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A strategic classification support system for brownfield redevelopment

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ABSTRACT

Brownfield redevelopment (BR) is an ongoing issue for governments, communities, and consultants around the world. It is also an increasingly popular research topic in several academic fields. Strategic decision support that is now available for BR is surveyed and assessed. Then a dominance-based rough-set approach is developed and used to classify cities facing BR issues according to the level of two characteristics, BR effectiveness and BR future needs. The data for the classification are based on the widely available results of a survey of US cities. The unique features of the method are its reduced requirement for preference information, its ability to handle missing information effectively, and the easily understood linguistic decision rules that it generates, based on a training classification provided by experts. The resulting classification should be a valuable aid to cities and governments as they plan their BR projects and budgets.

Software availability

Name: 4eMka2
Developer: Michal Lukasik, Maciej Luszczynski, Marcin Szumski and Marcin Zurawski
Contact address: Laboratory of Intelligent Decision Support Systems, Poznań University of Technology, Piotrowo 2, 60-965 Poznań, Poland
First available: 2001
Hardware: Windows 95 or later
Program size: 832KB
Availability: http://idss.cs.put.poznan.pl/site/4emka.html
Cost: free for any non-profit activities

Data availability
Name: US National Brownfields Survey
Developer: US Conference of Mayors
Contact address: The US Conference of Mayors, 1620 Eye Street, NW, Washington, DC 20006, USA
First available: 1998
Availability: http://www.usmayors.org/brownfields
Cost: free for any non-profit activities

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1. Introduction

The world's population increased rapidly over the last century, and was recently estimated at 6.65 billion (US Census Bureau, 2008). In turn, the demand for land also increased rapidly. But land is a scarce good for which production possibilities are minimal, so in most countries the total value of land and related real estate has steadily increased over the last 40 years (Isaac, 2002). It is hardly surprising that effective land use management is now an important issue for communities and governments around the world.

Brownfields are abandoned, idle, or underutilized commercial or industrial properties where an active potential for redevelopment is restrained by known or suspected environmental contamination caused by past actions (USEPA, 2005). It is clear that restoration and redevelopment of brownfields can provide a range of economic, social, and environmental benefits, including restoration of environmental quality and improvement of quality of life for citizens, elimination of health threats, provision of land for housing or commercial purposes, creation of employment opportunities, expansion of the tax base for all levels of government, and reduction in the pressure on urban centers to expand into greenfields (NRTEE, 2003).

Thus, brownfields have recently been the focus of attention for governments, communities, environmental advocates, scientists, and researchers around the world. The US Environmental Protection Agency (USEPA), like agencies of many other governments around the globe, has supported brownfield redevelopment (BR) with many programs including an assessment and revolving loan fund, cleanup grants, and job training support (USEPA, 2008). Considerable research has addressed BR issues including development of remediation technologies, environmental assessment, risk assessment and management, financial arrangements, and community and public involvement (Brebbia, 2006).

Many decision analysis tools have been applied to tackle challenging environmental management problems. For example, a fuzzy multicriteria method presented in Benetto et al. (2008) can help to interpret life cycle assessments by integrating uncertainty evaluations with application in electricity production scenarios. Nonetheless, strategic support for BR decisions at the government and community level is still lacking. One obvious problem is the lack of credible information about a city's situation—current and future—relative to other cities. In this paper, we take a major step toward the provision of this information by developing an approach to classify cities according to two basic BR characteristics. Unfortunately the only available dataset has substantial amounts of missing data, which was a problem for us to overcome.

Our classification approach, based on rough sets, has several features that helped us succeed. First, the method, based on linguistic rules for classification of new alternatives (elements, candidates, or, in this case, cities), retains much of its effectiveness despite missing data. Second, the input includes only minimal criterion preference information (direction only), and makes no assumptions about any pre-defined value (utility) function. The classification rules that are the heart of the system are developed from decisions furnished by DMs (experts) on a set of representative cases. It has been demonstrated that DMs often feel more at ease providing sample decisions than developing rigid model-based preference rules (Greco et al., 2001). Moreover, the fact that preference inputs were minimal made it feasible for us to achieve a consensus expert classification on the test sets.

The reminder of the paper is organized as follows: an overview of research on strategic level-based analysis of BR and the proposed strategic classification system are introduced in Section 2; rough set theory and the dominance-based rough set approach (DRSA) are explained in Section 3; DRSA is applied to produce a strategic classification of US cities according to two BR characteristics in Section 4; and some conclusions are presented in Section 5.

2. Strategic classification for brownfield redevelopment

2.1. Strategic analysis in brownfield redevelopment

Many research initiatives have examined issues in BR at the strategic decision level. These approaches can be roughly summarized into the following categories.

- *Survey-based investigation*: Several studies have relied on extensive surveys to investigate strategic issues in BR. For example, the five BR surveys (1998, 1999, 2000, 2003, 2006) conducted by the US Conference of Mayors examined BR problems faced by local communities throughout the US, focusing on the opportunities lost when properties remain idle and on the benefits of land recycling and return of brownfields to productive uses (US Conference of Mayors, 2008a). Another survey (George Washington University, 2008) estimated that in the US every brownfield acre that is redeveloped saves, on average, at least 4.5 acres of greenfields, which can be left undeveloped or devoted to other uses. Other surveys in BR have assessed project performance (Council for Urban Economic Development, 1999), the meaning of success (Lange and McNeil, 2004), and the characteristics of BR within a specific region (Wernstedt et al., 2008).
- *Qualitative approaches*: Both individual researchers and organizations have provided BR overviews of different regions and countries, or provided qualitative guides to practical BR activities. A comprehensive summary is available (see Brownfields Center, 2008) which includes a "road map" to assist BR stakeholders to identify and select innovative site characterization and cleanup technologies during the redevelopment process (USEPA, 2005); various economic, social, and environmental benefits to stakeholders in BR (NRTEE, 2003); and the brownfield experience overviews of four countries—United Kingdom, Germany, The Netherlands, and Canada—as well as insights into the role of the European Union (IEDC, 2005).
- *Quantitative analysis*: Some quantitative tools to support strategic analysis in BR have been proposed. For example, Chen et al. (2007) designed a two-level decision support procedure to integrate both qualitative and quantitative analysis methods to assist DMs in strategic BR decisions. Real option approaches designed in Erzi (2002) provide models of developers' investment choices incorporating various risk factors. A site ranking model is proposed to select brownfields for redevelopment in Thomas (2002).

In summary, qualitative BR research, especially survey-based, has been predominant, and there have been relatively few strategic-level quantitative tools to assist in BR decision analysis. Surveys that collect information about BR project attitudes and performance assessments from communities are needed. But so are sophisticated quantitative tools to examine survey data and extract information and knowledge to support decision making. Our proposal accomplishes this goal, as discussed next.

2.2. Strategic BR classification system

Classification constitutes a fundamental technique for assessing and understanding a situation. Much human progress can be attributed to the development of appropriate classification systems, like musical notation or the periodic table in chemistry. Classification not only facilitates understanding and development but also improves decision making. Under the umbrella of multiple criteria decision analysis (MCDA), a strategic classification model is designed for BR and applied to evaluation of the overall performance of BR in different US cities, based on the available survey information (US Conference of Mayors, 2008a). A brief introduction of MCDA and its role in classification analysis is given next.

2.2.1. MCDA and classification in MCDA

MCDA constitutes a set of techniques designed to evaluate and compare alternatives systematically, based on diverse criteria that are typically conflicting. For example, projects can be evaluated according to criteria that reflect environmental, economic, and social objectives. As discussed by (Roy, 1996), there are three fundamentally different models for the assessment of a set of alternatives, **A**:

- *Choice.* Choose the best alternative from **A**.
- *Ranking.* Rank the alternatives of **A** from best to worst.
- *Sorting.* Sort the alternatives of **A** into relatively homogeneous groups, arranged in preference order.

Of the many different approaches that have been proposed to tackle choice and ranking tasks, perhaps the best known are multiattribute utility theory (Keeney and Raiffa, 1976) and the analytic hierarchy process (Saaty, 1980). Recently, the sorting problem or more general classification has received more study (for example, Doumpos and Zopounidis (2002) and Greco et al. (2001)), and has been generalized to classification by dropping the "preference order" condition (see Chen et al., 2006).

2.2.2. Brownfield redevelopment performance classification in the US

A great deal of data on the BR experience in different US cities has been accumulated in the surveys periodically conducted by the US Conference of Mayors (2008a). The latest information is a 2006 report that summarizes the status of brownfield sites in more than 200 US cities (US Conference of Mayors, 2006). The information includes city population, numbers and areas of brownfield sites, in-progress sites, and redeveloped sites, estimated annual tax revenue gained from BR, estimated jobs created from BR and estimated population capacity. Although the report (US Conference of Mayors, 2006) includes a summary, it is clear that a more quantitative analysis will assist at assessing each city's BR success, and its correlation to other information. Since more than 200 cities are included in the survey, it is more efficient to group them into manageable and meaningful categories first, in order to design or identify policies appropriate to each group. We demonstrate below that such a classification is feasible and useful.

