南京航空航天大学

论 文 集

（二〇〇九年） 第41册

经济与管理学院

（第5分册）

南京航空航天大学科技部编

二〇一〇年五月

经济与管理学院

博士

序号	姓 名	职称	单位	论 文 题 目	刊物、会议名称	年、卷、期	类别
151	张荣 刘思峰	博士 教授	091	一种基于判断矩阵信息的多属性群决策方法	系统工程与电子技术	2009 年 31 卷 2 期	EI：20091311991375
152	张荣 刘思峰	博士 教授	091	A Method for Weight Assignment By Dominance-Based Rough Sets Approach	The 21st Chinese Control and Decision Conference	2009,Jun	EI 收录号码：20094712470351
153	丰立祥	博士	091	区域生态主导产业指标体系的构建	经济问题	2009.3	
154	苏春华	博士	091	The p-moment exponential robust stability for stochastic systems with distributed delays and interval parameters	Applied Mathematics and Mechanics	2009	
155	苏春华	博士	091	具有分布时滞的随机区间系统的鲁棒镇定	系统工程与电子技术	2009.31.10	
156	苏春华	博士	091	具有分布时滞和区间参数的随机系统的 P-阶矩指数鲁棒稳定性	应用数学和力学	2009.30.7	
157	苏春华	博士	091	具有时变灰参数的随机时滞系统的 P-阶矩指数鲁棒稳定性	数学的实践与认识	2009.39.1	
158	苏春华	博士	091	一类区间随机分布时滞系统的 P 阶矩指数稳定性	应用数学	2009.22.2	
159	陆志鹏	博士	091	基于民生视角的政府绩效评价灰色贝叶斯网络模型	系统工程	2009.27.9	
160	陆志鹏	博士	091	区间 DEA 模型求解算法及其在项目投资效率评价中的应用	中国管理科学	2009.17.4	
161	陆志鹏	博士	091	群决策中五类不确定性偏好的集成模型及应用	南京航空航天大学学报	2009.41.4	
162	王洁方	博士	091	基于交叉评价好竞争视野优化的多属性决策方法	控制与决策	2009.24.10	
163	王洁方	博士	091	基于区间定位和灰关联的区间 aDEA 效率指数测算与排序	系统工程与电子技术	2009.31.9	
164	石岩	博士	091	不对称信息下需求创新专利授权的价格机制	预测	2009.3	
165	石岩	博士	091	歧视价格市场的专利授权策略研究	科技进步与决策	2009.26.19	
166	石岩	博士	091	空间差异厂商间的专利授权分析	运筹与管理	2009.18.1	
167	石岩	博士	091	Hotelling 线形城市上的两种专利费提成方式研究	科技进步与对策	2009.26.15	
168	王萍	博士	091	基于熵值法的高新园区自主创新能力综合评价研究	科技管理研究	2009.7	
169	王萍	博士	091	基于 Lucas 模型的企业自主创新战略实施路径研究	企业经济	20094	
170	施红星	博士	091	科技生产力网络化流动问题研究	科学学与科学技术管理	2009.8	
171	施红星	博士	091	科技生产力流动与新兴产业成长问题研究	科技政策与管理	2009.12	

172	陈孝新	博士	091	一种部分权重信息的灰色多属性群决策方法	系统工程与电子技术	2009.31.4	
173	曾波	博士	091	灰色组合预测模型及其应用	中国管理科学	2009.17.5	
174	张苑苑	博士	091	企业核心竞争力的动态不确定多尺度决策研究	控制与决策	2009.24.4	
175	钟晓芳	博士	091	基于灰色关联度的动态稳健性设计	系统工程理论与实践	2009.29.9	
176	钟晓芳	博士	091	模糊德尔菲法和熵权法在不确定环境下产品设计中功能选择的应用	工业工程	2009.12.4	
177	刘晟	博士	091	灰色预测模型在机电工程造价中的应用	中国交通信息产业	2009.3	
178	崔立志	博士	091	非等间距 GM（1，1）模型时间响应函数的优化	统计与决策	2009.13	
179	崔立志	博士	091	关于新的弱化缓冲算子的研究及其应用	控制与决策	2009.24.8	
180	柯宏发	博士	091	电子战系统试验管理的灰色特性及其应用研究	兵工学报	2009.30.5	
181	白全礼	博士	091	国际农村流通体系建设比较及对中国的启示	河南师范大学学报（社科版）	2009.36.6	
182	袁潮清	博士	091	Research on energy-saving effect of technological progress based on Cobb-Douglas production function	ENERGY POLICY	2009.37.8	
183	袁潮清	博士	091	Research on the energy-saving effect of energy policies in China: 1982-2006	ENERGY POLICY	2009.37.7	
184	袁潮清	博士	091	The relationship among energy prices and energy consumption in China	ENERGY POLICY	2009.38	
185	李桥兴	博士	091	The grey input-occupancy-output analysis	Kybernetes	2009.38.3-4	
186	李桥兴	博士	091	Some results about grey mathematics	Kybernetes	2009.38.3-4	
187	李翀	博士	091	江苏省能源消耗与区域经济相关指标的灰关联分析	统计与决策	2009.3	
188	张可	博士	091	A Novel Algorithm of Image Edge Detection Based on Matrix Degree of Grey Incidences	The Journal of Grey System	2009.21.3	
189	胡啸红 江可申	博士	095	基于 SCP 的中国民航市场研究——以重组为主要视角	税务与经济	2009(5)	
190	胡啸红 江可申	博士	095	Productivity Change and Its Inherent in China’s Air lines for 2003-2008:An Analysis Employing Malmquist Productivity Index and GM(1,1) Model	IEEE GSIS	May 20,2009	
191	刘博 江可申	博士	095	The Study on the Interactive Relationship between High-Tech Industry Development and Economical Growth based on Grey Incidence Analysis	IEEE GSIS	May 20,2009	

192	白俊红 江可申	博士	095	应用随机前沿模型评测中国区域研发创新效率	管理世界	2009(10)	
193	白俊红 江可申	博士	095	中国地区研发创新的相对效率与全要素生产率增长分解——基于超越对数随机前沿模型的实证研究	数量经济技术经济研究	2009(3)	
194	白俊红 江可申	博士	095	中国区域创新系统创新效率综合评价及分析	管理评论	2009(9)	
195	白俊红 江可申	博士	095	区域创新效率的环境影响因素分析——基于 DEA-Tobit 两步法的实证检验	研究与发展管理	2009(2)	
196	白俊红 江可申	博士	095	军工技术转移过程中的制约因素分析	数理统计与管理	2009(6)	
197	金晔 江可申	博士	095	可持续消费研究综述	生态经济	2009（11）	
198	金晔 江可申	博士	095	南京地区军民两用技术市场化路径及保障体系的构建	江苏商论	2009（2）	
199	金晔 江可申	博士	095	可持续消费模式构建设想	价格月刊	2009（12）	
200	王惠 江可申	博士	095	江苏省城镇居民生活质量评估研究	江苏城市规划	2009(05)	
201	王惠 江可申	博士	095	企业信息资源管理水平实证分析	价值工程	2009(05)	
202	王惠 江可申	博士	095	多种评价方法综合应用的探讨-以江苏省城市竞争力综合评价为例	江苏社会科学	2009(07)	
203	李勇 江可申	博士	095	财务景气监测预警指标的分类方法及运用	价值工程	2009(8)	
204	陈学云 江可申	博士	095	基于博弈分析的国际航空联盟形成动因探讨	企业经济	2009(9)	
205	李邃 江可申	博士	095	我国制造业技术创新资源配置效率研究	工业技术经济	2009(8)	
206	曾小舟	博士	095	浅析我国机场建设投资管理	中国民用航空	2009(07)	
207	曾小舟	博士	095	中国民航在代码共享运营中存在的问题	中国民用航空	2009(03)	
208	汪本强 江可申	博士	095	我国航空工业融资体制的改革路径与资源“易得性”研究	经济纵横	2009（12）	
209	田泽永	博士	095	FDI 技术溢出对江苏制造业的影响	科研管理	2009.1	
210	田泽永	博士	095	FDI 技术溢出对江苏民营企业的影响	中国科技论坛	2009.3	

文章编号:1001-506X(2009)02-0373-03

一种基于判断矩阵信息的多属性群决策方法

张 荣[1,2], 刘思峰[1]
(1. 南京航空航天大学经济与管理学院, 江苏 南京 210016;
2. 河南农业大学信息与管理科学学院, 河南 郑州 450002)

摘 要: 对于多属性群决策中的属性和专家赋权问题,鉴于专家对于属性的权重信息和专家的权重信息完全蕴涵在专家给出的判断矩阵中,故应该充分挖掘判断矩阵的特征信息进行赋权。基于这种思想,提出了基于判断矩阵信息的多属性群决策方法,这种客观赋权法结构清晰、计算简便,而且还可以避免应用主观赋权时出现的对专家的主观评判与专家实际决策行为不一致的现象。算例验证证明,该方法具有合理性和有效性。

关键词: 多属性群决策; 客观赋权法; 判断矩阵
中图分类号: C 934 **文献标志码**: A

Multi-attribute group decision-making method based on the information of judgment matrixes

ZHANG Rong[1,2], LIU Si-feng[1]
*(1. Coll. of Economics and Management, Nanjing Univ. of Aeronautics and Astronautics, Nanjing 210016, China;
2. Coll. of Information and Management Science, Henan Agriculture Univ., Zhengzhou 450002, China)*

Abstract: To assign the weights of attributes and experts for multi-attribute group decision-making, seeing that the weight information of attributes and experts completely consists in the judgment matrixes given by the expert, so the feature information of the judgment matrixes should be explored enough to assign weights. Based on the above idea, a multi-attribute group decision-making method rooted in the judgment matrixes is developed. This objective method for assigning weights not only has a clear structure and simple algorithm, but also avoids the inconsistent phenomena that the subjective judgments for experts are different from the experts' actual decision-making performance. An illustrative example proves that the method is reasonable and valid.

