Review

COMMENTS ON "MULTIPLE CRITERIA DECISION MAKING (MCDM) METHODS IN ECONOMICS: AN OVERVIEW"

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Abstract. This paper offers comments on a previously published paper, titled "Multiple criteria decision making (MCDM) methods in economics: an overview," by Zavadskas and Turskis (2011). The paper's authors made great efforts to summarize MCDM methods but may have failed to consider several important new concepts and trends in the MCDM field for solving actual problems. First, the traditional model assumes the criteria are independently and hierarchically structured; however, in reality, problems are often characterized by interdependent criteria and dimensions and may even exhibit feedback-like effects. Second, relatively good solutions from the existing alternatives are replaced by aspiration levels to fit today's competitive markets. Third, the emphasis in the field has shifted from ranking and selection when determining the most preferable approaches to performance improvement of existing methods. Fourth, information fusion techniques, including the fuzzy integral method, have been developed to aggregate the performances. Finally, the original fixed resources in multi-objective programming are divided such that both decision and objective spaces are changeable. In this paper, we add new concepts and provide comments that could be thought of as an attempt to complete the original paper.

Keywords: MCDM (Multiple Criteria Decision Making), Interdependence, Information fusion, Non-additive, Changeable space, Economics.

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JEL Classification: C00, C02, C18, C54, C60, C61, D70, D78, O20.

Introduction

Zavadskas and Turskis' (2011) work, titled "Multiple criteria decision making (MCDM) methods in economics: an overview," has made a considerable contribution to the field. These researchers present a panorama of decision making methods in economics, summarizing the most important results and applications over the last five years. These authors present a thorough historical review and classify and illustrate the primary steps of MCDM methods. The authors go on to discuss several opportunities for future research. The methods illustrated were, however, mostly developed in the 1980s and 1990s but have recently been applied to new fields. We feel that important research into new methods and current trends was not adequately addressed in the paper.

For example, a new hybrid dynamic multiple-criteria decision making (HDMCDM) method for problem-solving in interdependent and feedback situations in the fields of economics and business has been proposed (Chen *et al.* 2011; Ho *et al.* 2011). For multiple-objective decision making (MODM) problems, several researchers developed a new changeable space including decision space and objective space (CDOS) method that incorporates many of the realities of a dynamic and changing environment. Tzeng and Huang (2012a) applied the De Novo method of optimization in the objective space, given constraints in the decision space, to determine the aspiration levels for all objectives (Huang, Tzeng 2007). With regard to non-traditional MCDM methods, Greco *et al.* (2010) developed a decision rule approach based on the dominance-based rough set theory. Deb *et al.* (2002, 2011) applied a genetic algorithm to solve MODM problems. In this paper, not only we discuss the Zavadskas and Turskis paper, but also provide more reference material for greater completeness. This supplemental material could help readers understand the complete scope of MCDM and demonstrate the benefits of MCDM in economics and business.

Fig. 1 illustrates the basic concepts of problem solving. Through either data collection or investigation of objectives, the responses and social and personal attributes of the objectives may be represented as a data set (e.g., crisp, fuzzy or rough set). These data can be further analyzed using data processing techniques (e.g., data mining, statistical/multivariate analysis, neural networks or logic reasoning) or forecasting models (e.g., regression, fuzzy regression, grey forecasting or Bayesian regression). The data could also be analyzed using MCDM. MCDM can be roughly separated into MODM (Multi-Objective Decision Making) and MADM (Multi-Attribute Decision Making) components. MODM includes goal programming (GP), multiple objective programming (MOP) and compromise solution methods. These problems can be solved using many methods including single level, fuzzy, multi-stage and dynamic methods. MADM includes structure relation methods (e.g., interpretive structural modeling (ISM), Decision Making Trial and Evaluation Laboratory (DEMATEL) or fuzzy cognitive map), weight analysis (e.g., Analytic Hierarchy Process (AHP), Analytic Network Process (ANP) or entropy measure) and performance aggregated methods (e.g., simple additive weight (SAW), Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), ELECTRE or grey relation for additive types and fuzzy integral for non-additive types). Data envelopment analysis (DEA) is a method to investigate problems with multiple
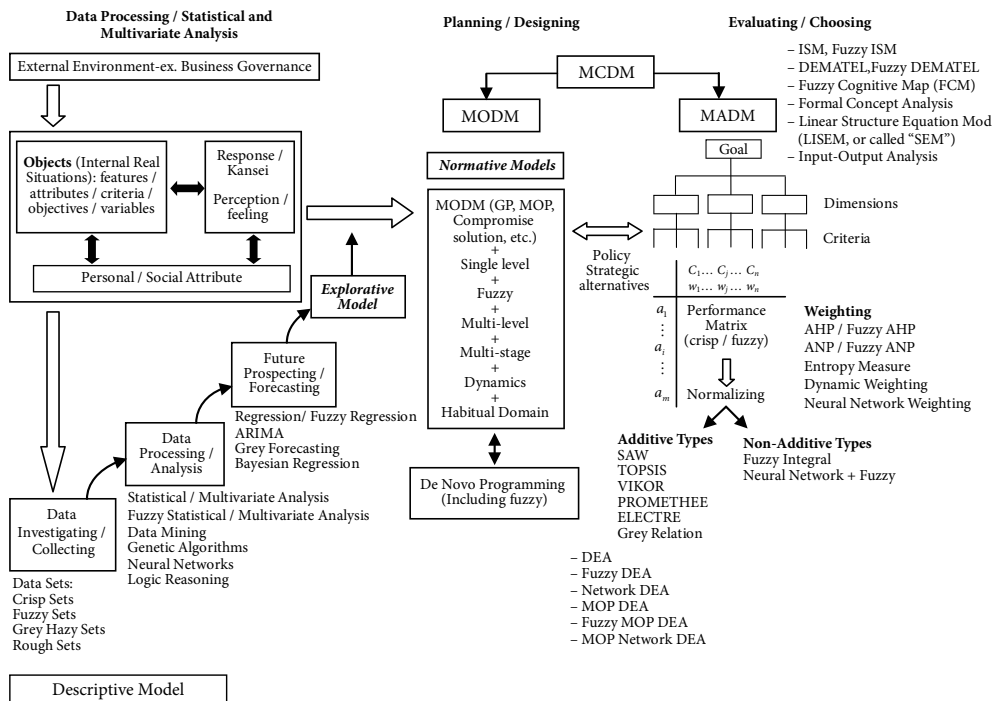
Data Processing / Statistical and Multivariate Analysis

External Environment-ex. Business Governance

Objects (Internal Real Situations): features / attributes / criteria / objectives / variables

Response / Kansei

Perception / feeling

Personal / Social Attribute

Explorative Model

Future Prospecting / Forecasting

Regression/ Fuzzy Regression
ARIMA
Grey Forecasting
Bayesian Regression

Data Processing / Analysis

Data Investigating / Collecting

Statistical / Multivariate Analysis
Fuzzy Statistical / Multivariate Analysis
Data Mining
Genetic Algorithms
Neural Networks
Logic Reasoning

Data Sets:
Crisp Sets
Fuzzy Sets
Grey Hazy Sets
Rough Sets

Descriptive Model

Planning / Designing

MCDM

MODM

MADM

Normative Models

MODM (GP, MOP, Compromise solution, etc.)
+
Single level
+
Fuzzy
+
Multi-level
+
Multi-stage
+
Dynamics
+
Habitual Domain

Policy Strategic alternatives

De Novo Programming (Including fuzzy)

Evaluating / Choosing

– ISM, Fuzzy ISM
– DEMATEL, Fuzzy DEMATEL
– Fuzzy Cognitive Map (FCM)
– Formal Concept Analysis
– Linear Structure Equation Mod (LISEM, or called "SEM")
– Input-Output Analysis

Goal

Dimensions

Criteria

$C_1 \dots C_j \dots C_n$
$w_1 \dots w_j \dots w_n$

a_1
$\vdots$
a_i
$\vdots$
a_m

Performance Matrix (crisp / fuzzy)

Normalizing

Weighting
AHP / Fuzzy AHP
ANP / Fuzzy ANP
Entropy Measure
Dynamic Weighting
Neural Network Weighting

Additive Types
SAW
TOPSIS
VIKOR
PROMETHEE
ELECTRE
Grey Relation

Non-Additive Types
Fuzzy Integral
Neural Network + Fuzzy

– DEA
– Fuzzy DEA
– Network DEA
– MOP DEA
– Fuzzy MOP DEA
– MOP Network DEA

Fig. 1. The basic concepts and framework in research methods for problem-solving

inputs and outputs. DEA is comprised of various methods including fuzzy DEA, network DEA and multi-objective programming (MOP) DEA. Fig. 2 compares the traditional approach with other methods for knowledge economy. Data mining techniques may be used to process the data to support meaningful conclusions and generate useful knowledge. With the current focus on technology in business, two of the most important questions organizations must answer are how to increase market share and how to incorporate new technologies into products. Marketing efforts can be enhanced through knowledge discovering and technology can be improved through innovation and creativity in intelligent systems. MCDM could help decision-makers when faced with multiple-objective or multiple-attribute problems.

The rest of this paper is structured as follows. In Section 2, we provide supplementary material about the development of MCDM and note the differences between Multiple Objective Decision Making (MODM) and Multiple Attribute Decision Making (MADM). Important new concepts and methodologies ignored in Zavadskas and Turskis's (2011) work are discussed in Section 3. We offer concluding arguments in Section 4.

