

# CHOOSING THE RIGHT EMPLOYEE: AN APPLICATION OF MAUT METHOD AND GREY RELATIONAL ANALYSIS ON ACADEMIC STAFF SELECTION PROCESS

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## **Abstract:**

*In order to select the most appropriate alternatives during the employee selection process various decision-making approaches have been implemented in the related literature. Although many alternatives are qualitative in nature the scholars are also often engage in to the quantitative methods. In this paper, two well-known quantitative methods Multi Criteria Decision Techniques, Grey Relational Analysis and MAUT Method, have been examined. These two techniques are compared with each other by the use of Kendall's tau correlation coefficient in terms of effectiveness and accuracy that they provide. Using these techniques, the choice of the most suitable candidate could be selected more objectively than the sole application of qualitative techniques. These techniques can also be implemented simultaneously with other qualitative methods. The findings of this study show that in fact, Grey Relational analysis increases the likelihood of the chosen the right employee. Findings of the study proof that more comprehensive employee selection techniques can be utilized for the academic staff selection process.*

**Keyword:** Academic Staff Selection, Multi-Criteria Decision-Making (MCDM), MAUT Method, Grey Relational Analysis, Kendall's Tau.

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## **1. Introduction**

Successful decision-making within an organizational context depends on many different criteria. There are three main considerations during the selection process. These are, person-environment fit, person- organization fit and person-job fit (Sekiguchi, 2004). Traditionally related literature focus on person-job fit. However, the aforementioned others are also equally of the importance (Adkins, Russell & Werbel, 1994). There are also some other factors influencing the decision-making process such as, intuition (Miles & Sadler-Smith, 2014) in fact, people can

be stubborn for their reliance on intuition (Highhouse, 2008). It has been established in the related literature that human being is not fully rationale in their selection process. Humans' decisions are cognitive processes that have two different and competing modes. The first mode is included to be cold, objective and analytical and the second mode comprises of to be subjective, hot and intuitive (Lieberman, 2007). Therefore, it is difficult to claim that the selection process is always rational and systematic and more importantly perhaps, fair.

It is partly because most of the time process mostly relies on qualitative approaches. The most popular of these approaches is to interviews. The problem in that as it is mentioned above it may get subjective and personnel factors can play roles including bias. Recently some alternative methods are discussed. One of these is the active use of social media for recruitment process (Roth, 2016). Nonetheless, in order to be fairer in the process quantitative approaches are also started to appear. However, it is not entirely clear in the related literature that which one of these methods can be most suitable candidate. This study strives to identify the effectiveness of two quantitative approaches—MAUT method and Grey relational analysis— during the employee selection process.

## **2. Literature Review**

### **2.1 Employee Selection Process**

There are two main approaches on employee selection process. These are the psychometric and the social process approach (Bolander & Sandberg, 2013). The psychometric approach assumes that each job has discrete tasks and candidate and job can be assessed independently. Whereas social process approaches discuss that selection tools can be unreliable due to the relationship may establish between candidates and organization. Therefore, organization should focus on the relationship between organization and individual (Herriot, 1993). One of the most important reasons is why organizations should choose the right person is that to improve their capabilities and abilities to realize their strategic objectives (Sears, 2003; Gatewood, Field & Barreck, 2015).

One of the other important arguments in the related literature is that if person-environment or person-job fit is more valid for recruitment process. In that, it is discussed that the first of these aforementioned concepts based on integrationist theory of behavior. In this view the interaction between personal and situational variables is matter most as neither personnel nor environmental variables alone can determine the behavior and attitudes. Furthermore, in person-job fit the biggest variance come from the relationship between demand of job and abilities and skills that candidates offer. This is the method that traditionally established as a first choice for employee selection method (Sekiguchi, 2004).

However, organizations cannot always objectively approach to selection process. This is because there is a significant role that individuals play during the decision-making process. Despite the fact that assisting decision making tools available for a long time yet organizations still resist to implement them for the purpose of employee decision making process (Highhouse, 2008). In fact, managers most often put faith in their ability to understand the candidates' qualities rather than relying readily available tools (Miles & Sadler-Smith, 2014). One of the most difficult things is to convince recruitment expert is to implement and use readily available tools. The main problem about these tools not to be implemented is that intuition is strongly defended and relied by managers (Highhouse, 2008).