Keywords: multi-attribute group decision-making; objective method for assigning weight; judgment matrix

0 引 言

在多属性群决策问题中,信息的集结起着重要的作用。一般地,对于一个方案不仅要将每个属性的信息集结为一个定量的指标,而且要将多个专家的决策最终集结为群体决策结果。这就需要决策者既知晓每个指标的权重,还要清楚每个专家的权重。涉及到给每个专家赋权的问题时,最为简单的考虑是认为各个专家的权重相等,即共有 n 个专家时,认为每个专家的权重为$\frac{1}{n}$。但这种做法过于理想,忽略了各个专家判断的差异性。目前,为专家赋权的常用方法有:主观赋权法[1]、客观赋权法[2-4]和基于主观和客观的组合赋权法[4-5]。

进一步地,当应用层次分析法进行决策时,每个专家对于属性权重的观点都会体现在量化的判断矩阵中。也就是说,一个判断矩阵集结了该专家关于属性权重观点的全部信息。因此,如何充分挖掘每个判断矩阵所蕴含的信息,从而既获得该专家对于属性的权重,又通过比较判断矩阵或者权重的质量获得专家的权重是非常值得关注的话题!基于专家给出的判断矩阵或属性权重的质量越高,则认为该专家的工作越有成效,继而赋予该专家更高的权重的思路,本文应用客观赋权法,设计了一种充分利用判断矩阵所包含的信息给每个专家赋权的群决策方法。之所以没有采用主观赋权法给专家赋权,本文是基于这样的考虑,通常聘请的专家往往具有大致相当的水平,而且对专家的学识、经验、能力等进行打分并不能一致反映专家对属性权重的观点。实际上,每个专家对属性权重的观点完全集结在其给出的判断矩阵或者属性权重中。

收稿日期:2007-09-17; **修回日期**:2008-05-24。
基金项目:国家自然科学基金资助课题(70473037)
作者简介:张荣(1973-),女,博士研究生,主要研究方向为多属性决策,系统评价方法。E-mail:zr.mis@163.com

基于判断矩阵信息的多属性群决策方法主要分两步：首先每个专家对各属性赋权；然后对各专家赋权。这两个步骤均基于每个专家给出的判断矩阵，认为判断矩阵中蕴涵了反映属性权重和专家权重的全部信息，并采用客观赋权法进行。本文详细地叙述了其方法步骤，并给出了算例分析。

类似于传统的多属性群决策问题，假设：该问题有方案集 $P=\{P_1, P_2, \cdots, P_m\}$、属性集 $H=\{H_1, H_2, \cdots, H_n\}$、规范化的决策矩阵为 $R=(r_{ij})_{m\times n}$，且该问题的属性权重完全未知。同时，聘请专家采用 9 级评分法分别对各个属性进行两两比较，得到判断矩阵。记专家 J_k 给出的判断矩阵为$_k(k=1,2,\cdots,K)$，由判断矩阵 A_k 得到的属性权重记为 W^k，有 $W^k=\{w_1^k, w_2^k, \cdots, w_n^k\}$，满足 $\sum_{j=1}^n w_j^k=1, w_j^k\geqslant 0$。

1 属性赋权

独立考虑各个专家给出的判断矩阵。当判断矩阵满足完全一致性要求时，可以认为下式成立，$a_{ij}=\dfrac{w_i}{w_j}$，即 $a_{ij}w_j=w_i$。由于客观事物的复杂性，人们认识的局限性和多样性，专家给出的判断矩阵一般不满足完全一致性要求。因此期望由判断矩阵 A_k 得到的属性权重 $w_i^k(i=1,2,\cdots,n)$ 应尽量满足一致性要求，使得差值 $|a_{ij}^k w_j^k - w_i^k|$ 越小越好[1,6]。由该思路可以得到求解属性权重的模型

$$
\begin{aligned}
\min Z_k &= \sum_{i=1}^n\sum_{j=1}^n (a_{ij}^k w_j^k - w_i^k)^2\\
\text{s.t.}\quad & \sum_{j=1}^n w_j^k = 1\\
& w_j^k > 0,\ j=1,2,\cdots,n\\
& k=1,2,\cdots,K
\end{aligned}
\tag{1}
$$

为求解该模型，特构造 Lagrange 函数得

$$
F(\omega_i,\lambda) = \sum_{i=1}^n\sum_{j=1}^n (a_{ij}^k w_j^k - w_i^k)^2 + 2\lambda\Big(\sum_{j=1}^n w_j^k - 1\Big)
$$

分别对 w_i 和 λ 求偏导数，得到 $n+1$ 元非齐次线性方程组为

$$
\begin{cases}
\sum_{i=1}^n (a_{il}^k w_l^k - w_i^k)a_{il} - \sum_{j=1}^n (a_{lj}^k w_j^k - w_l^k) + \lambda = 0,\\
\quad l=1,2,\cdots,n\\
\sum_{j=1}^n w_j^k = 1
\end{cases}
\tag{2}
$$

整理后得到

$$
\begin{cases}
\Big[\sum_{i=1,i\neq l}^n (a_{il}^k)^2 + n - 1\Big]w_l^k - \sum_{i=1,i\neq l}^n (a_{il}^k + a_{li}^k)w_i + \lambda = 0,\\
\quad l=1,2,\cdots,n\\
\sum_{j=1}^n w_j^k = 1
\end{cases}
\tag{3}
$$

用矩阵形式表示为

$$
QX = P \tag{4}
$$

式中，$Q=(q_{lj})$ 是 $n+1$ 阶方阵，$q_{ll}=\sum_{i=1,i\neq l}^n (a_{il}^k)^2 + (n-1)$，$q_{lj}=-(a_{lj}^k + a_{jl}^k)$，$q_{(n+1),l}=q_{l,(n+1)}=1$，$q_{(n+1),(n+1)}=0$，$(l\neq j, l,j=1,2,\cdots,n)$；$X=(w_1^k, w_2^k, \cdots, w_n^k, \lambda)^T$；$P=(0,0,\cdots,0,1)^T$。

易知矩阵 Q 可逆，故线性方程组的解为 $X=Q^{-1}P$，即：向量 X 的前 n 个分量就是由专家 J_k 的判断矩阵 A_k 计算出的属性权重 w^k[7]。

2 专家赋权

在给每个专家赋权时，应从两个方面考虑：判断矩阵的一致性和属性权重的一致性。一般认为，判断矩阵 A_k 的一致性越好，该专家对属性权重的判断越符合属性重要性两两比较后该满足的逻辑性。认为该专家此次对属性权重的判断效果越好，因此给该专家赋予较高的权重。用 Z_k 描述 A_k 的一致性，Z_k 越小 A_k 的一致性越好。对于属性权重的一致性，由不同专家得到的权重越接近，表明专家的意见较一致。因此通过比较不同专家得到的属性权重，得到每个专家的属性权重差异值。若该专家得到的属性权重与其他专家得到的属性权重比较后差异越小，说明该专家给出的权重更能够体现多数专家对属性权重达成的共识，赋予该专家较高的权重。定义专家 J_k 较其他专家的属性权重差异值为 D_k，且

$$
D_k = \sum_{l=1}^K\sum_{j=1}^n (w_j^k - w_j^l)^2 \tag{5}
$$

综合上述两个方面，由判断矩阵集结的全部信息得到计算专家权重的客观赋权模型：

$$
\begin{aligned}
\min\ & \sum_{k=1}^K v_k^2(Z_k + D_k)\\
\text{s.t.}\ & \sum_{k=1}^K v_k = 1\\
& v_k > 0,\ k=1,2,\cdots,K
\end{aligned}
\tag{6}
$$