2. Supplementary history and classification of MCDM

MCDM refers to methods for decision making in realistic and common scenarios in which multiple, often conflicting criteria (i.e., multiple attributes or objectives) must be taken into consideration. Many such problems are related to the measurement, design, evalua-
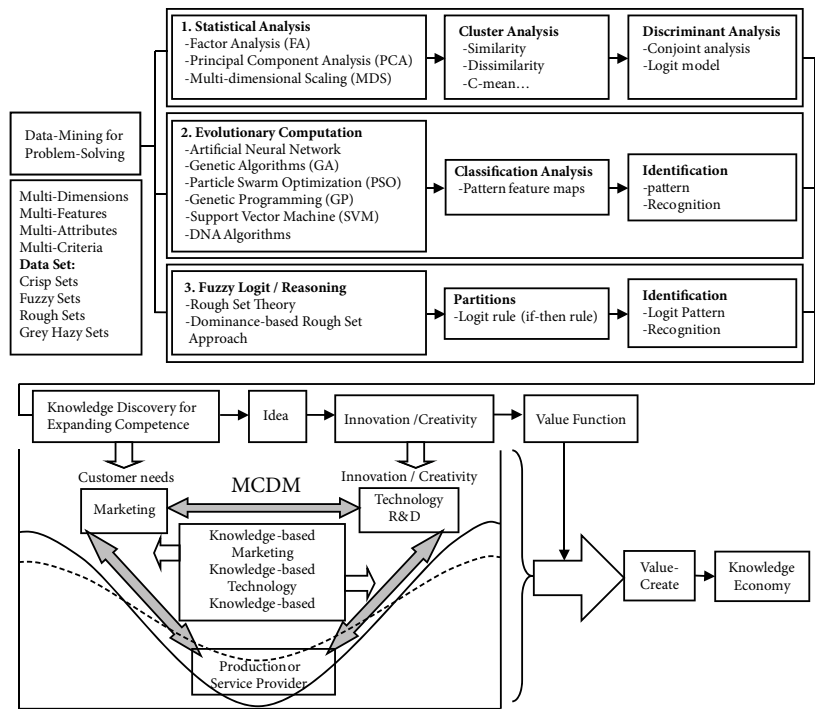
Fig. 2. Data processing for knowledge economy

tion, ranking, selection, and improvement of organizational initiatives. In this study, we will illustrate several important aspects of and new trends in MCDM that have not been adequately addressed.

(1) Planning/Design in MODM (Fig. 3): One of the primary functions of MODM is to analyze planning and design problems with multiple objectives and criteria based on a changeable decision-space in a dynamic environment (as opposed to traditional assumptions of unchangeable constraint conditions) and to bring objectives closer to their aspiration levels. One way to accomplish this is to maximize the extent of goal achievement (this is called fuzzy multi-objective programming and includes fuzzy goals, fuzzy parameters, and fuzzy variables). Alternatively, one may also redesign a decision space to achieve the desired aspiration level. This approach is called De Novo programming and is related to changeable decision-space improvement to achieve the aspiration level in objective-space (concept further explained in Appendix III). This method could be applied both in theory and practice, to real decision-making cases in planning or design, including changeable space (decision space and objective space). In addition to the methods described above, several other important methods have been developed since the 1990s including disaggregation methods (Zopounidis *et al.* 1999), preference programming (Liesiö *et al.* 2007) and stochastic multi-objective acceptability analysis (SMAA) (Kangas *et al.* 2006). The development of MODM is illustrated in Fig. 3. It is worth noting that this list is not exhaustive and is composed of only a few important authors and trends that appeared after the 1990s.
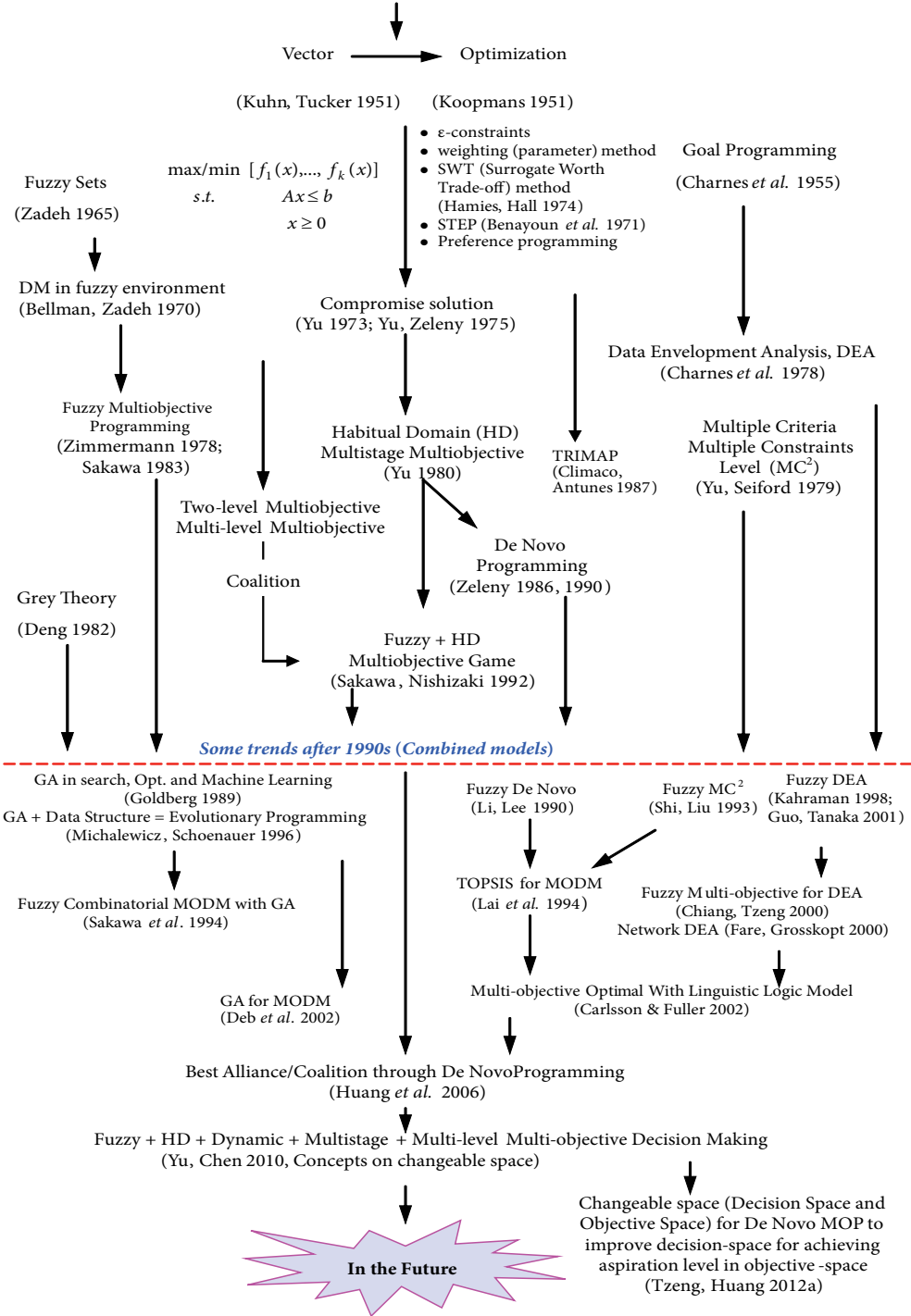
Vector ⟶ Optimization

(Kuhn, Tucker 1951)   (Koopmans 1951)

- ε-constraints
- weighting (parameter) method
- SWT (Surrogate Worth Trade-off) method (Hamies, Hall 1974)
- STEP (Benayoun *et al.* 1971)
- Preference programming

Goal Programming
(Charnes *et al.* 1955)

Fuzzy Sets
(Zadeh 1965)

$$\max/\min \; [f_1(x),..., f_k(x)]$$
$$s.t. \qquad Ax \leq b$$
$$\qquad\qquad x \geq 0$$

DM in fuzzy environment
(Bellman, Zadeh 1970)

Compromise solution
(Yu 1973; Yu, Zeleny 1975)

Data Envelopment Analysis, DEA
(Charnes *et al.* 1978)

Fuzzy Multiobjective Programming
(Zimmermann 1978; Sakawa 1983)

Habitual Domain (HD)
Multistage Multiobjective
(Yu 1980)

TRIMAP
(Climaco, Antunes 1987)

Multiple Criteria
Multiple Constraints
Level (MC^2)
(Yu, Seiford 1979)

Two-level Multiobjective
Multi-level Multiobjective

Coalition

De Novo
Programming
(Zeleny 1986, 1990)

Grey Theory
(Deng 1982)

Fuzzy + HD
Multiobjective Game
(Sakawa, Nishizaki 1992)

Some trends after 1990s (Combined models)

GA in search, Opt. and Machine Learning
(Goldberg 1989)
GA + Data Structure = Evolutionary Programming
(Michalewicz, Schoenauer 1996)

Fuzzy De Novo
(Li, Lee 1990)

Fuzzy MC^2
(Shi, Liu 1993)

Fuzzy DEA
(Kahraman 1998; Guo, Tanaka 2001)

Fuzzy Combinatorial MODM with GA
(Sakawa *et al.* 1994)

TOPSIS for MODM
(Lai *et al.* 1994)

Fuzzy Multi-objective for DEA
(Chiang, Tzeng 2000)
Network DEA (Fare, Grosskopt 2000)

GA for MODM
(Deb *et al.* 2002)

Multi-objective Optimal With Linguistic Logic Model
(Carlsson & Fuller 2002)

Best Alliance/Coalition through De NovoProgramming
(Huang *et al.* 2006)

Fuzzy + HD + Dynamic + Multistage + Multi-level Multi-objective Decision Making
(Yu, Chen 2010, Concepts on changeable space)

In the Future

Changeable space (Decision Space and Objective Space) for De Novo MOP to improve decision-space for achieving aspiration level in objective -space
(Tzeng, Huang 2012a)

Fig. 3. The development of MODM

(2) Evaluation/Improvement/Selection in MADM (Fig. 4): One of the trends within MADM is to analyze gaps between objectives and associated aspiration levels. The Influential Network Relation Map (INRM) could help decision makers understand the relationships among dimensions and criteria and thus enable them to propose sound strategies for improvement. This goal could be accomplished with additive or super-additive (non-additive) strategies based on the DEMATEL technique. A new hybrid MCDM method (Liu *et al.* 2012) has been developed using the DEMATEL technique and DANP (DEMATEL-based ANP, called DANP). Several methods based on the INRM can be used to evaluate problems and enhance aspiration level achievement, including additive (e.g., VIKOR (ViseKriterijumska Optimizacija I KOmpromisno Rešenje in Serbian translates as Multicriteria Optimization and Compromise Solution method) and grey relation method) and non-additive (also referred to as super-additive e.g., Fuzzy Integrals) (Hsu *et al.* 2012) combined MCDM models. The INRM can be derived using a variety of techniques, including DEMATEL (Tzeng *et al.* 2007), Interpretive Structural Modeling (ISM) (Huang *et al.* 2005), Fuzzy Cognitive Map (FCM) (Yu, Tzeng 2006), Structural Equation Modeling (SEM) (Lin *et al.* 2010), and Formal Concept Analysis (FCA) (Fang *et al.* 2012**).** Current MADM-related trends are toward the determination of how to establish strategic systems to reduce the gaps between existing performance values and aspiration levels for each criterion. Additional points of interest include the improvement and selection of the best option for decision making in new theories (e.g., DANP) and the application of these hybrid MADM methods to real problems. Furthermore, new methods, such as COPRAS (Zavadskas *et al.* 2007), MULTIMOORA (Brauers, Zavadskas 2010) and LINMAP (Li 2008) have been developed or extended for solving recent economic problems.

