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Simple Additive Weight Method in Comparison Problems: A Job Applicant Selection Problem

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Abstract: Selection problems where merit should be used have recently been infected with corrupt and unscientific subjective behaviours. The eventual problem of illogic that is rife thus far is lack of economic improvement among nations. The study demonstrates use of statistical methods in ensuring that merit selection of various candidates can be guaranteed. The method used is a common statistical method used for various purposes and this study applies it in selection problems to demonstrate the fairness that it endorses. The study demonstrates the quality of the Simple Additive Weight (SAW) statistic in performing selection in an impartial manner. The SAW method assisted the selection of a worthy competitor, objectively without the interference of the analyst.

Key words: Comparisons, decision problems, entropy, fuzzy logic, performances, weighting

INTRODUCTION

To select an alternative from several options is not always an easy task. Selection of applicants for available job opportunities is one such example. Some selections involve interview panels selecting applicants for a job position from a number of applicants, institutions selecting candidates for giving them opportunities to undertake internships, companies selecting recruits as new intakes to the jobs and so on. Example of selecting the applicant with highest marks for internships is common. In employment positions, normal practice is that one with the highest qualification is considered the best candidate. Therefore, in these two cases, merit refers to the highest qualification or the highest mark. However, this method is based on the assumption that the subjects written by the candidates whose marks were used in deriving the final mark, were weighing equally. There are other dimensions to merit though. One is that if grooming was tough, the candidate coming from that route becomes a strong one. This is not the only addition to the complexities. Due to this fact, the problems of this study entail assigning various attributes serving as criteria for selection. The question is then ‘How could these criteria be used equitably in a scientific method to select the worthy candidate from those participating in the competition for the post’?

Generally, though, the levels of importance for the different subjects are not equal. In every situation some subjects are more important than others. The same applies to considering difficult tasks. Candidates who handle more difficult tasks of a job are more likely to perform better in difficult subjects as well. It is therefore, necessary to believe that in selecting candidates, one who can perform more difficult tasks can be trusted to perform in difficult circumstances. In this case a candidate who passed the difficult subject better could be considered being able to perform harder tasks related to the subject. In order to qualify this though, if the candidate performs poorly in easier subjects, it may indicate weaknesses in easier tasks in the job. A balance of good performance is required in easier subjects and in more difficult subjects so that it becomes easier to believe that the candidate will perform both difficult and easy tasks. In terms of importance, therefore, the more difficult subjects are more important. If there are weights that indicate the relative level of importance, more difficult subjects would then be assigned larger weights. When considering these thoughts, then candidate selection would be an important and not straightforward function for anyone attempting to select the best candidate.

Furthermore, many criteria are used to make a decision to finalize the candidate selection process. In this study, values reflecting merit would be used based on the issues at hand. As a result, candidate selection is a Multiple-Criteria Decision Making (MCDM) problem that is affected by quantitative and qualitative factors. Consequently, selectors of a worthy candidate have to analyse the trade-off among the several conflicting criteria. MCDM techniques help the decision makers to

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evaluate a set of alternative candidates. According to Wang *et al*. (2004), in real-life situations for problems of this kind, the weights of the different criteria are different and depend on perceived or real importance of a criterion. In real-life situations it would seem that selectors would prefer candidates who perform well in difficult subjects but also doing satisfactorily in easier ones, thus, indicating the intent to achieve many objectives in a composite problem environment. This kind of environment is a complex Multi-Objective Decision Making (MODM) problem which is affected by several conflicting factors (Jadidi *et al*., 2008). Current trends in candidate selection where examination marks are used is that the highest mark is considered the best option identifier. The main problem is that the importance inherent in the relative importance of some subjects is not given due recognition. Examples can be drawn from work of practitioners in industry who developed models to select competitors given due recognition to the importance of the criteria being used. In another example, Chaudhry *et al*. (1993) developed a linear mixed integer programming for supplier selection. In the developed model delivery, price, quality and quantity discount are included.