The general plan for our strategic classification system is shown in Fig. 1. Let $\mathbf{A}$ =Brownfields Center$\{a^1,\ldots,a^{|A|}\}$ denote the set of cities under review. We focus on two key BR characteristics of cities: *effectiveness* and *future needs*. The evaluation of each characteristic is based on a specific set of criteria; we use $\mathbf{C} = \{c_1,\ldots,c_j,\ldots,c_{|C|}\}$ to denote the criteria for assessment of BR effectiveness and $\mathbf{C}' = \{c'_1,\ldots,c'_j,\ldots,c'_{|C|}\}$ to denote the criteria for evaluation of future needs. Specifically, the comprehensive survey data (US Conference of Mayors, 2006) appropriate to these characteristics is as follows:

For $\mathbf{C}$ (BR effectiveness)

1. c_1: number of redeveloped brownfield sites;
2. c_2: area of redeveloped brownfield sites (acres);
3. c_3: number of in-progress brownfield sites;
4. c_4: area of in-progress brownfield sites (acres);
5. c_5: conservative estimate tax revenue tax gained ($);
6. c_6: optimistic estimate tax revenue tax gained ($);
7. c_7: actual tax revenue tax gained ($);
8. c_8: jobs created during redevelopment;
9. c_9: permanent jobs created.

For $\mathbf{C}'$ (BR future needs)

1. c'_1: population;
2. c'_2: estimated number of brownfield sites;
3. c'_3: estimated area of brownfield sites (acres);
4. c'_4: number of redeveloped brownfield sites;
5. c'_5: area of redeveloped brownfield sites (acres);
6. c'_6: number of in-progress brownfield sites;
7. c'_7: area of in-progress brownfield sites (acres);
8. c'_8: estimated capacity to absorb population (with no increase in infrastructure);
9. c'_9: estimated number of "moth-balled" sites (A "moth-balled" site is a site that is probably a brownfield but cannot be assessed due to lack of cooperation by the owner.).

Note that other criteria that may be relevant to the evaluation of BR performance could not be included in $\mathbf{C}$ and $\mathbf{C}'$, because data was not available. For example, criteria referring to redevelopment cost, type of contamination and location of the BR within a city could contribute to the assessment of the potential redevelopment ability of a city. Furthermore, the extent of ongoing reclamation work negatively influences the ability of a city to undertake new initiatives. Criteria including capacity employed, budget spent on past projects and short-term area demand may better express the city's priority for new reclamation projects. It would be easy to incorporate additional criteria in the proposed method should suitable data become available.

A criterion is called positive if a higher measure on the criterion is associated with more of the characteristic, and negative if a higher measure on the criterion is associated with less of the characteristic. For example, all criteria in $\mathbf{C}$ are positive in that a higher measure on any one of the criteria is *prima facie* associated with greater BR effectiveness, whereas in $\mathbf{C}'$ criteria c'_1, c'_2, c'_3 and c'_9 are positive while c'_4, c'_5, c'_6, c'_7 and c'_8 are negative, i.e. higher measures on any criterion in the latter subgroup is associated with reduced values of BR future needs.

As depicted in Fig. 1, all cities are evaluated according to all criteria in each of the two sets and then classified into three groups, I, II and III, representing high, medium, and low values of the two

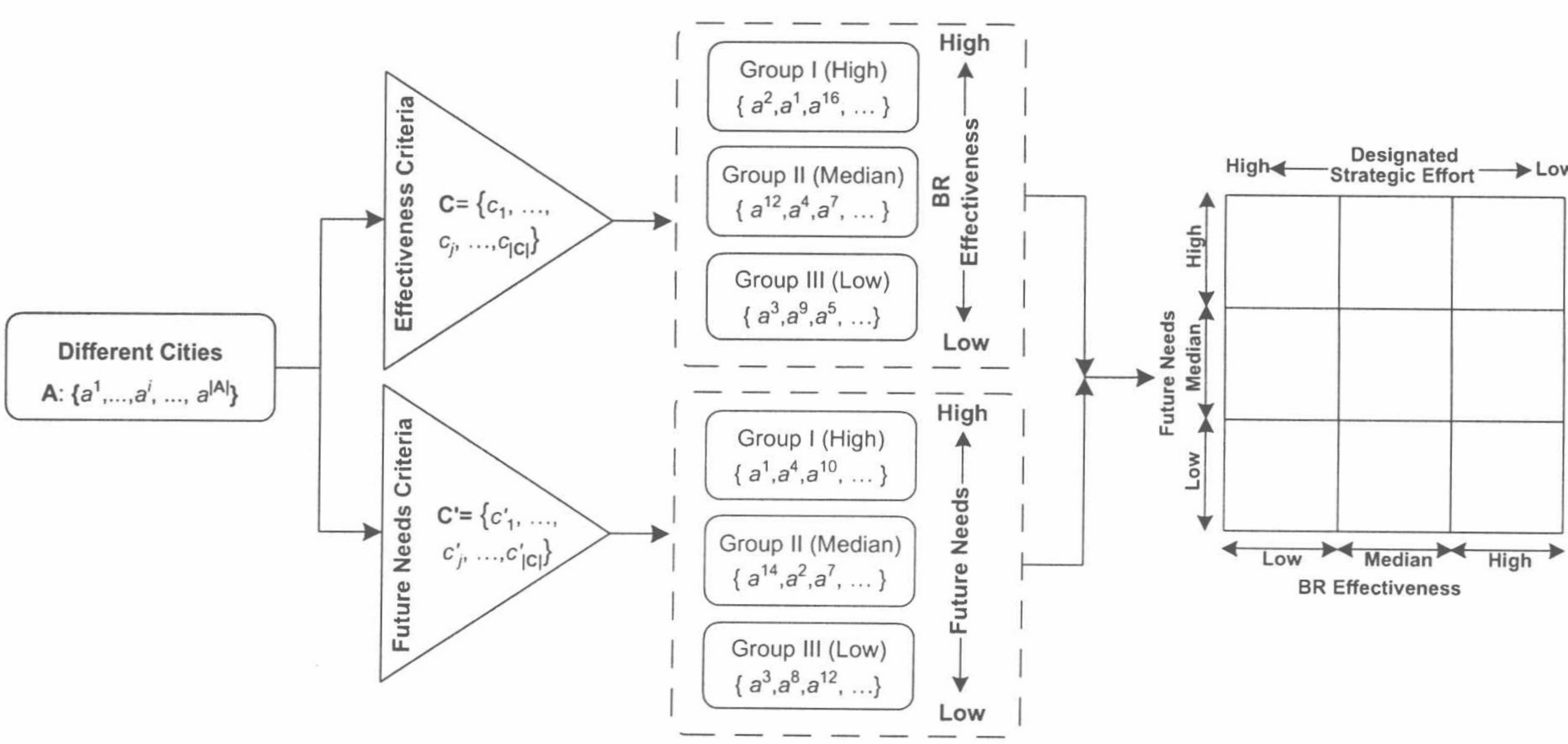


Fig. 1. Strategic BR classification framework.

characteristics. Of course the number of groups can be adjusted for convenience, and taking into account the amount of data available. Clearly strategic planning should take into account the characteristics of a city. For example, a city with a low level of BR effectiveness needs extra effort from governments and community groups, while a city with a low level of BR future needs can begin to reduce the priority of its BR programs.

A dominance-based rough set approach (DRSA) is a good choice as the primary analysis tool to classify cities according to the two characteristics because it requires minimal direct preference information, and incorporates easily understood linguistic rule-based judgments. A brief introduction of rough set theory and the DRSA is given next.

3. The dominance-based rough set approach

3.1. Rough set theory

Rough set theory was introduced by Pawlak (1982) in the early 1980s as a tool to describe dependencies among attributes, to evaluate the significance of individual attributes, and hence, to provide "automated transformation of data into knowledge" (Pawlak, 1982). Its unique approach to uncertainty or vagueness in data makes rough set theory complementary to probability theory, evidence theory, fuzzy set theory, and other methods. Recent advances in rough set theory have made it a powerful tool for data mining, pattern recognition, and information representation. For example, a rule-based procedure based on the modified rough set induction method has been found to be an efficient tool for the environmental life cycle assessment of alternative energy sources (Tan, 2005). A comprehensive literature review of rough set theory, including new research directions and applications, appears in Pawlak and Skowron (2007).

An important principle of rough sets of alternatives is that all relevant information, including both conditions and decision attributes, are expressed in the data (Pawlak, 1982). Condition attributes refer to the characteristics of the alternatives; for example, condition attributes describing a firm may include size, profitability, liquidity ratios and market position. Decision attributes define a partition of the alternatives into groups reflecting the overall situation of condition attributes. In terms of MCDA, condition and decision attributes can be interpreted as, respectively, criteria and final decision assessments (such as sorting results).

As pointed out in Greco et al. (2001), the original rough set approach cannot efficiently extract knowledge (such as a DM's preferences) from the analysis of a case set involving a human's decision judgments. The Dominance-based Rough Set Approach (DRSA) is an extension of rough set theory that is highly effective for MCDA because it replaces the *indiscernibility* relation with a *dominance* relation, providing a means to deal with inconsistent comparisons of alternatives according to a criterion, and in preference-ordered classes (groups). The main idea of DRSA is summarized below.

3.2. The dominance-based rough set approach

3.2.1. The basic structure

In an MCDA sorting problem, a set of alternatives $\mathbf{A} = \{a^1,\ldots, a^i,\ldots, a^{|\mathbf{A}|}\}$ is to be assigned to an ordered partition, $\mathbf{Cl} = \{cl_1,\ldots, cl_t,\ldots,cl_{|\mathbf{Cl}|}\}$. The subsets in the partition are called classes, and the assignment is to reflect a set of criteria $\mathbf{C} = \{c_1,\ldots,c_j,\ldots,c_{|\mathbf{C}|}\}$. The intent is that, if $1 \le g < h \le |\mathbf{Cl}|$, then the DM prefers every alternative in cl_g to any alternative in cl_h. Hence, $\mathbf{Cl}$ is often written $cl_1 \prec cl_2 \prec \cdots \prec cl_{|\mathbf{Cl}|}$, where $\prec$ denotes "is preferred to".