3. Current developments in MCDM

In this section, we will outline several important concepts that were not considered by Zavadskas and Turskis (2011) including (1) interdependent modeling, (2) aspiration levels, (3) improvement (in addition to ranking and selection), (4) information fusion (non-additive models), and (5) changeable space in the decision and objective spaces.

3.1. Interdependence and network structure

Zavadskas and Turskis listed many MCDM methods, but assumed independent criteria in a hierarchical structure (such as additive modeling and weighting by AHP). In reality, the evaluation criteria are seldom independent, and the relationships between them are frequently characterized by a degree of interactivity, interdependence and feedback effects. Saaty (1996) proposed using the Analytic Network Process (ANP), which relaxes the hierarchical structure restriction. However, two questions related to the ANP model warrant attention: how to generate the influential network relationship and how to evaluate the degree of influence (Liou 2012). Tzeng developed a DEMATEL-based ANP (DANP) model that can generate an INRM to consider the various degrees of influence. In this hybrid MCDM model, DEMATEL maps out the network of influences among the various dimensions and criteria to capture the interdependence and feedback dynamics (Tzeng, Huang 2011; Hsu *et al.* 2012). These results
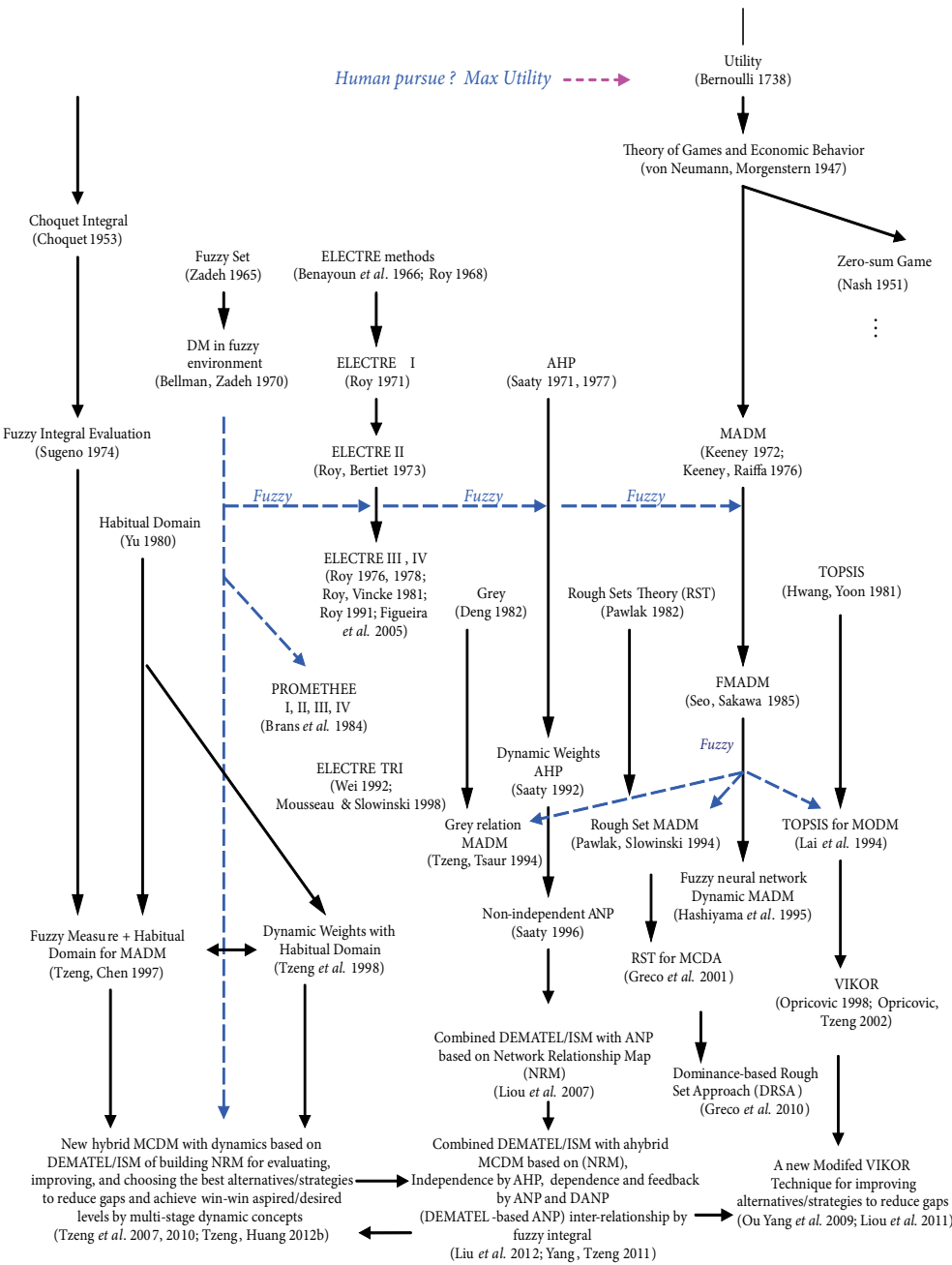
Human pursue ? Max Utility ⤑

Utility
(Bernoulli 1738)

Theory of Games and Economic Behavior
(von Neumann, Morgenstern 1947)

Zero-sum Game
(Nash 1951)

⋮

Choquet Integral
(Choquet 1953)

Fuzzy Set
(Zadeh 1965)

ELECTRE methods
(Benayoun et al. 1966; Roy 1968)

DM in fuzzy environment
(Bellman, Zadeh 1970)

ELECTRE I
(Roy 1971)

AHP
(Saaty 1971, 1977)

MADM
(Keeney 1972;
Keeney, Raiffa 1976)

Fuzzy Integral Evaluation
(Sugeno 1974)

ELECTRE II
(Roy, Bertiet 1973)

Fuzzy   Fuzzy   Fuzzy

Habitual Domain
(Yu 1980)

ELECTRE III , IV
(Roy 1976, 1978;
Roy, Vincke 1981;
Roy 1991; Figueira
et al. 2005)

Grey
(Deng 1982)

Rough Sets Theory (RST)
(Pawlak 1982)

TOPSIS
(Hwang, Yoon 1981)

PROMETHEE
I, II, III, IV
(Brans et al. 1984)

FMADM
(Seo, Sakawa 1985)

ELECTRE TRI
(Wei 1992;
Mousseau & Slowinski 1998)

Dynamic Weights
AHP
(Saaty 1992)

Fuzzy

Grey relation
MADM
(Tzeng, Tsaur 1994)

Rough Set MADM
(Pawlak, Slowinski 1994)

TOPSIS for MODM
(Lai et al. 1994)

Fuzzy Measure + Habitual
Domain for MADM
(Tzeng, Chen 1997)

Dynamic Weights with
Habitual Domain
(Tzeng et al. 1998)

Non-independent ANP
(Saaty 1996)

Fuzzy neural network
Dynamic MADM
(Hashiyama et al. 1995)

RST for MCDA
(Greco et al. 2001)

VIKOR
(Opricovic 1998; Opricovic,
Tzeng 2002)

Combined DEMATEL/ISM with ANP
based on Network Relationship Map
(NRM)
(Liou et al. 2007)

Dominance-based Rough
Set Approach (DRSA)
(Greco et al. 2010)

New hybrid MCDM with dynamics based on
DEMATEL/ISM of building NRM for evaluating,
improving, and choosing the best alternatives/strategies
to reduce gaps and achieve win-win aspired/desired
levels by multi-stage dynamic concepts
(Tzeng et al. 2007, 2010; Tzeng, Huang 2012b)

Combined DEMATEL/ISM with ahybrid
MCDM based on (NRM),
Independence by AHP, dependence and feedback
by ANP and DANP
(DEMATEL -based ANP) inter-relationship by
fuzzy integral
(Liu et al. 2012; Yang , Tzeng 2011)

A new Modifed VIKOR
Technique for improving
alternatives/strategies to reduce gaps
(Ou Yang et al. 2009; Liou et al. 2011)

Fig. 4. The development of MADM

are subsequently incorporated into the traditional ANP to create the new DANP method that yields more realistic weights for the respective dimensions and criteria. These weights could also be combined with other MCDM methods, such as additive types of VIKOR (Kuan *et al.* 2012), the grey relation (Liou *et al.* 2012) or non-additive types of fuzzy integrals (Larbani *et al.* 2011), to evaluate the performance criteria of various options and the extent to which the option achieve the desired aspiration level.

3.2. Replacement of the relatively good existing alternatives by aspiration levels

The traditional MADM ranks alternatives to select the best solution. However, Simon, who was awarded the Nobel Prize in economics in 1978, claimed that decision making does not obey the postulates of the "rational man." Humans do not solve problems by maximizing utility, but are "satisfiers" who set aspiration levels that a solution must satisfy. If humans are able to identify a solution that satisfies the stated aspiration levels, they accept the solution. A metaphor can be used to illustrate this difference. In the traditional method (which focuses only on ranking alternatives and selecting the overall best among them), we could pick one apple to be the benchmark from a basket of inferior apples; the benchmark is still an inferior apple. With the new concept, the decision maker sets an aspiration level as the benchmark, an alternative which might not exist in the current basket of apples, but decision-makers will understand the gaps between each alternative and the aspiration level. Decision-makers can therefore devise and implement a strategy to reduce the gaps. The current trend is toward improvement of the traditional decision-making concept, which is to choose the best from among inferior choices. The new concept is that decision makers should set an aspiration level as the benchmark and change the process to avoid this problem (Chen, Tzeng 2011; Liu *et al.* 2012).

3.3. Improving but not ranking alternatives

The development of MCDM has shifted the focus from ranking and selecting alternatives to improving their performance. The old models can only identify the gaps between competing alternatives. A new trend is to reduce the gap to achieve an aspiration level in a more realistic strategy. For example, if measures for scaling the performance value are from zero to ten (0, 1, 2,…, 10), we can set zero (0) to be the worst value and ten (10) to be the aspiration level. We can thus examine alternatives to reduce the gap based on an influential network relation map. This newly developed model helps decision-makers realize the gaps between current performance and aspiration levels and enhances competitiveness. Several researchers have proposed an improvement technique to lessen the gaps for each criterion obtained from VIKOR (Ou Yang *et al.* 2009). This technique is based on an influential relation map created by DEMATEL which is used to reduce gaps between current performance and aspiration levels. This approach can improve the traditional decision-making basic concept for alternatives ranking and selection only. It should be noted that another notably popular MCDM model, TOPSIS, has proven shortcomings with regard to ranking alternatives (Opricovic, Tzeng 2004).