In another research, Rosenthal *et al*. (1995) developed a mixed integer programming model for supplier selection with bundling in which a buyer has to buy various items from several suppliers whose quality, capacity and deliveries are limited and who offer bundled products at discounted prices. Single objective programming was used in their model. An integrated Analytic Hierarchy Process (AHP) and linear programming model was proposed by Ghodsypour and O’ Brien in order to help managers consider both quantitative and qualitative factors in their purchasing activity in a systematic approach. The researcher also considered quality and service and buyer’s limitations on budget and price discount. In real cases, for supplier selection problem, majority of the input information is not known precisely, so that, the values of many criteria are expressed in uncertain terms such as “good in price” or “very high in quality”. This vagueness cannot be easily considered by deterministic models. In these cases, the fuzzy theory which is one of the best tools to handle uncertainty, can help solve the supplier selection problem. In fuzzy programming, the problem is no longer forced to be formulated in precise and rigid form.

Based on fuzzy logic approaches, a model which combines the use of Fuzzy Set Theory (FST) with AHP and implements it to evaluate small suppliers in the engineering and machine sectors was developed by Morlacchi. Moreover, the application of FST was discussed by Holt (1998) and Erol and Ferrell (2003) in order to find the best supplier among supplied suppliers. These papers deal with a single-sourcing supplier selection problem where all buyer’s demands can be met by only one supplier. Fuzzy goal programming was proposed by Kumar *et al*. (2004) for supplier selection problems with multiple sourcing that include three objectives: minimizing the net cost, the net rejections and the net late deliveries subject to realistic constraints regarding supplier’s capacity and buyer’s demand. The researcher used Zimmermann (1978, 1991)’s weightless technique where there is no difference between objective functions. Related to the use of many criteria and many objectives in selection, there is use of many attributes (Multi-attribute Decision Making or MADM) (Hwang and Yoon, 1987). SAW is one method that can handle MADM, MCDM and MODM selection problems by assigning a rational set of weights in calculating scores used to select the final alternative desired for the problem at hand.

Problem context: When candidates are compared for, the highest average score is often used as the criterion for selection. In this case of applicants for a job opportunity the scores are the relative marks awarded for the various criteria. The average has as its main assumption that the subjects involved are of equal importance. Even though the average is common and easy to calculate, fairness of the highest mark in many selections problems cannot be established from a scientific viewpoint. Also, in cases where there is a need to trim and shortlist candidates, objective measures may require use of weights to reflect the relative importance in the subjects passed. It is therefore, absolutely necessary to offset the prejudice contained in the use of highest marks obtained from averaging, since, that averaging does not take into account the importance of relevant subjects. Since, instances desire bias towards more important attributes, some instances will require partiality towards some subjects than others. This study employs SAW as the scientific measure to enhance such objectivity by offsetting equal weighting of subjects and using larger weights to incline towards more important subjects.

Study problem: The problem of this study is that selecting the best candidate is often based on the highest average marks. Subjects differ in their importance according to the relevance to opportunities being sought or the priorities at hand. Use of common averages assumes equal importance of the subjects used. The study wants to illustrate the way ‘importance’ can be incorporated in averaging that uses objective higher weights on subjects of higher importance and lower weights on subjects of lower importance.

Decision making: This study entails making rational decisions of selecting a (close to ideal) candidate among applicants in a human resources recruitment environment. In actual practice it is known or believed that ideal solutions rarely exist. Hence, the best required should be as close to the ideal solution as possible and scientific methods exist to enable this possibility. Decision-making is the procedure to find the best alternative among a set of feasible alternatives (Chen, 2000). Sometimes, many criteria are involved in the selection. As a result decision-making problems tend to consider several criteria and are then called Multi-criteria Decision Making (MCDM) problems (Chen 2000; Wang and Lee, 2007). These techniques often require the decision makers to provide qualitative or quantitative assessments for determining the performance of each alternative with respect to each criterion as well as the relative importance of evaluation criteria with respect to the overall objective of the problems. Consequently, MCDM refers to screening, prioritizing, ranking or selecting a set of alternatives (also referred to as 'candidate's or 'action's) under usually independent, incommensurate or conflicting criteria (Fenton and Wang, 2006).

