行政院國家科學委員會專題研究計畫 成果報告

以 量子 事件 量子 事件 及灰關聯等方法分析
最有利標之比較研究

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計畫主持人：黃營芳

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ABSTRACT

In multiple criteria decision making, the difference between the units for each selection target will affect the decision results, or even lead to an incorrect one. Standard processing or pre-processing must be applied to all selection targets to standardize the units; that is, the units of all targets in the decision matrix are transformed into standard value without quantity and difference. In the Grey relational analysis, this is called data pre-processing or Grey relational generating. It aims to transform incomparable serials in a complete set of serials into comparable data for pre-processing to ensure that important factors are not neglected and no incorrect decision is made.

This study applies Grey relational analysis as a theoretical basis for conventional data pre-processing and linear data pre-processing. It calculates the Grey relation grade between two transformers and compares consistency between the best serial positions for these two data pre-processing transformers, the Spearman classic correlation coefficient among serial positions the Spearman rank order correlation coefficient of transformers and transformers’ MSEs. A smaller MSE indicates that the bias and variance of the data are smaller, thus implying a better estimator.

Using EXCEL’s random number generator, this study generates 24000 data \((x_q)\) to execute 50 times in the Grey relational analysis. The results indicate high replacement in the conventional data pre-processing transformer and the linear data pre-processing transformer. Additionally, for data structure, the MSE of the conventional data pre-processing transformer is smaller and with high accuracy in the serial ranking of transformer. Therefore, conventional data pre-processing should be adopted in the evaluation and selection of the best decision alternative through Grey relational analysis.

Key Words: Grey relational analysis, multiple criteria decision making (MCDM), mean squared error (MSE), Spearman classic correlation coefficient

1. Introduction

Multiple criteria decision making (MCDM) ranks feasible alternatives in order of preference according to the characteristics of each attribute of every alternative, and evaluates and selects one alternative that conforms the decision maker’s ideal (Yoon and Hwang, 1985). In multiple criteria decision making, the hierarchical additive weighting method, the simple additive weighting method, ELECTRE and TOPSIS have been commonly applied. For the last ten years,
Grey relational analysis of Grey system theory, proposed by Chu-Lung Deng has been used to handle uncertain information related to management. Grey relational analysis involves simple calculations, and so is widely applied in the field of management.

After a group of serial data have been compared and arithmetically ordered, Grey relational analysis can be used to on numbers of different characteristics and ranking of serials. When relation grade falls between zero and unity, If the factor change of serial is closer to the change of the standard serial, then serial is strongly related to the standard serial. Otherwise the relationship is weak.

In multiple criteria decision making, the difference between the units of each selection target affects the decision results, or lead to an incorrect decision’s being made. To standardize the units in the targets, standard processing or pre-processing must be applied to all selection targets ;that is ,the units of all targets in the decision matrix are transformed into standard values without quantities or difference between them(Lai et al.,1999) In Grey relational analysis, this is called data pre-processing or Grey relational generation. However, in multiple criteria decision making, it is called data standard processing .The two processes have the same characteristics, focusing on transforming incomparable serials in a complete set of serials into comparable data for pre-processing, to ensure that important factors are considered and that no the incorrect decision is made.

2. Standardization of Data
In Grey relational analysis, the common data pre-processing methods (Chang,2000; Chen and Hsia,2001; Hsia and Wu,1998; Hsia and Chang,2001; Wu and Chen,1999)include conventional data pre-processing and linear data pre-processing with transformers as in Table 1:

<table>
<thead>
<tr>
<th>Data Processing</th>
<th>Larger-the-Better (Benefit)</th>
<th>Smaller-the-Better (Cost)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional Data Pre-processing</td>
<td>$x_i^*(k) = \frac{x_i^{(0)}(k)}{\max[x_i^{(0)}(k)]}$</td>
<td>$x_i^<em>(k) = \frac{\min[x_i^{(0)}(k)]}{x_i^{(0)}(k)}$ or $x_i^</em>(k) = 1 - \frac{x_i^{(0)}(k)}{\max[x_i^{(0)}(k)]}$</td>
</tr>
<tr>
<td>Linear Data Pre-processing</td>
<td>$x_i^*(k) = \frac{x_i^{(0)}(k) - \min[x_i^{(0)}(k)]}{\max[x_i^{(0)}(k)] - \min[x_i^{(0)}(k)]}$</td>
<td>$x_i^*(k) = \frac{\max[x_i^{(0)}(k)] - x_i^{(0)}(k)}{\max[x_i^{(0)}(k)] - \min[x_i^{(0)}(k)]}$</td>
</tr>
</tbody>
</table>
This study adopts the data pre-processing transformers for conventional data pre-processing and linear data pre-processing.