## 2.2 Multi Criteria Decision Techniques

### 2.2.3 MAUT Method

MAUT method keeps in view the preferences in the form of the utility function, which is indicated over a set of attributes (Pohekar, Ramachandran, 2004). Utility function quantifies the preferences by assigning a numerical index to varying levels of satisfaction of a criterion (Mustafa, Ryan, 1990). For a single criterion ( $X$ ), the utility of satisfaction of a consequence  $x'$  is denoted by  $u(x')$ . The utility is measured as the sum of the marginal utilities (Figueroa, Greco, Ehr Gott, 2005). In this method, both quantitative and qualitative criteria can be used.

MAUT method is used both discrete and continuous alternative problems. Discrete type alternative problems include a set of limited alternatives. Continuous alternative problems also called multiple optimization problems, which consist of number of infinitely many alternatives (Wallenius, J. et. al., 2008). The most common method of multi criteria utility function is the additive model (Keeney, Raiffa, 1993). In this article, this technique is used additively separable with respect to single attribute utility.

$$U_i = \sum_{j=1}^m w_j U_{ij} \text{ for all } i$$

where

$U_i$  : Utility value (overall) of alternative  $i$

$U_{ij}$  : Utility value for the alternative of  $i$  (criteria for the  $j$ )

$n$  : Total number of criteria

$m$  : Total number of alternatives

MAUT method includes six important steps (Alp i. et.al., 2015);

Step 1: Construct the decision matrix

Determine the criteria ( $C_1, C_2, \dots, C_n$ ) and alternatives

Step 2: Calculate weight of each criteria:  $w_i, \sum_{i=1}^m w_i = 1$ .

Step 3: Construct the normalized decision matrix

Step 4: Calculate utility values;

$$\text{For criteria to be maximized: } u_i(x_i) = \frac{x - x_i^-}{x_i^+ - x_i^-}$$

$$\text{For the criteria to be minimized: } ui(x_i) = \frac{x_i^+ - x}{x_i^+ - x_i^-}$$

where

$x_i^+$  = the best value of the alternatives

$x_i^-$  = the worst value of the alternatives

Step 5: Calculate total utility

$$U_i = \sum_{j=1}^m w_j U_{ij} \text{ for all } i.$$

Step 6: Rank the alternatives according to total utility values (greater utility values are better alternatives).

### 2.2.4 Grey Relational Analysis

Grey relational analysis (GRA) is part of grey system theory proposed by Deng (1982), and is suitable for solving problems with complicated interrelationships between multiple factors and variables (Morán et al. 2006).

Step 1: Construct the decision matrix:  $X_{n \times m}$

$$X_{n \times m} = [X_{ij}] = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1m} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & x_{n3} & \dots & x_{nm} \end{bmatrix},$$

where, m: number of criteria and n number of alternatives

Step 2: Construct the Reference Sequence  $[RS]=RS_{1 \times m}$

$$[RS] = [RS_{11} \quad RS_{12} \quad \dots \quad RS_{1(m-1)} \quad RS_{1m}]$$

In this step, considering all the alternatives an ideal target has to be defined.

Step 3: Construct the normalized decision matrix:  $N_{n \times m}$

In this step, the values of any alternative have to be normalized and this means that all values are transformed to values between 0 and 1. According to Fung (2003), the normalization can be made in four different ways. Three ways can be explained with the help of the structure of the criteria. If researcher want to maximize the value of the criteria that means if the value of this criteria is greater the better, use (1).

$$x_{ik}^* = \frac{x_{ik} - \max\{x_{11}, x_{21}, x_{31}, \dots, x_{n1}\}}{\max\{x_{11}, x_{21}, \dots, x_{n1}\} - \min\{x_{11}, x_{21}, \dots, x_{n1}\}} \quad (1)$$

If the value of criteria is smaller the better, use (2).

