International Journal of Database Theory and Application
Vol.8, No.3 (2015), pp.1-14
http://dx.doi.org/10.14257/ijdta.2015.8.3.01

Study of Multi-attribute Comprehensive Evaluation Method Based on Attribute Theory

Xu Guanglin[1], Liu Nianzu[2] and Duan Xueyan[3]

[1,2]College of Mathematics and Information, Shanghai Lixin University of Commerce, Shanghai China
[3]College of Economics and Management, Shanghai Maritime University, Shanghai, China
glxu@outlook.com, liunianzu@lixin.edu.cn, 328236505@qq.com

Abstract

The study of Comprehensive Evaluation Model of Attribute Theory has gained fruitful achievements in both theory and practice. But the current preference curve of evaluator is assumed to be a smooth quadratic equation which fails to well reflect the change of evaluator's preference when indicators increase. After analyzing the principle of comprehensive evaluation model, this paper does simulation experiments to prove the rationality of the preference curve. By increasing the interpolation points and comparing the evaluator's preference curves respectively generated by the polynomial interpolation and cubic spline interpolation, a conclusion is reached that cubic spline interpolation is better than the polynomial interpolation, and 4 full-score hyperplanes are to be adopted to get the most rational curve to reflect the change of evaluator's preference. The main contributions of this paper are the analysis of the rationality of different preference curves under comprehensive evaluation model based on the attribute theory and the finding that the most reasonable curve depend on the selection of different hyperplane S2.

.

Keywords: *Attribute Theory, Comprehensive Evaluation, Newton's Interpolation Formulae, Barycentric Coordinates, Preference Curve*

1. Introduction

The comprehensive evaluation method of attribute coordinate is a means of prediction and evaluation based on qualitative mapping theory. Featured as very close to man's normal way of thinking, it can accurately show the evaluator's preference and figure out the corresponding preference curve, hence has been widely applied in many fields. For example, Li Jianli applied it in the comprehensive assessment of supplier in SCM [1], Duan Xueyan evaluated the 3PL's core competence [2] by it. A great deal of work has been done on the comprehensive evaluation method itself or its applicaton in some other areas by other researchers [3-10]. However, the current preference curve is assumed to be a smooth quadratic equation. When indicators increase, the quadratic equation fails to well reflect the change of evaluator's preference curve. This paper tries to do the simulation experiments to prove the rational of the preference curve, by increasing the interpolation points and using the polynomial interpolation and cubic spline interpolation, reaches a conclusion that for preference curve cubic spline interpolation is better than the polynomial interpolation and adopting 4 full hyperplanes is more rational to reflect the change of evaluator's preference curve.

ISSN: 2005-4270 IJDTA

2. Overview of Comprehensive Evaluation Method Based on Attribute Theory

The comprehensive evaluation is used to decide whether the alternative is good or not. When all the attribute values of alternatives are given with certain unified dimension, the optimal alternative is the one with all attribute values at full score. Suppose the full score is 100, the solution is $A = (100, \dots 100)$. But generally in practical evaluation the satisfaction principle is applied in the comprehensive evaluation instead of the optimal principle. So, the final outcome is the satisfactory solution, not the optimal solution.

As a result, the comprehensive evaluation only requires the most satisfactory solution that meets certain conditions of weighting, which is described as the extreme value problem of utility function u of formula 1:

$$\max_i \left\{ u = \sum_{j=1}^{m} w_j x_{ij} \right\} \quad (1)$$

among which $0 \le x_{ij} \le 100$ is the value of the ith alternative corresponding to the jth evaluation attribute, while $\vec{W} = (w_1, \cdots, w_m)$ is the preference weighting of evaluator towards the attribute vector ($a_1, \dots, a_m$) that satisfies $\sum_{j=1}^{m} w_j = 1$. Theoretically speaking, even if the solution of problem (1) exists, it will be extremely difficult to find it in the entire utility value space U={u=$\sum_{j=1}^{m} w_j x_{ij}$ }. For a comprehensive evaluation, it is worth considering how the evaluator's preference can be reflected in the evaluation model. Through the comprehensive evaluation of attribute coordinates, i.e., the study of evaluator's preference, a satisfactory solution to problem (1) can be achieved.

3. Establishment of Multi-attribute Comprehensive Evaluation Model Based on Attribute Theory

3.1 Local Most Satisfactory Solution under Certain Restrictive Conditions

For the local most satisfactory solution to problem (1), we may divide it into several sub-problems. Suppose $S_T = \left\{ x_i = (x_{i1}, \dots x_{im}) \mid \sum_{j=1}^{m} x_{ij} = T \right\}$ is the hyperplane with full score of T, the intersection of S_T and X $S_T \cap X$ is the simplex of (n-1) dimensions. For example, △ABC in Fig.1 is a three-dimensional simplex.