3. Grey Relational Analysis

The term “Grey system” appeared for the first time at the Sino-US Control System Seminar, held at Shanghai in 1981. In 1982, (Deng, 1982) Chu-Lung Deng published “Control Problems of Grey Systems” in “System & Control Letters” Grey systems have since been widely discussed in academia. Grey theory pinpoints the uncertainty of a system model, which is associated with the condition of incomplete information. Restated, Grey theory aims to deal effectively with uncertainty, multi-input and discrete data concerning an event, as well as data incompleteness.

Based on addition measure concept, Grey relational analysis applies an integration operation to each attribute of each system alternative. The relationship among systems or alternatives is measured according to similarity and dissimilarity. General Grey relational evaluation establishes an independent hypothesis concerning the system attributes and scale, weighting each attribute, and calculating the Grey relation grade through operation and to make the sequence. Basic concepts in Grey relational analysis are as follows.

Standard serial \( x_i^{(0)} \) contain \( k \) elements and \( n \) comparative sequences \( x_1, x_2, x_3, \ldots, x_n \).

They are indicated as follows.

\( x_i^{(0)}(k) \) is the standard serial including \( k \) elements.

\( x_i(k) \) is the comparative sequence.

\( x_i = \{x_i(1), x_i(2) \ldots x_i(j), x_i(k)\} \)

\( x = \{x(1), x(2) \ldots x(j), x(k)\} \)

\( \vdots \)

\( x = \{x(1), x(2) \ldots x(j), x(k)\} \)

The Grey relation coefficient of the standard series \( x_i^{(0)} \) and the comparative sequence \( x_i \) at point \( k \) are calculated as follows.

This study uses conventional data pre-processing and linear data pre-processing to perform standardization processing.

The Grey relation grade between each serial and the standard serial is

\[ \Gamma_{i,j}(k) = \sum w(k) * r_{i,j}(k) \] 

where \( w(k) \) is the weighting of each selection factor

4. Correlation Coefficient and Measure of Variability

4.1 Spearman Rank Correlation Coefficient

The Spearman rank correlation coefficient is part of a nonparametric statistical method and is applicable when the population distribution of two variables \( X \) and \( Y \) is unknown or when these variables are classified as characteristic data. Then, the relation between two samples cannot be determined using a parametric statistical method to calculate the correlation coefficient, since such a method only considers the observing sequences \( X \) and \( Y \) and does not consider the exact observed numerical values when testing the rank correlation of \( X \) and \( Y \) observing values[1].

The simple formula for the Spearman rank correlation coefficient is

\[ r_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \]

Where \( r_s \) is a rank correlation coefficient

\( d_i \) is the ranking gap between two
observing samples 

\[ n \] is the number of observed pair-wise samples

When the ranks of two samples are identical, then \( r = 1 \); when the ranks of two samples are completely opposite, then \( r = -1 \), so \( -1 \leq r \leq 1 \).

4.2 Spearman Rank-Order Correlation Coefficient

\( (X_1, Y_1), (X_2, Y_2), \ldots, (X_n, Y_n) \) are set to population random variables with two distribution functions; the correlation coefficient among the samples is

\[
\begin{align*}
    r & = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2 \sum_{i=1}^{n} (Y_i - \bar{Y})^2}} \\
    & = \frac{1}{\sqrt{n(n-1)}} \left[ \sum_{i=1}^{n} R_i S_i \right]
\end{align*}
\]

(Yen, 1993)

Deriving the population distribution of the \( r \) distribution function is difficult. Additionally, the population distribution is an abnormal distribution, and can not applied to the correlation coefficient \( r \). Spearman therefore proposed the Spearman rank-order correlation coefficient in place of the correlation coefficient \( r \), and gave the ranking order of the observed values \( (X_1, X_2, \ldots, X_n) \).