$$x_{ik}^* = \frac{\min\{x_{11}, x_{21}, x_{31}, \dots, x_{n1}\} - x_{ik}}{\max\{x_{11}, x_{21}, \dots, x_{n1}\} - \min\{x_{11}, x_{21}, \dots, x_{n1}\}} \quad (2)$$

If there is a target value or an ideal value for the criteria, use (3).

$$x_{ik}^* = 1 - \frac{|x_{ik} - x_{idealk}|}{\max\{\max\{x_{11}, x_{21}, \dots, x_{n1}\} - x_{idealk}, x_{idealk} - \min\{x_{11}, x_{21}, \dots, x_{n1}\}\}} \quad (3)$$

where  $x_{ideal}$  is the ideal value for the related criteria

Step 4: Construct the difference matrix:  $M_{n \times m}$

By subtracting the reference series from the normalized decision matrix, the difference matrix is obtained.

$$\begin{bmatrix} M_{11} & M_{12} & M_{13} & \dots & M_{1m} \\ M_{21} & M_{22} & M_{23} & \dots & M_{2m} \\ \dots & \dots & \dots & \dots & \dots \\ M_{n1} & M_{n2} & M_{n3} & \dots & M_{nm} \end{bmatrix} = \begin{bmatrix} |rs_{11} - N_{11}| & |rs_{12} - N_{12}| & |rs_{13} - N_{13}| & \dots & |rs_{1m} - N_{1m}| \\ |rs_{11} - N_{21}| & |rs_{12} - N_{22}| & |rs_{13} - N_{23}| & \dots & |rs_{1m} - N_{2m}| \\ \dots & \dots & \dots & \dots & \dots \\ |rs_{11} - N_{n1}| & |rs_{12} - N_{n2}| & |rs_{13} - N_{n3}| & \dots & |rs_{1m} - N_{nm}| \end{bmatrix}$$

Step 5: Calculation of Grey Relational Coefficient Matrix:  $G_{n \times m}$

$$G_{ij} = \frac{\Delta min + \vartheta \Delta max}{M_{ij} + \vartheta \Delta max}$$

where  $\vartheta$  is distinguishing coefficient and takes a value in the range of [0,1].

Step 6: The calculation of degree of relation

For each alternative assume the grey relational coefficients are discrete random variables according to the weights of each criteria and calculate expected value of each alternative. These expected values are degree of relation.

## 2. Application

In this paper, three main criteria namely work factors, academic factors and individual factors are chosen to select the suitable (right) employee. Work factors include four main criteria such as GRE score, foreign language, GPA and presentation. Academic factors include again 4 sub-criteria that measures the teaching and research skills of any academic staff such as if they have any teaching experience and have any administrative experience. The other 2 sub-criteria of the academic factor can be thought as the criteria that determine up to date knowledge of candidates. Individual factors include three main criteria such as age, self-confidence and compatibility. Table 1 illustrates the information of all the criteria with their definition.

**Table 1:** Criteria' of Academic Staff Selection Problem

	Criteria	Definition
<b>Work Factors</b>	C <sub>1</sub>	GRE Score
	C <sub>2</sub>	Foreign Language
	C <sub>3</sub>	GPA
	C <sub>4</sub>	Presentation
<b>Academic Factors</b>	C <sub>5</sub>	Teaching Experience
	C <sub>6</sub>	Administrative Task Experience
	C <sub>7</sub>	Research Paper
	C <sub>8</sub>	Team Work
<b>Individual Factors</b>	C <sub>9</sub>	Self Confidence
	C <sub>10</sub>	Compatibility
	C <sub>11</sub>	Age

We randomly create 20 academic staff information that we want to rank from best to worst to choose the right one. In other words, in this study alternatives can be thought as potential candidates. For the MAUT method the weights were assumed to be equally distributed. As a first step we changed the raw values to normalized values by using maximizing and minimizing and the results are shown in Table 2.

