difficult to make successful decisions because the number of alternatives was growing, logistics and resource planning became more sophisticated. Results of wrong management decisions were devastating [Singiresu, Rao (2009)]. Decision making problems can also be found in various autonomous smart systems like sensor grids with centralized or distributed data processing [Alexandrov, A. (2014)].

For these reasons, in the process of decision-making, along with the personal qualities of the management staff, there was a need of techniques, approaches and software systems based on quantitative analyzes and mathematical approaches. These analyzes are the subject of a study by the "Operations research" (OR) scientific discipline.

Many tasks for planning, control and analysis in manufacturing, transportations, logistics, ecology, education and other areas can be defined as multiple-criteria decision problems (MCDA) [White, (1990)]. Based on their formulation, they can be divided into two main classes: problems for multiple-criteria decision analyses [Dyer (2004)], and problems for multiple-criteria optimization [Sawaragi, Nakayama et. (1985)]. In the first class a finite set of alternatives are defined in table form. Those are problems for decision making with discrete alternatives. In the second class a finite set of subjects, define infinite set of alternatives. Those are problems for multiple-criteria optimization. In both cases main problem is to optimize simultaneously more than one criterion in a set of possible alternatives. Usually these criteria are contradicting and there is no single alternative that is optimal according to every single criterion. But there is a special subset of the alternatives that has the important common characteristic: Any improvement of the value of single criterion, leads to deterioration of the value of at least one other criterion. This characteristic was first noticed in 1896 by the Italian scientist Vilfredo Pareto and therefore in 1951 was named to him – the set of nondominated (Pareto-optimal) alternatives [Collette, Siarry (2013)].

From mathematical view point, any Pareto-optimal alternative can be a final solution of the multiple-criteria optimization problem. In practice, there is a need for some additional information that will lead to the final choice of one alternative. That information must come from the person that has to makes the decision – decision maker or DM. This information reflects his personal preferences regarding the qualities of the wanted alternative.

2. Multiple-criteria Decision Analysis Problem Formulation

The MCDA problem can be defined as following:

- A finite set of explicitly listed alternatives.
- A finite set of criteria that the alternatives will be evaluated upon, where for every criterion is given its type (quantitative, qualitative, ranking, etc. …) and whether a bigger or a smaller value is desired (min or max).
- The values of every alternative for every criterion given in a matrix form.

The matrix is of the form A(n*k).

Table 1. Alternatives matrix

	a1	a2	…	an
f1(.)	f1(a1)	f2(a1)	…	fk(a1)
f2(.)	f1(a2)	f2(a2)	…	fk(a2)
…	…	…	…	…
fk(.)	f1(an)	f2(an)	…	fk(an)

where:

a_i – means alternative with index *i, i=1…, n;*

$f_j(.)$ – means criterion with index *j, j=1…, k;*

I is the set of alternatives indexes;

J is the set of criteria indexes.

The evaluation of the *i*-th alternative according to each criterion is defined with vector-column $(a_{i1}, a_{i2}, ..., a_{ik})^T$ or $(f_1(a_i), ..., f_k(a_i))^T$.

The evaluation of all alternatives according to *j*-th criterion is defined with vector-row $(a_{1j}, a_{2j}, ..., a_{nj})$ or $(f_j(a_1), ..., f_j(a_n))$.

Based on the alternative matrix A, three different problems can be defined:

Problem 1. Choosing the best alternative, according to decision maker's preferences. Also called problem for multiple-criteria choice.

Problem 2. Alternatives sorting (ascendant or descendant). Also called multiple-criteria ranking problem.

Problem 3. Alternatives grouping. Also called multiple-criteria classification problem.

Criterion is a measure for evaluation of effectiveness and appears as an attribute in objective function.

Attribute is a measurable problem property. Each alternative can be described as a property set. Attributes can be quantitative or qualitative.

Objective function is the target that must be achieved as much as possible. It defines the direction of desired changes.

The criterion is a common term. It appears as an **objective function** when formalization is possible, and as **an attribute** when such formalization is not possible.

Alternative with index i' is called **nondominated** if there is no other alternative with index *i* that satisfies the condition:

$a_{ij} \le a_{i'j}$, j = 1…, k

and at least for one index j=s to satisfy the condition:

$a_{is} < a_{i's}$.

