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.

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
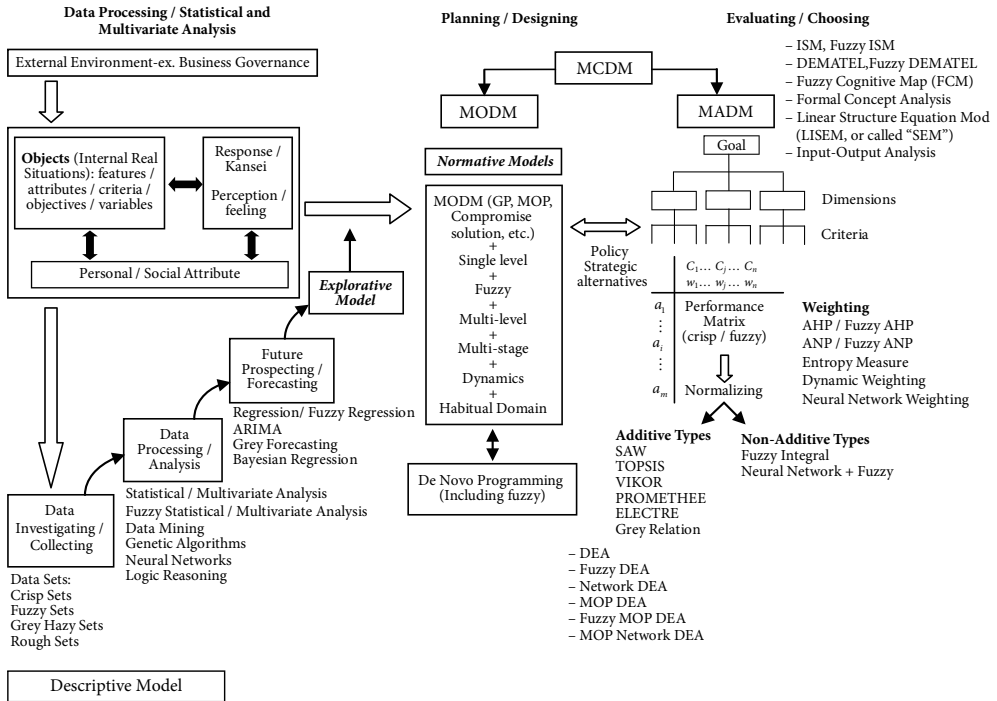
Data Processing / Statistical and Multivariate Analysis

Planning / Designing

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

External Environment-ex. Business Governance

MCDM

MODM — MADM

Goal

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

Response / Kansei

Perception / feeling

Personal / Social Attribute

Explorative Model

Normative Models

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

Policy Strategic alternatives

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

Future Prospecting / Forecasting

Regression/ Fuzzy Regression
ARIMA
Grey Forecasting
Bayesian Regression

Data Processing / Analysis

De Novo Programming (Including fuzzy)

Additive Types
SAW
TOPSIS
VIKOR
PROMETHEE
ELECTRE
Grey Relation

Non-Additive Types
Fuzzy Integral
Neural Network + Fuzzy

Data Investigating / Collecting

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

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

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

Descriptive Model

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-
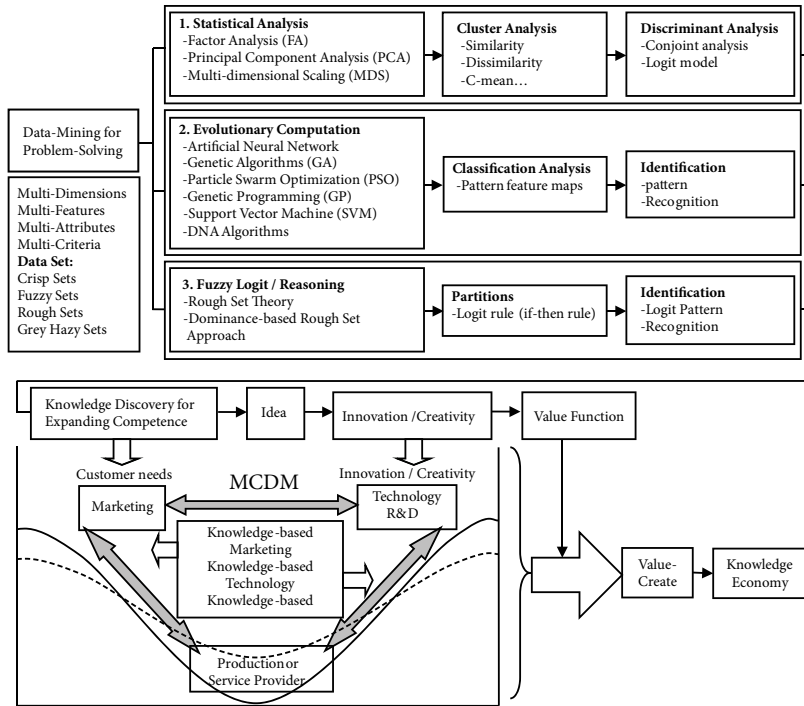
Fig. 2. Data processing for knowledge economy