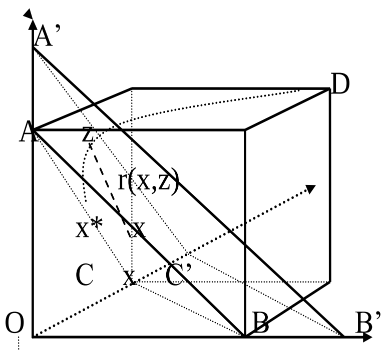

Figure 1. Local Most Satisfactory Linear Solution

The mathematical meaning of factor weighting $\vec{W}$=($w_1,\ldots,w_m$) is the segmentation of a whole according to the weightings. So in the simplex $S_{100}\cap X$ of full score (=100), the solution of dividing 100 by weighting $\vec{W}$=($w_1,\ldots,w_m$) into m attributes is to be $x^*=(x_1^*,\ldots x_m^*)=100\times\vec{W}=(100\times w_1,\ldots,100\times w_m)$, where $\vec{W}$=($w_1,\ldots,w_m$) is just the barycentric coordinate of x^* in the simplex $S_{100}\cap X$, namely $x^*=(w_1,\ldots,w_m)$, $\sum_{j=1}^{m} w_j = 1$. Its physical meaning can be interpreted as: if the weights w_j,j=1,…m are placed on the vertex a_j of $S_{100}\cap X$, x^* happens to be the physical gravity center of $S_{100}\cap X$. Thus we could see whether in terms of the mathematic meaning of weighting itself, or in terms of physics, algebraic topology or linear space theory, $x^*=(100\times w_1,\ldots,100\times w_m)$ should be the most satisfactory solution in $S_{100}\cap X$ that is distributed on the weightings of $\vec{W}$=($w_1,\ldots,w_m$).

Let $\{x_k,k=1,\ldots,s\}\subseteq S_T\cap X$ be the set of sample solution x_i with the full score of T. If the evaluator z selects t sets of satisfactory solutions from $\{x_k\}$, $\{x_h,h=1,\ldots,t\}$ and are evaluated as $v^h(x^h)$. Since the space X on $v^h(x^h)$ is a convex set, the gravity center $b\left(\left\{x^h(z)\right\}\right)$ of $\{x^h(z)\}$ can be calculated by means of weighted average $v^h(x^h)$ as weighting).

$$b\left(\left\{x^h(z)\right\}\right)=\left(\frac{\sum_{h=1}^{t} v_1^h x_1^h}{\sum_{h=1}^{t} v_1^h},\ldots,\frac{\sum_{h=1}^{t} v_m^h x_m^h}{\sum_{h=1}^{t} v_m^h}\right) \qquad (2)$$

$b(\{x^h(z)\})\in S_T\cap X$ is obtained via learning, so when T comes across the interval [100,100×n], we get the set of all local most satisfactory solutions $\{b(\{x^h(z)\})|T\in[100,100\times n]\}$.

Hence the change of $b(\{x^h(z)\})|T\in[100,100\times n]$ corresponding to T can be deemed as continuous. In other words, the set $b(\{x^h(z)\})|T\in[100,100\times n]\}$ will be a line, marked as $L(b(\{x^h(z)\}))$. It can be called as the local most satisfactory linear solution or standard preference line of evaluator z.

As the space solution $X=\{x_i=(x_{i1},\ldots,x_{im})$ is closed and compact topology space, if X has infinite cover, the space can be covered by definitive cover. So the subset of X or the local most satisfactory linear solution $L\left(b\left(\left\{x^h(z)\right\}\right)\right)$ of z is also a definitively-covered space. Therefore, $L\left(b\left(\left\{x^h(z)\right\}\right)\right)$ can be attained by interpolation or curve-fitting method.

3.2 Determination of Local Most Satisfactory Linear Solution $L(b(\{x^h(z)\}))$

There is a hypothesis in the interpolation method of the original local most satisfactory solution $L\left(b\left(\left\{x^h(z)\right\}\right)\right)$ that the preference curve T of evaluator Z is continuous and smooth. But there exist some problems in reality that when there are too many indicators and big evaluation data set in the evaluation indicator system, the preference curve of z towards T may be continuous but not smooth. Therefore, the paper optimizes the algorithm for the most satisfactory linear solution $L\left(b\left(\left\{x^h(z)\right\}\right)\right)$ by

Newton's Interpolation and takes $L\left(b\left(\left\{x^{h}\left(z\right)\right\}\right)\right)$ for cubic polynomial. The other advantages of Newton's Interpolation include: for every added node, there is only one additional interpolation polynomial; and its computational complexity is less than that of Lagrange interpolation.