Decision making problems will usually result in uncertain, imprecise, indefinite and subjective data being present which makes the decision-making process complex and challenging. In other words, decision-making often occurs in a fuzzy environment where the information available is imprecise/uncertain. Therefore, the application of fuzzy set theory to multi-criteria evaluation methods under the framework of utility theory has proven to be an effective approach (Kuo *et al*., 2007). The problems also appreciate the randomness of possibilities and the incorporation of stochastic methods in developing feasible solutions to the problems. The overall utility of the alternatives with respect to all criteria is often represented by a fuzzy number which is named the fuzzy utility and is often referred to by fuzzy multicriteria evaluation methods. Wang and Lee (2007) state that the ranking of the alternatives is based on the comparison of their corresponding fuzzy utilities.

The general concepts of domination structures and non-dominated solutions play an important role in describing the decision problems and the decision maker's revealed preferences described in multicriteria decision making (Triantaphyllou, 2000). Methods are available for use in decision making. However, efficiencies are not always clear and their quality cannot always be measured. Monahan (2000) informs that so far, various approaches have been developed as the decision aid. Further, complexity is that in MCDM problems, there does not necessarily exist the solution that optimises all the objectives functions. Consequently, the concept which is called Pareto optimal solution (or efficient solution) was introduced. Usually, there exist a number of Pareto optimal solutions which are considered as candidates of final decision making solution. It is an issue though, how decision makers decide the best one from the set of Pareto optimal solutions as the final solution (Karasakal and Koksalan, 2009).

Purpose of the study: The principal aim of this study is to intensely reduce (or even eliminate where possible) the bias of applicant's average marks in comparing them for selection to the various opportunities after completing their qualifications by considering the importance of different subjects while taking care of the easier subjects in the allocation of priority scores in the calculation of scores needed for comparisons. The objectives of this study were:

- To demonstrate the way to use SAW scores in candidate selection
- To illustrate objective weighting that does not depend on the selector
- To use the scores to select candidates for opportunities

Simple additive weight: Relatively scarce effective models have been developed for objective selection problems of candidates and simultaneously addressing unstructured relevant information and imprecise input data and different weights of evaluative criteria (Amid *et al*., 2009). Amid *et al*. (2009) developed a fuzzy multi-objective and mixed integer linear programming for the supplier selection problem to consider different weights of evaluative criteria.

SAW is consider both quantitative and qualitative factors for choosing the best candidate and defines the optimum quantities among the selected candidates under conditions of several subjects. SAW is a fuzzy multi-objective model where selectors consider the imprecision of information and the relative importance of each item. The intention is to reduce unfairness in selection of candidates for identified opportunities of various forms.

One element of prominence in SAW is using weight to reflect the relative level of importance of each criterion (or attribute) relative to others in an analysis. The weights ensure shifting from using the common averages such as mean, mode or median. Common averages are calculated with all the values contributing equally to the final value. The most important values contribute to the final score in the same way as the least important ones. An objective final score would contribute to the final score in a balanced way to reflect the level/extent of importance relative to the other scores being used. Therefore, proportionate allocation of weights to the values would ensure the balance in calculating the final score.

Selection decision problems: Selection process decisions can be complex as they are based on many objectives or many attributes or many criteria. Hence, the respective associated decisions based on these conditions are usually classified as MODM, MADM and MCDM. Among the MCDM problems that are encountered in real life is the problem of employee selection for positions in a company. This study explores the use of various scoring methods in a employee selection problem applied to the context of MCDM. In general, MCDM problems have attracted the interest of many researchers and practitioners. One class of approaches that deal with subjectivity includes techniques based on the well-known Analytic Hierarchy Process (AHP) which reduces complex decisions to a series of pairwise comparisons and synthesizes the results. For example, AHP and its extensions have been utilized extensively in the selection of Human Resources (HR). Coincidentally, the employee selection problem is an HR problem. Typical AHP applications include those presented in the readings by Lai (1995), Iwamura and Lin (1998) and Labib *et al*. (1998). Further, Albayrak and Erensal (2004) used AHP which determines the global priority weights for different management alternatives to improve HR performance outcomes. A detailed review of various applications of AHP in different settings is provided by Vaidya and Kumar (2006).