引入 Lagrange 函数求解上述模型有

$$
L = \sum_{k=1}^K v_k^2(Z_k + D_k) + 2\theta\Big(\sum_{k=1}^K v_k - 1\Big)
$$

分别对 v_k 和 θ 求导得到

$$
\begin{cases}
\dfrac{\partial L}{\partial v_k} = 2v_k(Z_k + D_k) + 2\theta = 0\\
\sum_{k=1}^K v_{ki} = 1
\end{cases}
\tag{7}
$$

从而解得

$$
v_k = \frac{1}{Z_k + D_k}\,\frac{1}{\sum_{k=1}^K \dfrac{1}{Z_k + D_k}} \tag{8}
$$

3 决策方法

归纳上述推理，可以得到基于判断矩阵信息的多属性群决策模型的具体步骤。

步骤 1 利用式(4)由判断矩阵 A_k 计算每个专家的属性权重 w^k，$k=1,2,\cdots,K$；

步骤 2　利用式(5)和式(8)计算专家权重 v_k, $k=1,2,\cdots,K$;

步骤 3　利用线性加权法集结属性信息,得到专家 J_k 关于方案 P_i 的判断结果,记为 P_i^k,且 $P_i^k=\sum_{j=1}^{n} r_{ij} w_j^k$, $i=1,2,\cdots,m$, $k=1,2,\cdots,K$;

步骤 4　利用线性加权法集结专家信息,得到方案 P_i 的最终排序结果,记为 P_i,且 $P_i=\sum_{k=1}^{K} P_i^k v_k$, $i=1,2,\cdots,m$;

步骤 5　由 $\max_{1\le i\le m}\{P_i\}$ 选出最优方案。

4　算例与分析

利用文献[4]给出的算例进行比较分析。假设由 4 位专家给出的判断矩阵为

$$A_1=\begin{bmatrix}1&7&5&4\\1/7&1&1&1/2\\1/5&1&1&1/3\\1/4&2&3&1\end{bmatrix},\quad A_2=\begin{bmatrix}1&6&7&5\\1/6&1&1&1\\1/7&1&1&1\\1/5&1&1&1\end{bmatrix},$$

$$A_3=\begin{bmatrix}1&6&8&4\\1/6&1&1&1/2\\1/8&1&1&1\\1/4&2&1&1\end{bmatrix},\quad A_4=\begin{bmatrix}1&3&2&1\\1/3&1&1/2&1/3\\1/2&2&1&2\\1&3&1/2&1\end{bmatrix}$$

步骤 1　由判断矩阵 A_k 计算每个专家的属性权重 w^k $(k=1,2,3,4)$。

由式(4)得到从判断矩阵计算出的专家的属性权重分别为

$$w^1=(0.631\,1\quad 0.091\,1\quad 0.107\,1\quad 0.170\,7),$$
$$w^2=(0.663\,4\quad 0.110\,9\quad 0.096\,7\quad 0.129\,0),$$
$$w^3=(0.651\,9\quad 0.104\,6\quad 0.084\,6\quad 0.158\,9),$$
$$w^4=(0.381\,3\quad 0.114\,8\quad 0.264\,0\quad 0.239\,9)$$

步骤 2　计算每个专家的权重 v_k $(k=1,2,3,4)$。

先计算 Z_k,在计算 w^k 的同时可得到 Z_k 分别为

$$Z_1=0.038\,3,\ Z_2=0.003\,7,\ Z_3=0.016\,5,\ Z_4=0.140\,2$$

然后计算 D_k,由(5)可得到 D_k 分别为

$$D_1=0.096\,9,\ D_2=0.124\,4,\ D_3=0.114\,5,\ D_4=0.324\,3$$

最后,由式(8)得到专家权重分别为

$$v_1=0.296\,0,\ v_2=0.312\,4,\ v_3=0.305\,5,\ v_4=0.086\,2$$

步骤 3　利用线性加权法集结属性信息和专家信息,并选出最优方案。

该算例比较简单直观,可以用定性分析来验证定量计算的结果。观察 4 个判断矩阵,可以发现 4 个专家中有 3 个专家 J_1, J_2, J_3 都认为属性 1 最为重要,而属性 2,3,4 的重要性相对接近且相对于属性 1 的重要性要小。因此定性分析的结论为:

(1) 由专家 J_1, J_2, J_3 得到的属性权重应该较为一致;

(2) J_1, J_2, J_3 这 3 个专家给出的属性权重结构都应该是:属性 1 的权重最大,属性 2,3,4 的权重较小且权重数量值接近;

(3) J_1, J_2, J_3 的专家权重数值应该接近且大于 J_4 的专家权重。

从算例的计算结果看,w^1, w^2, w^3 一致性较好,属性权重差异值数值 D_1, D_2, D_3 接近,介于 0.096 9 与 0.114 5 之间,而专家 J_4 的属性权重差异值 $D_4=0.324\,3$ 最大,且 w^1, w^2, w^3 结构相同,均是属性 1 的权重最大,且介于 0.631 1 与 0.663 4 之间;而属性 2,3,4 的权重较小且数值接近,介于在 0.084 6 与 0.170 7 之间。最后得到的专家权重 v_1, v_2, v_3 数值接近,均大于 v_4,同时,专家 J_2 的判断矩阵一致性最好,因此在 v_1, v_2, v_3 这三个数值接近的权重中,v_2 最大。可以看出,这些定量计算的结果与上述定性分析一致。故本文基于判断矩阵信息挖掘属性权重和专家权重的客观赋权方法是有效的,而且具有计算方法简单明了的特点。

5　结束语

在多属性群决策问题中,应用主观赋权法为专家赋权容易出现对专家的主观判断与专家在该决策问题中的实际决策行为不一致的现象。由于专家关于某个实际决策问题的判断完全蕴涵在其给出的判断矩阵中,因此应充分挖掘判断矩阵信息,从而得到属性权重和专家权重。本文利用判断矩阵,基于对判断矩阵的一致性和不同专家属性权重的一致性要求,提出了一种为属性和专家赋权的客观赋权法,并得到了解决该决策问题的决策模型。经算例证明,该方法简单可行。

参考文献:

[1] 张忠诚. 多属性决策问题的一种新方法[J]. 武汉理工大学学报, 2006, 28(4):117-120.

[2] 郭春香,郭辉煌. 属性具有不同形式偏好信息的群决策方法[J]. 系统工程与电子技术, 2005, 27(1): 63-65. (Guo Chunxiang, Guo Huihuang. Aproach of multiple-attribute group decision making with different forms of preference information [J]. *Systems Engineering and Electronics*, 2005, 27(1):63-65.)

[3] 宋光兴,邹平. 多属性群决策中决策者权重的确定方法[J]. 系统工程, 2001, 19(4):84-89.

[4] 梁樑,熊立,王国华. 一种群决策中专家客观权重的确定方法[J]. 系统工程与电子技术, 2005, 27(4):652-655. (Liang Liang, Xiong Li, Wang Guohua. New method of determining the objective weight of decision makers in group decision making [J]. *Systems Engineering and Electronics*, 2005, 27(4): 652-655.)

[5] Ma Jian, Fan Zhi-ping, Huang Li-hua. A subjective and objective integrated approach to determine attribute weights[J]. *European Journal of Operational Research*, 1999, 112: 397-404.

[6] Chu A T W, Kalaba R E, Spingarm K. A comparison of two methods for determining the weights of belonging to fuzzy sets [J]. *Journal of Optimization Theory and Applications*, 1979, 27(4): 531-538.

[7] 徐玖平,吴巍. 多属性决策的理论与方法[M]. 北京:清华大学出版社,2006.

A Method for Weight Assignment By Dominance-Based Rough Sets Approach

Zhang Rong[1,2], Liu Sifeng[1], Liu Bin[2]

1. College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 210016
E-mail: zr.mis@163.com

2. College of Information and Management Science, Henan Agricultural University, Zhengzhou 450002
E-mail: liubhnau@163.com

Abstract: In many real problems, it does not consider the ranking characteristic of criteria to make multi-criteria decision with classical rough sets theory. By Dominance-based Rough Sets Approach (DRSA), this paper develops methods for weight assignment respectively under two settings, with decision sorting classes and without decision sorting classes. Compared to present methods, the advantage of our methods is that: from descriptive set of the given problem, extracts the inherent rules implied by alternatives dominance relations with respect to each attribute, and avoids excessively depending on experts' experience; realizes completely data driving. Finally an example illustrates our methods are effective and reasonable.