Alternative with index i is called satisfactory alternative if satisfies the condition:

$a_{ij} \le \overline{a_j}, j = 1...k$,

where $\overline{a_j}$ is the aspiration level of the criterion with index j, j= 1…, k.

Alternative with index i^* is called ideal alternative is satisfies the condition:

$i^* = (a_1^*, a_2^*, ..., a_n^*)$, where $a_j^* = \min_{1 \le i \le n} a_{ij}$.

Usually such alternative does not exist.

The nondominated alternative is called most preferred alternative if satisfies the most all decision makers preferences.

Two major models are used to solve MCDA problems – **compensatory** and **noncompensatory [**Clemen, (1996)].

The noncompensatory model does not allow compromises among criteria. The bad value on one criterion cannot be compensated on account of other criteria values.

The compensatory model on the other hand, allows compromises among criteria. In these models each multidimensional alternative characteristic has numeric representation. This numeric representation is defined by different approaches which are separated in three groups:

Resultative model – defines the alternative that has greatest value of the *value function*. The main problem here is how to define this *value function*.

Compromising model – defines the alternative that is closest to the ideal alternative. In this model the alternatives are points in the criteria set.

Model of agreement – defines set of relations that satisfy the most the corresponding agreement measure.

When modeling and solving MCDA problems, the following questions immerge:

How to interpret certain quantitative attribute.

How to compare quantitative and qualitative attributes.

How to compare more than two qualitative attributes.

The first problem is related to measurement scale. There are three scales for quantitative: **ordinal**, **interval** and **proportional**.

In ordinal scale the measured quantities are put in ascending or descending order. Here the accent is on the position but not on the distance.

In interval scale the different values have equal distance from neighbors. The value is measured as a distance to freely chosen initial point.

In proportional scale different values have again equal distance from neighbors. The value is measured as a distance from the natural beginning. For this scale are valid all arithmetical operations.

The second problem is solved by converting qualitative attributes in quantitative using the interval scale. One of the most popular transformation is by using the so-called *bipolar scale*. For example, 10-points system is regarded. 10 points are given to the attribute with maximum value. The average 5 points are used for separation of good and attribute bad values.

To solve the third problem there is a need of transformation of the qualitative attributes in quantitative. Two of the popular transformations are:

Using the L2 norm. In this transformation the element a_{ij} of the alternative's matrix A are transformed into r_{ij} as follows:

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{l=1}^{n} a_{lj}^2}}, i = 1,...,n; j = 1,...,k.$$

Main disadvantage of this transformation is that the attributes does not have same values diapason.

Linear transformation. In this transformation, the element a_{ij} from the column vector $(a_{1j}, a_{2j}, ..., a_{nj})^T$ is divided by the max element of the vector. The result is a new element r_{ij}:

$$r_{ij} = \frac{a_{ij}}{\max_i a_{ij}}, i = 1,...,n; j = 1,...,k$$ – for attributes that have to be maximized

and

$$r_{ij} = \frac{\frac{1}{a_{ij}}}{\max_i \left(\frac{1}{a_{ij}} \right)}, i = 1,...,n; j = 1,...,k$$ – for attributes that have to be minimized.

The advantage here is that all oft the result values vary between 0 and 1.

The decision maker has a key role in the process of MCDA problem solving. His preferences define the final solution. Methods for solving MCDA problems differ mainly by how decision maker's preferences are obtained and processed.

The developed methods for solving MCDA problems can be separated in three main classes:

Methods, where global preferences are aggregated as a result of one common criterion (utility theory approach). These are the utility theory methods [Farquhar (1984)] and methods based on the Analytic Hierarchy Process (AHP) [Saaty (1980)].

Methods, where global preferences are aggregated as a result of one ore many preferences relations among the alternatives (outranking approach). Method ELECTRE [Roy (1991)] belongs to this class.

Method, where local preferences are aggregated iteratively by direct or indirect comparisons among two or more alternatives (interactive approach). Interactive methods are very useful where there are many alternatives and decision maker cannot make direct alternative comparison [Jaszkiewicz and Slowinski (1997)], [Korhonen (1988)].