3.4. Information fusion techniques

Many methods based on multiple attribute utility theory (MAUT) have been proposed (e.g., the weighted sum and the weighted product methods in an additive model) to deal with MADM problems. The concept of MAUT is to aggregate all criteria to a specific dimension (the utility function) to evaluate alternatives. The main issue is to find a rational and suitable aggregation operator that represents the decision maker's preferences. Although the aggregation operator of MAUT has often been discussed (Fishburn 1970), the primary remaining challenge is the assumption of preferential independence (Hillier 2001; Grabisch 1995).

Preferential independence can be described as the preferential outcome of one criterion over another that is not influenced by the remaining criteria. However, in practical MADM application, the criteria are sometimes interactive. For example, in supplier selection, the cost, risk and quality are often interdependent. To overcome the problem of non-additivity, the Choquet integral was proposed (Choquet 1953; Sugeno 1974). The Choquet integral can represent a certain kind of interaction between criteria using the concept of redundancy and synergy and has been applied in many fields (Liou, Tzeng 2007; Chu *et al.* 2007). Another fusion approach can be seen in Peng *et al.* (2011a, 2011b).

3.5. Changeable decision space

In the original iteration of the MODM, it was assumed that the decision space was fixed and that the decision-maker can only choose solutions from an existing region. Zeleny (1986, 1990) proposed De Novo programming to redesign the feasible region to maximize the achievement levels of objectives to ideal solutions or aspiration levels (concept described in more detail in Appendix III). Tzeng applied the De Novo method of optimization in the objective space given constraints in the decision space (relaxing assumptions) to achieve the aspiration levels for all objectives (Huang *et al.* 2006). Tzeng also focused on applications of the new hybrid dynamic multiple-criteria decision making (HDMCDM) and changeable space, including decision space and objective space (CDOS) methods, in a wide range of industries in the fields of economics and business as a way to solve practical problems in management, create value in innovation and increase win-win competitiveness. The new concept is illustrated in Fig. 5. The traditional method looks for a solution from the Pareto solutions in the existing feasible decision space. De Novo programming pursues the ideal solution and redesigns the original decision space. The new concept has decision makers setting an aspiration level, though it may not be reachable using current resources, or simply redesigning the decision space. However, the aspiration level could be attained by expanding employees' competence set (e.g., training) or adding or changing new resources (e.g., through strategy alliance, innovation or creativity) to expand the original decision space.
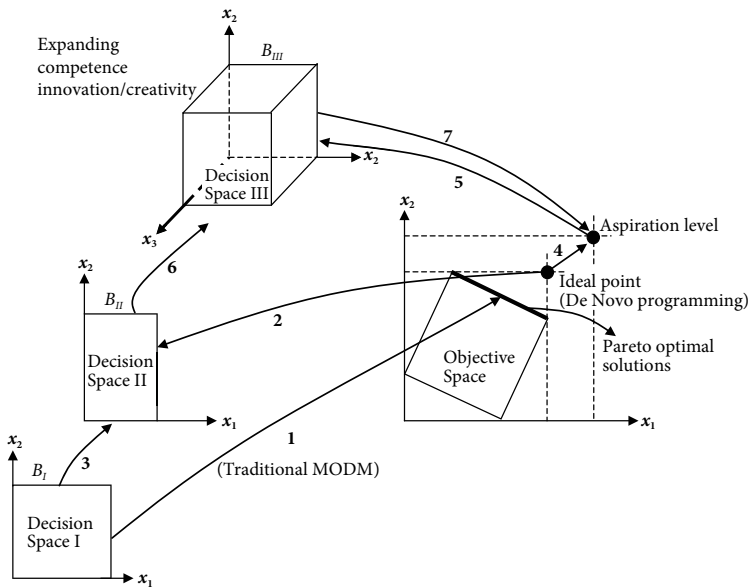
Fig. 5. The concepts of changeable decision space and aspiration level

4. Conclusions

This paper discusses several important concepts that were not addressed in Zavadskas and Turskis' (2011) work. We provide a historical review of MCDM with supplementary material and note several of the key authors in each stage (see Figs 3 and 4). Several significant concepts, such as building interrelationships (dependence and feedback) among criteria and improvement of criteria in general to achieve the aspiration level, are introduced. We also offer some techniques to integrate performance (information fusion) in super-additive/non-additive value function situations. Finally, we present ways in which the decision space may be modified to achieve aspiration level of the objective space in changeable space situations. These concepts are designed to solve real problems encountered using traditional methods. This supplemental paper can be viewed as a companion to the original work and could contribute to a more comprehensive understanding of the MCDM framework and enhance the available set of techniques available for economic problem solving.

In addition to identifying new trends in MCDM, we illustrate the future outlook. The current MCDM methods depend on a decision-maker or a group of decision-makers, which group could be replaced by all stakeholders. Comparisons between statistical methods (regression or structural equation modeling (SEM)) and MCDM techniques are welcome. Future research could include the examination of more effective ways, e.g., linguistic variables or fuzzy logic, to reflect decision-makers opinions combined with new MCDM techniques.

References

Bellman, R. E.; Zadeh, L. A. 1970. Decision-making in a fuzzy environment, *Management Science* 17(4): 141–164. http://dx.doi.org/10.1287/mnsc.17.4.B141

Benayoun, R.; Roy, B.; Sussman, B. 1966. *ELECTRE: Use method pour guider le choix en presence de points devue multiple*, Direction Scientifique. Working Paper.

Benayoun, R.; de Montgolfier, J.; Tergny, J.; Laritchev, O. 1971. Linear programming with multiple objective functions: step method (STEM), *Mathematical Programming* 1(1): 366–375. http://dx.doi.org/10.1007/BF01584098

Bernoulli, D. 1738. Specimen Theoriae Novae de Mensura Sortis, St. Pertersburg. (Cited in *The economics of uncertainty*, in K. Borch. *Econometric Research Program Research Memorandum* No. 54, 1963)

Brans, J. P.; Marechal, B.; Vincke, P. 1984. *PROMETHEE: A new family of outranking methods in multicriteria analysis, Operational Research*, IFORS'84, North Holland, 477–490.

Brauers, W. K. M.; Zavadskas, E. K. 2010. Project management by MULTIMOORA as an instrument for transition economies, *Technological and Economic Development of Economy* 16(1): 5–24. http://dx.doi.org/10.3846/tede.2010.01

Carlsson, C.; Fuller, R. 2002. *Fuzzy reasoning in decision making and optimization*. Physica-Verlag, a Springer-Verlag Company.

Charnes, A.; Cooper, W. W.; Ferguson, R. 1955. Optimal estimation of executive compensation by linear programming, *Management Science* 1(2): 138–151. http://dx.doi.org/10.1287/mnsc.1.2.138

Charnes, A. ; Cooper, W. W.; Rhodes, E. 1978. Measuring the efficiency of decision units, *European Journal of Operational Research* 2(4): 429–444. http://dx.doi.org/10.1016/0377-2217(78)90138-8

Chen, C. H.; Tzeng, G. H. 2011. Creating the aspired intelligent assessment systems for teaching materials, *Expert Systems with Applications* 38(10): 12168–12179. http://dx.doi.org/10.1016/j.eswa.2011.03.050

Chen, F. H.; Hsu, T. S.; Tzeng, G. H. 2011. A balanced scorecard approach to establish a performance evaluation and relationship model for hot spring hotels based on a hybrid MCDM model combining DEMATEL and ANP, *International Journal of Hospitality Management* 30(4): 908–932. http://dx.doi.org/10.1016/j.ijhm.2011.02.001

Chiang, C. I.; Tzeng, G. H. 2000. A multiple objective programming approach to Data envelopment analysis, in Shi, Y.; Zeleny, M. (Eds.). *New Frontiers of Decision Making for the Information Technology Era*. World Science Publishing Company, 270–285.

Choquet, G. 1953. Theory of capacities, *Annales de L'Institut Fourier* 5(1): 131–295.

Chu, M. T.; Shyu, J. Z.; Tzeng, G. H. 2007. Using non-additive fuzzy integral to assess performances of organization transformation via communities of practice, *IEEE Transactions on Engineering Management* 54(2): 327–339. http://dx.doi.org/10.1109/TEM.2007.893987

Climaco, J.; Antunes, C. 1987. TRIMAP – An interactive tricriteria linear programming package, *Foundations of Control Engineering* 12(3): 101–119.

Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T. 2002. A fast and elitist multi-objective genetic algorithm: NSGA-II, *IEEE Transactions on Evolutionary Computation* 6(2): 182–187. http://dx.doi.org/10.1109/4235.996017

Deb, K.; Steuer, R. E.; Tewari, R.; Tewari, R. 2011. Bi-objective portfolio optimization using a customized hybrid NSGA-II procedure, *Evolutionary Multi-criterion Optimization*, in Takahashi, R. H. C., *et al.* (Eds.). EMO, LNCS 6576, 358–373.

Deng, J. L. 1982. Control problems of grey systems, *Systems & Control Letters* 1(5): 288–294. http://dx.doi.org/10.1016/S0167-6911(82)80025-X

Fang, S. K.; Shyng, J. Y.; Lee, W. S.; Tzeng, G. H. 2012. Combined data mining techniques for exploring the preference of customers between financial companies and agents based on TCA, *Knowledge-Based Systems* 27(1): 137–151. http://dx.doi.org/10.1016/j.knosys.2011.09.003

Fare, R.; Grosskopt, S. 2000. Network DEA, *Socio-Ecominic Planning Sciences* 34(1): 35–49. http://dx.doi.org/10.1016/S0038-0121(99)00012-9

Fishburn, P. C. 1970. *Utility theory for decision making*, New York: Wiley.

Figueira, J.; Mousseau, V.; Roy, B. 2005. Multiple criteria decision analysis: state of the art surveys, *International Series in Operations Research & Management Science* 78(3): 133–153. http://dx.doi.org/10.1007/0-387-23081-5_4

Goldberg, D. E. 1989. *Genetic Algorithms in Search, Optimization, and Machine Learning*, USA: Addison-Wesley.