The most satisfactory solution of evaluator z in $S_{Tk}\cap X$ by training can be got through calculation of (2), and since $x^{*}=(100\times w_1,\ldots,100\times w_m)$ and D=(100,…,100) are the most satisfactory solutions to $S_{100}\cap X$ and $S_{100}\times n\ \cap X$ respectively, together with $\{b_k(\{x^h(z)\})|T_k\in(100,100\times m)\}$, there are altogether n+2 most satisfactory solutions to different simplexes. Hence we let the below polynomial function as the interpolation formula for fitting of the local most satisfactory solution $L\left(b\left(\left\{x^{h}\left(z\right)\right\}\right)\right)$.

Below is the illustration of the interpolation method of the local most satisfactory solution with only three interpolation points.

As the number of decision attributes is m, the attribute values are $x_1,\ldots,x_m$, and then the interpolation polynomial is:

$$G(T)=G\left(g_1(T),\ldots,g_m(T)\right) \quad (3)$$

Where :

$$\begin{cases} g_1(T)=a_{10}+a_{11}T+a_{12}T^2+a_{13}T^3 & (3-1)\\ \vdots \\ g_j(T)=a_{j0}+a_{j1}T+a_{j2}T^2+a_{j3}T^3 & (3-2)\\ \vdots \\ g_m(T)=a_{m0}+a_{m1}T+a_{m2}T^2+a_{m3}T^3 & (3-3)\end{cases}$$

By formula (4), the evaluator z has m local most satisfactory solutions of $\left\{S_i \cap X \mid i=0,\ldots m-1\right\}$:

The local most satisfactory solutions is

$$S_i\cap X: x^{*}|_i=b(\{x^h(z)\})=\left(\frac{\sum_{h=1}^{t}v_1^h x_1^h}{\sum_{h=1}^{t}v_1^h},\ldots,\frac{\sum_{h=1}^{t}v_7^h x_7^h}{\sum_{h=1}^{t}v_7^h}\right) \quad (4)$$

Then by the Newton's Interpolation Formulae (5) below:

$$\begin{aligned} g_i(T) &= g_i[x_0^*]+g_i[x_0^*,x_1^*](x^*-x_0^*)+\\ &g_i[x_0^*,x_1^*,x_2^*](x^*-x_0^*)(x^*-x_1^*)\\ &+\cdots+g_i[x_0^*,x_1^*,\cdots,x_m^*]\\ &(x^*-x_0^*)(x^*-x_1^*)\cdots(x^*-x_{m-1}^*) \quad (5)\end{aligned}$$

we got the equation of interpolation curve (3) of the most satisfactory solution $L\left(b\left(\left\{x^{h}\left(z\right)\right\}\right)\right)$. Then by the equation set:

$$\begin{cases} \sum_{j=1}^{m} x_{ij} = T \\ G(T)=G(g_1(T),\ldots,g_m(T)) \end{cases} \quad (6)$$

we can work out the local most satisfactory solution $b\left(\left\{x^h(z)\right\}\right)|_T$ in any simplex $S_T \cap X, T \in [100, 100\times m]$. If $b\left(\left\{x^h(z)\right\}\right)|_T$ happens to be a certain actual solution, such $b\left(\left\{x^h(z)\right\}\right)|_T$ is the local most satisfactory solution in the $S_T \cap X$, or otherwise we take $b\left(\left\{x^h(z)\right\}\right)|_T$ as the benchmark, as the (6) decider z can make satisfactory evaluation of any solution $x_i=(x_{i1},\ldots,x_{im}) \in S_T \cap X$, so the solution with the biggest satisfaction can be deemed as the local most satisfactory solution in $S_T \cap X$.

Then three hyperplanes are selected, S_1 stands for the most satisfactory score, S_3 stands for the minimum score, and S_2 stands for a random hyperplane between S_1 and S_3. The preference curve obtained by this method is a conic, just as Fig.2 obtained in [6].