Key Words: Dominance-based rough set, Multi-attribute decision-making, Weight, Unsupervised learning

1 INTRODUCTION

Multi-attribute decision problems widely consist in many fields. When weights of attributes are completely unknown, it is a key problem to assign weight in the field of multi-attribute decision. So researchers extensively study the problem. Now there are three types of methods to assign the weights, and they are objective method, subjective method, and combining methods from two forenamed [1-5]. The objective method obtains the weights only based on the known data of the problem, which is certainly objective, but needs to standardize the original data; the subjective method generally needs corresponding transcendent information or experts' opinions. Now there are distinct differences on the weights got from different methods and there are not explicit meanings of weight assignment in some methods. So the multi-attribute decision, of which the weights of attributes is completely unknown, still need to further explore.

The most outstanding distinguish between rough sets theory and other theories of dealing with uncertainty and inaccurate problem is that does not need any transcendent information except for the data set being dealt with of the problem, and rough sets theory is an effective tool to mine out concealed rule from the apparent data. Some researchers have developed the method for weight assignment by rough sets theory [6-8], which do not need to obtain in advance the quantitative descript of some characteristics or some attributes and find the inherent rule concealed in the problem from the descript set of the given problem. So the method avoids excessively depending on the experts' experiences and realizes completely data driving to finally obtain the weights by making the most of the data from decision problem itself. However, this kind of methods just takes the classification characteristic of attribute into consideration but ignores the preference-orders of attribute domains or criteria. As well as the preference-orders of attributes is very important in many real problems. Moreover classical rough set approach requires dispersing the values of attribute, which induces information loss. Researchers discover, in the process of rough set method being applied to multi-criteria decision analysis, classical rough sets theory is not adapt to the attribute that possesses dominance relations and can not completely declare the knowledge consistent with the dominance principle in the decision table in which attribute values have preferential orders. Greco et al. hybrid the classical rough sets theory with dominance theory and replace indiscernibility relations or similarity relations with dominance relations to develop the DRSA [9-11]. At present the DRSA is widely applied to many fields such as engineering, aviation, military affairs, finance et al. [12-14].

Now in many practices it is important to take preference-orders of criteria into consideration, so it shows more important to induce the proper weight information from the preferential information of alternatives. Thereby it satisfies the real requirement of preference-orders of criteria to resolve the weights assignment problem with DRSA. Further more, when the data have preference relations, the actual range of criterion can be discrete or continuous and the values of criteria do not need to be dispersed, so the information loss can be avoided during the process of dispersing data.

The rest of this paper is organized as follows. In section 2, a general view of classical rough sets is given first, and then the method for weight assignment by classical rough

This paper is partially supported by National Natural Science Foundation of China under Grant No.70473037.

sets is introduced. In section 3, a general view of DRSA is given first, and then the methods for weight assignment by DRSA are develops. In Section 4, an empirical study and results analysis is carried on. Section 5 draws conclusions.

2 METHOD OF WEIGHT ASSIGNMENT BY CLASSICAL ROUGH SETS

2.1 A general view of classical rough sets

Given an information system $S=(U,A,V,f)$, where U is a finite set of objects and is universe, A is a finite set of attributes, $V=\bigcup_{a\in A}V_a$, and V_a is the actual range of attribute a, $f: U\times A\to V$ is information function for each $x\in U$ and $a\in A$ such that $f(x,a)\in V_a$.

Definition 1: On U for each subset $R\subset A$ the indiscernibility relation is denoted by

$ind(R)=\{(x,y)\in U\times U \mid f(x,r)=f(y,r), \forall r\in R\}$.

In the information system S the family of all the equivalence classes with regard to indiscernibility relation $ind(R)$ is denoted by U/R, and one of the equivalence classes is $Y\in U/R$.

Definition 2: Subset $X\subseteq U$ and R is an indiscernibility relation on U, then the $R-$ lower approximation of X is $\underline{R}(X)=\bigcup\{Y\in U/R \mid Y\subseteq X\}$.

Definition 3: In the information system $S=(U,A,V,f)$, $R,P\subset A$ is an indiscernibility relation on U, and $pos_R(P)=\bigcup_{X\in U/P}\underline{R}(X)$ is positive region of P with regard to class R, for short relative positive-region.

R positive region of P is the set of objects, which can be correctly partitioned to the equivalence class by the information of class U/R.

Definition 4: A quality of the approximation of P by means of the attributes from R is defined as $\gamma_R(P)=\dfrac{card(pos_R(P))}{card(U)}$, representing the relative frequency of the objects correctly classified by means of the attributes from R.

Definition 5: In information system $S=(U,A,V,f)$, $R,P\subset A$ is an indiscernibility relation on U, for $\forall r\in R$, and the relative importance of attribute r is $\gamma_r=\gamma_R(P)-\gamma_{R-r}(P)$.

2.2 The method for weight assignment by classical rough sets

The multi-attribute decision problem of the weight information completely unknown, $X=\{x_1,x_2,\dots,x_m\}$ is a finite set of alternatives; the attribute set is $A=\{a_1,a_2,\dots,a_n\}$; the value of alternative x_i with regard to attribute a_j is denoted as v_{ij}, and $v_{ij}\in V_{a_j}$, V_{a_j} is the domain of attribute a_j; the weights of attributes are $W=\{w_1,w_2,\dots,w_n\}$, satisfy $\sum_{j=1}^{n}w_j=1$, $w_j>0$, and the information of weights are completely unknown. Then to solve the problem, the weights of attributes need to be first obtained, and then all alternatives are synthetically evaluated to get $f_i=\sum_{j=1}^{n}w_jv_{ij}$, $i=1,2,\dots m$, on which the rank ordering of alternatives are drawn.

Here we plan to assign weight with classical rough set method, and it is assumed that the data table has been pre-treated, including the attribute values of alternatives are dispersed and the repeating alternative has been deleted, namely two alternatives are not completely the same, for $\forall x_i,x_j\in X$, $\exists a_k\in A$ such that $v_{ik}\neq v_{jk}$. We think the multi-attribute decision problem as an information system $S=(U,A\bigcup D,V,f)$, where the set of alternatives X is universe U, the set of condition attribute is the attribute set A of multi-attribute decision problem, D is the set of decision attribute shows the synthetic judge to X. With the assumption that there are not two completely same alternatives in existence, we think that the decision class is $U/D=\{\{x_1\},\{x_2\},\dots,\{x_m\}\}$.

By definition 5 we can get the equivalent method to compute the attribute importance with classical rough set in the context of multi-attribute decision.

Theorem 1: For this multi-attribute decision problem $S=(X,A\bigcup D,V,f)$, the importance of condition attribute $a_j\in A$ with respect to the decision class D is as formula (1).

$$\gamma_{a_j}=1-\frac{card(pos_{A-a_j}(D))}{card(X)} \tag{1}$$

Proof: to consider the multi-attribute decision problem as an information system $S=(X,A\bigcup D,V,f)$, and then the relative importance of attribute $a_j\in A$ is

$$\gamma_{a_j}=\gamma_A-\gamma_{A-a_j}=\frac{card(pos_A(D))-card(pos_{A-a_j}(D))}{card(U)}.$$

Due to $pos_A(D)=\bigcup_{Y\in U/D}\underline{A}(Y)=\{x_1,x_2,\dots,x_n\}=X$, and $U=X$, then

$card(pos_A(D))=card(U)=card(X)$. Q.E.D.

After getting γ_{a_j} with definition 5 or theorem 1, normalize it and get weight of attribute $a_j\in A$ is

$$w_j=\frac{\gamma_{a_j}}{\sum_{j=1}^{n}\gamma_{a_j}},\quad j=1,2,\dots,n.$$

3 METHODS FOR WEIGHT ASSIGNMENT BY DRSA

3.1 A general view of DRSA

For information system $S=(U,A,V,f)$, let $Cl=\{Cl_t, t\in T\}$, $T=\{1,2,\ldots,n\}$ is a set of decision class of U such that $\forall x\in U$ belongs to one and only one class $Cl_t\in Cl$. We assume that for $\forall r,s\in T$ and $r>s$ such that each element of Cl_r is preferred to each element of Cl_s.

Definition 6: Let S_a is an outranking relation on U with reference to criterion $a\in A$, for $\forall x,y\in U$, $xS_a y$ means that x is at least as good as y with respect to criterion a, namely $f(x,a)\geq f(y,a)$.

Definition 7: For $\forall q\in P$ and $P\subseteq A$, if there is $xS_q y$, then x is dominating to y with respect to the set of attribute P, and denoted $xD_P y$.

Definition 8: Given $P\subseteq A$ and $x\in U$, let $D_P^+(x)=\{y\in U\mid yD_P x\}$ represents $P-$dominating set with respect to x, and $D_P^-(x)=\{y\in U\mid xD_P y\}$ represents $P-$dominated set with respect to x.

Definition 9: The sets of upward unions and downward unions are respectively $Cl_t^{\geq}=\bigcup_{s\geq t} Cl_s$, $Cl_t^{\leq}=\bigcup_{s\leq t} Cl_s$.

In dominance-based rough set approach, the sets to be approximated are the sets of upward unions and downward unions of classes, and the granules of knowledge used for this approximation are the dominating sets and the dominated sets.