The DRSA requires a representative case set for data training and elicitation of linguistic decision rules. The inferred rules are then applied globally to evaluate all alternatives. The DM is asked to partition $\mathbf{T} = \{t^1,\ldots,t^i,\ldots,t^{|\mathbf{T}|}\}$ into $\mathbf{Cl}$ in such a way that $cl_t \neq \emptyset$ and $\cup_{t=1}^{|\mathbf{T}|} cl_t = \mathbf{T}$ for all $t = 1,\ldots,|\mathbf{T}|$ and, of course, so that the subsets of the partition are arranged according to preference, as described above.

The procedure to apply DRSA to sort $\mathbf{A}$ is illustrated in Fig. 2. Note that m^i_j is the performance (consequence) measurement of case t^i over criterion j. It is assumed that the DM's preference over performance on each criterion is monotonic, i.e., that each criterion c_j is either positive or negative. Once this preference direction is specified for each criterion, the DRSA can be utilized to extract a set of linguistic rules, $\mathbf{R}$, that captures the preferential information inherent in the sorting of $\mathbf{T}$ supplied by the DM, and apply $\mathbf{R}$ to sort $\mathbf{A}$ into $|\mathbf{Cl}|$ classes, $cl_1 \prec cl_2 \cdots \prec cl_{|\mathbf{Cl}|}$.

Define the *upward union* (denoted by the superscript "$\geqslant$") and the *downward union* (denoted by the superscript "$\leqslant$") by $cl_r^{\geqslant} = \cup_{s \le r} cl_s$ and $cl_r^{\leqslant} = \cup_{s \ge r} cl_s$, respectively, where $r = 1,\ldots,|\mathbf{Cl}|$. It is easy to demonstrate that $cl_{|\mathbf{Cl}|}^{\geqslant} = cl_1^{\leqslant} = \mathbf{Cl}$, $cl_1^{\geqslant} = cl_1$ and $cl_{|\mathbf{Cl}|}^{\leqslant} = cl_{|\mathbf{Cl}|}$.

3.2.2. Approximation of partitions

Fix a subset of the criteria $\mathbf{P} \subseteq \mathbf{C}$. Given the sorting of the case set $\mathbf{T}$ supplied by the DM, we can define $D_{\mathbf{P}}$, a binary preference relation on $\mathbf{T}$ where, for any $t^i, t^l \in \mathbf{T}$, $t^i D_{\mathbf{P}} t^l$ means that "t^i is at least as preferred as t^l with respect to $\mathbf{P}$" in the sorting of $\mathbf{T}$. Assume that $D_{\mathbf{P}}$ is a complete preorder, i.e. $D_{\mathbf{P}}$ is a relation that is reflexive, transitive, and complete. Given $t^i \in \mathbf{T}$, define the $\mathbf{P}$-dominating set $t^i, D^+_{\mathbf{P}}(t^i) = \{t^l \in \mathbf{T}: t^l D_{\mathbf{P}} t^i\}$, and the $\mathbf{P}$-dominated set for $t^i, D^-_{\mathbf{P}}(t^i) = \{t^l \in \mathbf{T}: t^i D_{\mathbf{P}} t^l\}$, respectively.

Next, define $\mathbf{P}$-lower and $\mathbf{P}$-upper approximations of $cl_t^{\geqslant}$ to be $\underline{\mathbf{P}}(cl_t^{\geqslant}) = \{t^i \in \mathbf{T}: D^+_{\mathbf{P}}(t^i) \subseteq cl_t^{\geqslant}\}$ and $\overline{\mathbf{P}}(cl_t^{\geqslant}) = \{t^i \in \mathbf{T} : D^-_{\mathbf{P}}(t^i) \cap cl_t^{\geqslant} \neq \emptyset\}$, respectively. Similarly, the $\mathbf{P}$-lower and $\mathbf{P}$-upper approximations of $cl_t^{\leqslant}$ are $\underline{\mathbf{P}}(cl_t^{\leqslant}) = \{t^i \in \mathbf{T}: D^-_{\mathbf{P}}(t^i) \subseteq cl_t^{\leqslant}\}$ and $\overline{\mathbf{P}}(cl_t^{\leqslant}) = \{t^i \in \mathbf{T} : D^+_{\mathbf{P}}(t^i) \cap cl_t^{\leqslant} \neq \emptyset\}$, respectively.

It is easy to verify that the $\mathbf{P}$-lower and $\mathbf{P}$-upper approximations defined above satisfy the following conditions for each $r = 1,2,\ldots,|\mathbf{Cl}|$: $\underline{\mathbf{P}}(cl_r^{\geqslant}) \subseteq cl_r^{\geqslant} \subseteq \overline{\mathbf{P}}(cl_r^{\geqslant})$ and $\underline{\mathbf{P}}(cl_r^{\leqslant}) \subseteq cl_r^{\leqslant} \subseteq \overline{\mathbf{P}}(cl_r^{\leqslant})$. Now define the $\mathbf{P}$-boundaries of $cl_r^{\geqslant}$ and $cl_r^{\leqslant}$ by $Bn_{\mathbf{P}}(cl_r^{\geqslant}) = \overline{\mathbf{P}}(cl_r^{\geqslant}) - \underline{\mathbf{P}}(cl_r^{\geqslant})$ and $Bn_{\mathbf{P}}(cl_r^{\leqslant}) = \overline{\mathbf{P}}(cl_r^{\leqslant}) - \underline{\mathbf{P}}(cl_r^{\leqslant})$, respectively. Then a reasonable measure of the quality of the approximation to $\mathbf{Cl}$ using only the criteria $\mathbf{P}$ on the test set $\mathbf{T}$ is

$$\gamma_{\mathbf{P}}(\mathbf{Cl}) = \frac{\left|\mathbf{T} - \left[\left(\bigcup_{cl_t \in \mathbf{Cl}} Bn_{\mathbf{P}}\left(cl_t^{\geqslant}\right)\right) \cup \left(\bigcup_{cl_t \in \mathbf{Cl}} Bn_{\mathbf{P}}\left(cl_t^{\leqslant}\right)\right)\right]\right|}{|\mathbf{T}|}.$$

3.2.3. Decision rules elicitation

The approximations obtained through dominance analysis can be used to construct decision rules that capture the preference information underlying the sorting of the case set. Assume that all

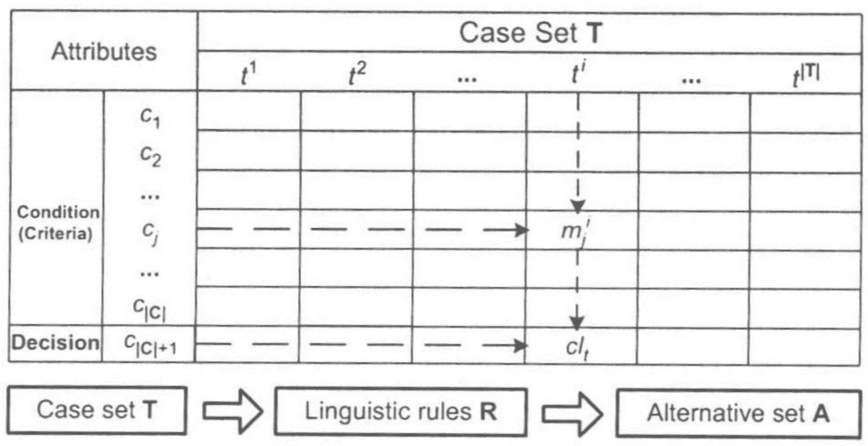


Fig. 2. Procedure to apply DRSA.

Table 1
Representative case set for BR effectiveness, **T**

City	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	Group
Akron (t^1)	9	40	7	27	1900000	2500000	1650000	1100	1400	*H*
Albuquerque (t^2)	5	15	5	20	5000000	1300000	7920000	150	450	*H*
Athens (t^3)	1	2	1	100	500000	1000000	100000	30	180	*L*
Baton Rouge (t^4)	28	41	12	21	250000	500000	175000	75	175	*M*
Buffalo (t^5)	18	300	5	150	5000000	15000000	350000	725	825	*H*
Charleston (t^6)	6	30	7	35	1000000	2500000	57000	35	75	*L*
Clearwater (t^7)	70	100	20	45	2000000	3500000	1000000	729	773	*H*
Columbus (t^8)	12	50	2	75	2000000	200000	500000	1500	2000	*M*
Elizabeth (t^9)	12	195	9	30	30000000	45000000	6600000	5250	7250	*H*
Emeryville (t^{10})	30	150	50	50	3000000	6000000	2000000	8000	8500	*H*
Fitchburg (t^{11})	2	12	2	12	100000	250000	200000	20	50	*L*
Frisco (t^{12})	18	82	5	8	140000001	180000001	103885604	15	50	*H*
Indianapolis (t^{13})	40	8	15	10	5000000	10000000	1000000	225	725	*H*
La Crosse (t^{14})	5	10	3	5	1000000	4000000	600000	900	925	*M*
Lafayette (t^{15})	2	5	1	3	1000000	10000000	15000000	150	350	*M*
Las Vegas (t^{16})	6	10	5	8	150000	750000	35356	136	290	*L*
Lynn (t^{17})	8	5	1	19	8000000	20000000	400000	100	110	*L*
Montgomery (t^{18})	2	11	1	2	1000000	6000000	1000000	300	550	*M*
New Orleans (t^{19})	28	60	11	35	5000000	20000000	2000000	300	785	*M*
Ocala (t^{20})	12	20	5	18	25000	50000	60000	300	320	*L*
Pittsburgh (t^{21})	25	700	10	200	5000000	50000000	10000000	10000	15000	*H*
Richmond (t^{22})	5	20	2	10	300000	1000000	1000000	60	210	*M*
Rochester (t^{23})	20	285	13	75	50000000	150000000	4000000	193	233	*H*
Springfield (t^{24})	1	3	3	13	15000000	36000000	1300000	20	35	*M*
Trenton (t^{25})	50	100	20	50	1500000	2500000	1000000	500	1000	*H*
Waco (t^{26})	8	38	3	13	637500	900000	176000	300	750	*M*
West Hollywood (t^{27})	1	4	1	3	4000000	10000000	1500000	800	925	*H*
Winston-Salem (t^{28})	5	50	2	40	200000	1000000	75000	30	35	*L*