Grabisch, M. 1995. Fuzzy integral in multicriteria decision making, *Fuzzy Sets and Systems* 69(3): 279–298. http://dx.doi.org/10.1016/0165-0114(94)00174-6

Greco, S.; Matarazzo, B.; Slowinski, R. 2001. Rough sets theory for multicriteria decision analysis, *European Journal of Operational Research* 129(1): 1–47.

Greco, S.; Matarazzo, B.; Słowiński, R. 2010. Dominance-based rough set approach to decision under uncertainty and time preference, *Annals of Operations Research* 176(1): 41–75. http://dx.doi.org/10.1016/S0377-2217(00)00167-3

Guo, P.; Tanaka, H. 2001. Fuzzy DEA: a perceptual evaluation method, *Fuzzy Sets and Systems* 119(1): 149–161. http://dx.doi.org/10.1016/S0165-0114(99)00106-2

Haimes, Y. Y.; Hall, W. A. 1974. Multiobjectives in water resource systems analysis: the surrogate worth trade off method, *Water Resource Research* (10)4: 615–624. http://dx.doi.org/10.1029/WR010i004p00615

Hashiyama, T.; Furuhashi, T.; Uchikawa, Y. 1995. A study on varying degrees of attention in multi-attribute decision making processes, *Journal of Japan Society for Fuzzy Theory and Systems* 7(4): 826–838.

Hillier, F. S. 2001. *Evaluation and decision models: a critical perspective*. Boston: Kluwer.

Ho, W. R. J.; Tsai, C. L.; Tzeng, G. H.; Fang, S. K. 2011. Combined DEMATEL technique with a novel MCDM model for exploring portfolio selection based on CAPM, *Expert Systems with Applications* 38(1): 16–25. http://dx.doi.org/10.1016/j.eswa.2010.05.058

Hsu, C. H.; Wang, F. K.; Tzeng, G. H. 2012. The best vendor selection for conducting the recycled material based on a hybrid MCDM model combining DANP with VIKOR. *Resources*, *Conservation & Recycling* (Forthcoming). http://dx.doi.org/10.1016/j.resconrec.2012.02.009

Huang, C. Y.; Tzeng, G. H. 2007. Post-merger high technology R&D human resources optimization through the De Novo perspective, in Shi, Y.; Olson, D. L.; Stam, A. (Eds.). *Advances in Multiple Criteria Decision Making and Human Systems Management: Knowledge and Wisdom,* IOS Press, 47–64.

Huang, J. J.; Tzeng, G. H.; Ong, C. S. 2005. Multidimensional data in multidimensional scaling using the analytic network process, *Pattern Recognition Letters* 26(6): 755–767. http://dx.doi.org/10.1016/j.patrec.2004.09.027

Huang, J. J.; Tzeng, G. H.; Ong, C. S. 2006. Choosing best alliance partners and allocating optimal alliance resources using the fuzzy multi-objective dummy programming model, *Journal of Operational Research Society* 57(10): 1216–1223. http://dx.doi.org/10.1057/palgrave.jors.2602108

Hwang, C. L.; Yoon, K. 1981. *Multiple Attribute Decision Making: Methods and Applications, Lecture Notes in Economics and Mathematical Systems*, New York, Berlin: Springer-Verlag. http://dx.doi.org/10.1007/978-3-642-48318-9

Kahraman, C. 1998. Data envelopment analysis using fuzzy concept, in *The 28th IEEE International Symposium on Multiple-Value Logic,* Fukuoka, Japan, 338–343.

Kangas, A.; Kangas, J.; Lahdelma, R.; Salminen, P. 2006. Using SMAA-2 method with dependent uncertainties for strategic forest planning, *Forest Policy and Economics* 9(2): 113–125. http://dx.doi.org/10.1016/j.forpol.2005.03.012

Keeney, R. L. 1972. Utility functions for multiattributed consequences, *Management Science* 18(5): 276–287. http://dx.doi.org/10.1287/mnsc.18.5.276

Keeney, R. L.; Raiffa, H. 1976. *Decision with multiple objectives: Preferences and value tradeoffs*. New York: John Wiley and Sons.

Koopmans, T. C. 1951. Analysis of production as an efficient combination of activities, in Koopmans, T. C. (Ed.). *Activity Analysis of Production and Allocation*, Cowles Comm. Monogr., 13, New York: John Wiley, 33–97.

Kuan, M. J.; Tzeng, G. H.; Hsiang, C. C. 2012. Exploring the quality assessment system for new product development process by combining DANP with MCDM model, *International Journal of Innovative Computing, Information and Control* (Special issue), (Forthcoming).

Kuhn, H. W.; Tucker, A. W. 1951. Nonlinear programming, in *Proceedings of the second Berkeley Symposium on Mathematical Statistics and Probability*, 481–492.

Lai, Y. J.; Liu, T. Y.; Hwang, C. L. 1994. TOPSIS for MODM, *European Journal of Operational Research* 76(3): 486–500. http://dx.doi.org/10.1016/0377-2217(94)90282-8

Larbani, M.; Huang, C. Y.; Tzeng, G. H. 2011. A novel method for fuzzy measure identification, *International Journal of Fuzzy Systems* 13(1): 24–34.

Li, D. F. 2008. Extension of the LINMAP for multiattribute decision making under Atanassov's intuitionistic fuzzy environment, *Fuzzy Optimization and Decision Making* 7(1): 17–34. http://dx.doi.org/10.1007/s10700-007-9022-x

Li, R. J.; Lee, E. S. 1990. Fuzzy approaches to multicriteria De Novo programs, *Journal of Mathematical Analysis and Applications* 153(1): 13–20. http://dx.doi.org/10.1016/0022-247X(90)90268-K

Liesiö, J.; Mild, P.; Salo, A. 2007. Preference programming for robust portfolio modeling and project selection, *European Journal of Operational Research* 181(3): 1488–1505. http://dx.doi.org/10.1016/j.ejor.2005.12.041

Lin, C. S.; Tzeng, G. H.; Chin, Y. C.; Chang, C. C. 2010. Recommendation sources on the intention to use e-books in academic digital libraries, *The Electronic Library* 28(6): 844–857. http://dx.doi.org/10.1108/02640471011093534

Liou, J. J. H. 2012. Developing an integrated model for the selection of strategic alliance partners in the airline industry, *Knowledge-Based Systems* 28(1): 59–67. http://dx.doi.org/10.1016/j.knosys.2011.11.019

Liou, J. J. H.; Tzeng, G. H. 2007. A non-additive model for evaluating airline service quality, *Journal of Air Transport Management* 13(3): 131–138. http://dx.doi.org/10.1016/j.jairtraman.2006.12.002

Liou, J. J. H.; Tsai, C. Y.; Lin, R. H.; Tzeng, G. H. 2011. A modified VIKOR multiple-criteria decision method for improving domestic airlines service quality, *Journal of Air Transport Management* 17(2): 57–61. http://dx.doi.org/10.1016/j.jairtraman.2010.03.004

Liou, J. J. H.; Tzeng, G. H.; Chang, H. C. 2007. Airline safety measurement using a hybrid model, *Journal of Air Transport Management* 13(4): 243–49. http://dx.doi.org/10.1016/j.jairtraman.2007.04.008

Liou, J. J. H.; Tzeng, G. H.; Hsu, C. C.; Yeh, W. C. 2012. Reply to "Comment on using a modified grey relation method for improving airline service quality", *Tourism Management* 33(3): 719–720. http://dx.doi.org/10.1016/j.tourman.2011.07.007

Liu, C. H.; Tzeng, G. H.; Lee, M. H. 2012. Improving tourism policy implementation - the use of hybrid MCDM models, *Tourism Management* 33(2): 239–488. http://dx.doi.org/10.1016/j.tourman.2011.05.002

Michalewicz, Z.; Schoenauer, M. 1996. Evolutionary algorithms for constrained parameter optimization problems, *Evolutionary Computation* 4(1): 1–32. http://dx.doi.org/10.1162/evco.1996.4.1.1

Mousseau, V; Slowinski, R. 1998. Inferring an ELECTRE TRI model from assignment examples, *Journal of Global Optimization* 12(12): 157–174. http://dx.doi.org/10.1023/A:1008210427517

Nash, J. 1951. Non-cooperative game, *The Annals of Mathematics* 54(2): 286–295. http://dx.doi.org/10.2307/1969529

Opricovic, S. 1998. *Multicriteria optimization of civil engineering systems*. Belgrade: Faculty of Civil Engineering (in Serbian).

Opricovic, S.; Tzeng, G. H. 2002. Multicriteria planning of post-earthquake sustainable reconstruction, *Computer-Aided Civil and Infrastructure Engineering* 17(3): 211–220. http://dx.doi.org/10.1111/1467-8667.00269

Opricovic, S.; Tzeng, G. H. 2004. Compromise solution by MCDM Methods: a comparative analysis of VIKOR and TOPSIS, *European Journal of Operational Research* 156(2): 445–455. http://dx.doi.org/10.1016/S0377-2217(03)00020-1

Opricovic, S.; Tzeng, G. H. 2007. Extended VIKOR method in comparison with outranking methods, *European Journal of Operational Research* 178(2): 514–529. http://dx.doi.org/10.1016/j.ejor.2006.01.020

Ou Yang, Y. P.; Shieh, H. M.; Tzeng, G. H. 2009. A VIKOR-based multiple criteria decision method for improving information security risk, *International Journal of Information Technology and Decision Making* 8(2): 267–287. http://dx.doi.org/10.1142/S0219622009003375

Pawlak, Z. 1982. Rough sets, *International Journal of Computer and Information Science* 11(5): 341–356. http://dx.doi.org/10.1007/BF01001956

Pawlak, Z.; Stowinski, R. 1994. Rough set approach to multi-attribute decision analysis, *European Journal of Operational Research* 72(3): 443–459. http://dx.doi.org/10.1016/0377-2217(94)90415-4

Peng, Y.; Kou, G.; Wang, G.; Shi, Y. 2011a. FAMCDM: a fusion approach of MCDM methods to rank multiclass classification algorithms, *Omega* 39(6): 677–689. http://dx.doi.org/10.1016/j.omega.2011.01.009

Peng, Y.; Kou, G.; Wang, G.; Wu, W.; Shi, Y. 2011b. Ensemble of software defect predictors: an AHP-based evaluation method, *International Journal of Information Technology & Decision Making* 10(1): 187–206. http://dx.doi.org/10.1142/S0219622011004282

Roy, B. 1968. Classement et choix en presence de points de vue multiples (la methode Electre), *Revue Francaise d'Informatique et de Recherche Operationnelle* 8(1): 57–75.