**Table 2:** Normalized Matrix: Equally Weighted, MAUT Method

	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>5</sub>	C <sub>6</sub>	C <sub>7</sub>	C <sub>8</sub>	C <sub>9</sub>	C <sub>10</sub>	C <sub>11</sub>
<b>A<sub>1</sub></b>	0.00	0.50	0.50	0.00	1.00	0.50	0.40	0.14	0.50	0.00	0.52
<b>A<sub>2</sub></b>	0.25	0.25	0.75	0.50	0.25	0.50	0.60	0.00	0.50	0.25	0.62
<b>A<sub>3</sub></b>	0.50	0.50	0.25	0.50	0.33	0.50	0.80	0.29	0.75	0.50	0.45
<b>A<sub>4</sub></b>	0.75	0.25	0.50	0.75	0.58	0.75	1.00	0.43	0.25	1.00	0.00
<b>A<sub>5</sub></b>	0.50	0.00	0.75	0.50	0.42	1.00	0.60	0.29	0.50	0.00	0.93
<b>A<sub>6</sub></b>	1.00	0.25	0.00	0.75	0.83	0.25	0.40	1.00	0.75	0.75	0.24
<b>A<sub>7</sub></b>	0.25	0.50	0.25	0.50	0.00	0.00	0.00	0.29	0.00	1.00	0.86
<b>A<sub>8</sub></b>	0.50	0.50	0.50	1.00	0.67	0.50	0.20	0.14	1.00	0.25	1.00
<b>A<sub>9</sub></b>	0.25	0.75	1.00	0.75	0.17	0.75	0.40	0.00	0.25	0.75	0.90

A <sub>10</sub>	0.00	0.75	1.00	0.50	0.08	0.00	0.60	0.29	0.50	0.25	0.52
A <sub>11</sub>	0.25	1.00	0.50	0.25	0.17	0.00	0.80	0.43	0.25	0.00	0.59
A <sub>12</sub>	0.50	0.00	0.25	0.50	0.25	0.00	1.00	0.29	0.75	1.00	0.55
A <sub>13</sub>	0.75	0.25	0.00	0.00	0.33	0.50	0.60	0.14	1.00	0.00	0.10
A <sub>14</sub>	0.00	0.50	0.25	0.25	0.42	0.75	0.80	0.29	1.00	0.75	0.07
A <sub>15</sub>	0.25	0.75	0.50	0.75	0.50	0.75	1.00	0.43	0.00	0.00	0.62
A <sub>16</sub>	0.50	0.25	0.75	0.50	0.25	0.50	0.20	0.14	0.25	1.00	0.72
A <sub>17</sub>	0.75	1.00	1.00	0.50	0.33	0.75	0.40	0.14	0.50	0.00	0.79
A <sub>18</sub>	1.00	0.00	0.75	0.75	0.25	0.25	0.00	0.43	0.25	0.50	0.83
A <sub>19</sub>	0.00	0.25	1.00	1.00	0.33	0.00	1.00	0.57	0.75	0.00	0.93
A <sub>20</sub>	0.25	0.50	0.00	0.00	0.42	0.50	0.20	0.14	0.00	0.25	0.90

In the second step, normalized values have been multiplied by the importance level (weight) of each criteria and by the help of these values total utility values have been calculated.