Meanwhile, \( R_i \) is taken as the rank values of \( X_i \), \( i = 1, 2, 3, \ldots, n \). The observed values \( (Y_1, Y_2, \ldots, Y_n) \) are ranked such Thaterefore \( S_i \) are the \( Y_i \) rank values, \( i = 1, 2, 3, \ldots, n \). Therefore, the Spearman rank-order correlation coefficient \( r_{sp} \) is

\[
\begin{align*}
    r_{sp} & = \sum_{i=1}^{n} (R_i - \frac{n+1}{2})(S_i - \frac{n+1}{2}) \\
    & = \sum_{i=1}^{n} R_i S_i - n(\frac{n+1}{2})^2 = \\
    & = 12\left[ \sum_{i=1}^{n} R_i S_i - n\left(\frac{n+1}{2}\right)^2 \right] \\
    & \quad \div n(n^2-1)
\end{align*}
\]

Among which, \( r_{sp} \) is the rank-order correlation coefficient, \( -1 \leq r_{sp} \leq 1 \).

\( R_i \) is \( X_i \) rank

\( S_i \) is \( Y_i \) rank

\( n \) is number of observed pair-wise samples

4.3 Mean Squared Error (MSE)

The mean squared error (MSE) is used to measure the data variation and evaluate the goodness and badness of the estimator. The mean squared error is the estimator, while the estimator is a function of the error and the variation.

MSE is usually applied to test the deviation of the estimator; it is also used to evaluate its accuracy. A smaller MSE is preferred as it indicates that the sum of the error and the variance is smaller.

\[
\begin{align*}
    \text{MSE} & = \frac{1}{n-m} \sum_{i=1}^{n} \sum_{j=1}^{m} (x_{ij} - \bar{x}_j)^2 = \frac{\sum_{i=1}^{m} (n-1)S_j^2}{n-m}
\end{align*}
\]

This study uses conventional data pre-processing and linear data pre-processing as transformers; calculates the Grey relation between two transformers; compares the consistency of the best serial positions for these two standardized data pre-processing transformers; obtains the Spearman classic correlation coefficient and the Spearman rank order correlation coefficient among the serial positions between the two transformers, and compares the MSE values of the two transformers.

4.3.1 Standard Deviation of Transformer for Conventional Data Pre-Processing and Linear Data Pre-processing

1. Standard deviation of conventional data pre-processing transformer
(1) Larger-the-better (benefit):

\[ f_i^* = \max [x_i^{(0)}(k)], (1 \leq i \leq n) \]

\[ f_2^* = \max [x_i^{(0)}(k)], (1 \leq i \leq n) \]

\[ \vdots \]

\[ f_m^* = \max [x_i^{(0)}(k)], (1 \leq i \leq n) \]

\[ V(v_1^{(1)}) = V(\frac{x_y}{f_1}) = \frac{1}{(f_1^*)^2} V(x_y) \]

\[ V(v_2^{(1)}) = V(\frac{x_y}{f_2}) = \frac{1}{(f_2^*)^2} V(x_y) \]

\[ \vdots \]

\[ V(v_m^{(1)}) = V(\frac{x_y}{f_m}) = \frac{1}{(f_m^*)^2} V(x_y) \]

\[ \sqrt{V(v_1^{(1)})} = S(v_1^{(1)}) = \frac{1}{f_1} S(x_y) \]

\[ \sqrt{V(v_2^{(1)})} = S(v_2^{(1)}) = \frac{1}{f_2} S(x_y) \]

\[ \vdots \]

\[ \sqrt{V(v_m^{(1)})} = S(v_m^{(1)}) = \frac{1}{f_m} S(x_y) \]

2. Standard deviation of linear data pre-processing transformer

(1) Larger-the-better (benefit)

\[ f_1^* = \max [x_i^{(0)}(k)], (1 \leq i \leq n) \]

\[ f_2^* = \max [x_i^{(0)}(k)], (1 \leq i \leq n) \]

\[ \vdots \]

\[ f_m^* = \max [x_i^{(0)}(k)], (1 \leq i \leq n) \]

(2) Smaller-the-better (cost):

\[ f_1^* = \max [x_i^{(0)}(k)], (1 \leq i \leq n) \]

\[ f_2^* = \max [x_i^{(0)}(k)], (1 \leq i \leq n) \]

\[ \vdots \]

\[ f_m^* = \max [x_i^{(0)}(k)], (1 \leq i \leq n) \]
\[ f'_{m} = \min[x_{i}^{(0)}(k)], (1 \leq i \leq n) \]
\[ v_{i}^{21} = \frac{x_{g} - f'_{i}}{f'_{i} - f'_{m}}, (1 \leq i \leq n) \]
\[ v_{2}^{21} = \frac{x_{g} - f'_{2}}{f'_{2} - f'_{2}}, (1 \leq i \leq n) \]
\[ v_{m}^{21} = \frac{x_{g} - f'_{m}}{f'_{m} - f'_{m}}, (1 \leq i \leq n) \]