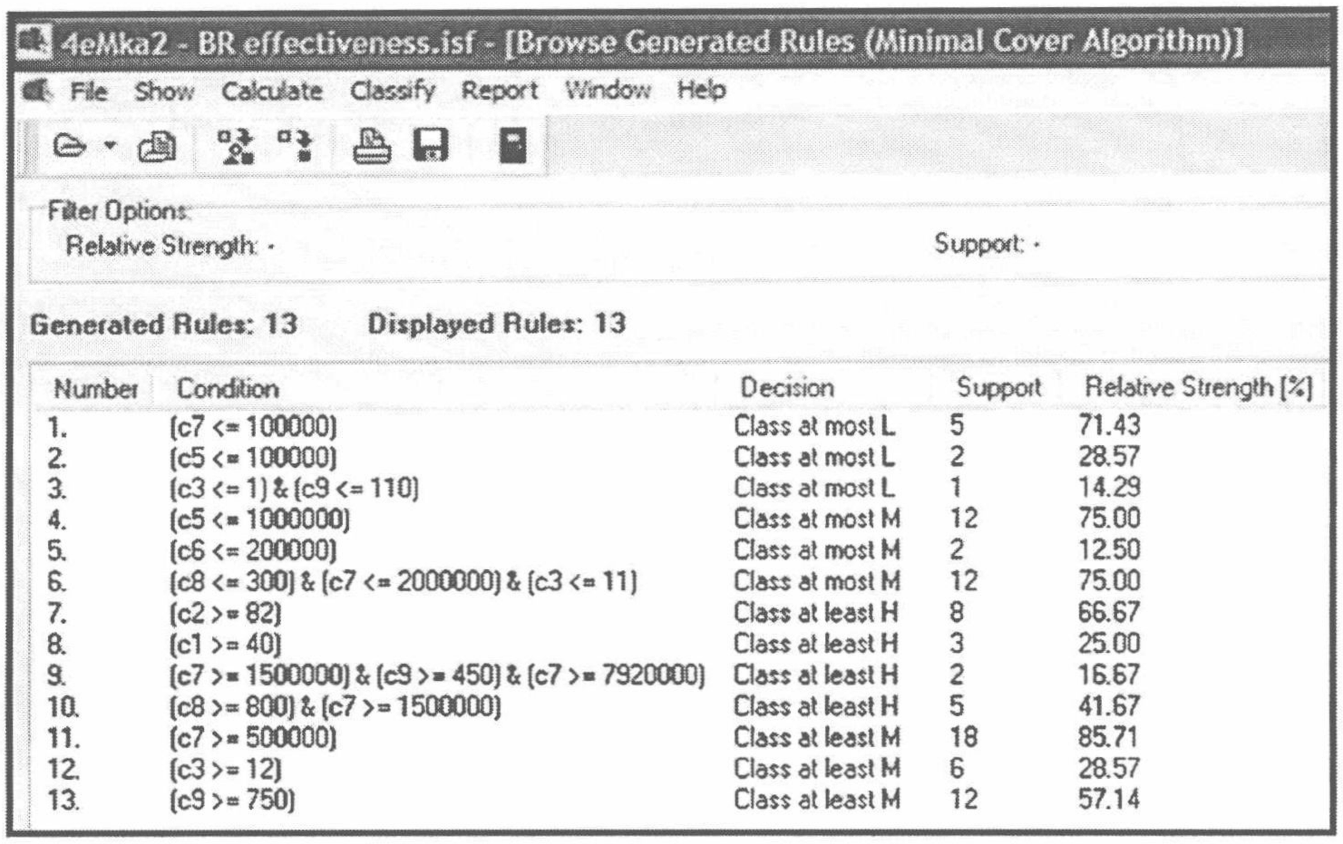
criteria are positive, i.e. that $m_j(t^i) \geq m_j(t^l)$ implies $t^i D_{c_j} t^l$ for all $c_j \in \mathbf{C}$ and all $t^i, t^l \in \mathbf{T}$. Then, three types of decision rules, to be used to sort **A** into **Cl**, can be generated from the non-empty set of criteria $\mathbf{P} \subseteq \mathbf{C}$.

- $D_{\geqslant}$-decision rule: If $m_j(t^i) \geq r_j$, for all $c_j \in \mathbf{P}$, then $t^i \in cl^{\geqslant}_t$, where $r_j \in \mathbb{R}$ is a performance threshold for criterion c_j.
- $D_{\leqslant}$-decision rule: If $m_k(t^i) \leq r_k$, for all $c_k \in \mathbf{P}$, then $t^i \in cl^{\leqslant}_t$, where $r_k \in \mathbb{R}$ is a performance threshold for criterion c_k.
- $D_{\geqslant\leqslant}$-decision rule: If $m_j(t^i) \geq r_j$, for all $c_j \in \mathbf{O}$ and $m_k(t^i) \leq r_k$, for all $c_k \in \{\mathbf{P} - \mathbf{O}\}$, then $t^i \in cl_t \cup cl_{t+1} \cup \cdots \cup cl_s$, where $r_j, r_k \in \mathbb{R}$ are performance thresholds for criteria c_j and c_k, respectively.

A set of decision rules is *complete* iff every case in the case set **T** can be classified into one or more groups according to the rules, i.e. no alternative remains unclassified. A set of decision rules is *minimal* if it is complete and non-redundant, i.e. exclusion of any rule makes

Table 2
Representative case set for BR future needs, **T′**

City	c'_1	c'_2	c'_3	c'_4	c'_5	c'_6	c'_7	c'_8	c'_9	Groups
Akron (t'^1)	217074	44	200	9	40	7	27	6000	12	*M*
Bridgeport (t'^2)	139529	250	300	7	15	5	15	7000	20	*M*
Buffalo (t'^3)	292648	300	2000	18	300	5	150	300000	20	*L*
Calumet City (t'^4)	39071	11	46	4	6	2	3	0	7	*H*
Charleston (t'^5)	96650	100	600	6	30	7	35	0	6	*H*
Council Bluffs (t'^6)	58268	5	30	1	3	1	2	10000	3	*M*
Detroit (t'^7)	951270	1000	10000	150	3000	50	1500	300000	600	*H*
Easthampton (t'^8)	15994	12	60	3	6	3	8	3000	2	*M*
Emeryville (t'^9)	6882	150	200	30	150	50	50	5000	50	*M*
Gainesville (t'^{10})	95447	75	200	3	15	6	40	5000	40	*M*
Harrisburg (t'^{11})	48950	18	90	7	9	5	20	25000	9	*L*
Indianapolis (t'^{12})	791926	400	500	40	8	15	10	50000	25	*L*
Las Vegas (t'^{13})	478434	20	40	6	10	5	8	25000	5	*M*
Lowell (t'^{14})	105167	365	1000	30	100	20	50	10	5	*H*
Marlborough (t'^{15})	36255	3	6	1	3	2	3	12000	1	*L*
Ocala (t'^{16})	45943	140	300	12	20	5	18	5000	3	*M*
Owensboro (t'^{17})	54067	100	180	1	2	1	2.5	10000	4	*H*
Pittsburg (t'^{18})	56769	15	250	3	20	4	50	2500	5	*M*
Port Arthur (t'^{19})	57755	30	226	1	1	15	31	4000	14	*M*
Providence (t'^{20})	173618	250	2500	1	10	10	100	15000	25	*H*
Rochester (t'^{21})	219773	1000	975	20	285	13	75	75000	200	*H*
Rock Island (t'^{22})	39684	50	50	5	27	5	15	10000	1	*M*
South Bend (t'^{23})	107789	243	350	11	137	4	180	30000	200	*H*
Terre Haute (t'^{24})	59614	10	80	2	10	2	65	10000	6	*L*
Toledo (t'^{25})	313619	100	1200	7	345	6	360	90	10	*H*
Westland (t'^{26})	86602	9	111	1	35	1	35	20000	1	*L*
Wilmington (t'^{27})	72664	275	1500	100	100	10	20	50000	5	*L*