**Table 3:** Total Utility Values: Equally Weighted, MAUT Method

	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>5</sub>	C <sub>6</sub>	C <sub>7</sub>	C <sub>8</sub>	C <sub>9</sub>	C <sub>10</sub>	C <sub>11</sub>	Total Utility
A <sub>1</sub>	0.00	0.05	0.05	0.00	0.09	0.05	0.04	0.01	0.05	0.00	0.05	0.37
A <sub>2</sub>	0.00	0.13	0.38	0.00	0.25	0.25	0.24	0.00	0.25	0.00	0.32	1.81
A <sub>3</sub>	0.13	0.13	0.19	0.25	0.08	0.25	0.48	0.00	0.38	0.13	0.28	2.28
A <sub>4</sub>	0.38	0.13	0.13	0.38	0.19	0.38	0.80	0.12	0.19	0.50	0.00	3.18
A <sub>5</sub>	0.38	0.00	0.38	0.38	0.24	0.75	0.60	0.12	0.13	0.00	0.00	2.97
A <sub>6</sub>	0.50	0.00	0.00	0.38	0.35	0.25	0.24	0.29	0.38	0.00	0.22	2.60
A <sub>7</sub>	0.25	0.13	0.00	0.38	0.00	0.00	0.00	0.29	0.00	0.75	0.21	1.99
A <sub>8</sub>	0.13	0.25	0.13	0.50	0.00	0.00	0.00	0.04	0.00	0.25	0.86	2.15
A <sub>9</sub>	0.13	0.38	0.50	0.75	0.11	0.38	0.08	0.00	0.25	0.19	0.90	3.65
A <sub>10</sub>	0.00	0.56	1.00	0.38	0.01	0.00	0.24	0.00	0.13	0.19	0.46	2.97
A <sub>11</sub>	0.00	0.75	0.50	0.13	0.01	0.00	0.48	0.12	0.13	0.00	0.30	2.42
A <sub>12</sub>	0.13	0.00	0.13	0.13	0.04	0.00	0.80	0.12	0.19	0.00	0.32	1.85
A <sub>13</sub>	0.38	0.00	0.00	0.00	0.08	0.00	0.60	0.04	0.75	0.00	0.06	1.91
A <sub>14</sub>	0.00	0.13	0.00	0.00	0.14	0.38	0.48	0.04	1.00	0.00	0.01	2.17
A <sub>15</sub>	0.00	0.38	0.13	0.19	0.21	0.56	0.80	0.12	0.00	0.00	0.04	2.42
A <sub>16</sub>	0.13	0.19	0.38	0.38	0.13	0.38	0.20	0.06	0.00	0.00	0.45	2.27
A <sub>17</sub>	0.38	0.25	0.75	0.25	0.08	0.38	0.08	0.02	0.13	0.00	0.57	2.88
A <sub>18</sub>	0.75	0.00	0.75	0.38	0.08	0.19	0.00	0.06	0.13	0.00	0.66	2.99
A <sub>19</sub>	0.00	0.00	0.75	0.75	0.08	0.00	0.00	0.24	0.19	0.00	0.77	2.79
A <sub>20</sub>	0.00	0.13	0.00	0.00	0.14	0.00	0.20	0.08	0.00	0.00	0.83	1.38

A<sub>9</sub> is the best candidate and A<sub>1</sub> is the worst candidate for the equally weighted MAUT method and Table 4 illustrates ranking of potential candidates from best to worst with their total utility.

**Table 4:** Ranking MAUT Method

Ranking	Alternatives	Total Utility	Ranking	Alternatives	Total Utility
1	A <sub>9</sub>	3.65	11	A <sub>3</sub>	2.28
2	A <sub>4</sub>	3.18	12	A <sub>16</sub>	2.27
3	A <sub>18</sub>	2.99	13	A <sub>14</sub>	2.17
4	A <sub>10</sub>	2.97	14	A <sub>8</sub>	2.15
5	A <sub>5</sub>	2.97	15	A <sub>7</sub>	1.99
6	A <sub>17</sub>	2.88	16	A <sub>13</sub>	1.91
7	A <sub>19</sub>	2.79	17	A <sub>12</sub>	1.85
8	A <sub>6</sub>	2.60	18	A <sub>2</sub>	1.81
9	A <sub>15</sub>	2.42	19	A <sub>20</sub>	1.38
10	A <sub>11</sub>	2.42	20	A <sub>1</sub>	0.37

For the right academic staff selection problem we thought that some of the criteria does not need to be a maximum or minimum value, they need to take an optimum value. The criteria’s which we assumed to take an ideal value are criteria’s such as age. These are C<sub>1</sub>, C<sub>2</sub>, C<sub>3</sub>, C<sub>9</sub> and C<sub>10</sub> and the results of this analysis is illustrated in Table 5.