Let \( f^* - f_{1}^{*} = f_{d1}, (1 \leq i \leq n) \)
\[ f^* - f_{2}^{*} = f_{d2}, (1 \leq i \leq n) \]
\[ v_{1}^{22} = \frac{f^* - x_{g}}{f^* - f_{d1}}, (1 \leq i \leq n) \]
\[ v_{2}^{22} = \frac{f^* - x_{g}}{f^* - f_{d2}}, (1 \leq i \leq n) \]
\[ v_{m}^{22} = \frac{f_{m} - x_{g}}{f_{m} - f_{m}}, (1 \leq i \leq n) \]

Let \( f^* - f_{1}^{*} = f_{d1}, (1 \leq i \leq n) \)
\[ f^* - f_{2}^{*} = f_{d2}, (1 \leq i \leq n) \]
\[ v_{1}^{22} = \frac{f_{m} - x_{g}}{f_{m} - f_{m}}, (1 \leq i \leq n) \]
\[ v_{2}^{22} = \frac{f_{m} - x_{g}}{f_{m} - f_{m}}, (1 \leq i \leq n) \]
\[ v_{m}^{22} = \frac{f_{m} - x_{g}}{f_{m} - f_{m}}, (1 \leq i \leq n) \]

(2) Smaller-the-better(cost):
\[ f^*_1 = \max[x_{i}^{(0)}(k)], (1 \leq i \leq n) \]
\[ f^*_2 = \max[x_{i}^{(0)}(k)], (1 \leq i \leq n) \]
\[ f^*_m = \max[x_{i}^{(0)}(k)], (1 \leq i \leq n) \]
\[ f^*_1 = \min[x_{i}^{(0)}(k)], (1 \leq i \leq n) \]
\[ f^*_2 = \min[x_{i}^{(0)}(k)], (1 \leq i \leq n) \]
\[ f^*_m = \min[x_{i}^{(0)}(k)], (1 \leq i \leq n) \]
\[ V(v_{ij}^{22}) = \frac{1}{f_{d2}^2} V(x_i) \]

\[ \vdots \]

\[ V(v_{im}^{22}) = \frac{1}{f_{dm}^2} V(x_i) \]

\[ \sqrt{V(v_{1i}^{22})} = S(v_{1i}^{22}) = \frac{1}{f_{d1}} S(x_i) \]

\[ \sqrt{V(v_{2i}^{22})} = S(v_{2i}^{22}) = \frac{1}{f_{d2}} S(x_i) \]

\[ \vdots \]

\[ \sqrt{V(v_{mi}^{22})} = S(v_{mi}^{22}) = \frac{1}{f_{dm}} S(x_i) \]

\[ S(v_{ij}^{11}) = \frac{1}{f_{d1}} S(x_i) = \frac{f_{d1}}{f_{d1}} \]

\[ S(v_{ij}^{21}) = \frac{1}{f_{d2}} S(x_i) = \frac{f_{d2}}{f_{d2}} \]

\[ \vdots \]

\[ S(v_{mi}^{11}) = \frac{1}{f_{dm}} S(x_i) = \frac{f_{dm}}{f_{dm}} \]

Because \( f_{d1}^* \geq f_{d1} \): \( S(v_{1i}^{11}) \leq S(v_{1i}^{21}) \)

Because \( f_{d2}^* \geq f_{d2} \): \( S(v_{2i}^{11}) \leq S(v_{2i}^{21}) \)

\[ \vdots \]

Because \( f_{dm}^* \geq f_{dm} \): \( S(v_{mi}^{11}) \leq S(v_{mi}^{21}) \)

\[ \text{Therefore} \sum_{j=1}^{m} S(v_{ij}^{11}) \leq \sum_{j=1}^{m} S(v_{ij}^{21}) \]

When \( i \) and \( j \) of sequence \( (x_{ij}) \) are inter-depended, then \( \text{COV}(x_{ij}) = 0 \)