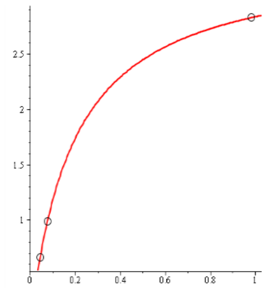

Figure 2. The Conic Preference Curve

When T goes through the interval $(100, 100\times m)$, the local most satisfactory solution $L\left(b\left(\left\{x^h(z)\right\}\right)\right)$ can be calculated by the aforesaid means. The following part illustrates how to get the global most satisfactory solution in $L\left(b\left(\left\{x^h(z)\right\}\right)\right)$

3.3 Calculation of Global Satisfaction

To decide a global most satisfactory solution in $L\left(b'\left(\left\{x_h(z)\right\}\right)\right)$, it is necessary for us to give an evaluation function to evaluate all solutions in $L\left(b'\left(\left\{x_h(z)\right\}\right)\right)$ from a global perspective. After testing we find that Formula (7) can turn the local satisfaction into the global satisfaction [11].

$$\lambda(x, Z) = \left(\frac{\sum_{i=1}^{m} x_{ij}}{\sum_{j=1}^{m} X_j}\right)^S \quad (7)$$

where $\sum_{j=1}^{m} X_j$ is sum of full scores X_j of all attributes, $\sum_{ij=1}^{m} x_{ij}$ is the sum of all attribute values x_{ij} in solution x_i, and $\left(\frac{\sum_{j=1}^{m} X_j}{\sum_{i=1}^{m} x_{ij}}\right)$. When put into (8),

$$\text{set}(x,z) = \left(\frac{\sum_{i=1}^{m} x_{ij}}{\sum_{j=1}^{m} X_j} \right)^S * \exp\left(- \frac{\sum_{j=1}^{m} w_j \left| x_j - b(x^h(z_j)) \right|}{\sum_{j=1}^{m} w_j (b(x^h(z_j)) - \delta_j)} \right) \qquad (8)$$

which S_2 is a random hyperplane between S_1 and S_3. Whether this method of selection is rational and able to truly reflect the change of evaluators' psychology has great influence on the rationality of the final result of evaluation. In order to test its effectiveness, a case analysis of the model of China Inland Port Comprehensive Competitiveness Evaluation is conducted. The indicators in the model of China Inland Port Comprehensive Competitiveness Evaluation are listed in Table 1, including 3 first-grade indicators, i.e., Natural Conditions and Infrastructure, Port Scale and Operation Efficiency and Economic Level of the Backland.

The indicator of "Port Scale and Operation Efficiency" also includes 4 second-grade indicators, i.e., Cargo Throughput (10,000 tons) , Cargo Throughput Growth Rate (%), Container Throughput (10,000TEU) and Container Throughput Growth Rate (%). Corresponding to the 4 second –class indicators, 22 data of the China Inland Ports are taken from "China Ports Yearbook 2012" and the "2011 Statistical Bulletin for the National Economic and Social Development" and are normalized by the method of linear function. The Normalized data are listed in Tab. 2.

Formula (7) can reach consistent satisfaction set(x_i,z) in the entire solution space, so λ(x,z) is called the global consistency coefficient. Formula (7) shows: the base number reflects the total score $\sum_{ij=1}^{m} x_{ij}$ of all attribute values and the proportion in the full score $\sum_{j=1}^{m} X_j o$, but in turn the index $\lambda(x,z)$ controls as a whole. In other words, by Formula (8) the evaluator can have the global satisfaction from evaluation of the targets in the whole decision space.

5. The Study of Accuracy of Preference Curve

One core technology in the model of Multi-attribute Comprehensive Evaluation is the application of the barycentric curve which simulates the psychological change of the evaluators. This curve is monotonically increasing with the change of full-score S. With the original comprehensive evaluation algorithm, in order to calculate the barycentric curve, generally 3 full-score hyperplanes will be selected in.

Table 1. The Evaluation Indicator System of the Inland Port Comprehensive Competitiveness

Natural Conditions and infrastructure	Port Scale and Operation Efficiency	Economic Level of the Backland
Berth length (m)	Cargo throughput (10000 tons)	Port city GDP (100 million Yuan)
Berth number	Cargo throughput growth rate (%)	Port city industrial output (100 million Yuan)
	Container throughput (10000TEU)	Total imports and exports of the port city (dollar)
	Container throughput growth rate (%)	

Note: the indicator data are taken from *China Ports Yearbook 2012,* the 2011 statistical bulletin for the national economic and social development.