The solving process is interactive and involves many and sophisticated mathematical calculation. This makes necessary the usage of computer aids – software systems, developed to assist decision makers. Decision support systems are interactive software, designed to assist decision makers to solve non-formalized or weak formalized MCDA problems [Miettinen (1994)]. These systems can be divided into three categories: commercial; for scientific or educational purposes and experimental [Clemen (1996)].

3. MCDA Problem Solving

One typical problem for multiple-criteria decision analysis is the facility location problem. Let's consider a hypothetical example, where a company wants to invest in building a hotel. There are seven possible locations in different cities, each one with its costs, advantages and disadvantages. After initial research, managers define 19 criteria, separated in three groups:

- Initial investments criteria. This group contains initial expenses as land cost, government permits, labor costs etc. (*table 2*).
- Maintenance costs criteria. Here are the expenses that will cost the hotel maintenance after it is functional (*table 3*).
- Benefits criteria. Here we put criteria related to benefits and profits (*table 4*).

Table 2. Initial investment cost criteria

Criteria name	Criteria type
Land cost	Quantitative
Permits cost	Quantitative
Material logistics costs	Quantitative
Labor cost for building	Quantitative
Heavy machines access conditions	Qualitative

The software system Multichoice [Genova, Vassilev (2004)] [Andonov, Genova, et. (2003)] is used as a computer aid to solve this MCDA problem.

First step of the solution process is to build the alternatives matrix A, that contains all criteria values for the corresponding alternatives. Potential locations are described as cities, ordered from smallest (City 1) to biggest (City 7) as columns, and alternatives are represented as rows (*table 5*).

Table 3. Maintenance cost criteria

Criteria name	**Criteria type**
Local taxes	Quantitative
Labor cost	Quantitative
Criteria name	Criteria type
Community services cost	Quantitative
Food market accessibility	Qualitative
Food cost	Qualitative

Table 4. Benefits criteria

Criteria name	**Criteria type**
Touristic significance of the city	Qualitative
Distance from city center	Quantitative
Significant tourist attractions within 1 km	Quantitative
Significant tourist attractions within 3 km	Quantitative
Restaurants within 1 km	Quantitative
Distance from international airport	Quantitative
Distance from railway station	Quantitative
Public transport infrastructure in the area	Qualitative
Environmental noise factor	Qualitative

Table 5. Alternative's matrix A

Criteria/ Alternative	**City 1**	**City 2**	**City 3**	**City 4**	**City 5**	**City 6**	**City 7**
Land cost	100	120	130	150	180	200	220
Permits cost	6	8	12	10	14	12	18
Material logistics costs	30	45	35	40	50	58	60
Labor cost for building	25	30	25	35	28	42	38
Heavy machines access conditions	10	5	6	8	7	3	2
Local taxes	40	30	35	38	28	54	61
Labor cost	450	500	650	780	900	800	1000
Community services cost	6800	6800	7500	7300	7500	8800	9000
Food market accessibility	3	5	8	6	9	9	10
Food cost	300	280	210	220	480	500	450
Touristic significance of the city	10	8	7	10	6	9	8
Distance from city center	3	1	1	4	3	2	1
Significant tourist attractions within 1 km	9	11	10	8	13	12	15
Significant tourist attractions within 3 km	17	12	10	10	15	18	23
Restaurants within 1 km	9	8	6	7	5	9	8
Distance from international airport	3	6	8	12	6	28	30
Distance from railway station	1	4	1	3	2	1	1
Public transport infrastructure in the area	4	4	6	9	5	10	10
Environmental noise factor	8	10	5	6	5	3	4

This *table* represents the problem definition. Next step is to enter the data into the Multichoice system. This begins with entering all the criteria, their type – quantitative or qualitative and criteria goals – minimizing or maximizing and defining alternatives (*figure 1*). Next step is to define criteria values for each alternative. Multichoice provides separated interfaces for quantitative and qualitative criteria (*figure 2, figure 3*).

When data is ready, the system makes initial alternatives assessment and announces if there are any dominated alternatives. This means alternative that is worse than the others in each criterion. In this case there are no dominated alternatives. The next interface system interface is a choice which method will be used to solve the problem (*figure 4*).