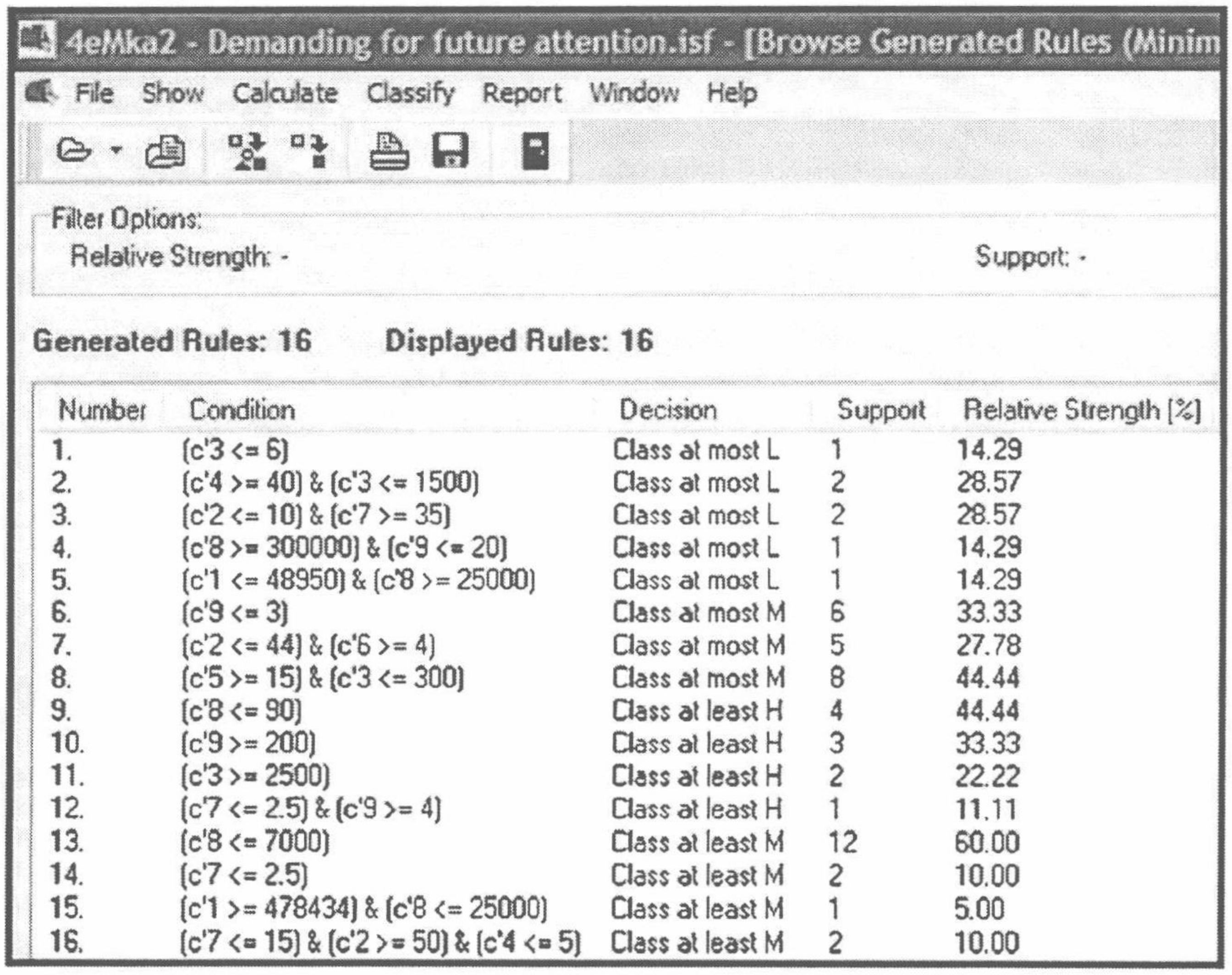
Number	Condition	Decision	Support	Relative Strength [%]
1.	(c7 <= 100000)	Class at most L	5	71.43
2.	(c5 <= 100000)	Class at most L	2	28.57
3.	(c3 <= 1) & (c9 <= 110)	Class at most L	1	14.29
4.	(c5 <= 1000000)	Class at most M	12	75.00
5.	(c6 <= 200000)	Class at most M	2	12.50
6.	(c8 <= 300) & (c7 <= 2000000) & (c3 <= 11)	Class at most M	12	75.00
7.	(c2 >= 82)	Class at least H	8	66.67
8.	(c1 >= 40)	Class at least H	3	25.00
9.	(c7 >= 1500000) & (c9 >= 450) & (c7 >= 7920000)	Class at least H	2	16.67
10.	(c8 >= 800) & (c7 >= 1500000)	Class at least H	5	41.67
11.	(c7 >= 500000)	Class at least M	18	85.71
12.	(c3 >= 12)	Class at least M	6	28.57
13.	(c9 >= 750)	Class at least M	12	57.14

Fig. 3. Decision rules generated for BR effectiveness.

the set incomplete (Greco et al., 2001). Let $\mathbf{R} = \{r_1,...,r_i,...,r_{|\mathbf{R}|}\}$ be a set of decision rules generated from the classification of **T**. The relative strength of decision rule r_i is $\beta(r_i)$, the ratio of the number of cases supporting r_i to the cardinality of the lower approximation of the classes with which the decision rule r_i is associated. The most popular rule induction for DRSA is DOMLEM, which has been implemented in the software 4eMka2 (ICS, 2008).

4. Data analysis and results

Our objective was to classify a data set consisting of 201 US cities with brownfield redevelopment (BR) projects (see US Conference of Mayors, 2006) according to BR effectiveness and BR future needs. We followed the DRSA analysis procedure described in Section 3. Our plan was to use a relatively small test set in order to present



Number	Condition	Decision	Support	Relative Strength [%]
1.	(c'3 <= 6)	Class at most L	1	14.29
2.	(c'4 >= 40) & (c'3 <= 1500)	Class at most L	2	28.57
3.	(c'2 <= 10) & (c'7 >= 35)	Class at most L	2	28.57
4.	(c'8 >= 300000) & (c'9 <= 20)	Class at most L	1	14.29
5.	(c'1 <= 48950) & (c'8 >= 25000)	Class at most L	1	14.29
6.	(c'9 <= 3)	Class at most M	6	33.33
7.	(c'2 <= 44) & (c'6 >= 4)	Class at most M	5	27.78
8.	(c'5 >= 15) & (c'3 <= 300)	Class at most M	8	44.44
9.	(c'8 <= 90)	Class at least H	4	44.44
10.	(c'9 >= 200)	Class at least H	3	33.33
11.	(c'3 >= 2500)	Class at least H	2	22.22
12.	(c'7 <= 2.5) & (c'9 >= 4)	Class at least H	1	11.11
13.	(c'8 <= 7000)	Class at least M	12	60.00
14.	(c'7 <= 2.5)	Class at least M	2	10.00
15.	(c'1 >= 478434) & (c'8 <= 25000)	Class at least M	1	5.00
16.	(c'7 <= 15) & (c'2 >= 50) & (c'4 <= 5)	Class at least M	2	10.00

Fig. 4. Decision rules generated for BR future needs.

Table 3
Classification results

		BR effectiveness						Summary
		H	*M*	*L*	*H* ∪ *M*	*M* ∪ *L*	*H* ∪ *M* ∪ *L*	
BR future needs	*H*	5	11	5	1	2	14	38
	M	6	8	2	3	5	7	31
	L	4	2	3	4	4	7	24
	H ∪ *M*	2	3	3	4	3	15	30
	M ∪ *L*	0	2	4	5	3	7	21
	H ∪ *M* ∪ *L*	8	8	5	3	10	23	57
	Summary	25	34	22	20	27	73	201

a problem of manageable size to our experts (and not to demand too much time).

4.1. Expert and representative case set identification

The input for DRSA depends on a case set of representative cases for which experts' holistic assessments is required for each BR characteristic. Formally, the 201 cities listed in the survey report constitute the alternative set, **A**. However, only 28 cities had complete information for all nine criteria for BR effectiveness (**C**), and only 27 cities had complete information for all nine criteria for BR future needs, **C**′. Therefore the case set on each characteristic consisted of the 27 or 28 cities for which complete information was available. In principle, it is not a problem to generalize this data to all 201 cities, since the DRSA can handle missing data. The two case sets were denoted **T** (for BR effectiveness) and **T**′ (for BR future needs), respectively.

We approached several groups of experts, including members of our research group and their colleagues at four universities, officials in charge of BR activities in the City of Kitchener, Ontario, and project managers for professional environmental consultants. Depending on the time they had available, we presented experts with the full case sets, **T** and **T**′, or randomly selected subsets of appropriate size. The experts were asked to assign cities into three pre-defined groups, *H*, *M*, and *L*, representing high, medium, and low groups of BR effectiveness and BR future needs. There were some variations of judgment initially. We shared the data, and after a few iterations, a unanimous judgment was reached. The complete data sets and classifications of **T** and **T**′ are shown in Tables 1 and 2, respectively.

4.2. Decision rule generation

The software, 4eMka2 (ICS, 2008), was employed for data training and decision rule generation. The main steps are *data input*, *dominance relationship identification*, and *linguistic decision rule elicitation*. Using the minimal cover algorithm (Greco et al., 2001), 13 rules were identified for classification of BR effectiveness, as shown in Fig. 3, and 16 rules were generated for classification of BR future needs, as displayed in Fig. 4.

4.3. Results and insights

The linguistic decision rules were then applied to classify all 201 cities for the two BR characteristics. The detailed calculations are omitted here. The overall classification results can be conveniently displayed in the joint classification matrix shown Table 3. Ambiguities in the classification are indicated using "∪" to represent "or". For example, a city labelled "*H* ∪ *M*" belongs to either the *H* or *M* group, and a city labelled "*H* ∪ *M* ∪ *L*" could be placed in any group, i.e., it cannot be distinguished by the decision rules.