Table 2. Normalized Data of Port Scale and Operation Efficiency of 22 China Inland Ports

	Port scale and operation efficiency				
	Cargo throughput	Cargo throughput growth rate	Container throughput	Container throughput growth rate	Score
1	0.001916667	0.27806873	0.0277083	0.06534653	0.37304
2	0.012138889	0.92075472	0.0014583	0.06485149	0.999203
3	0.033527778	0.86792453	0.029375	0.05742574	0.988253
4	0.039111111	0.65830189	0.0185417	0.0669505	0.782905
5	0.043277778	0.57730552	0.015625	0.0310358	0.667244
6	0.046388889	0.84716981	0.083125	0.06930693	1.045991
7	0.056361111	0.90188679	0.0020833	0.00700314	0.967334
8	0.072388889	0.69622642	0.0164583	0.13277228	0.917846
9	0.075638889	0.51415094	0.6075	0.03498937	1.232279
10	0.110055556	0.6154717	0.00375	0.56732673	1.296604
11	0.136166667	0.00473789	0.14875	0.0502812	0.339936
12	0.132583333	0.75471698	0.045625	0.09336634	1.026292
13	0.149472222	0.64696039	0.0033333	0.03954895	0.839315
14	0.176027778	0.71698113	0.0320833	0.06435644	0.989449
15	0.221944444	0.748913	0.0077083	0.93069307	1.909259
16	0.247388889	0.88679245	0.1422917	0.06059406	1.337067
17	0.252944444	0.71698113	0.0760417	0.05920792	1.105175
18	0.259388889	0.90037736	0.0247917	0.05747525	1.242033
19	0.284277778	0.57169811	0.2322917	0.04990099	1.138169
20	0.406416667	0.79245283	0.1122917	0.05623762	1.367399
21	0.406472222	0.84528302	0.3835417	0.06613861	1.701436
22	0.980722222	0.80377358	0.9758333	0.06789109	2.82822

In this simulation experiment, the influence of selecting different hyperplane S_2 on the barycentric curve is evaluated first, then the influence of selecting more hyperplanes on the barycentric curve is analyzed.

5.1 The Influence of Different Hyperplane S_2 on the Barycentric Curve

According to the selection rule of hyperplanes, samples 3, 5 and 22 are chosen from the sample space of Inland Ports and tested. Sample 3 approximates the minimum score, sample 22 approximates the standard score, and sample 15 approximates the most satisfactory score. Polynomial(10) is got through the interpolation formulae. The curve generated by polynomial (10) is the preference curve. By analyzing Fig 3, we find that the polynomial (10) reach the minimum, i.e., x=1.145739609, on open interval (0,1). This is contradictory to our hypothesis that the mapping of hyperplane S_1 is the minimum x=0.988253049. It means that polynomial (9) does not increase monotonically. Therefore, the psychological curve got by this method is not rational and could not reflect the preference of the evaluator.

$$y = 0.3375677219x^2 - 0.7735294193x + 0.4682870649 \quad (9)$$

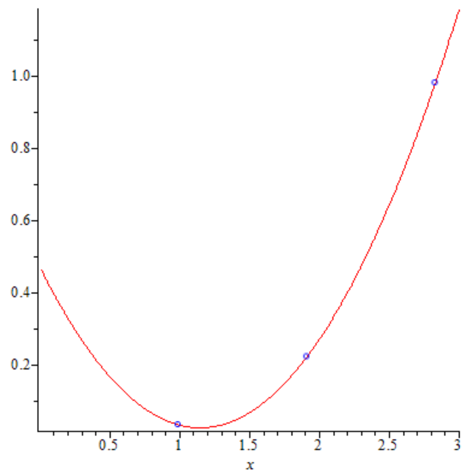

Figure 3. The Preference Curve Generated by Randomly-selected S_2

Then through the fitting of preference curve by the quadratic and cubic spline interpolation, we get Fig.4-1 and Fig.4-2.

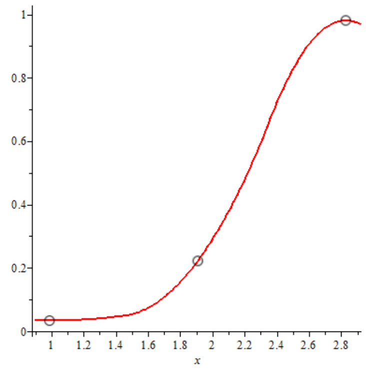

Figure 4-1. The Preference Curve Generated by Quadratic Spline Interpolation

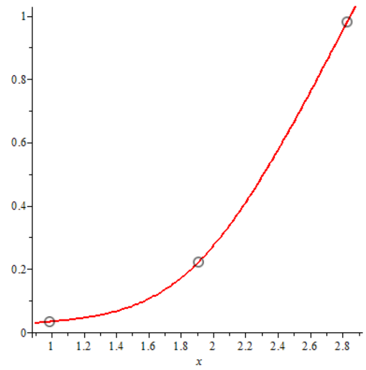

Figure 4-2. The Preference Curve Generated by Cubic Spline Interpolation

Both Fig.4-1 and Fig.4-2 are monotonically increasing, and can fit the preference curve of evaluators, and Curve 4-2 is smoother than Curve 4-1.