Definition 10: For $t\in T$ and $P\subseteq A$, the $P-$upper approximation, $P-$lower approximation and $P-$boundary of $Cl_t^{\geq}$ and $Cl_t^{\leq}$ are respectively defined as follows:

$$\underline{P}(Cl_t^{\geq})=\{x\in U\mid D_P^+(x)\subseteq Cl_t^{\geq}\},$$
$$\underline{P}(Cl_t^{\leq})=\{x\in U\mid D_P^-(x)\subseteq Cl_t^{\leq}\},$$

$$\overline{P}(Cl_t^{\geq})=\bigcup_{x\in Cl_t^{\geq}} D_P^+(x)=\{x\in U\mid D_P^-(x)\cap Cl_t^{\geq}\neq\varnothing\},$$
$$\overline{P}(Cl_t^{\leq})=\bigcup_{x\in Cl_t^{\leq}} D_P^-(x)=\{x\in U\mid D_P^+(x)\cap Cl_t^{\leq}\neq\varnothing\},$$

$$bn_P(Cl_t^{\geq})=\overline{P}(Cl_t^{\geq})-\underline{P}(Cl_t^{\geq}),$$
$$bn_P(Cl_t^{\leq})=\overline{P}(Cl_t^{\leq})-\underline{P}(Cl_t^{\leq}).$$

Definition 11: The quality of approximation of partition Cl by means of the set of criteria $P\subseteq A$, or briefly quality of sorting is defined as formula (2).

$$\gamma_P(Cl)=\frac{card(U-((\bigcup_{t\in T} bn_P(Cl_t^{\geq}))\cup(\bigcup_{t\in T} bn_P(Cl_t^{\leq}))))}{card(U)} \tag{2}$$

3.2 Methods for weight assignment by DRSA

In the multi-criteria decision problem a criterion generally has certain dominance relations. So to mine the sorting characteristic based on criteria with classical rough set approach does not completely declare the ordering characteristic of alternatives with respect to criteria. Hence, we can try to obtain the criterion importance based on the dominance relations of alternatives with dominance-based rough sets. Meanwhile data just have ordering relation and can be continuous as well, which do not need to be dispersed.

Referring to the concept of relative importance of attribute in classical rough sets, above all we define the relative importance of criterion in terms of decision sorting class based on the dominance relations.

Definition 12: For information system $S=(U,A,V,f)$, $R\subset A$ is a dominance relation on U, for classification Cl and $\forall r\in R$, the importance of criterion r in terms of decision sorting class is defined as $\gamma_r(Cl)=\gamma_R(Cl)-\gamma_{R-r}(Cl)$, or briefly the relative importance of criterion.

With regard to the multi-criteria decision problem of weight information completely unknown $S=(X,A,V,f)$, the decision aim is to rank or choose one from alternatives. As well as the approximated sets are the sets of upward unions and downward unions of decision sorting classes in the dominance-based rough set approach. So without decision sorting classes we cannot assign weights of criteria with the approximation method by granules of knowledge. However though the decision sorting classes are unknown, the dominance relations of alternatives with respect to condition attribute is the objective existence. Moreover, decision classes do not influence these dominance relations on the basis of condition attribute. So we can refer to the method of computing the relative importance of attribute with classical rough sets. By deleting a criterion, then to examine the change of dominating set of each alternative before and after deleting the criterion, we can mine the importance of the criterion in terms of dominance relations of alternatives. Because in this way the importance of criterion does not be decided in terms of decision sorting classes, so we call it criterion importance.

Definition 13: A multi-criteria decision problem $S=(X,A,V,f)$, which criteria have dominance relations, then the importance of criterion $a_j\in A$ is defined as formula (3).

$$\gamma_{a_j}=1-\frac{card(\{x_i\in X\mid D_{A-a_j}^+(x_i)\subseteq D_A^+(x_i)\})}{card(X)} \tag{3}$$

For $\forall x_i\in X$, the alternative in the set of alternatives X can be divided into 3 types. One type is the set of elements dominating x_i with regard to criterion set A, namely $D_A^+(x_i)$; another type is the set of elements dominated x_i with regard to condition attribute A, namely

$D_A^-(x_i) - \{x_i\}$; the third type is the set of elements that cannot be definitely judged dominating or dominated x_i, namely $U - D_A^+(x_i) - D_A^-(x_i)$. Now we examine the change of dominance relations of alternative x_i after getting rid of $a_j \in A$. We know $\forall x_k \in D_A^+(x_i)$ means $f(x_k, a) \geq f(x_i, a)$ for $\forall a \in A$. On $A - a_j$ after deleting criterion a_j, there is still $f(x_k, a) \geq f(x_i, a)$, so $x_k \in D_{A-a_j}^+(x_i)$, namely the element in set $D_A^+(x_i)$ still is the element in $D_{A-a_j}^+(x_i)$; $\forall x_j \in D_A^-(x_i) - \{x_i\}$, there is $f(x_i, a) \geq f(x_j, a)$ for $\forall a \in A$. On $A - a_j$ after deleting criterion a_j, 2 results come out. One is still $f(x_i, a) \geq f(x_j, a)$, namely the element in set $D_A^-(x_i) - \{x_i\}$ is still in set $D_{A-a_j}^-(x_i) - \{x_i\}$; another may be $f(x_i, a) = f(x_j, a)$, namely the element in set $D_A^-(x_i) - \{x_i\}$ may change to $D_{A-a_j}^+(x_i)$; $\forall x_l \in U - D_A^+(x_i) - D_A^-(x_i)$, some $a \in A$ makes $f(x_i, a) \geq f(x_l, a)$, but other $b \in A$ makes $f(x_i, b) < f(x_l, b)$, so on $A - a_j$ 3 results come out. When deleting the criterion a_j making $f(x_i, a_j) < f(x_l, a_j)$, then x_l changes to $D_{A-a_j}^+(x_i)$. When deleting the attribute a_j making $f(x_i, a_j) \geq f(x_l, a_j)$, then x_l changes to $D_{A-a_j}^-(x_i)$. The third result is still that x_l cannot be compared with x_i. To sum up, after deleting one attribute, the element in $D_A^+(x_i)$ is still in $D_{A-a_j}^+(x_i)$, the element in $D_A^-(x_i) - \{x_i\}$ is still in $D_{A-a_j}^-(x_i) - \{x_i\}$ or changes to $D_{A-a_j}^+(x_i)$, and the element in $U - D_A^+(x_i) - D_A^-(x_i)$ is still in $U - D_{A-a_j}^+(x_i) - D_{A-a_j}^-(x_i)$, or changes to $D_{A-a_j}^+(x_i)$ or $D_{A-a_j}^-(x_i)$. If one criterion influences the dominance relations of alternatives, then the results of $D_{A-a_j}^+(x_i) \supset D_A^+(x_i)$ or $D_{A-a_j}^-(x_i) \supset D_A^-(x_i)$ may come out. As well as the dominating relation and the dominated relation is in relative terms. For example, x_i must dominate x_l because x_l is dominated by x_i. So after deleting some criterion $a_j \in A$, for $\forall x_i \in X$ we just need to compare $D_A^+(x_i)$ with $D_{A-a_j}^+(x_i)$ instead. As $D_{A-a_j}^+(x_i) \subseteq D_A^+(x_i)$, it shows that criterion a_j has no influence on the dominance relations of alternative x_i.

4 EMPIRICAL STUDY

4.1 A Case

We carry on empirical study with the case in literature [6]. The set of alternatives is $U = \{1, 2, 3, 4, 5\}$, the set of condition attributes is $A = \{a, b, c, d\}$, and the set of decision attributes is $D = \{e\}$ (Table 1). Based on classical rough set approach, we just take the indiscernibility relation into consideration and get the attribute weights $w_a = 0.25$, $w_b = 0.25$, $w_c = 0$, and $w_d = 0.5$.

In the data table all the alternatives have the same value in terms of attribute c, so we think the attribute is redundancy and delete it. About patients' disease symptom and health condition, we think that attribute domains have preference-orders, namely think the value 1 is preferred to the value 0 and they do not only show different classification. The classes of decision attributes are sorting classes. Let $Cl = \{Cl_1, Cl_2\}$, then $Cl_2^{\geq} = Cl_2 = \{3, 4, 5\}$, $Cl_1^{\leq} = Cl_1 = \{1, 2\}$. But here the decision table is inconsistent. So we cannot compute the relative importance of attribute based on upper approximation and lower approximation of the sets of upward unions and downward unions of sorting classes Cl. The reason is that: $\underline{A}(Cl_2^{\geq}) = \varnothing$, $\overline{A}(Cl_2^{\geq}) = U$, $bn_A(Cl_2^{\geq}) = U$, and according to complementarity property $bn_A(Cl_2^{\geq}) = bn_A(Cl_1^{\leq})$, so the whole set of alternatives is not completely approximated in terms of decision sorting classes Cl with respect to condition attribute A.