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.
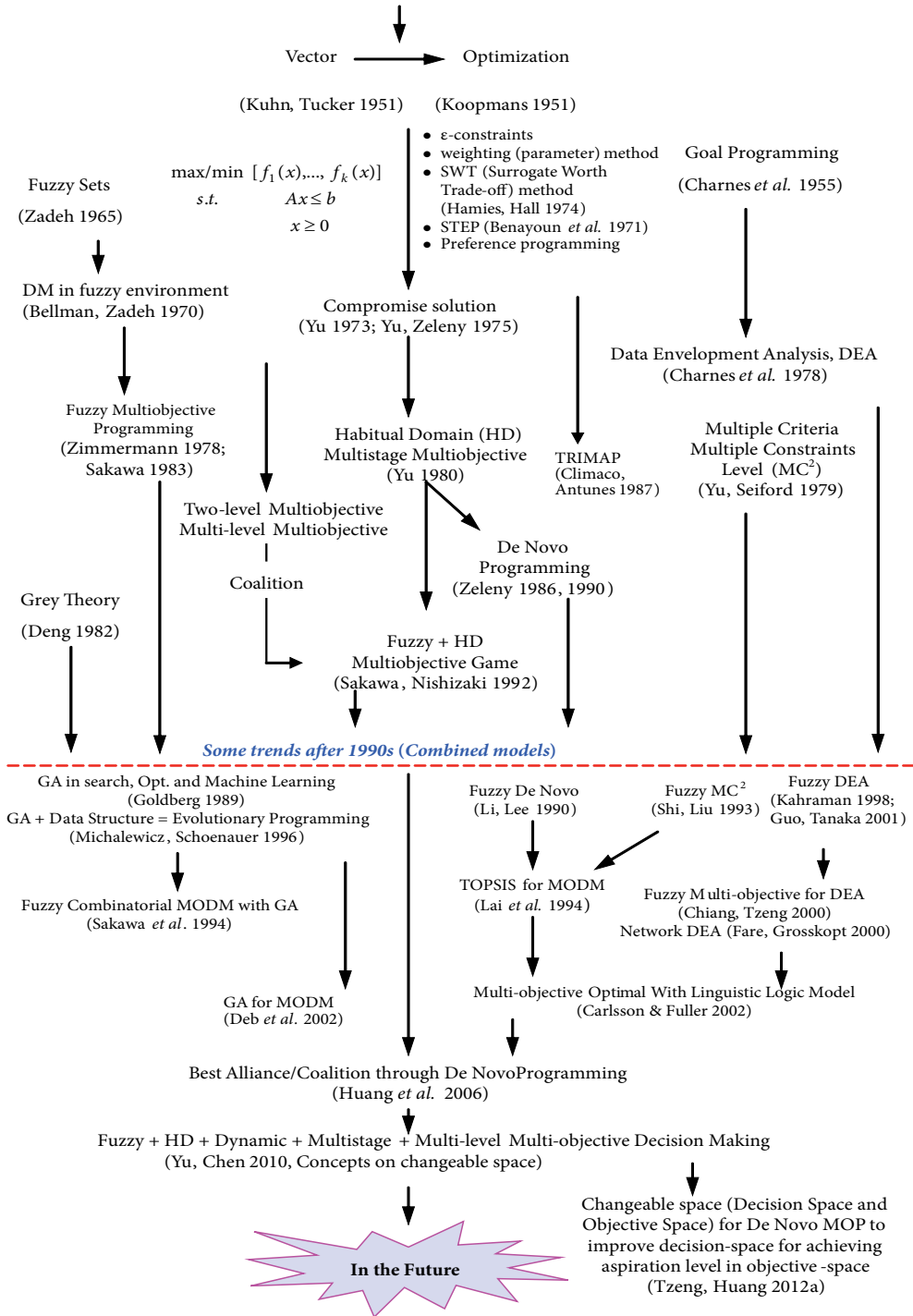
Vector ⟶ Optimization