By analyzing Fig.3, Fig.4-1 and Fig.4-2, it could be found that if S_2 is selected randomly, a problem might exist in the preference curve calculated by polynomial interpolation. The cause of this problem is that the selected median S_2 is too near the minimum score or hyperplane S_1. Therefore, if polynomial interpolation formulae is applied to calculate the preference curve, then the S_2 which is near the most satisfactory score S_3 should be selected.

According to the selection rule of hyperplanes, samples 3, 4 and 22 are selected from the Inland Port sample space and tested. Sample 3 approximates the minimum score, sample 22 stands for the most satisfactory score, and sample 4 stands for a random hyperplane. Polynomial(10) is got through the polynomial interpolation Thus the curve generated by polynomial (10) is the preference curve, just as in Fig.5. By analyzing Fig 5, we find that polynomial (9) reach minimum (x= 0.9368831406) on closed interval [0,1], which is contradictory to our hypothesis. Therefore, this preference curve is not rational.

$$y = 0.2649852868x^2 - 0.4965204954x + 0.2654193575 \quad (10)$$

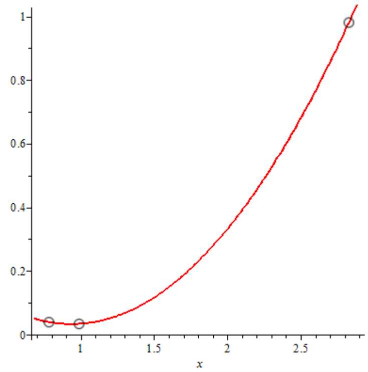

Figure 5. Preference Curve Generated by Polynomial (10)

Then through fitting of preference curve using cubic spline interpolation, we get the preference curve in Fig 6.This curve is not monotonically increasing and is also irrational. Analysis shows that the cause of this problem is that the full scores of the indicator of "Port scale and Operation Efficiency" of Sample 3, 4 and 22 do not increase with the second-class indicator "Cargo Throughput". Therefore, we conclude that in choosing samples, monotony should be guaranteed.

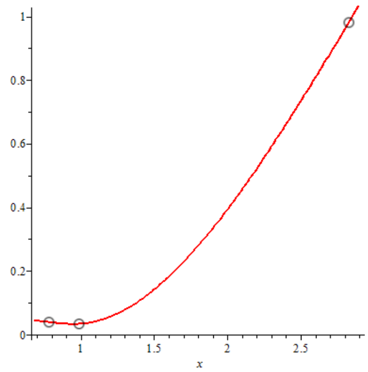

Figure 6. Preference Curve Generated by Cubic Spline Interpolation

According to the selection rule of hyperplanes, samples 3, 21 and 22 are selected from the Inland Port sample space and tested. Sample 3 approximates the minimum score, sample 22 stands for the most satisfactory score, and sample 21 stands for a random hyperplane. Polynomial(11) is got through the interpolation formulae(5). The curve generated by polynomial (11) is the preference curve, just as in Fig 7. This curve is approximately a straight line and thus could not reflect the weight of the evaluator's psychology toward the indicator change with the full score S. Therefore, although this curve is in line with our hypothesis, it has no practical significance.

$$y = -0.007225102915x^2 + 0.5423631834x - 0.4954079376 \quad (11)$$

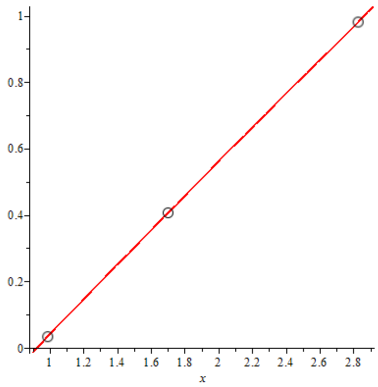

Figure 7. The Preference Curve which Approximates Straight Line

Comparison and analysis of Fig.3, Fig.4-1, Fig.4-2, Fig.5, Fig.6 and Fig.7 shows that even if the same set of data and evaluator are given, very different preference curves could be generated due to different selection of S2. This illustrates that the subtle change of S2 will influence the calculated preference curve and thus leads to the total different ranking of the samples. How to avoid this problem? This paper attempts to solve it by adding more full-score hyperplanes.