Roy, B. 1971. Problems and methods with multiple objective functions, *Mathematical Programming* 1(1): 239–266. http://dx.doi.org/10.1007/BF01584088

Roy, B.; Bertier, P. 1973. La méthode ELECTRE II - Une application aumedia-planning, in Ross, M. (Ed.). OR 72: 291–302, North Holland, Amsterdam.

Roy, B. 1976. From optimization to multicriteria decision aid: three main operational attitudes, in Thiriez, H.; Zionts, S. (Eds.). *Multiple Criteria Decision Making, vol. 130 of Lecture Notes in Economics and Mathematical Systems,* Berlin: Springer-Verlag, 1–34.

Roy, B. 1978. ELECTRE III: Un algorithme de classements fondé sur une représentation floue des préférences en présence de critéres multiples, *Cahiers du Centre d'Etudes de Recherche Opérationnelle* 20: 3–24.

Roy, B.; Vincke, Ph. 1981. Multicriteria analysis: survey and new directions, *European Journal of Operational Research* 8(3): 207–218. http://dx.doi.org/10.1016/0377-2217(81)90168-5

Roy, B. 1991. The outranking approach and the foundations of Electre methods, *Theory and Decision* 31(1): 49–73. http://dx.doi.org/10.1007/BF00134132

Saaty, T. 1971. On polynomials and crossing numbers of complete graphs, *Journal of Combinatorial Theory* 10(2): 183–184. http://dx.doi.org/10.1016/0097-3165(71)90024-0

Saaty, T. 1977. A scaling method for priorities in hierarchical structures, *Journal of Mathematical Psychology* 15(3): 234–281. http://dx.doi.org/10.1016/0022-2496(77)90033-5

Saaty, T. 1992. A natural way to make momentous decisions, *Journal of Science and Industrial Research* 51: 561–571.

Saaty, T. L. 1996. *Decision making with dependence and feedback: analytic network process*, Pittsburgh: RWS.

Sakawa, M. 1983. Interactive computer programs for fuzzy linear programming with multiple objectives, *International Journal of Man-Machine Studies* 18(5): 489–503. http://dx.doi.org/10.1016/S0020-7373(83)80022-4

Sakawa, M.; Nishizaki, I. 1992. A solution concept based on fuzzy decision in n-person cooperative games, in Trappl, R. (Ed.). *Cybernetics and Systems Research'92*, World Scientific Publishing, 423–430.

Sakawa, M.; Inuiguchi, M.; Sunada, H.; Sawada, K. 1994. Fuzzy multiobjective combinatorial optimization through revised genetic algorithms, *Japanese Journal of Fuzzy Theory and Systems* 6(1): 177–186.

Seo, F; Sakawa, M. 1985. Fuzzy multiattribute utility analysis for collective choice, *IEEE Transactions on Systems, Man, & Cybernetics* 15(1): 45–53. http://dx.doi.org/10.1109/TSMC.1985.6313393

Shi, Y.; Liu, Y. H. 1993. Fuzzy potential solutions in multi-criteria and multi-constraint levels linear programming problems, *Fuzzy Sets and Systems* 60(2): 163–179. http://dx.doi.org/10.1016/0165-0114(93)90344-H

Sugeno, M. 1974. *Theory of fuzzy integrals and its applications*: Ph.D. thesis. Tokyo Institute of Technology, Tokyo, Japan.

Tzeng, G. H.; Chen, T. Y.; Wang, J. C. 1998. A weight-assessing method with habitual domains, *European Journal of Operational Research* 110(2): 342–367. http://dx.doi.org/10.1016/S0377-2217(97)00246-4

Tzeng, G. H.; Chiang, C. H.; Li, C. W. 2007. Evaluating intertwined effects in e-learning programs: a novel hybrid MCDM model based on factor analysis and DEMATEL, *Expert Systems with Applications* 32(4): 1028–1044. http://dx.doi.org/10.1016/j.eswa.2006.02.004

Tzeng, G. H.; Chen, J. J.; 1997. Developing Taipei automobile driving cycles for emissions, *Energy & Environment* 8(3): 227–238.

Tzeng, G. H.; Chen, W. H.; Yu, R.; Shih, M. L. 2010. Fuzzy decision maps- a generalization of the DEMATEL methods, *Soft Computing* 14(11): 1141–1150. http://dx.doi.org/10.1007/s00500-009-0507-0

Tzeng, G. H.; Huang, J. J. 2011. *Multiple Attribute Decision Making: Methods and Applications*, CRC Press, Taylor & Francis Group, a Chapman & Hall Book.

Tzeng, G. H.; Huang, J. J. 2012a. *Multiple Objective Decision Making: Methods and Applications*, CRC Press, Taylor & Francis Group, a Chapman & Hall Book.

Tzeng, G. H.; Huang, C. Y. 2012b. Combined DEMATEL technique with hybrid MCDM methods for creating the aspired intelligent global manufacturing & logistics systems, *Annals of Operations Research* (Forthcoming). http://dx.doi.org/10.1007/s10479-010-0829-4

Tzeng, G. H.; Tasur, S. H. 1994. The multiple criteria evaluation of grey relation model, *The Journal of Grey System* 6(2): 87–108.

Von Neumann, J.; Morgenstern, O. 1947. *The Theory of Games and Economic Behavior*, 2nd ed. Princeton, NJ.: Princeton University Press.

Wei, Y. 1992. *Methodological aspects and a user's guide of the computer program*, Report NO. LAMSADE-D -92-74, University of Paris-Dauphine, Lamsade, France.

Yang, J. L.; Tzeng, G. H. 2011. An integrated MCDM technique combined with DEMATEL for a novel cluster-weighted with ANP method, *Expert Systems with Applications* 38(3): 1417–1424. http://dx.doi.org/10.1016/j.eswa.2010.07.048

Yu, P. L. 1973. A class of solutions for group decision problems, *Management Science* 19(8): 136–946. http://dx.doi.org/10.1287/mnsc.19.8.936

Yu, P. L. 1980. Behavior bases and habitual domains of human decision/behavior: concepts and applications, in Fandel, G.; Gal, T. (Eds.). *Multiple Criteria Decision-Making: Theory and Applications*, New York: Springer-Verlag, 11–539. http://dx.doi.org/10.1007/978-3-642-48782-8_34

Yu, P. L.; Chen, Y. C. 2010. Dynamic multiple criteria decision making in changeable spaces: from habitual domains to innovation dynamics, *Annals of Operations Research* (Forthcoming). http://dx.doi.org/10.1007/s10479-010-0750-x

Yu, P. L.; Seiford, L. 1979. Potential solutions of linear systems: the multicriteria, multiple constraint level program, *Journal of Mathematical Analysis and Applications* 69(2): 283–303. http://dx.doi.org/10.1016/0022-247X(79)90143-4

Yu, P. L.; Zeleny, M. 1975. The set of all nondominated solutions in linear cases and a multicriteria simplex method, *Journal of Mathematical Analysis and Applications* 49(2): 430–468. http://dx.doi.org/10.1016/0022-247X(75)90189-4

Yu, R. C.; Tzeng, G. H. 2006. A soft computing method for multi-criteria decision making with dependence and feedback, *Applied Mathematics and Computation* 180(1): 63–75. http://dx.doi.org/10.1016/j.amc.2005.11.163

Zadeh, L. 1965. Fuzzy sets, *Information and Control* 8(3): 338–53. http://dx.doi.org/10.1016/S0019-9958(65)90241-X

Zavadskas, E. K.; Kaklauskas, A.; Peldschus, F.; Turskis, Z. 2007. Multi-attribute assessment of road design solutions by using the COPRAS method, *Baltic Journal of Road and Bridge Engineering* 2(4): 195–203.

Zavadskas, E. K.; Turskis, Z. 2011. Multiple criteria decision making (MCDM) methods in economics: an overview, *Technological and Economic Development of Economy* 17(2): 397–427. http://dx.doi.org/10.3846/20294913.2011.593291

Zeleny, M. 1986. Optimal system design with multiple criteria: de novo programming approach, *Engineering Costs and Production Economics* 10(1): 89–95. http://dx.doi.org/10.1016/0167-188X(86)90029-7

Zeleny, M. 1990. Optimizing given systems vs. designing optimal systems: the De Novo programming approach, *International Journal of General Systems* 17(3): 295–307. http://dx.doi.org/10.1080/03081079008935113

Zimmermann, H. J. 1978. Fuzzy programming and linear programming with several objective functions, *Fuzzy Sets and Systems* 1(1): 45–55. http://dx.doi.org/10.1016/0165-0114(78)90031-3

Zopounidis, C.; Doumpos, M.; Zanakis, S. H. 1999. Stock evaluation using a preference disaggregation methodology, *Decision Sciences* 30(2): 313–336. http://dx.doi.org/10.1111/j.1540-5915.1999.tb01612.x

APPENDIX I.

An example of the DEMATEL method for building influential network relation maps

If a manager wanted to understand the network relationship between evaluating attributes and developing strategies for the reduction of gaps between the aspiration levels of a company and its suppliers (such as the VIKOR method), he or she could use the DEMATEL method. The DEMATEL method reveals the total and net degrees of influence of attributes. The INRM can provide ideas for improvement. The steps in the DEMATEL method and INRM can be summarized as follows:

Step 1. Calculate the direct relation average matrix.

Respondents are asked to propose the degree of direct influence each perspective or criterion i exerts on each perspective/criterion j, which is denoted by d_{ij}, using a scale such that 0, 1, 2, 3 and 4 represent the range from "no influence" (0) to "very high influence" (4).

A direct relation matrix is produced for each respondent, and an average matrix A is subsequently derived from the mean of the same perspectives and criteria in the respective direct matrices for all respondents. The average matrix A is given by:

$$
A = \begin{bmatrix}
a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\
\vdots & & \vdots & & \vdots \\
a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\
\vdots & & \vdots & & \vdots \\
a_{n1} & \cdots & a_{nj} & \cdots & a_{nn}
\end{bmatrix} .
\tag{A1}
$$

Step 2. Calculate the initial direct influence matrix.