Table1. Original Data Table

	a	b	c	d	e
1	1	1	0	1	0
2	0	0	0	1	0
3	0	0	0	0	1
4	0	1	0	1	1
5	1	1	0	0	1

Due to the data table inconsistent in terms of classes Cl, next we do not take the decision attribute e into consideration and just compare with the attribute values of alternatives to extract the importance of each condition attribute in terms of the dominance relations of alternatives (table 2).

Table.2 The Data Table after Deleting the Redundancy Attribute and Decision Attribute

	a	b	d
1	1	1	1
2	0	0	1
3	0	0	0
4	0	1	1
5	1	1	0

On the whole set of condition attributes A:

$D_A^+(1) = \{1\}$, $D_A^+(2) = \{1, 2, 4\}$, $D_A^+(3) = U$, $D_A^+(4) = \{1, 4\}$, $D_A^+(5) = \{1, 5\}$;

After deleting one attribute a:

$D_{A-a}^+(1) = \{1, 4\}$, $D_{A-a}^+(2) = \{1, 2, 4\}$, $D_{A-a}^+(3) = U$, $D_{A-a}^+(4) = \{1, 4\}$, $D_{A-a}^+(5) = \{1, 4, 5\}$;

After deleting one attribute b:

$D_{A-b}^+(1) = \{1\}$, $D_{A-b}^+(2) = \{1, 2, 4\}$, $D_{A-b}^+(3) = U$, $D_{A-b}^+(4) = \{1, 4\}$, $D_{A-b}^+(5) = \{1, 4, 5\}$;

After deleting one attribute d:

$D_{A-d}^+(1) = \{1, 5\}$, $D_{A-d}^+(2) = U$, $D_{A-d}^+(3) = U$, $D_{A-d}^+(4) = \{1, 4, 5\}$, $D_{A-d}^+(5) = \{1, 5\}$;

According to definition 13, compute the importance of attribute:

$$\gamma_a = \frac{2}{5},\ \gamma_b = \frac{1}{5},\ \gamma_a = \frac{3}{5};$$

After normalizing, then we get the weights of attributes: $w_a = 0.3333$, $w_b = 0.1667$, $w_d = 0.5$.

Furthermore to solve the multi-criteria ranking problem of weight information completely unknown, we compute the comprehensive score of simple additive weighting as follows:

$f(1) = 1$, $f(2) = 0.5$, $f(3) = 0$, $f(4) = 0.6667$, $f(5) = 0.5$.

Then the ranking of alternatives is $1 \succ 4 \succ 2 \succ 3$ and $1 \succ 4 \succ 5 \succ 3$.

4.2 Compare two methods for weight assignment by above case

The result of examination shows that the method in this paper can get some conclusions that the classical rough set approach cannot get. For example, after respectively getting rid of attribute a and b, according to indiscernibility relations, the classification results with classical rough set approach are

$$U/A = \{\{1\}, \{2\}, \{3\}, \{4\}, \{5\}\},$$

$$U/(A-a) = \{\{1, 4\}, \{2\}, \{3\}, \{5\}\},$$

$$U/(A-b) = \{\{1\}, \{2, 4\}, \{3\}, \{5\}\}.$$

So the importance of attribute a and b are the same; however we can get more abundant results with dominance-based rough set approach: deleting attribute a, the dominance relations of not only alternative 4, but also alternative 5 change; but deleting attribute b, the dominance relations of only alternative 4 change. So we know attribute a is more important than attribute b. Thereby, we can get but the classification characteristic of alternatives with regard to attributes with classical rough set approach, moreover with DRSA we are just able to explore the outranking characteristic of alternatives with regard to attributes.

5 CONCLUSIONS

In many real problems, it is important to consider the outranking characteristic of attribute. However as assigning weight with classical rough set approach, we cannot explore the kind of outranking characteristic. By DRSA, this paper develops methods for weight assignment, which can effectively improve above limitation. Further, these methods are completely based on data driving and are objective weight assignment methods, and if the decision makers hope to combine their or experts' subjective opinions with the objective weights, they can realize it with simple additive weighting method that is simple to implement.

ACKNOWLEDGEMENT

The authors thank the editor and anonymous referees for their helpful comments and suggestions, which have improved the exposition of this paper.

REFERENCES

[1] M. Weber, K. Borcherding, Behavioural influences on weight judgments in multi-attribute decision-making, European Journal of Operational Research, Vol.67, No.1, 1-12, 1993.

[2] J. Ma, Z. P. Fan, L. H. Huang, A subjective and objective integrated approach to determine attribute weights, European Journal of Operational Research, Vol.11, No.2, 397-404, 1999.

[3] Z. P. Fan, Q. Zhang, J. Ma, An Integrated Approach to Determining Weights in Multiple Attribute Decision Making, Journal of Management Sciences in China, Vol.11, No.3, 50-53, 1998.

[4] Y. J. Pang, K. D. Liu, B. W. Zhang, The Method of Determining the Objective Index Weight in the Synthetic Evaluation System, Systems Engineering-Theory and Practice, Vol.21, No.8, 37-42, 2001.

[5] G. T. Chi, J. Hao, Z. Xu, Z. Y. Zhu, Cluster Analysis for Weight of Credit Risk Evaluation Index, Systems Engineering-Theory Methodology Application, Vol.10, No.1, 64-67, 2001.

[6] X. Y. Cao, J. G. Liang, The Method of Ascertaining Attribute Weight Based on Rough Sets Theory, Chinese Journal of Management Science, Vol.10, No.5, 98-100, 2002.

[7] D. X. Huang, Z. Y. Wu, Y. Z. Zong, An Impersonal Multi-Attribute Weight Allocation Method Based on Attribute Importance, Systems Engineering-Theory Methodology Application, Vol.13, No.3, 203-207, 2004.

[8] L. F. Jiang, Y. W. Shi, J. Man, S. Q. Yang, Comprehensive evaluation of building industry based on fuzzy aggregation and rough set theory, Journal of Dalian University of Technology, Vol.47, No.5, 729-734, 2007.

[9] S. Greco, B. Matarazzo, R. Slowinski, Rough set approach to multi-attribute choice and ranking problems. Multiple-Criteria Decision Making, Proceedings of the 12th International Conference, Berlin: Springer, 318-329, 1997.

[10] S. Greco, B. Matarazzo, R. Slowinski, Rough

approximation of preference relation by dominance relations, European Journal of Operational Research, Vol.117, No.1, 63-68, 1999.

[11] S. Greco, Rough approximation by dominance relation, International Journal of Intelligent Systems, Vol.17, No.2, 153-171, 2002.

[12] G. Mavrotas, P. Trifillis, Multicriteria decision analysis with minimum information: combining DEA with MAVT, Computers & Operations Research, Vol.33, No.8, 2083-2098, 2006.

[13] Y. Y. Jiang, H. X. Zhang, K. Meng, J. Jie, Research and Application of Multi-Criteria Decision Making Method based on Order Relation and Rough Set, Systems Engineering-Theory and Practice, Vol.27, No.6, 161-165, 2007.

[14] Y. Q. He, S. S. Hu, A Study of Preference Selection of Air Force Air Materiel Supply Site Based on the Rough Sets, Systems Engineering-Theory and Practice, Vol.23, No.7, 95-99, 2003.

区域生态主导产业指标体系的构建

丰立祥

(南京航空航天大学 管理工程学院,南京 210016)

摘 要:随着共同、和谐及可持续发展战略在世界范围内的普遍实施,基于生态效益主导产业的建设在发达国家渐成潮流。生态主导产业的发展是一个趋势,也是区域内主导产业建设的目标。基于对生态工业指标体系理论的研究,阐述了山西进行生态主导产业战略性选择的基本观点。

关键词: 生态主导产业;指标体系;战略选择

中图分类号:F061.5 **文献标识码**:A **文章编号**:1004 - 972X(2009)03 - 0122 - 04

一、区域生态主导产业评价指标体系的构建

主导产业的选择依据体系的确立,既要参照国内理论研究成果,也必须考虑到所研究区域目前的经济发展水平。1957年,日本经济学家筱原三代平提出了著名的“筱原两基准”,即收入和需求弹性基准与生产率上升基准,但对产业间的联系考虑不够。1958年,赫尔希曼提出“关联效应”理论,认为区域主导产业应与其他产业有较大的投入产出联系。本文针对我国的实际,认为生态主导产业的选择应当考虑以下几方面的因素:一是其他国家和地区工业化进程中表现出来的生态主导产业成长一般规律;二是区域现有产业结构问题的特殊性及对结构调整的影响;三是区域具体情况中的一些特殊因素的影响;四是区域目前结构状况下各产业之间的关联度及其变化趋势;五是区域现行产业结构的成长趋势以及顺应这种趋势的各种产业结构变化的要求;六是为了改变区域现存产业结构主要弊端而要求生态主导产业所必须具备的结构性功能;七是区域的基本情况。因此,生态主导产业的选择不应当只依据一两个基准,而应有一个判断体系。为此,本文从能源消耗、工业废水排放量、需求收入弹性、技术进步、产业关联强度、就业规模、经济效益七个方面入手,构建指标如下。