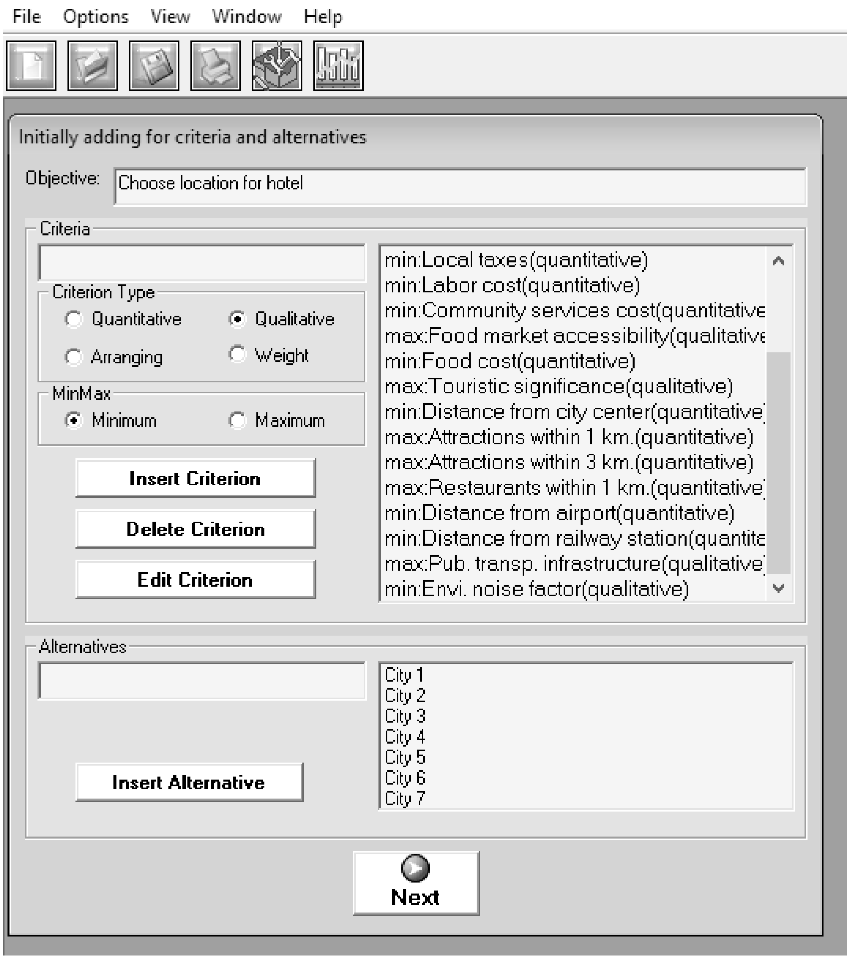

Figure 1. Multichoice – Defining criteria and their type

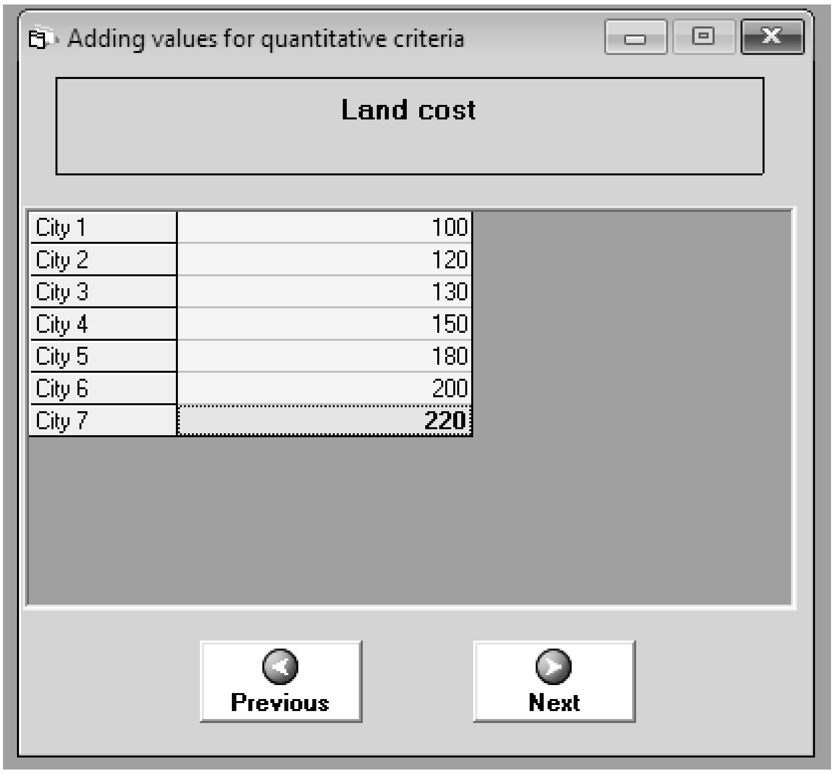

Figure 2. Multichoice – Defining quantitative criteria values

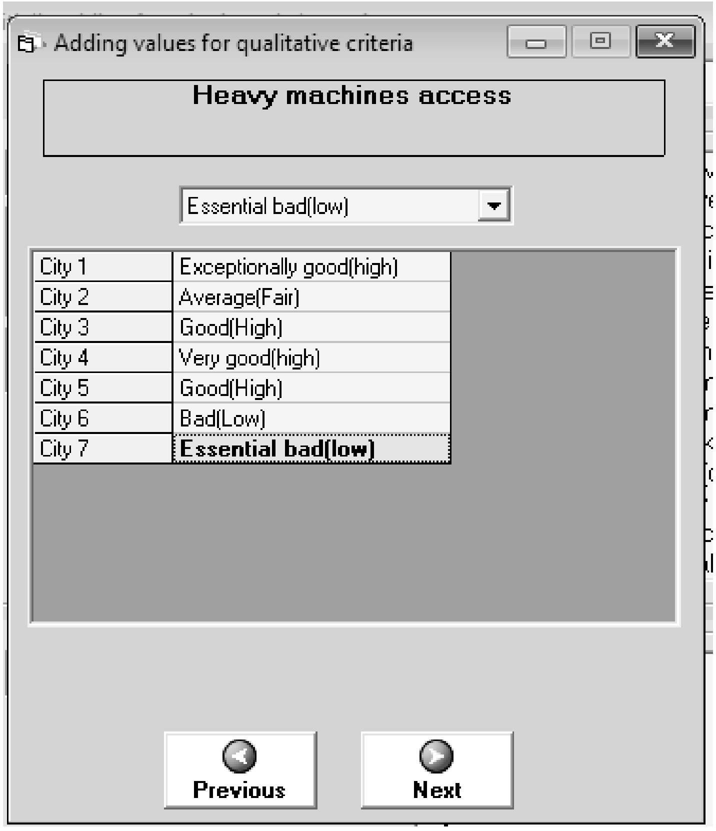

Figure 3. Multichoice – Defining qualitative criteria values

Figure 4. Multichoice – Choosing method for problem solving

Selecting a method for solving a MCDA problem is MCDA problem by itself. This is because several factors should be taken into consideration:

- **The number of criteria.** The reason is that weighting methods usually extract weights by expecting the user to make pairwise comparison of every pair of criteria. When the number of pairs is high this leads to the quality of DM-provided weights and functions to deteriorate due to excessive cognitive load.
- **The number of alternatives.** Some outranking methods use similar pairwise comparison of the alternatives. The comparison is not done manually, but for large problems that can lead to some large computation times.
- **The DM's experience.** Weighting methods for example expect the DM to be familiar only with the concept of weights, which is easy to grasp. In contrast, outranking methods give more expressive power to the DM at the cost that the DM should have prior knowledge about all the parameters at his/her disposal.

As our problems have reasonably small number of criteria and being developers of the system, we are familiar with the required additional information, we chose Promethee II to solve the problem and showcase the decision process with the system.

The additional information that is required by this method includes criteria weights and preference evaluation functions for every criterion. This makes the method a good candidate for solving problems where each criterion is best to be evaluated by different function.

Multichoice has predefined evaluation functions that differ mainly in what thresholds are defined and how significant is the difference in the criteria absolute values (*figure 5*).

For natural reasons, criteria from the first group – initial investments, will have the least criteria weights (1-5). The reason is that these expenses are made just once and don't affect the feature incomes. For the same reason, the criteria from the last group – benefits criteria, will have the highest weights (11-15), because they will make the difference between profit and expenses (second criteria group – maintenance costs (6-10)). The chosen criteria weights, evaluation functions and thresholds are represented in *table 5.*

With this information set, the Promethee II method gives a full order of the alternatives from best to worst (*figure 6*).