As long as \( \sum_{j=1}^{m} S(v_{ij}^{11}) \leq \sum_{j=1}^{m} S(v_{ij}^{21}) \) and \( n, m \) are fixed constants, then \( \text{MSE}(v_{ij}^{11}) \leq \text{MSE}(v_{ij}^{21}) \)

(2) Smaller-the-better (cost):

\[ \sqrt{V(v_{1i}^{12})} = S(v_{1i}^{12}) = \frac{1}{f_{d1}} S(x_i) \]

\[ \sqrt{V(v_{2i}^{12})} = S(v_{2i}^{12}) = \frac{1}{f_{d2}} S(x_i) \]

\[ \vdots \]

\[ \sqrt{V(v_{mi}^{12})} = S(v_{mi}^{12}) = \frac{1}{f_{dm}} S(x_i) \]
\[ \sqrt{V(v_{1m}^{12})} = S(v_{1m}^{12}) = \frac{1}{f_m^{*}} S(x_{i}) \]
\[ \sqrt{V(v_{1}^{22})} = S(v_{1}^{22}) = \frac{1}{f_{d1}} S(x_{i}) \]
\[ \sqrt{V(v_{2}^{22})} = S(v_{2}^{22}) = \frac{1}{f_{d2}} S(x_{i}) \]
\[ \vdots \]
\[ \sqrt{V(v_{m}^{22})} = S(v_{m}^{22}) = \frac{1}{f_{dm}} S(x_{i}) \]

\[ S(v_{1}^{12}) \]
\[ = \frac{1}{f_{1}^{*}} S(x_{i}) \]
\[ = \frac{1}{f_{d1}} S(x_{i}) \]
\[ S(v_{1}^{22}) \]
\[ = \frac{1}{f_{2}^{*}} S(x_{i}) \]
\[ = \frac{1}{f_{d2}} S(x_{i}) \]
\[ \vdots \]
\[ S(v_{m}^{12}) \]
\[ = \frac{1}{f_{m}^{*}} S(x_{i}) \]
\[ = \frac{1}{f_{dm}} S(x_{i}) \]

Because \( f_{1}^{*} \geq f_{d1} \) \( \therefore S(v_{1}^{12}) \leq S(v_{1}^{22}) \)

Because \( f_{2}^{*} \geq f_{d2} \) \( \therefore S(v_{2}^{12}) \leq S(v_{2}^{22}) \)
\[ \vdots \]

Because \( f_{m}^{*} \geq f_{dm} \) \( \therefore S(v_{m}^{12}) \leq S(v_{m}^{22}) \)

Therefore \( \sum_{j=1}^{m} S(v_{ij}^{12}) \leq \sum_{j=1}^{m} S(v_{ij}^{22}) \)

When \( i \) and \( j \) of sequence \( (x_{ij}) \) are inter-dependence, then \( COV(x_{ij}) = 0 \)

As long as \( \sum_{j=1}^{m} S(v_{ij}^{12}) \leq \sum_{j=1}^{m} S(v_{ij}^{22}) \) and \( n, m \) are fixed constants, then \( MSE(v_{ij}^{12}) \leq MSE(v_{ij}^{22}) \)

In this study, \( i \) and \( j \) of sequence \( (x_{ij}) \) are independence and \( n, m \) are fixed constants, so \( MSE(v_{ij}^{11}) \leq MSE(v_{ij}^{21}) \)

Therefore, with respect to the cost and benefit targets, the transformer MSE of conventional data pre-processing is smaller than that of linear data pre-processing. Hence the transformer of conventional data pre-processing is more effective, with more accurate serial ranking.

5. Empirical Study

Using EXCEL’s random generator was used to generate 24000 basic data \((x_{ij})\). Eight selection factors were hypothesized, such that \( j \) has 8 columns \((j = 1,2,3,\ldots,m, m = 8)\), and sequence \( i \) is 30, 20 and 10 rows, such that \((i = 30,20,10)\) given
\[ x_{i} = 15\% \text{ (Larger-the-better)}, \]
\[ x_{2} = 10\% \text{ (Larger-the-better)}, \]
\[ x_{3} = 15\% \text{ (Smaller-the-better)}, \]
\[ x_{4} = 10\% \text{ (Larger-the-better)}, \]
\[ x_{5} = 15\% \text{ (Larger-the-better)}, \]
\[ x_{6} = 15\% \text{ (Smaller-the-better)}, \]
\[ x_{7} = 15\% \text{ (Larger-the-better)}, \]
\[ x_{8} = 10\% \text{ (Larger-the-better)} \]