(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)

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

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
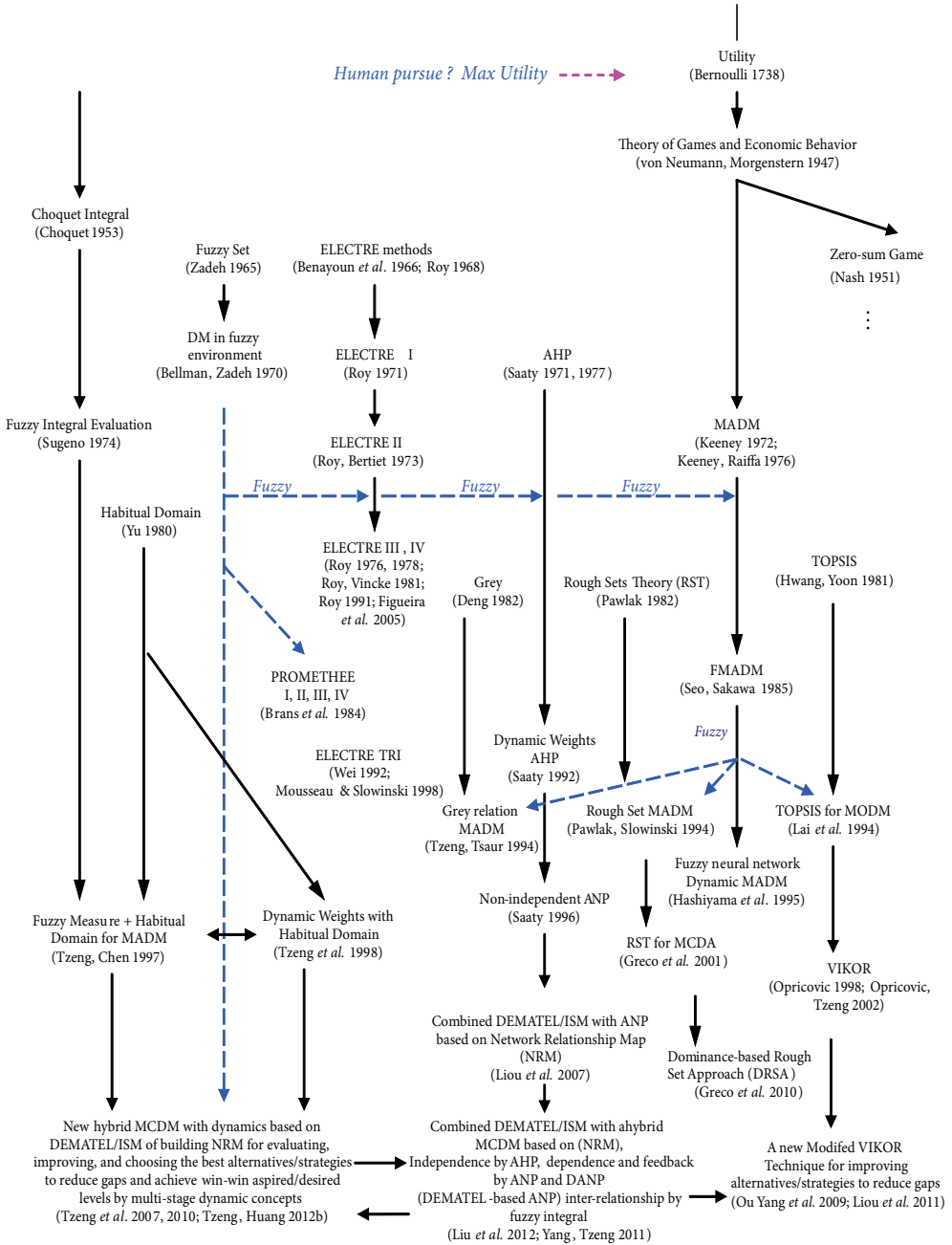
Fig. 4. The development of MADM