4. Conclusion

In today's business environment, managers from all levels have to make everyday decisions, related to multiple choice problems. Solving such problems is not an easy task, especially when it involves many alternatives with many criteria to compare. There are many scientific methods

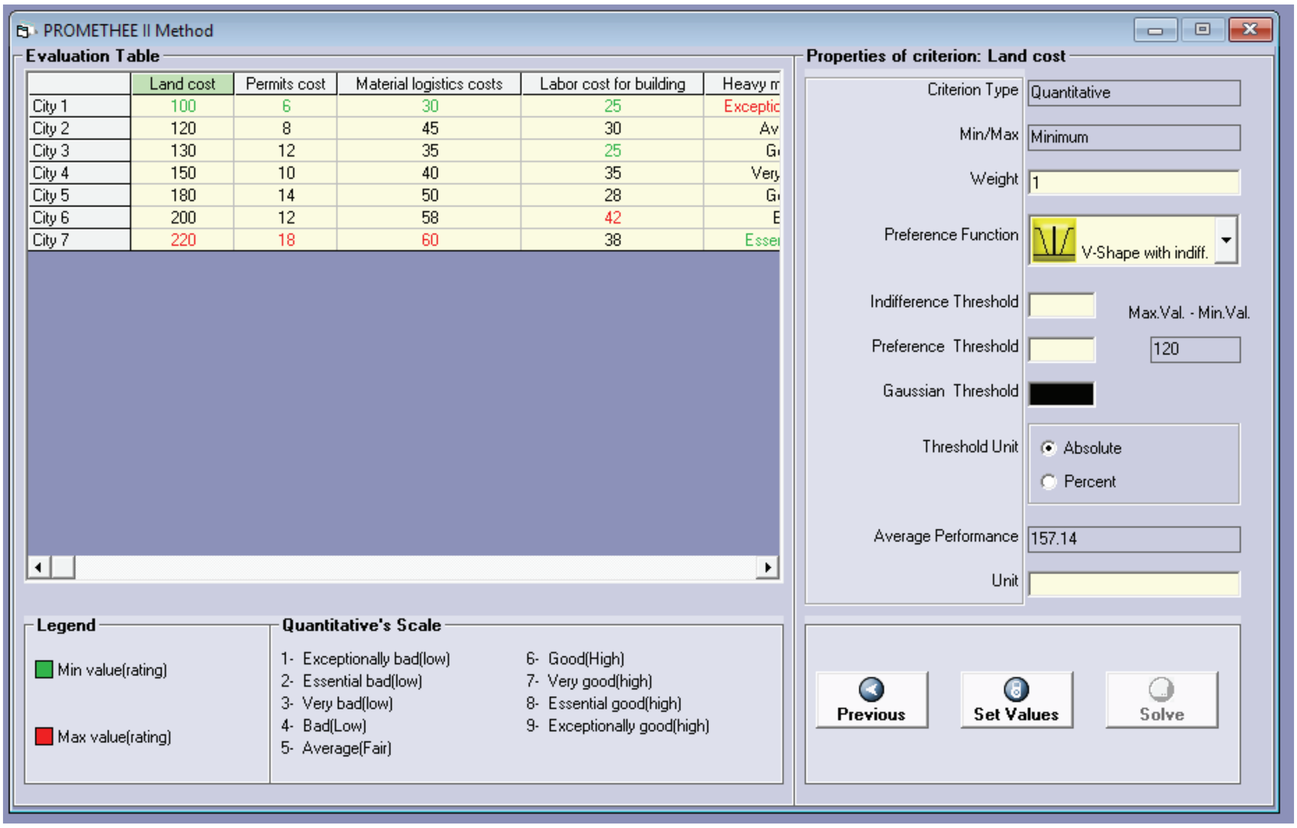

Figure 5. Multichoice – Choosing method for problem solving

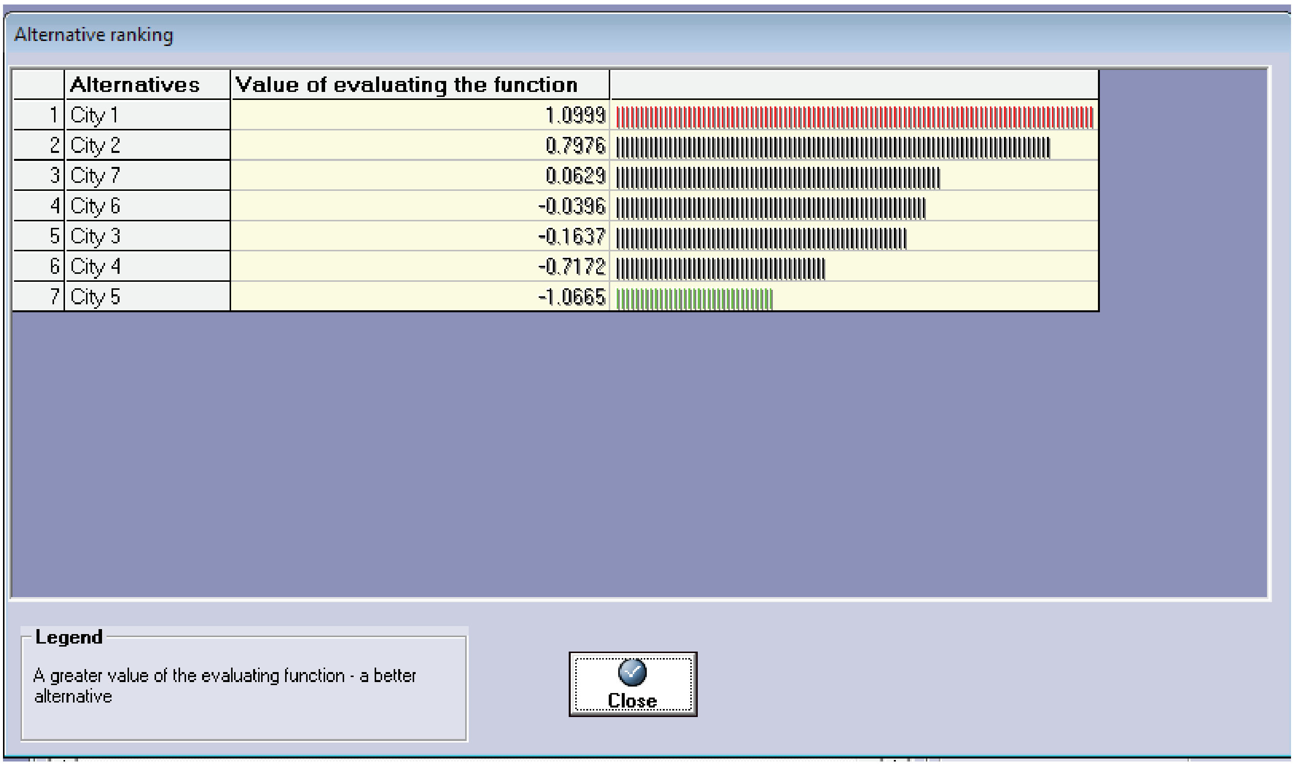

Figure 6. Multichoice – Solution. Full alternatives order

Table 6. Criteria weights and evaluation functions

Land cost	5	U-shape	20		
Permits cost	4	Usual			
Material logistics costs	2	Usual			
Labor cost for building	1	U-shape	5		
Heavy machines access conditions	3	Level (9-point)	2	5	
Local taxes	9	V-shape		10	
Labor cost	10	Gaussian			100
Community services cost	8	Gaussian			1000
Food market accessibility	7	Level (9-point)	2	4	
Food cost	6	Gaussian			50
Touristic significance of the city	14	Usual criterion			
Distance from city center	15	V-shape		1	
Significant tourist attractions within 1 km	13	U-shape	1		
Significant tourist attractions within 3 km	12	U-shape	2		
Restaurants within 1 km	14	U-shape	1		
Distance from international airport	12	V-shape		5	
Distance from railway station	12	V-shape		1	
Public transport infrastructure in the area	11	Level (9-point)	1	2	
Environmental noise factor	10	Level (9-point)	1	2	

that are designed to help decision makers with this process. In order to be practically useful, these methods are implemented by software systems that provide user friendly interface to define problems, enter necessary information and find solutions. These systems are very powerful tools, because they provide not only mathematical and scientific justification of the final decision, but also help decision makers to be more convenient and feel more secure about their choices.