The initial direct influence matrix X can be obtained by normalizing the average matrix A. In addition, the matrix X can be obtained through equations (2) and (3), in which all principal diagonal criteria are equal to zero.

$$
X = s \cdot A
\tag{A2}
$$

$$
s = \min \left\{ \frac{1}{\max_i \sum_{j=1}^{n} |d_{ij}|}, \frac{1}{\max_j \sum_{i=1}^{n} |d_{ij}|} \right\} .
\tag{A3}
$$

Step 1: Derive the total influence matrix

A continuous decrease of the indirect effects of problems along the powers of X, e.g., $X^2, X^3, ..., X^h$ and $\lim_{h \to \infty} X^h = [0]_{n \times n}$, where $X = [x_{ij}]_{n \times n}$, $0 \le x_{ij} < 1$, $0 < \sum_i x_{ij} \le 1$, $0 < \sum_j x_{ij} \le 1$ and at least one column sum $\sum_j x_{ij}$ or one row sum $\sum_i x_{ij}$ equals 1. The total influence matrix T is

$$
T = X + X^2 + ... + X^h = X(I - X)^{-1} , \text{ when } \lim_{h \to \infty} X^h = [0]_{n \times n} ,
\tag{A4}
$$

where $T = [t_{ij}]_{n \times n}$, for $i, j = 1, 2, ..., n$ and $(I - X)(I - X)^{-1} = I$. Additionally, this method presents each row sum and column sum of influential matrix $T = [t_{ij}]_{n \times n}$ separately, expressed as vector r and vector s through the Eqs. (5) – (6):

$$
r = (r_i)_{n \times 1} = [\sum_{j=1}^{n} t_{ij}]_{n \times 1} ,
\tag{A5}
$$

$$
s = (s_j)_{n \times 1} = (s_j)'_{1 \times n} = [\sum_{i=1}^{n} t_{ij}]'_{1 \times n} ,
\tag{A6}
$$

where the superscript $'$ denotes transpose; ri denotes the row sum of the ith row of matrix T and shows the sum of the direct and indirect effects of perspective or criterion i on the other perspectives and criteria. Similarly, s_j denotes the column sum of the jth column of matrix T and shows the sum of direct and indirect effects that perspective or criterion j has received from the other perspectives and criteria. In addition, when $i = j$ (i.e., the sum of the row and column aggregates) $r_i + s_i$ provides an index of the strength of influence given and received, that is, $r_i + s_i$ illustrates the extent to which criterion i plays a central role in

the problem. If $r_i - s_i$ is positive, then criterion *i* affects other criteria, and if $r_i - s_i$ is negative, then criterion *i* is influenced by other criteria. Based on the total influence matrix, the INRM can be draw as Fig. A1.
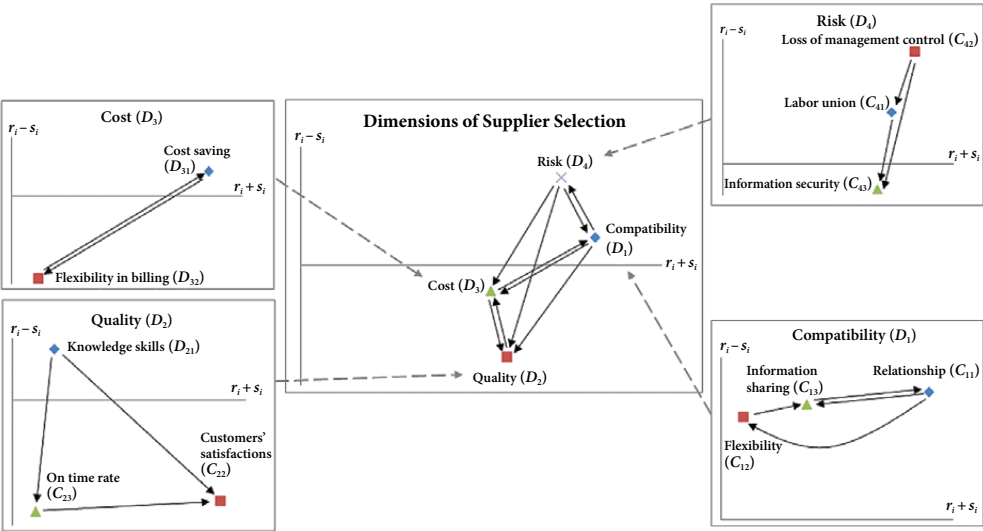

Fig. A1. Influential network relationship map for supplier selection

APPENDIX II.

VIKOR method for reducing performance gaps to improve the alternatives

Opricovic and Tzeng (2004) proposed the compromise ranking method (VIKOR) as one applicable technique to implement within MCDM. Suppose that the feasible alternatives are represented by $V_1, V_2, \ldots, V_k, \ldots, V_m$. The performance scores of alternative V_k and the *j*th criterion is denoted by f_{kj}. w_j is the influential weight (relative importance) of the *j*th criterion, where $j = 1, 2, \ldots, n$ and *n* is the number of criteria. Development of the VIKOR method began with the following form of the L_p-metric:

$$L_k^p = \left\{ \sum_{j=1}^{n} [w_j (|f_j^* - f_{kj}|) / (|f_j^* - f_j^-|)]^p \right\}^{1/p} , \tag{A7}$$

where $1 \le p \le \infty$; $k = 1, 2, \ldots, m$ and influential weight w_j is derived from the DANP. $L_k^{p=1}$ (as S_k) and $L_k^{p=\infty}$ (as Q_k) are used by the VIKOR method to formulate the ranking and gap measures.

$$S_k = L_k^{p=1} = \sum_{j=1}^{n} [w_j (|f_j^* - f_{kj}|) / (|f_j^* - f_j^-|)], \tag{A8}$$

$$Q_k = L_k^{p=\infty} = \max_j \left\{ (|f_j^* - f_{kj}|) / (|f_j^* - f_j^-|) \big| j = 1, 2, \ldots, n \right\}. \tag{A9}$$

The compromise solution $\min_k L_k^p$ showed the synthesized gap to be minimized, and it will be selected such that its value will be the closest to the aspiration level. In addition, the group utility is emphasized when p is small (such as $p = 1$). If, however, p approaches infinity, the individual maximum regrets/gaps obtain more importance in prior improvement in each dimension/criterion. Consequently, $\min_k S_k$ stresses the maximum group utility; however, $\min_k Q_k$ stresses the selection of the minimum and maximum individual regrets/gaps for a demonstrated improvement of priority. The compromise-ranking algorithm VIKOR has four steps according to the abovementioned factors:

Obtain an aspiration or tolerable level. We calculated the best f_j^* values (aspiration level) and the worst f_j^- values (tolerable level) of all criterion functions, $j = 1, 2,…, n$. Suppose the jth function denotes benefits: $f_j^* = \max_k f_{kj}$ and $f_j^- = \min_k f_{kj}$ (these values can also be set by decision makers) i.e., f_j^* is the aspiration level and f_j^- is the worst value. In this research, we use the performance scores from 0 to 10 (very bad ←0, 1, 2,…, 9, 10→very good) in questionnaires; therefore, the aspiration level can be set at a score of 10 and the worst value at a score of zero. Therefore, in this research and contrary to traditional research, we set $f_j^* = 10$ as the aspiration level and $f_j^- = 0$ as the worst value. This approach avoids the problems associated with choosing the best among inferior choices (i.e., avoids picking the best apple from a barrel of rotten apples). The steps can be thought of as follows:

Step 1: First, an original rating matrix can be converted into a normalized weight-rating matrix with the following equation.

$$r_{kj} = \left(\left|f_j^* - f_{kj}\right|\right) / \left(\left|f_j^* - f_j^-\right|\right). \tag{A10}$$

Step 2: Calculate the group utility mean and maximum regret. The values can be computed using $S_k = \sum_{j=1}^{n} w_j r_{kj}$ (the average synthesized gap for all criteria) and $Q_k = \max_j \{r_{kj} | j = 1, 2,…, n\}$ (the maximum gap in k criterion for priority improvement) respectively.

Step 3: Calculate the index value using Eq. (A11).

$$R_k = v(S_k - S^*) / (S^- - S^*) + (1-v)(Q_k - Q^*) / (Q^- - Q^*), \tag{A11}$$

where $k = 1, 2,…, m$, $S^* = \min_i S_i$ or $S^* = 0$ (when all criteria have been achieved to the aspiration level) and $S^- = \max_i S_i$ or $S^- = 1$ (the worst situation); $Q^* = \min_i Q_i$ or setting $Q^* = 0$ and $Q^- = \max_i Q_i$ or setting $Q^- = 1$, and v is presented as the weight of the strategy of the maximum group utility (priority improvement). Conversely, $1- v$ is the weight of individual regret. Therefore, we can rewrite $R_k = vS_k + (1-v)Q_k$, when $S^* = 0$, $S^- = 1$, $Q^* = 0$ and $Q^- = 1$.

APPENDIX III.

Extension of De Novo programming to changeable spaces for an MOP problem

Multi-objective programming (MOP) problems can mathematically be represented as

$$\max\left[f_1(\boldsymbol{x}), f_2(\boldsymbol{x}),..., f_k(\boldsymbol{x}) \right] \Rightarrow \text{Objective space}$$

$$s.t. \quad \begin{aligned} \boldsymbol{Ax} &\le \boldsymbol{b} \\ \boldsymbol{x} &\ge \boldsymbol{0} \end{aligned} \quad \Rightarrow \quad \text{Decision space,} \quad \begin{cases} \boldsymbol{p'Ax} \le \boldsymbol{p'b} = \boldsymbol{B} \\ \boldsymbol{x} \ge \boldsymbol{0} \end{cases}$$

where $\boldsymbol{p}$ denotes a vector of unit prices of resources. The superscript $'$ denotes transpose.

Traditional MOP problems find the objective space subject to the decision space, which assumes that the decision space cannot be changed. We developed new "changeable spaces" method to relax these assumptions for MOP problems based on De Novo programming (Zeleny 1986, 1990).

$$\min \boldsymbol{cx}$$

$$s.t. \quad f_i(\boldsymbol{x}) \ge f_i^*, \ i = 1, 2,..., k \ \text{(or setting } f_i^* \text{ to be an aspiration level)}$$

$$\boldsymbol{x} \ge \boldsymbol{0} ,$$

where vector $\boldsymbol{c} = \boldsymbol{p'A}$ denotes unit prices of decision variables, and f_i^* denotes the ideal point of objective i (we also can set f_i^* to be an aspiration level).