1. 能源消耗。能源是人类赖以生存、繁衍和进步的基础,是现代社会文明和经济发展的生命线,经济越是发展,社会越是进步,对能源的依赖程度也越高。安全可靠的能源供应和高效清洁的能源利用是实现社会经济持续发展的基本保证。因此,开发利用和节约能源已经成为当今世界普遍关心的问题。我国人均资源占有量远远低于世界平均值,而且能源利用效率也明显低于发达国家,建立节约型社会是我国当前发展的历史必然。生态主导产业在生产的过程中自然有能源约束,它不仅要求高产出,同时也要求低投入,即要求生态主导产业应是低能源消耗的产业,这里以万元GDP能耗作为评价指标。万元GDP能耗公式为:

$$c_i(t) = \frac{C_i(t)}{Y_i(t)} \tag{1}$$

式中,$C_i(t)$为i产业第t年标准煤能耗总量;$Y_i(t)$为i产业第t年生产总值(万元)。

2. 工业废水排放量。随着国民经济的发展和工业规模的扩大,区域内各个产业对水的需求量日益增大,同时,工业废水的排放量也会随之增加。因此,做好水资源的合理利用和保护工作就显得十分重要。区域生态主导产业应是低污染的产业,工业废水排放量应作为选择生态主导产业指标之一。工业废水排放量的大小受工业发展水平、产业结构、产品结构、技术工艺及设备水平、管理政策、环境法规等多因素的综合影响。在制定区域各个产业水资源的利用和保护规划中,需要预测工业废水排放量,预测时通常以万元GDP工业排放量为基础。万元GDP工业排放量公式为:

$$q_i(t) = \frac{Q_i(t)}{Y_i(t)} \tag{2}$$

式中,$Q_i(t)$为i产业第t年工业废水排放总量。

3. 需求收入弹性指标。从市场层面考察,收入需求弹性要高。从根本上说,产业结构的变动是由社会需求结构变化引起的。产业结构的演进往往随社会需求变化而兴起,并逐步发展成熟,然后随着边际效用递减而趋于衰退。在市场经济条件下,国民收入经过初次分配和再分配,最终形成对各种产品具有支付能力的需求。改革开放以来,随着人民收入水平的逐步提高,社会对各种产品需求的结构与层次发生了

收稿日期:2008 - 12 - 25

作者简介:丰立祥(1957 —),男,山西山阴人,南京航空航天大学管理工程学院在读博士研究生。

很大变化。反映市场需求程度可以用收入需求弹性来衡量,在价格不变的情况下,某种产品的需求增长率与人均国民收入增长率之比越大,则该产业的收入需求弹性就越高。从市场层面分析,需求收入弹性高的产品,在预测期内,随着人均国民收入增长,在市场上逐渐畅销。由于人口需求弹性大体一致,并考虑到需求的示范效应影响,后发展地区可以运用发达国家和地区在同一收入水平时的需求弹性系数来考察产业与产品的市场前景。在不同的收入水平下,新增收入往往会相对集中于某几类商品的消费。这些行业具有较大的国内和国际市场需求,可以以较高的速度增长,因此,政府应选择与培育这些收入需求弹性较高的产业。需求收入弹性公式为:

$$e_i(t) = \frac{\lambda Y_i(t) / Y_i(t)}{\lambda N(t) / N(t)} \tag{3}$$

式中,$\lambda Y_i(t) / Y_i(t)$ 为 i 产业第 t 年的生产总值增长率;$\lambda N(t) / N(t)$ 为同期国民收入增长率。

4. 技术进步指标。从生产潜力标准考察,生产率上升率要高,生产率主要用劳动生产率和资金产出率来衡量,在现实生活中,二者往往呈现此消彼长或一快一慢的变化。技术进步率正是这一过程的综合反映。从供给角度分析,某一产业的产品能否打入和占领市场,还取决于供给成本。不同产业部门的技术进步率不同,在其他条件相同的情况下,技术进步快的产业部门,产量上升也快,从而成本下降也快,最终能开拓市场,即是生产率上升率高。按生产率上升率高的标准来选择和培育生态主导产业,就是要选择技术要素最密集、技术进步最快的产业。技术水平公式为:

$$A_i(t) = \frac{Y_i(t)}{K_i^{\rightarrow}(t) L_i^{\updownarrow i}(t)} \tag{4}$$

式中,$K_i(t)$ = 为 i 产业第 t 年拥有的资金总额;$L_i(t)$ = 为 i 产业第 t 年平均职工人数;$\leftrightarrow i$ 为 i 产业资金产值弹性;$\updownarrow i$ 为 i 产业劳动力产值弹性。

技术进步速度公式为:

$$U_i = \frac{\ln A_i(t_n) - \ln A_i(t_0)}{t_n - t_0} \tag{5}$$

技术进步速度对产值增长发展的贡献公式为:

$$\rightarrow_{Ai} = U_i / \ell_i \tag{6}$$

式(4)、式(5)中,U_i 为 i 产业技术进步速度;$\ell_i = [\ln Y_i(t_n) - \ln Y_i(t_0)] / (t_n - t_0)$ 表示 i 产业产值在 t_0 年至 t_n 之间的年均增长速度。

5. 产业关联强度指标。由于国民经济各部门是一个相互联系、相互依存的整体,产业间存在着横向的经济联系和纵向的生产技术联系,一个产业的产出往往是与之相关联的产业的投入。各产业部门之间包括前向关联、后向关联和旁侧关联,通过依次递阶影响,形成波及效应,一个产业的发展会导致其他产业或部门的发展。生态主导产业之所以能够起主导作用,最重要的是需求。当每一部门对它的需求以及它对各个部门的需求都比较高时,优先发展这一部门便可以为发展其他部门创造条件,或是促进其他部门的加速发展。因此,当那些关联度大的生态主导产业优先发展时,必然要影响到与其有关产业的发展,受到影响的产业又进一步影响到了与它有关的更多产业的发展,一环套一环,产生连锁反应,从而推动和促进地区产业的发展。因此,政府在选择和培育生态主导产业时必须考虑产业关联强度指标,该指标体现了生态主导产业的发展是共同发展。主要表现为产业推动系数指标,产业推动系数(感应度系数)公式为:

$$F_i(t) = \frac{\sum_{j=1}^{n} R_{ij}(t)}{\frac{1}{n}\sum_{j=1}^{n}\sum_{i=1}^{n} R_{ij}(t)} \tag{7}$$

式中,$R_{ij}(t)$ 为第 t 年里昂惕夫逆系数。

6. 就业规模指标。不同的产业和行业具有不同的人口就业容量。在一般情况下,轻工业、建筑业等劳动密集型产业就业容量较大,而技术密集型产业、资金密集型产业的就业容量相对较小。我国人口规模大、劳动适龄人口多、劳动力供应充足、剩余劳动力多,而且从总体上看,人口素质相对较低,在生态主导产业的选择与培育中,不能不考虑适当发展一些就业容量大的产业,以缓解劳动力供应的压力。该指标体现了生态主导产业的发展是和谐发展。就业规模指标公式为:

$$S_L(t) = \frac{L_i(t)}{\sum L_i(t)} \tag{8}$$

式中,$L_i(t)$ 为第 t 年 i 产业劳动力数量。

7. 经济效益指标。生态主导产业是一个动态概念,它们不是固定不变的,而是随着经济发展而演进和变化的。经济效益是衡量产业对资源合理使用的程度,即产出与投入比。生态主导产业的选择应该有利于工业经济效益的提高。因此,只有那些投入少、产出高、生态效益好的产业才可能作为生态主导产业。该指标体现生态主导产业的发展是高效、可持续发展的指标。主要表现为劳动资金产出率、劳动资金产出率,其公式为:

$$G_i(t) = L_i^2(t) / K_i(t) L_i(t)$$

二、山西生态主导产业的选择

1. 指标及数据的说明。基于山西的实际情况,山西在选择和培育生态主导产业时,首先要考虑产业的关联强度,生态主导产业应能够带动其他产业共同发展;工业废水的排放量是生态主导产业选择的重要基准;在生态主导产业的选择与培育中,也应考虑适当发展一些就业容量大的产业,以缓解劳动力供应的压力;在生态主导产业的选择与培育中要考虑到生态主导产业的经济效益,生态主导产业应向着高效、可持续的方向发展。另外,生态主导产业要求能够促进技术进步,减少能源消耗,提高产品的需求收入弹性。鉴于以上考虑,评价指标权重由高到低依次排序为产业推动系数、万元 GDP 工业废水排放量、就业规模、劳动资金产出率、技术进步速度对产值增加的贡献、万元 GDP 能耗和需求收入弹性。