Grey relational analysis is used as the theoretical basis to apply conventional data pre-processing and linear data pre-processing as transformers; to calculate the Grey relation between two transformers; to compare the consistency of the best serial positions of these two standardized data pre-processing transformers; to obtains the Spearman rank correlation coefficient and the Spearman rank-order correlation coefficient of...
the serial positions between two transformers, and data pre-processing

to compares the MSEs of the two transformers yielding the results indicated in Tables 2, 3 and 4:

Table 2. Spearman rank correlation coefficient among serial positions and Spearman rank-order correlation coefficient of transformers in conventional data pre-processing and linear data pre-processing

<table>
<thead>
<tr>
<th>Number of Samples n</th>
<th>Mean Spearman rank Correlation Coefficient</th>
<th>Mean Spearman Rank-Order Correlation Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>0.9461</td>
<td>0.9483</td>
</tr>
<tr>
<td>20</td>
<td>0.9546</td>
<td>0.9563</td>
</tr>
<tr>
<td>10</td>
<td>0.9053</td>
<td>0.9053</td>
</tr>
</tbody>
</table>

The mean Spearman rank correlation coefficient among serial positions of transformers in conventional data pre-processing and linear data pre-processing are 0.9461, 0.9546 and 0.9053, and the mean Spearman rank-order correlation coefficients are 0.9483, 0.9563 and 0.90567, respectively.

Table 3. Consistency among transformers used in conventional data pre-processing and linear data pre-processing

<table>
<thead>
<tr>
<th>Number of Sample n</th>
<th>Times of Consistency</th>
<th>Consistency Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>47</td>
<td>94%</td>
</tr>
<tr>
<td>20</td>
<td>46</td>
<td>92%</td>
</tr>
<tr>
<td>10</td>
<td>46</td>
<td>92%</td>
</tr>
</tbody>
</table>

The consistency ratios of the best serial in the transformers of conventional data pre-processing and linear data pre-processing are 94%, 92% and 92%, indicating high mutual replacement.

Table 4. Transformers’ mean MSEs of conventional data pre-processing and linear

<table>
<thead>
<tr>
<th>Number of Samples n</th>
<th>The transformers’ MSE mean of Conventional Data Pre-processing</th>
<th>The transformers’ MSE mean of Linear Data Pre-processing</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>0.5373</td>
<td>1.0252</td>
</tr>
<tr>
<td>20</td>
<td>0.6675</td>
<td>1.2323</td>
</tr>
<tr>
<td>10</td>
<td>1.8433</td>
<td>4.6336</td>
</tr>
</tbody>
</table>

The transformers’ mean MSEs for conventional data pre-processing are 0.5373, 0.6675 and 1.8433, while those for linear data pre-processing are MSE 1.0252, 1.2323 and 4.6336, indicating that when the number of samples is n=30, n=20 or n=10, the transformer MSE for conventional data pre-processing is the smaller.

6. Conclusions and Suggestions

6.1 Conclusions
Grey relational analysis is used as a theoretical basis to, employ EXCEL’s random number function to generate 24000 data (x_y).

Transformers of conventional data pre-processing and linear data pre-processing are used as standardized transformers that are applied 50 times under the conditions of n=30, n=20 and n=10 to calculate Grey relation grade between these two estimators. The results are as follows; the mean Spearman rank correlation coefficient among serial positions for the conventional data pre-processing transformer and for the linear data pre-processing transformer are 0.9461, 0.9546 and 0.9053, while the mean Spearman rank-order correlation coefficients are 0.9483, 0.9563 and 0.90567. The consistency among of the best serial positions for the conventional data pre-processing transformer
and the linear data pre-processing transformer are 94%, 92% and 92%. Therefore transformers of conventional data pre-processing and linear data pre-processing can be mutually replaced. The mean MSEs for the conventional data pre-processing transformer are 0.5373, 0.6675 and 1.8433. Those for the linear data pre-processing transformer are 1.0252, 1.2323 and 4.6336. The results indicate high replacement in the conventional data pre-processing transformer and the linear data pre-processing transformer. Additionally, the MSE value of the conventional data pre-processing transformer is the smaller, and yields a highly accurate serial ranking.

6.2 Suggestions:
Conventional data pre-processing should be adopted to evaluate and select the best decision alternative through Grey relational analysis.

References