Some observations directly from Table 3 are summarized next.

- Information for roughly 30% of the cities (73 for BR effectiveness and 57 for future need) is insufficient to classify them in any way at all, i.e. they are placed in *H* ∪ *M* ∪ *L*. The inability to classify these cities is primarily due to the large amount of missing data.
- In fact, an enormous amount of data is missing from the survey results; less than 15% of the cities had complete data sets. DRSA, because of its unique reliance on linguistic rule-based decision judgments, can often overcome problems of missing information. For example, if a city has 50 redeveloped brownfield sites, then according to decision rule 8 of Fig. 3 (if $c_1 \geq 40$, set in class *H*) then the city is classified as high on the BR effectiveness characteristic. In other words, such a city can be definitively put into class *H* on BR effectiveness, even though all other performance measures may be missing. Thus, we conclude that DRSA did a good job despite all of the missing information in this case. The proportion of ambiguous or inconclusive classifications (group *H* ∪ *M* ∪ *L*) to cases with missing data was 73:173 for BR effectiveness and 57:174 for future needs, roughly 40% for each characteristic.
- Overall, more cities were assessed as high on future needs (there were 38 cities in class *H*) than were evaluated as low on BR effectiveness (22 in class *L*). This suggests that the experts were more concerned about future demand for brownfield redevelopment than about the success of previous redevelopment efforts.

4.4. Implications for practice

Based on the analytic results displayed above, we suggest some implications for practice.

- Improvements in the quality of BR surveys of US cities (US Conference of Mayors, 2006) would enable quantitative analysis tools to produce more conclusive and precise results. The online survey submission system that has recently been established may make information collection more convenient and expeditious (US Conference of Mayors, 2008b). Better information will give all cities a better picture of their position with respect to brownfield redevelopment.
- In procedures relying on holistic group judgments, the determination of representative cases plays a role in the generation of linguistic classification rules that is difficult to measure, but potentially important. For this reason, it would be interesting to cross-validate the study using the judgments of different sets of DMs, perhaps on subsets of the cities. Also, more experts should be approached to obtain a broader sampling of test-case classifications. An alternative might be to obtain more comprehensive evaluations, perhaps facilitated by a website to encourage not only a broader range of experts but also a survey of a larger number of cases. But expanding the test set in this way will probably make it impractical to reach a unanimous judgment, as was done above. Then the first step to finding a consensus view would be to employ statistical tests such as the Friedman test (Friedman, 1937) to detect whether there is

any significant difference among ordinal rankings across evaluations. Aggregation procedures can then be designed to generate an overall result, which can be fed into the DRSA for elicitation of decision rules.

- Additionally, it is useful to compare cities' efforts to reclaim land and to assess the potential that can be tapped. This assessment may be important, e.g. to allocate funds from higher levels of government as effectively as possible. The proposed method can be adapted to prioritize redevelopment projects. In future research, a variety of classification tools including rough set theory will be compared in terms of their classification ability for brownfield redevelopment. One potentially useful data source is a report prepared by the US Council for Urban Economic Development (1999) summarizing hundreds of US brownfield redevelopment projects, identifying important evaluation criteria and proposing benchmarks on each criterion that "can be evaluated and [applied] to a wide variety of projects".

5. Conclusions

Brownfields are the legacy of a century of industrialization (NRTEE, 2003). But they are much more than just contaminated or blighted land; they represent opportunities for large-scale urban improvements, and for reduction of expansion pressure into surrounding greenfields. In this paper, brownfield redevelopment (BR) and strategic decision support for BR are broadly reviewed, and a rough set-based approach is designed for strategic classification of cities, based on a published BR survey of US cities with BR records. The proposed method classifies cities according to their levels of BR effectiveness and BR future needs. Ready availability of a credible classification of cities will be useful to all of them as they make their strategic plans with respect to BR projects and budgets.

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Using a Benchmark in Case-Based Multiple-Criteria Ranking

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***Abstract*—A benchmark-based method is proposed for multiple-criteria ranking, and a case study is presented to demonstrate that the procedure can be efficient and effective in practice. Multiple-criteria ranking aims to help a decision maker (DM) assess a finite set of alternatives according to several criteria, usually conflicting, in order to rank the full set. The relation of benchmarks to multiple-criteria decision analysis is investigated systematically, and then, an approach based on distance from a benchmark is designed to incorporate information about a DM's judgements so as to produce a full ranking. The procedure is applied to rank 81 U.S. brownfield redevelopment projects based on available data and an accepted benchmark.**

***Index Terms*—Case-based distance approach (CBDA), multiple-criteria decision analysis (MCDA), multiple-criteria ranking, preference disaggregation, project evaluation.**

I. Motivation

MULTIPLE-CRITERIA decision making (MCDM) is often supported by a set of techniques that help decision makers (DMs) identify, compare, and evaluate alternatives according to diverse, usually conflicting, criteria. For example, it may be desirable to assess development plans in light of environmental, economic, legal, social, and other criteria. Generally speaking, MCDM can be divided into two main branches: multiple-objective optimization (MOO) and multiple-criteria decision analysis (MCDA).

MOO focuses on applying mathematical algorithms to identify alternatives that are optimal or efficient, under certain constraints, with respect to a few objectives that are expressed mathematically using decision variables [23]. The decision variables are usually continuous; therefore, most MOO problems have infinitely many alternatives which are defined by distinct combinations of values for decision variables.

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MCDA, on the other hand, aims to help DMs assess and compare alternatives from a finite set and includes techniques to assist in eliciting their preferences. The criteria are predefined and usually conflicting. As discussed by Roy [21], three *problématiques* (fundamental problems) can be applied to the assessment of a set of alternatives **A**.

1) *Choice*. Choose the best alternative from **A**.
2) *Sorting*. Sort the alternatives of **A** into relatively homogeneous groups, which can then be arranged in preference order.
3) *Ranking*. Rank the alternatives of **A** from best to worst.

One primary point of comparison of MOO and MCDA is that MOO focuses on *choice* problems with infinitely many alternatives, whereas MCDA considers all three problems, although within a finite set of alternatives. Over the last 40 years, many MCDA methods have been proposed for *choice* and *ranking* problems, including the multiattribute utility theory [19], the analytic hierarchy process [22], and outranking methods [20]. Recently, MCDA research on *sorting* has come to the fore. Doumpos and Zopounidis [7] wrote the first book on this subject and presented a comprehensive review of the MCDA literature on sorting [28]. A related branch of MCDA sorting research is the extension of traditional sorting to nominal classification, which has been carried out by Chen *et al.* [4] and Malakooti and Yang [16].

In general, a *benchmark* is a standard by which something is evaluated or measured. Originally, a "benchmark" was a chiseled horizontal mark, made by a surveyor, into which an angle iron could be placed to bracket (or "bench") a leveling rod, ensuring that the rod could be positioned in exactly the same place in the future [26]. The concept of benchmarks is now applied in many distinct contexts. The prices of West Texas Intermediate and Brent Blend are crude oil benchmarks and are widely accepted as indicators of prices in the petroleum sector. In computing, times and other execution characteristics of programs called benchmarks are used as measures of hardware or software performance. In strategic management, it is common to benchmark an organization, which means to compare its performance to best practices in its industry or sector.

In this paper, the possibility of applying benchmarks in MCDA is investigated, and an approach to multiple-criteria ranking problems based on distance to a benchmark is proposed. To begin, Section II summarizes MCDA and discusses how benchmarks could be valuable in MCDA. Then, Section III details a distance approach that uses benchmarks to solve ranking problems. In Section IV, a case study is presented to show how the method could be applied to evaluate data

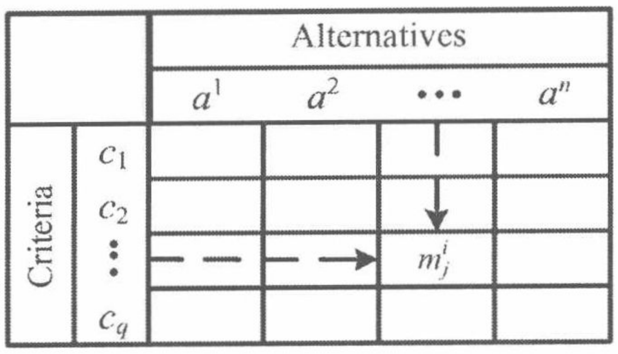

Fig. 1. Performance matrix in MCDA.

on brownfield redevelopment projects. Some conclusions are offered in Section V.

II. MCDA AND BENCHMARKS

A. MCDA Analysis Procedure and Basic Structure

The analysis of an MCDA problem involves three key steps: 1) problem construction, the process of defining objectives, translating them into criteria, identifying all possible alternatives, and measuring the *consequence* (performance) of each alternative on each criterion; 2) preference elicitation and aggregation, the process of modeling the DM's preferences for performance on each criterion and the DM's relative weights for the different criteria, thereby obtaining an overall evaluation of each alternative; and 3) implementation, the process of assessing the evaluations of the alternatives in order to choose from, sort, or rank $\mathbf{A}$ as aid to decision making.

The fundamental structure of an MCDA problem, the performance matrix (or information matrix), is established in step 1), as shown in Fig. 1. Here, $\mathbf{A} = \{a^1, a^2, \ldots, a^n\}$ is the set of alternatives, and $\mathbf{C} = \{c_1, c_2, \ldots, c_q\}$ is the set of criteria. The consequence of alternative a^i measured on criterion c_j, denoted as m_j^i, appears in the jth row and ith column of the table. Note that a consequence is a direct measurement of the success of an alternative according to a criterion, such as cost in dollars or capacity in millions of liters per day. Insofar as possible, it is an objective physical measurement and does not include preferential information.