5.2 The Influence of Adopting More Hyperplanes on the Preference Curve

In order to minimize the influence of selecting different S2 on the result of evaluation, also to allow the calculated preference curve well fit the psychological change of the evaluators, more sample points are selected to conduct the fitting of preference curve. First, 4 sample data are chosen, i.e., Sample 2, 9, 15, 22. Sample 2 approximates the minimum score, Sample 22 stands for the most satisfactory score, and sample 8 and 15 stand for random hyperplanes. Polynomial (12) is got through interpolation formulae (5), and the curve generated by polynomial (12) is the preference curve, just as in Fig 8.

$$y = 0.2426709433x^3 - 1.066733252x^2 + 1.743256922x - 0.9067864233 \qquad (12)$$

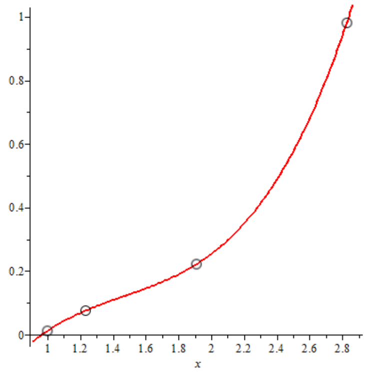

Figure 8. Preference Curve Approximates Straight Line Generated by Polynomial

The extreme points on the closed interval[0,1] appear at hyperplane S1 and S3, which is in line with our hypothesis. By comparing with Fig 4-1, it is found that with the increase of full-score S, the second-grade indicator “Cargo Throughput” is no longer a fixed weight in the evaluator’s mind. At the same time, conic can not totally reflect the law of variation of evaluator’s preference. Cubic curve is more precise than conic in representing the evaluator's preference, and could effectively avoid the appearance of approximate straight line appeared in Fig 7.

Since cubic curve is more precise than the conic one, we might assume that quartic curve or higher-plane curves are much better. So this time 5 sample data are chosen , i.e., sample 2, 9, 16, 21 and 22. Sample 2 approximates the minimum score and sample 22 stands for the most satisfactory score, sample 9, 16 and 21 stand for random hyperplanes. Polynomial (13) is got through interpolation formulae, and the curve generated by polynomial (13) is the preference curve, just as in Fig 9. This curve is not monotonically increasing, and there are even negatives on closed interval [0,1]. Therefore it is not in line with our hypotheses about the preference curve and is not rational.

$$y = 6.039427264x^4 - 41.23729700x^3 + 99.74856822x^2 - 101.6686258x + 37.12868379 \quad (13)$$

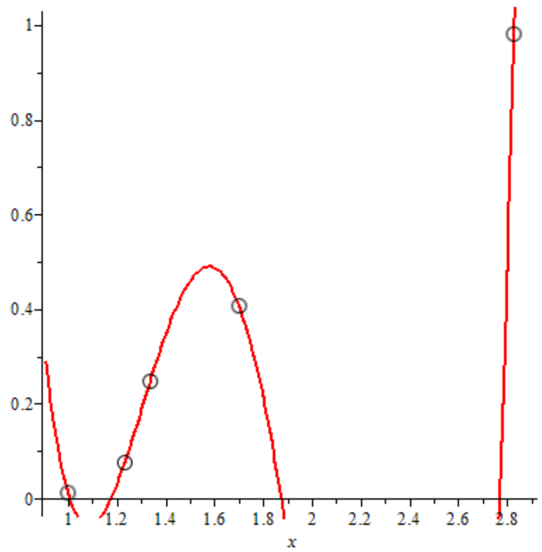

Figure 9. Approximate Preference Curve Generated by Polynomial

Then cubic spline interpolation formulae is adopted and generates the preference curve in Fig.10. This curve is not monotonically increasing either, therefore is not in line with our hypothesis and is irrational.

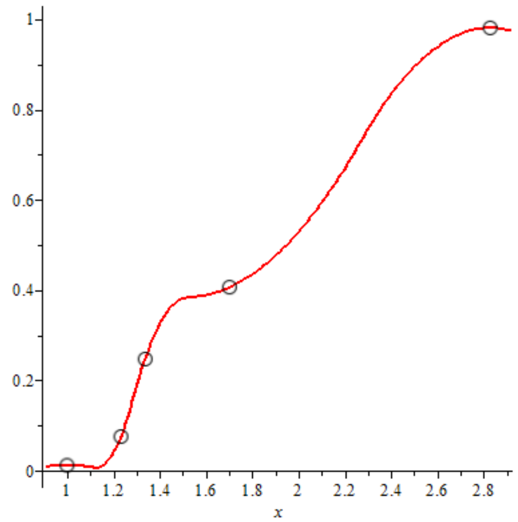

Figure 10. The Approximate Preference Curve Generated by Cubic Spline Interpolation