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.
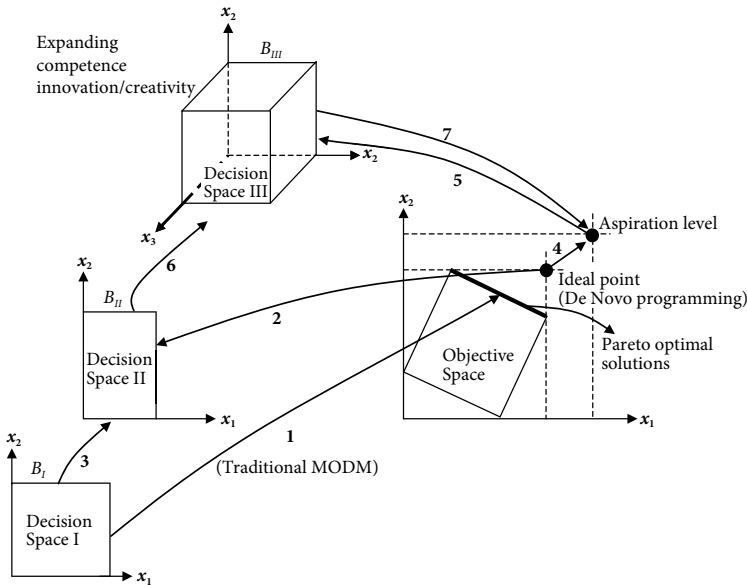
Fig. 5. The concepts of changeable decision space and aspiration level

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.

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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 dij, 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.
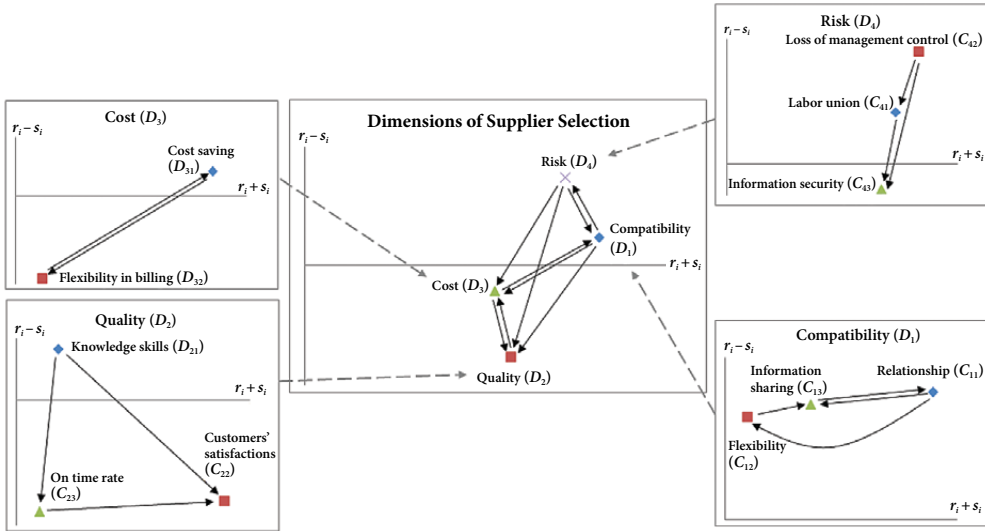

Fig. A1. Influential network relationship map for supplier selection

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.