**Table 5:** Grey Relational Analysis: Maximum-Optimum

Ranking	Alternative	Coefficient	Ranking	Alternative	Coefficient
1	A <sub>20</sub>	0.62	11	A <sub>1</sub>	0.53
2	A <sub>3</sub>	0.60	12	A <sub>14</sub>	0.52
3	A <sub>5</sub>	0.59	13	A <sub>4</sub>	0.52
4	A <sub>8</sub>	0.58	14	A <sub>9</sub>	0.50
5	A <sub>15</sub>	0.57	15	A <sub>18</sub>	0.49
6	A <sub>12</sub>	0.56	16	A <sub>17</sub>	0.48
7	A <sub>2</sub>	0.56	17	A <sub>10</sub>	0.46
8	A <sub>19</sub>	0.55	18	A <sub>11</sub>	0.46
9	A <sub>6</sub>	0.55	19	A <sub>7</sub>	0.45
10	A <sub>16</sub>	0.55	20	A <sub>13</sub>	0.41

According to GRA, A<sub>20</sub> is the best candidate and A<sub>13</sub> is the worst candidate. However, we want to compare the results of two methods, to do it in an accurate way, we again rank the potential candidates with grey analysis and considered as the criteria’s should take maximum or minimum values only and the results of this analysis is illustrated in Table 6.

**Table 6:** Grey Relational Analysis: Max-Min

Ranking	Alternative	Coefficient	Ranking	Alternative	Coefficient
1	A <sub>8</sub>	0.63	11	A <sub>18</sub>	0.54

2	A <sub>19</sub>	0.63	12	A <sub>16</sub>	0.54
3	A <sub>6</sub>	0.61	13	A <sub>3</sub>	0.51
4	A <sub>4</sub>	0.60	14	A <sub>7</sub>	0.50
5	A <sub>17</sub>	0.59	15	A <sub>10</sub>	0.50
6	A <sub>9</sub>	0.59	16	A <sub>20</sub>	0.50
7	A <sub>12</sub>	0.57	17	A <sub>11</sub>	0.49
8	A <sub>5</sub>	0.56	18	A <sub>13</sub>	0.49
9	A <sub>14</sub>	0.55	19	A <sub>1</sub>	0.48
10	A <sub>15</sub>	0.54	20	A <sub>2</sub>	0.48

From Table 6, it can be easily seen that A<sub>8</sub> is the best candidate and A<sub>2</sub> is the worst candidate. To compare the results of two methods Kendall rank correlation coefficient were used. This coefficient was developed as nonparametric measure of the association between two variables based on the number of concordances and discordances in paired observations.

**Table 7:** Results of GRA and MAUT Method

Potential Candidate	GRA	MAUT	Potential Candidate	GRA	MAUT
A <sub>1</sub>	19	20	A <sub>11</sub>	17	10
A <sub>2</sub>	20	18	A <sub>12</sub>	7	17
A <sub>3</sub>	13	11	A <sub>13</sub>	18	16
A <sub>4</sub>	4	2	A <sub>14</sub>	9	13
A <sub>5</sub>	8	5	A <sub>15</sub>	10	9
A <sub>6</sub>	3	8	A <sub>16</sub>	12	12
A <sub>7</sub>	14	15	A <sub>17</sub>	5	6
A <sub>8</sub>	1	14	A <sub>18</sub>	11	3
A <sub>9</sub>	6	1	A <sub>19</sub>	2	7
A <sub>10</sub>	15	4	A <sub>20</sub>	16	19

GRA and MAUT columns of Table 7 are the variables that we want to determine the level of concordance and the value of the coefficient is 0.3579.

## 5. Conclusion

The right employee selection is a difficult and old problem to handle and can be considered as multi-criteria decision making process. The most crucial features of this process is uncertainty. As explained before, we aimed to choose the most suitable candidate or employee for a certain position and in this study as an application two methods -GRA and MAUT- had been used to select the most eligible academic staff.

The orders of two methods thought as two variables and the concordance between these variables was calculated and we found weakly positive concordance. If we can found highly positive concordance we can suggest that for selection problem you can use one of the method instead of the other one. As for future work, it is suggested that other multi-criteria decision making process approaches such as TOPSIS, ELECTRE, Fuzzy TOPSIS be applied and compared in academic staff selection



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