[Example]

Graph Example

max f₁ …… profit

max f₂ …… quality

Reshaping the feasible set to include the missing "*Good*" alternative

Given design with natural quality – profit trade-offs as follows:
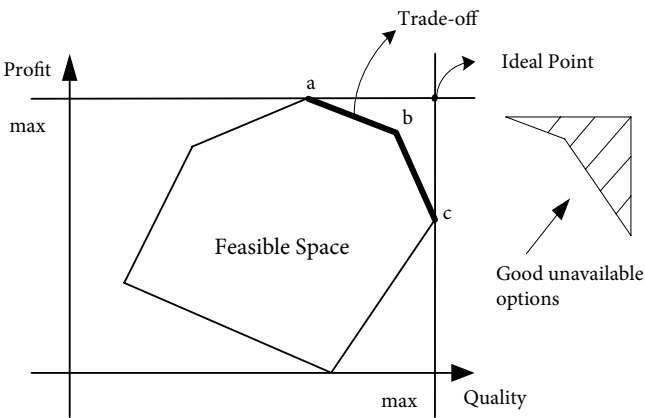

Fig. A2. Graphic example of De Novo programming

– A simple production problem involving two products: suits and dresses in quantities x_1 and x_2, with each of them consuming five different resources (unit market prices of resources are given).

According to De Novo programming, the Maximum levels of two products can be calculated by mathematical programming:

Profit: max $f_1(x_1, x_2) = 400x_1 + 300x_2$

Quality: max $f_2(x_1, x_2) = 6x_1 + 8x_2$

$$\text{s.t. } \begin{aligned} 4x_1 &\leq 20 \\ 2x_1 + 6x_2 &\leq 24 \\ 12x_1 + 4x_2 &\leq 60 \\ 3x_2 &\leq 10.5 \\ 4x_1 + 4x_2 &\geq 26 \\ x_1, x_2 &\geq 0 \end{aligned} \Rightarrow \begin{bmatrix} 4 & 0 \\ 2 & 6 \\ 12 & 4 \\ 0 & 3 \\ 4 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq \begin{bmatrix} 20 \\ 24 \\ 60 \\ 10.5 \\ 26 \end{bmatrix}, \left(\begin{aligned} \text{s.t. } \quad & \boldsymbol{Ax} \leq \boldsymbol{b} \\ & x_1, x_2 \geq 0 \end{aligned} \right)$$

The data are summarized as follows:

Unit price $	Resources (Raw material)	Technological coefficients (Resource Requirement)		No. of units (Resource portfolio)
		x_1	x_2	
30	Nylon	4	0	20
40	Velvet	2	6	24
9.5	Silver thread	12	4	60
20	Silk	0	3	10.5
10	Golden thread	4	4	26

– The costs of the given resources portfolio:

$(30 \times 20) + (40 \times 24) + (9.5 \times 60) + (20 \times 10.5) + (10 \times 26) = \$2600$

– Unit costs of producing one unit of each of the two products:

$x_1 : (30 \times 4) + (40 \times 2) + (9.5 \times 12) + (20 \times 0) + (10 \times 4) = \$354$

$x_2 : (30 \times 0) + (40 \times 6) + (9.5 \times 4) + (20 \times 3) + (10 \times 4) = \$378$

Ideal point as follows.

– Maximum $f_1(x_1, x_2)$ in profit:

$f_1(x_1, x_2)$ max $f_1(x_1, x_2) = 400x_1 + 300x_2$

s.t. $\boldsymbol{Ax} \leq \boldsymbol{b}$

$x_1, x_2 \geq 0$

Answer: $x_1 = 4.25, x_2 = 2.25;$ $f_1^* = 400 \times 4.25 + 300 \times 2.25 = \$2375$

– Maximum $f_2(x_1, x_2)$ in total quality index

$$\max f_2(x_1, x_2) = 6x_1 + 8x_2$$
$$s.t. \quad Ax \le b$$
$$x_1, x_2 \ge 0$$

Answer: $x_1 = 3.75, x_2 = 2.75$; $f_2^* = 6 \times 3.75 + 8 \times 2.75 = \$44.5$

Multi-objective programming:

$$\max \{f_1(x), ..., f_i(x), ..., f_k(x)\}$$

$$s.t. \quad Ax \le b \qquad s.t. \quad p'Ax \le p'b \qquad s.t. \quad c'x \le B$$
$$x \ge 0 \quad \Rightarrow \qquad x \ge 0 \quad \Rightarrow \qquad x \ge 0 \quad ,$$

where vector p denotes vector unit price of each resource; vector $c' = p'A$ denotes "product unit cost", B denotes budget.

De Novo programming:

$$\min cx$$
$$f_i(x) \ge f_i^*, \quad i = 1, 2, ..., k$$
$$x \ge 0$$

Example:

$$\min cx = 354x_1 + 378x_2$$
$$s.t. \quad f_1(x_1, x_2) = 400x_1 + 300x_2 \ge 2375$$
$$f_2(x_1, x_2) = 6x_1 + 8x_2 \ge 44.5$$
$$x_1, x_2 \ge 0$$

– Maximum $f_1(x_1, x_2)$ in profit equal \$2375:

Answer: $x_1 = 4.03, x_2 = 2.54$; $f_1^* = 400 \times 4.03 + 300 \times 2.54 = \$2375$

– Maximum $f_2(x_1, x_2)$ in total quality index:

Answer: $x_1 = 4.03, x_2 = 2.54$; $f_2^* = 6 \times 4.03 + 8 \times 2.54 = \$44.5$

– Cost of the newly designed system:

Answer: $(30 \times 16.12) + (40 \times 23.3) + (9.5 \times 58.52) + (20 \times 7.62) + (10 \times 26.28) = \$2386.74$

The data are summarized as follows:

Unit price $	Resources (Raw material)	Technological coefficients (Resource Requirement)		No. of units (Resource portfolio)
		x_1	x_2	Original New design
30	Nylon	4	0	20 > 16.12
40	Velvet	2	6	24 > 23.3
9.5	Silver thread	12	4	60 > 58.52
20	Silk	0	3	10.5 > 7.62
10	Golden thread	4	4	26 < 26.28

Toward a MCDM New Era – Professor Tzeng's Roadmap

Philosophy **Taking True Responsibility,** **Creating Added Value, and** **Making Contribution through MCDM Knowledge to Global Society**

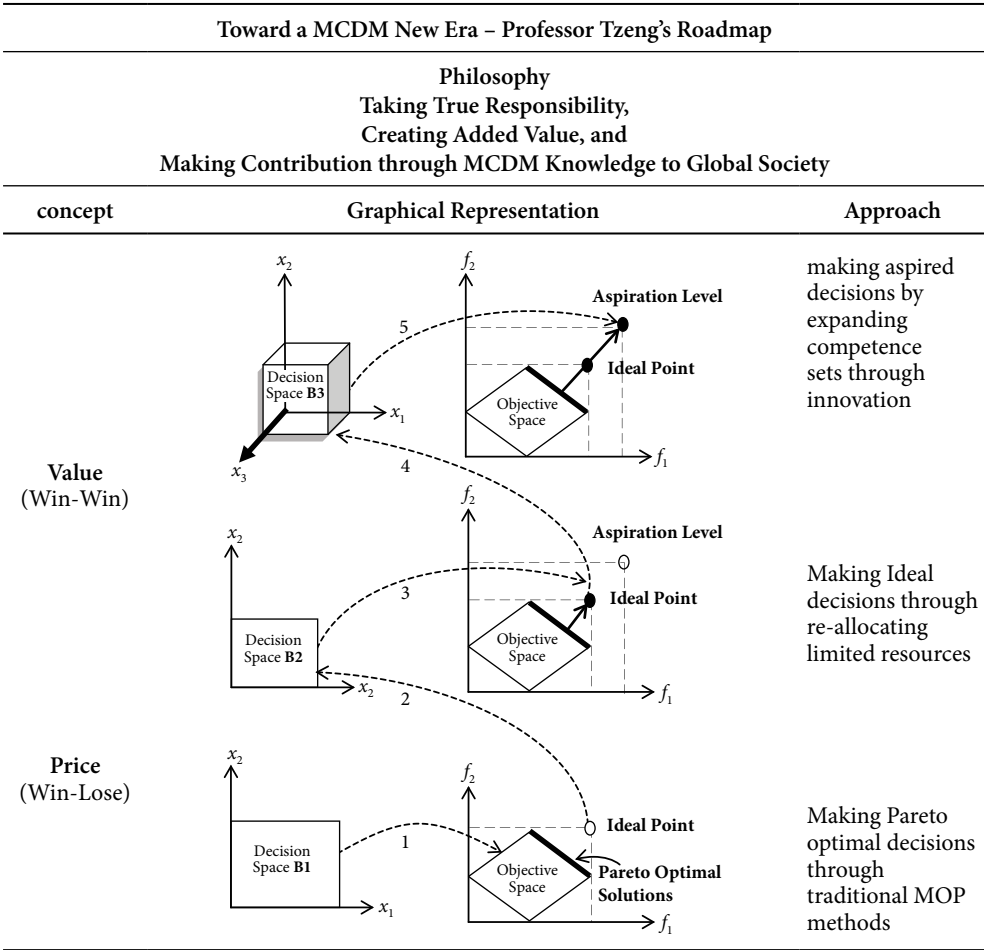| concept	Graphical Representation	Approach
Value (Win-Win)		making aspired decisions by expanding competence sets through innovation
		Making Ideal decisions through re-allocating limited resources
Price (Win-Lose)		Making Pareto optimal decisions through traditional MOP methods

Fig. A3. Extension of changeable decision space and aspiration level

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He has got the MCDM Edgeworth-Pareto Award from the International Society on Multiple Criteria Decision Making (June 2009), has got the Pinnacle of Achievement Award 2005 of the world, and had got the National Distinguished Chair Professor and Award (highest honor offered) of the Ministry of Education Affairs of Taiwan and three times of distinguished research award and two times of distinguished research fellow (highest honor offered) of National Science Council of Taiwan. Fellow IEEE Member (from September 30, 2002). He organized a Taiwan affiliate chapter of the International Association of Energy Economics in 1984 and he was the Chairman of the Tenth international Conference on Multiple Criteria Decision Making, July 19–24, 1992, in Taipei; the Co-Chairman of the 36th International Conference on Computers and Industrial Engineering, June 20–23, 2006, Taipei, Taiwan; the Chairman of the International Summer School on Multiple Criteria Decision Making 2006, July 2–14, Kainan University, Taiwan. He is a member of IEEE, IAEE, ISMCDM, World Transport, the Operations Research Society of Japan, the Society of Instrument and Control Engineers Society of Japan, the City Planning Institute of Japan, the Behaviormetric Society of Japan, the Japan Society for Fuzzy Theory and Systems; and participating many Society of Taiwan. He is editors-in-Chief of International Journal of Information Systems for Logistics and Management, and so on.