References

1. Alexandrov, A., V. Monov. ZigBee Smart Sensor System with Distributed Data Processing. Proc. of the 7-th IEEE Conference Intelligent Systems, Warsaw, Poland, 24-28 September, 2, 2014, 259-268. Advances in Intelligent Systems and Computing, Springer, 323, ISBN: 978-3-319-11309-8, DOI: 10.1007/978-3-319-11310-4_23.
2. Alexandrov, A., V. Monov. Implementation of a Service Ori-

ented Architecture in Smart Sensor Systems Integration Platform. Proc. of the Third International Conference on Telecommunications and Remote Sensing – ICTRS'14, 26-27 June 2014, Luxembourg, Grand Duchy of Luxembourg, DOI 10.5220/0005422101140120, ISBN 978-989-758-033-8, 114-118.

3. Andonov, F., K. Genova, B. Staykov, M. Vassileva. Software System for Multicriteria Decision Making. Proceedings of International Conference ICEST'2003, Sofia, Bulgaria, 2003, 351-354.

4. Clemen, T. Making Hard Decisions: An Introduction to Decision Analysis, 2nd Edition. Belmont, Duxbury Press, ISBN: 978-0534260347, 1996, 79-96.

5. Collette, Y., P. Siarry. Multiobjective Optimization: Principles and Case Studies. Springer Science & Business Media. ISBN: 3662088835, 2013, 77-98.

6. Dyer, J. MAUT: Multiattribute Utility Theory. Multiple Criteria Decision Analysis: State of the Art Surveys. (J. Figueira, S. Greco, and M. Ehrgott, Eds.), London, Springer Verlag, ISBN 978-0-387-23081-8, 2004, 265-285.

7. Farquhar, P. Utility Assessment Methods. Management Science. ISSN: 0025-1909, 30, 1984, 1283-1300.

8. Genova, K., V. Vassilev, F. Andonov, M. Vassileva, S. Konstantinova. A Multiobjective Analysis Decision Support System. Proceeding CompSysTech'04 – 5th International Conference on Computer Systems and Technologies, ISBN: 954-9641-38-4, 2004, 1-6.

9. Jaszkiewicz, A., R. Slowinski. The LBS-Discrete Interactive Procedure for Multiple Criteria Analysis of Decision Problems. Multiobjective Analysis (J. Climaco, Ed.), Berlin, Springer-Verlag, ISBN: 978-3-642-64500-6, 1997, 320-330.

10. Korhonen, P. A Visual Reference Direction Approach to Solving Discrete Multiple Criteria Problems. European Journal of Operational Research, ISSN: 0377-2217-34, 1988, 152-159.

11. Miettinen, K. On the Methodology of Multiobjective Optimization with Applications. Report 60 (Doctoral Thesis), University of Jyväskylä, Department of Mathematics, Jyväskylä, 1994, 48-56.

12. Roy, B. The Outranking Approach and Foundations of ELECTRE Methods. – *Theory and Decision,* 31, 1991, No. 1, 49-73, ISSN: 0040-5833.

13. Saaty, T. The Analytic Hierarchy Process. New York, McGraw-Hill, ISBN: 978-0070543713, 1980, 181-196.

14. Sawaragi, Y., H. Nakayama, T. Tanino. Theory of Multiobjective Optimization. Elsevier, ISBN: 0080958664, 1985, 72-84.

15. Sierksma, G. Linear and Integer Programming: Theory and Practice. ISBN-0-8241-0673-0, 2001, 189-216.

16. Singiresu, S., S. Rao. Engineering Optimization: Theory and Practice. 4th Edition, ISBN 978-0-470-18352-6, 2009, 124-132.

17. Vincke, P. Multiobjective Decision-Aid. New York, John Wiley & Sons, ISBN: 978-0-471-93184-3, 1992, 112-137.

18. White, D. A Bibliography of the Applications of Mathematical Programming Multiple Objective Methods. – *Journal of the Operational Research Society,* 41, 1990, No. 8, 669-691, ISSN: 0160-5682.

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