Through the study on the accuracy of preference curve, it can be concluded that in the simulation of evaluator's preference curve involving 3 full-score hyperplanes, the method of polynomial might generate irrational curves, while the curves generated by cubic spline interpolation are comparatively rational, but the situation of approximate straight line might appear due to improper selection of S2. The simulation result adopting 4 full hyperplanes is more rational. The simulation adopting 5 full hyperplanes is not in line with the hypothesis therefore not applicable.

6.Conclusion

The paper studies the extension of attribute coordinate comprehensive evaluation model to the unsmooth change of evaluator's standard preference curve. Better corresponding mathematical method is applied too, which is helpful to multi-attribute evaluation and improving algorithm efficiency. In order to test its effectiveness, a case analysis of the model of China Inland Port Comprehensive Competitiveness Evaluation has been conducted. Through simulation experiments, conclusions can be drawn as follows: ①For the attribute coordinate comprehensive evaluation model to get the more accurate preference curve, more hyperplanes should be selected, however, the computational complexity will be increased. How to find a balance between computational complexity and accuracy of preference curve is the next problem worthy of study; ② This curve generated by polynomial interpolation sometimes might not be monotonically increasing, for preference curve, cubic spline interpolation is better than polynomial interpolation; ③ Very different preference curves could be generated due to different selection of S2. If S2 is chosen from the point too near the minimum score or hyperplane S1, the curve will be approximately a straight line and thus could not reflect the evaluator' weight.

References

[1] J.L. Li and Y. Liu, "Comprehensive Assessment & Optimized Selection of Supplier in SCM Based on Attribute Theory", Logistics Technology, vol. 26, no. 5, **(2007)**.

[2] X. Duan and Y. Liu, "Evaluation on 3PL's core competence based on method of attribute theory", Journal of Shanghai Maritime University 2006, vol. 27, no. 1.

[3] Q. Wu and J. Feng, "A Kind of Evaluation and Decision Model Based on Analysis and Learning of Attribute Coordinate", Journal of Nanjing University(Natural Science), vol. 39, no. 2, **(2003)**.

[4] J.-L. Feng and T. Zhao, "A KDD Model Based on Conversion of Quantity-Quality Features of Attributes", Journal of Computer Research and Development, vol. 37, no. 9, **(2000)**.

[5] J. Feng and J.J Feng, "Granularity transformation of qualitative criterion, orthogonality of qualitative mapping system, and pattern recognition", IEEE International Conference on Granular Computing – GRC, **(2006)**.

[6] G.L. Xu, Y.C. Liu, "Evaluation of Chinese Software Enterprises' Core Competence in Attribute Theory", Journal of Guangxi Normal University (Natural Science Edition), vol. 24, no. 4, **(2006)**.

[7] X.-Y. Duan, S.-Q. Yu, G.-L. Xu, J.L. Feng, "Evaluation on Comprehensive Competitiveness of Inland Port Based on The Method of Attribute Theory", Journal of Pattern Recognition & Image Processing, vol. 4, **(2013)**, pp. 373-380.

[8] G. Xu, L. Wang, "Evaluation of Aberrant Methylation Gene Forecasting Tumor Risk Value in Attribute Theory", Journal of Basic Science and Engineering, **(2008)**, vol. 16, no. 2.

[9] J.-L. Feng, B.I. Jing-ying, "Lung Cancer Cells' Recognition Based on Attribute Theory", Journal of Guangxi Normal University(Natural Science Edition), **(2011)**, vol. 29, no. 3.

[10] G. Xu, L. Wang, "Evaluation of aberrant methylation gene tumour-risk forecasting value using attribute theory", International Journal of Low Radiation, **(2008)**, vol. 5, no. 1.

[11] G Xu, S. Min, "Research on multi-agent comprehensive evaluation model based on attribute coordinat", Granular Computing (GrC), IEEE International Conference, **(2012)**.

Authors

Xu Guanglin, he obtained his doctorate from the shanghai maritime university in 2008. His research focuses on Attribute network, Machine learning, Pattern Recognition, and Decision Making.

Liu Nianzu, he was born in Shanghai in December 1955. His research focuses on Computer Applications and computing graph theory.

Duan Xueyan, she was born in December 1979. Her research focuses on Transport economics and management .