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

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 $R_k = v S_k + (1-v)Q_k$, 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

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

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

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).

$$\min \boldsymbol{cx}$$

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

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

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

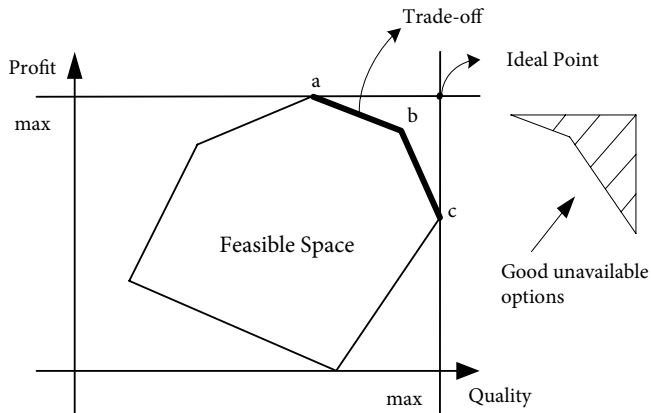Given design with natural quality – profit trade-offs as follows:

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

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

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:

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

$s.t.\quad \mathbf{Ax} \leq \mathbf{b}$

$x_1, x_2 \geq 0$

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:

$$\max \{f_1(x), ..., f_i(x), ..., f_k(x)\}$$
$$s.t. \quad Ax \le b \qquad s.t. \quad p'Ax \le p'b \qquad s.t. \quad c'x \le B$$
$$\quad\quad x \ge 0 \quad \Rightarrow \quad\quad x \ge 0 \quad \Rightarrow \quad\quad x \ge 0 \quad ,$$

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:

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

– 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

concept	Graphical Representation	Approach

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
Price (Win-Lose)		Making Ideal decisions through re-allocating limited resources
		Making Pareto optimal decisions through traditional MOP methods

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

James J. H. LIOU received his Ph.D. degree from the Department of Mechanical and Aerospace Engineering of University of Missouri-Columbia, USA in 1996. After working for airline industry for 8 years, he became an assistant professor in the Department of Air Transportation at the Kainan University, Taiwan. He turned out to be an associate professor in 2008. Currently, he is an associate professor in the Department of Industrial Engineering and Management at National Taipei University of Technology. Dr Liou's primary research interest is data mining, including feature selection, clustering, ensemble methods, and decision support system. Recently, he became interested in applying data mining algorithms to solve some business problems in customer targeting, e-commerce, and safety science. He has publications in numerous journals, including Journal of Air Transport Management, Expert Systems with Applications, International Journal of Production Research, Applied Soft computing, Information Sciences and European Journal of Operational Research etc.

Gwo-Hshiung TZENG was born in 1943 in Taiwan. In 1967, he received the Bachelor's degree in business management from the Tatung Institute of Technology (now Tatung University), Taiwan; in 1971, he received the Master's degree in urban planning from Chung Hsing University (Now Taipei University), Taiwan; and in 1977, he received the Ph.D. degree course in management science from Osaka University, Osaka, Japan.

He was an Associate Professor at Chiao Tung University, Taiwan, from 1977 to 1981, a Research Associate at Argonne National Laboratory from July 1981 to January 1982, a Visiting Professor in the Department of Civil Engineering at the University of Maryland, College Park, from August 1989 to August 1990, a Visiting Professor in the Department of Engineering and Economic System, Energy Modeling Forum at Stanford University, from August 1997 to August 1998, a professor at Chaio Tung University from 1981 to 2003, and a Chair Professor at Chiao Tung University. He got National Distinguished Chair Professor (Highest Honor offered by the Ministry of Education Affairs, Taiwan) and Distinguished Research Fellow (Highest Honor Offered by NSC, Taiwan) in 2000. His current research interests include statistics, multivariate analysis, network, routing and scheduling, multiple criteria decision making, fuzzy theory, hierarchical structure analysis for applying to technology management, energy, environment, transportation systems, transportation investment, logistics, location, urban planning, tourism, technology management, electronic commerce, global supply chain, etc. He has got a Highly Cited Paper (March 13, 2009) ESI "Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS" published in the "European Journal of Operational Research" on July 16th, 156(2), 445–455, in 2004 it has been recently identified by Thomson Reuters' *Essential Science Indicators*^{SM} to be one of the most cited papers in the field of Economics.

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.