The DM's preferences are a fundamental input in any MCDA problem; therefore, their elicitation and representation are obviously important. It is natural to distinguish two kinds of preferences, preferences on consequences or *values*, and preferences on criteria or *weights*.

Values are refined data reflecting the assessment of a consequence according to the DM's needs and objectives. The relationship between consequence and value can be expressed as $v_j^i = f_j(m_j^i)$, where $v_j^i = v_j(a^i)$ and m_j^i are a value and a consequence, respectively; $f_j(\cdot)$ maps a consequence datum to its value, usually a real number, representing its worth to the DM. The DM's values over all criteria for alternative a^i constitute the *value vector* $\mathbf{v}(a^i) = (v_1(a^i), v_2(a^i), \ldots, v_q(a^i))$.

Weights, or preferences on criteria, reflect the relative importance of each criterion relative to the others. The weight for criterion $c_j \in \mathbf{C}$ is $w_j \in \mathbb{R}^+$. Note that no criterion is negligible; therefore, $w_j > 0$ for all $c_j \in \mathbf{C}$. Since preferences on criteria are relative, weights are normalized by requiring $\sum_{j=1}^q w_j = 1$. The *weight vector* is $\mathbf{w} = (w_1, w_2, \ldots, w_q)$.

After the preferences have been acquired, a global model is used to aggregate preferences for alternatives and use them to solve the required problématique. For $a^i \in \mathbf{A}$, $V(a^i) = F(\mathbf{v}(a^i), \mathbf{w})$, where $V(a^i) \in \mathbb{R}$ is the evaluation of alternative a^i and $F(\cdot)$ is the real-valued mapping from value vectors $\mathbf{v}(a^i)$ and weight vector $\mathbf{w}$ that produces the evaluation of a^i. A typical example is the *linear additive value function* $V(a^i) = \sum_{j=1}^q w_j \cdot v_j(a^i)$.

B. Application of Benchmarks in MCDA

MOO and MCDA procedures that use a specific point, analogous to a benchmark, include goal programming [3], compromise programming [27], reference point approaches [25], Technique for Order Preference by Similarity to Ideal Solution [9], the aspiration level interactive method [14], and the elimination method [15]. In these procedures, the predefined point may be related to the data but is typically an ideal or anti-ideal point and is unrealizable. Benchmarks, on the other hand, are realizable points of reference. For example, feasible benchmarks for performance, often called best practices, have been established and are widely used in performance evaluations of businesses and other organizations [2]. In this paper, we consider measurements relative to a realizable point of reference, such as a median. In other words, a benchmark is, or could be, achieved by an actual alternative.

As far as we know, there has been no analysis of how to use such a point of reference in solving MCDA problems. In this paper, we explore systematically the utilization of a benchmark in MCDA and develop an approach based on distance from a benchmark to solve ranking problems.

Except for preference information, the data of an MCDA problem—the set of alternatives $\mathbf{A}$, the set of criteria $\mathbf{C}$, and the consequence of each alternative on each criterion—are shown in Fig. 1. The solution of the MCDA problem must apply the DM's preferences, over consequences and criteria, to these data. We henceforth assume that all consequences (entries of the performance matrix) are real numbers and that the DM's preferences over consequences are *monotonic*, i.e., that $\mathbf{C} = \mathbf{C}^+ \cap \mathbf{C}^-$, where $\mathbf{C}^+$ is the set of *positive criteria* (the greater the consequence, the more preferred the alternative, *ceteris paribus*, e.g., capacity) and $\mathbf{C}^-$ is the set of *negative criteria* (the greater the consequence, the less preferred the alternative, e.g., cost).

Alternative a^l *dominates* alternative a^m iff $m_j(a^l) \geq m_j(a^m)$ for all $c_j \in \mathbf{C}^+$ and $m_j(a^l) \leq m_j(a^m)$ for all $c_j \in \mathbf{C}^-$, provided at least one of these inequalities is strict. If so, we write $a^l \succ a^m$. Alternatives a^l and a^m are *nondominating* iff neither $a^l \succ a^m$ nor $a^m \succ a^l$. We denote the nondominance of a^l and a^m by $a^l \sim a^m$.

Suppose that $b = (b_1, b_2, \ldots, b_q) \in \mathbb{R}^q$ is fixed and satisfies $\min_{a^i \in \mathbf{A}} m_j(a^i) < b_j < \max_{a^i \in \mathbf{A}} m_j(a^i)$ for all $c_j \in \mathbf{C}$. Then, we can interpret b as a *benchmark* and compare all alternatives in $\mathbf{A}$ to it. Clearly, $\mathbf{A}$ is partitioned into three subsets by b. The *superior group* of alternatives is $\mathbf{A}^+(b) = \mathbf{A}^+ = \{a^i \in \mathbf{A} : a^i \succ b\}$, the *inferior group* of alternatives is $\mathbf{A}^-(b) = \mathbf{A}^- = \{a^i \in \mathbf{A} : b \succ a^i\}$, and the *nondominant group* of alternatives is $\mathbf{A}^\sim(b) = \mathbf{A}^\sim = \mathbf{A} - \mathbf{A}^+(b) - \mathbf{A}^-(b)$.

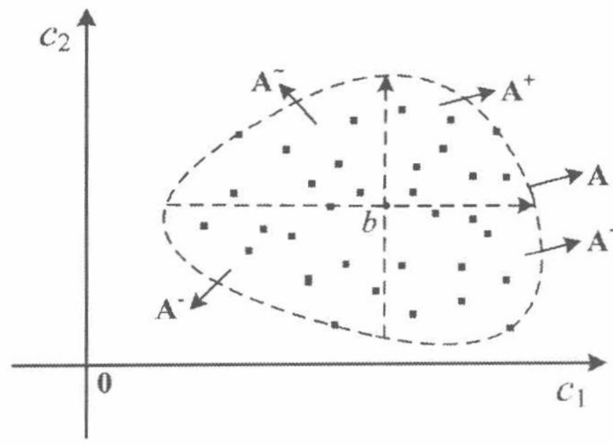

Fig. 2. Relationship among $\mathbf{A}^+$, $\mathbf{A}^\sim$, and $\mathbf{A}^-$.

Fig. 2 shows these three subsets in the context of two positive criteria. Note that $\mathbf{A}^\sim(b)$ has two components unless the benchmark b is itself an alternative, i.e., unless $b \in \mathbf{A}$.

III. Benchmarks, Distances, and Ranking

In principle, all of the DM's preference information is required to generate a full ranking of $\mathbf{A}$. In MCDA, this information is normally disaggregated into preferences on consequences (values, given by real functions of one variable) and preferences on criteria (weights, given as a weight vector). The efficient acquisition of this preference information is the key challenge of MCDA. There are two broad classes of techniques for preference elicitation, direct judgment and case based. Both employ a model of preference which, when calibrated, represents the DM's preferences explicitly. In direct-judgement methods, the DM is asked to specify the model by providing explicit values for all parameters. In case-based approaches, the DM is asked to make global preference judgements on selected cases (alternatives or potential alternative), which are then input into optimization programs that find the parameters of the preference model that is most consistent with the input. Here, we adapt previous work [5] to show how benchmarks can be integrated into case-based methods based on distance models of preference.

The case-based distance approach (CBDA) originates from preference disaggregation methodologies [11], [12]. The CBDA begins with a predefined ideal (or anti-ideal) point and supposes that the DM's preference can be identified with distance from this reference point. Specifically, decreasing preference corresponds to increasing distance from the ideal point (or decreasing distance to the anti-ideal point), but only if the "right" distance metric is employed. For example, under the weighted Euclidean distance assumption, optimization programs are designed to identify the most suitable information of criterion weights and group thresholds for multiple-criteria sorting problems in [5]. We now extend this approach to reference points that are not extreme, like ideal or anti-ideal points, but instead, are achievable benchmarks.

A. Procedural Inputs

Assume that a fixed benchmark $b \in \mathbb{R}^q$ is given. The DM is asked to provide three nonempty case sets $\mathbf{T}_+$, $\mathbf{T}_\sim$, and $\mathbf{T}_-$ that are representative of $\mathbf{A}^+$, $\mathbf{A}^\sim$, and $\mathbf{A}^-$, respectively. Note that $\succ$ and $\prec$ indicate dominance relationships, and $\sim$ indicates that there is no dominance relationship. Consistent with these usages, $\succ_P$ and $\prec_P$ indicate preference and $\sim_I$ lack of preference or indifference. In particular, $t \succ_P b$ if $t \in \mathbf{T}^+$, $t \sim_I b$ if $t \in \mathbf{T}^\sim$, and $t \prec_P b$ if $t \in \mathbf{T}^-$. The DM may construct the case sets by selecting alternatives from $\mathbf{A}$, by modifying historical records or simply based on experience.

Suppose that the DM provides $\mathbf{T}_+ = \{t_+^1, \ldots, t_+^r, \ldots, t_+^{m+}\}$, $\mathbf{T}_\sim = \{t_\sim^1, \ldots, t_\sim^r, \ldots, t_\sim^{m\sim}\}$, and $\mathbf{T}_- = \{t_-^1, \ldots, t_-^r, \ldots, t_-^{m-}\}$. Note that $|\mathbf{T}_+| = m_+$, $|\mathbf{T}_\sim| = m_\sim$, and $|\mathbf{T}_-| = m_-$. Define $\mathbf{T} = \mathbf{T}^+ \cup \mathbf{T}^\sim \cup \mathbf{T}^-$.