在综合考虑山西各产业的感应力系数的基础上,结合确定山西主导产业的七项基准,选取山西国民经济中占重要地位的煤炭、机械、冶金、电力、化工和食品六个产业作为研究对象,通过资料计算出 2006 山西和上述六个主要产业的各项指标,见表 1。

表 1　　山西主要产业各指标值

指标 / 产业	万元 GDP 能耗(吨标准煤)	万元 GDP 工业废水排放量(吨)	需求收入弹性	技术进步速度对产值增加的贡献	产业推动系数	就业规模	劳动资金产出率
煤炭	0.3410	0.2548	0.7323	1.5850	2.4230	0.4548	0.5062
机械	0.0651	0.0442	1.5620	0.7273	1.4942	0.1439	2.5838
冶金	0.8618	1.4910	1.3695	0.7450	3.6405	0.1810	4.7259
电力	0.1563	1.3717	0.3512	0.0153	1.8896	0.0666	0.8332
食品	0.0639	0.2339	0.8210	0.2480	0.7715	0.0406	0.8398
化工	0.1229	1.8519	6.2999	0.0270	2.5250	0.1131	6.7910

2. 基于极大熵准则的山西生态主导产业选择。由上述构建的模型,评价指标包含万元 GDP 能耗、万元 GDP 工业废水排放量、需求收入弹性、技术进步速度对产值增加的贡献、产业推动系数、就业规模和劳动资金产出率指标,分别用 P_1、P_2、P_3、P_4、P_5、P_6 和 P_7 表示,并对山西产业 Q_1、Q_2、Q_3、Q_4、Q_5、Q_6 评价和排序。六个被评价项目所对应的初始指标值用初始矩阵 A 表示为:

$$A=\begin{bmatrix} 0.3410 & 0.2548 & 0.7323 & 1.5850 & 2.4230 & 0.4548 & 0.5062 \\ 0.0651 & 0.0442 & 1.5620 & 0.7273 & 1.4942 & 0.1439 & 2.5838 \\ 0.8618 & 1.4910 & 1.3695 & 0.7450 & 3.6405 & 0.1810 & 4.7259 \\ 0.1563 & 1.3717 & 0.3512 & 0.0153 & 1.8896 & 0.0666 & 0.8332 \\ 0.0639 & 0.2339 & 0.8210 & 0.2480 & 0.7715 & 0.0406 & 0.8398 \\ 0.1229 & 1.8519 & 6.2999 & 0.0270 & 2.5250 & 0.1131 & 6.7910 \end{bmatrix}$$

通过初始矩阵 A 可以得到矩阵 $\tilde{A}$:

$$\tilde{A}=\begin{bmatrix} 0.3410 & 0.2548 & 0.7323 & 1.5850 & 2.4230 & 0.4548 & 0.5062 \\ 0.0651 & 0.0442 & 1.5620 & 0.7273 & 1.4942 & 0.1439 & 2.5838 \\ 0.8618 & 1.4910 & 1.3695 & 0.7450 & 3.6405 & 0.1810 & 4.7259 \\ 0.1563 & 1.3717 & 0.3512 & 0.0153 & 1.8896 & 0.0666 & 0.8332 \\ 0.0639 & 0.2339 & 0.8210 & 0.2480 & 0.7715 & 0.0406 & 0.8398 \\ 0.1229 & 1.8519 & 6.2999 & 0.0270 & 2.5250 & 0.1131 & 6.7910 \\ 0.2685 & 0.8746 & 1.8560 & 0.5579 & 2.1240 & 0.1667 & 2.7133 \end{bmatrix}$$

通过对矩阵 $\tilde{A}$ 作当量化处理,可以得到矩阵 $\tilde{R}$:

$$\tilde{R}=\begin{bmatrix} 1.2700 & 0.2913 & 0.3946 & 2.8410 & 1.1408 & 2.7283 & 0.1866 \\ 0.2425 & 0.0505 & 0.8416 & 1.3036 & 0.7035 & 0.8632 & 0.9523 \\ 3.2097 & 1.7048 & 0.7379 & 1.3354 & 1.1740 & 1.0858 & 1.7418 \\ 0.5821 & 1.5684 & 0.1892 & 0.0274 & 0.8896 & 0.3995 & 0.3071 \\ 0.2380 & 0.2674 & 0.4423 & 0.4445 & 0.3632 & 0.2436 & 0.3095 \\ 0.4577 & 2.1174 & 3.3943 & 0.0484 & 1.1888 & 0.6785 & 2.5029 \\ 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \end{bmatrix}$$

将矩阵 $\tilde{R}$ 中的数值带入到公式中,并且给 δ 赋不同的值:0.2、0.4、0.6 和 0.8,可以得到四组不同的赋权策略。

结合主导产业的生态效益的约束条件,指标权重排序如下:

$w_5 > w_2 > w_6 > w_7 > w_4 > w_1 > w_3$

即指标权重排序要求依次为产业推动系数、万元 GDP 工业废水排放量、就业规模、劳动资金产出率、技术进步速度对产值增加的贡献、万元 GDP 能耗和需求收入弹性。

可以选取四种赋权策略中最优的一种,即当 $\delta = 0.2$ 的时候,此时:

$(w_1, w_2, w_3, w_4, w_5, w_6, w_7)^T = (0.0766, 0.1456, 0.0662, 0.0942, 0.3422, 0.1442, 0.1310)^T$

根据综合值的计算公式 $U_i = \sum_{j=1}^{m} w_j r_{ij}$,计算各个被评价对象最终的评价值,如下所示:

$(U_1, U_2, U_3, U_4, U_5, U_6)^T = (1.2221, 1.0539, 2.3354, 1.0018, 0.4965, 2.4686)^T$

根据上述计算结果,得山西生态产业的排序为:

$U_6 > U_3 > U_1 > U_2 > U_4 > U_5$

因此,基于生态效益的产业排序依次为化工、冶金、煤炭、机械、电力和食品。

3. 结果分析。从上述计算结果可知,在山西的生态主导产业中,产业排序依次为化工、冶金、煤炭、机械、电力和食品。综合考虑各种因素,从和谐及可持续发展的角度,山西要最大限度地保护良好的生态环境,必须大力抓好化工、冶金和煤炭产业的生态建设。化工、冶金和煤炭既是山西的支柱产业,也是山西未来的生态发展方向,山西应充分利用这些产业的优势,发挥前向关联、后向关联和波及效应,带动山西生态经济发展。此外,主导生态产业选择是一个动态的过程,随着经济的发展和产业消耗指标的变化及时代要求的不同,其主导产业在不断变化。

(1) 大力发展以化工和冶金为主的原材料工业。把原材料工业作为山西的生态主导产业,主要是化工和冶金产业,这也符合地区优势准则。山西铁、铝、铜储藏丰富,易于开采。依托资源优势的山西能源工业相对发达,这就为化工和冶金产业的发展奠定了基础。山西的能源、原材料工业形成紧密的工业链,相互依托发展,能充分发挥山西的地区优势。而且化工和冶金产业一直是我国的瓶颈产业,国内市场的需求旺盛。化工和冶金产业在山西工业中具有一定的规模和实力,应发挥山西在化工和冶金方面的人才和技术优势,强化化工和冶金产业,发展以高效、环保、清洁生产为主的主导产业。

(2) 深入发展以煤炭为主的能源工业。山西为满足国家宏观经济发展的要求,应继续建设和发展山西的能源工业,主要是煤炭产业。山西的资源结构状况符合地区优势准则,山西煤炭资源丰富、品种多、煤质好、易开采,且山西煤炭工业在技术、工艺、管理等方面实力雄厚。另外,能源工业是全国的基础产业,也是全国的瓶颈产业。国家对山西的能源的要求在短时期内是不可能有根本改变的,山西作为全国能源基地的作用在今后若干年内不会改变。山西被确定为全国能源基地,为支撑全国经济的发展,同时也为了使山西变资源优势为经济优势,煤炭产业作为能源工业,必须大力发展。但是,这并不意味着仍以牺牲山西的持续发展目标为代价来支持全国经济的发展,而应该本着既满足国家经济发展的要求,提高山西人民的收入水平、消费水平和生活质量,又要满足山西产业的共同、和谐和可持续发展的生态发展目标。

(3) 继续发展传统优势产业。应尽快实现传统产业的技术升级,扶持、培养和强化优势产业,提高劳动生产率。山西在机械制造、电力、食品、纺织业、酿造等方面存在着一定程度的优势,是山西产业主体中的优势产业,提高这些产业的竞争力和经济效益,尽力延长这些传统产业在产业寿命周期