The DM is now asked to rank $\mathbf{T}$ in decreasing order of preference. For example, if $1 \leq g < h \leq m_+$, then either $t_+^g \succ_P t_+^h$ or $t_+^g \sim_I t_+^h$ and similarly within $\mathbf{T}^\sim$ and $\mathbf{T}^-$. The monotonicity of preference implies that any element of $\mathbf{T}_+$ is strictly preferred to any element of $\mathbf{T}_-$ but implies nothing about the relative preference of an element of $\mathbf{T}_+$ and an element of $\mathbf{T}_\sim$, or about the relative preference of an element of $\mathbf{T}_\sim$ and an element of $\mathbf{T}_-$. In most optimization software, including Matlab and Lingo, there is no distinction between calculations based on constraints such as "equal or greater than" ($\geq$) versus "greater than" ($>$); for this reason, we do not emphasize weak preferences ($\succeq_P$) here and usually assume that all preferences are strict.

B. Distance Assumptions

Define $\mathbf{A}' = \mathbf{A} \cup \mathbf{T}$. For each $c_j \in \mathbf{C}$, set

$$d_j^{\max} = \max_{\forall a \in \mathbf{A}'} |m_j(a) - m_j(b)| \tag{1}$$

where $|x|$ is the absolute value of $x \in \mathbb{R}$. Then, $d_j^{\max}$ is the *normalization factor* for criterion c_j, and the signed normalized distance between $a \in \mathbf{A}'$ and b on criterion c_j is

$$d_j(a,b) = d_j(a) = \frac{m_j(a) - m_j(b)}{d_j^{\max}}. \tag{2}$$

Note that $0 \leq d_j(a) \leq 1$ if $a \in \mathbf{A}^+ \cup \mathbf{T}^+$, $-1 \leq d_j(a) \leq 0$ if $a \in \mathbf{A}^- \cup \mathbf{T}^-$, and $-1 \leq d_j(a) \leq 1$ if $a \in \mathbf{A}^\sim \cup \mathbf{T}^\sim$.

To aggregate the signed normalized distances between $a \in \mathbf{A}'$ and b over all q criteria, we use a distance related to the so-called p-norm, where $p \in \mathbb{N}^+$. The most commonly used norms are $p = 1$ and $p = 2$. Given a weight vector $\mathbf{w} = (w_1, w_2, \ldots, w_q)$, the weighted signed p-power distance is

$$DW(a) = \sum_{j=1}^{q} w_j \cdot |d_j(a)|^p \cdot \frac{d_j(a)}{|d_j(a)|}.$$

Note that $DW(a)$ may be positive or negative, depending on whether the positive or negative values of $d_j(a)$ predominate. The signed distance from alternative $a \in \mathbf{A}'$ to b is then

$$D(a,b) = D(a) = \sqrt[p]{|DW(a)|} \cdot \frac{DW(a)}{|DW(a)|}. \tag{3}$$

When $p = 1$, D is the signed 1-norm or signed Manhattan distance from the benchmark, and it is easy to verify that

$D(a) = \sum_{j=1}^{q} w_j \cdot d_j(a^i)$. When $p = 2$, D is the signed 2-norm or signed Euclidean distance from b, and

$$D(a) = \begin{cases} \sqrt{DW(a)}, & \text{if } DW(a) \geq 0 \\ -\sqrt{|DW(a)|}, & \text{if } DW(a) < 0. \end{cases}$$

Both of these signed distance norms have clear geometric interpretations and are usually easy for the DM to understand.

It is obvious that $D(a) \in [-1, 1]$ for all $a^i \in \mathbf{A}'$; greater values of $D(a)$ represent more preferred outcomes relative to the benchmark b. Also, if $D(a) = 0$, then $a \sim_I b$.

C. Graphical Demonstration

Fig. 3 shows the idea in the context of two positive criteria with the signed $p = 1$ and $p = 2$ norms. The case sets $\mathbf{T}^+$, $\mathbf{T}^\sim$, and $\mathbf{T}^-$ are displayed in the first panel in the original consequence space. Note that there are five, nine, and six alternatives in $\mathbf{T}^+$, $\mathbf{T}^\sim$, and $\mathbf{T}^-$, respectively.

In the second panel, (1) and (2) have been used to transfer the case sets to normalized consequence space. Here, c_1' and c_2' are the normalized versions of criteria c_1 and c_2, respectively; notice that the origin of the coordinate system is now replaced by the benchmark b.

In the third panel, (3) has been used to measure the relative preference of each alternative in $\mathbf{T}$ according to its signed weighted distance from b. Under the assumptions that $p = 1$ and that c_1' and c_2' are weighted equally, the parallel straight lines from lower right to upper left contain points that are equally preferred because they are at equal aggregated distances to the benchmark b. For instance, the line passing through b includes all alternatives equally preferred to b (i.e., at distance zero from b); any line below and to the left represents equally preferred alternatives that happen to be less preferred than b (at negative distance from b); and any line above and to the right represents equally preferred alternatives that are preferred to b (at positive distance from b).

Similarly, if $p = 2$ and c_1' and c_2' remain equally weighted, the alternatives preferred to b (at a fixed positive distance from b) lie on an arc of a circle in the first quadrant (upper right) and then become rectangular hyperbolae on crossing the horizontal or vertical axis. All of these hyperbolae are asymptotic to the 0-distance line, which is the straight line passing through the benchmark b. Thus, all equally preferred lines (other than the 0-distance line) start off close to the 0-distance line at the bottom right, then slowly separate from it, then bend around, and finally approach the 0-distance line again in the upper left. In the case when c_1' and c_2' are not equally preferred, the circle and rectangular hyperbola in the aforementioned description are replaced by an ellipse and a nonrectangular hyperbola.

In the fourth panel, the signed distances from b of the alternatives in the different case sets are shown. Note that the distances of all alternatives in $\mathbf{T}^+$ are strictly positive and the distances of all alternatives in $\mathbf{T}^-$ are strictly negative. In $\mathbf{T}^\sim$, three alternatives are preferred to b (at positive distance from b), two alternatives happen to be indifferent to b (at distance zero), and four alternatives are less preferred than b (at negative distance from b).

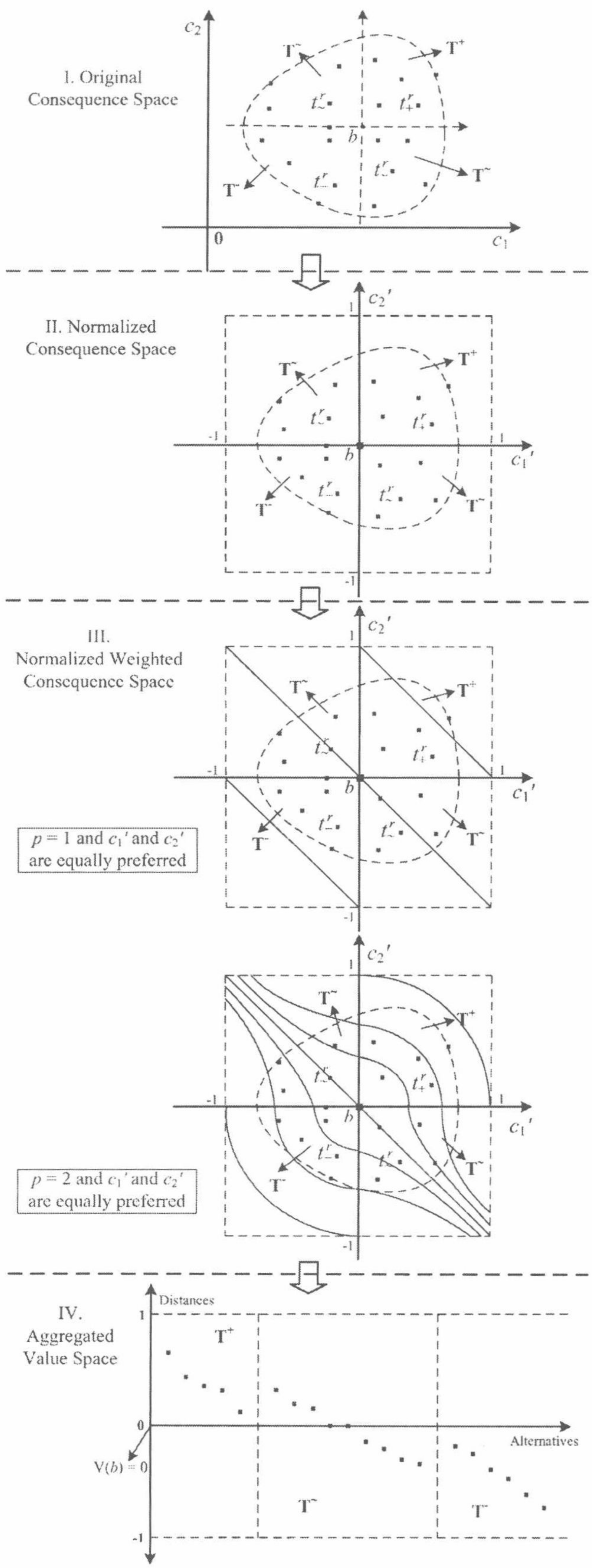

Fig. 3. Benchmark-based distance with two positive criteria under $p = 1, 2$.