The other modern methods in the selection problem are artificial intelligence techniques that are the fuzzy sets and neural networks. In contrast to conventional sets where a given value is either included or not included in a set in fuzzy set theory each value is associated with a certain grade of membership in set. This grade is expressed by a membership function that reflects the extent to which it can be argued that value is included in. Examples of such approaches can be found in Laing and Wang (1992), Yaakob and Kawata (1999), Lovrich (2000), Choo and Wedley (2004), Wang *et al*. (2006) and Wei and Chen (2009). Lazarevic (2001) introduces a two-level fuzzy model for minimizing subjective judgment in the process of identifying the right person for a position. Moreover, Royes *et al*. (2003) propose a combination of fuzzy sets and multi-criteria tools for employee selection.

Weighting approaches: Even though the criteria set are all important, there are cases where some criteria are more important than others. In the cases of selecting a candidate for a post in a company, the relative importance of the criteria is decided according to the company needs. The level of education is highly prioritised because every person selected for an advertised post is expected to be exemplary in education through impressive credentials. The weights are assigned to the different criteria. These are used in to calculate scores to identify a leading candidate according to the set criteria. Weights are given as numerical values. The higher weights indicate higher importance.

Relative importance of weights: Common average or mean is calculated with all the values contributing equally to the final value. The most important values contribute to the final score in the same way as the least important ones. An objective final score, however, should contribute to the final score in a way to reflect the level of importance relative to the other scores being used. Thus, proportionate allocation of weights to the values would ensure the balance in calculating the final score.

Assigning weights: Several ways to assign weights exist. However, they differ from situation to situation and from one environment to another. No single technique of assigning the weights is considered universally suitable, but many of the methods contain the subjectivity of the user. A common approach that is not complicated is to start by ranking the attributes from 1 to m where 1 stands for the most important attribute and is for the least important of the attributes. This is then followed by adding all the ranks to obtain $\sum_{j=1}^{m} j = m(m+1)/2$. The selection process is followed by defining the weights for the ranked criterion as:

$$w_i = \frac{i}{\sum_{j=1}^{m} j} \tag{1}$$

This is given by

$$w_i = \frac{2i}{\left[m(m+1)/2\right]} \tag{2}$$

In this setting w_i is the weight of the most important attribute, the weight of the second most important attribute w_2 and so on up to w_m as the weight of the least important. The two basic properties of significance to these weights which can also be shown are:

$$0 < w_i < 1$$

$$\sum_{i=1}^{m} w_i = 1$$

The problem with this weight is that its objectivity cannot be justified. Hence, fairness of this weighting extends only up to the corresponding ranks of the attributes.

Objective assigning of weights: The weighting method using entropy removes bias and subjectivity. Entropy is a measure to calculate the amount of disorder in a system (Deng *et al*., 2000; Golan *et al*., 1996; Koksalan *et al*., 2011). It is essentially, a measure of the number of ways in which a system may be arranged. It measures 'disorder' such that higher entropy signals higher disorder (Baierlein, 2003; Jungermann, 2006). According to Atkins and De Paula (2006), entropy quantifies, in the sense of an expected value, the information contained in a message carried in the system being analysed. Shannon and Weaver (1949) applied entropy for measuring the relative contrast intensities of performances using a transformed matrix from D to represent the average intrinsic information transmitted to the decision maker (Leave for later the details of the matrix D.) The relative performance of an alternative indicated in given data carries the weight for the analysis used. In fact, entropy is a measure of certainty/uncertainty in the information formulated according to probability theory. It indicates the amount of decision information that each performance index contains (Deng et al. 2000; Hwang and Yoon, 1987). It indicates that a broad distribution represents more uncertainty than does a sharply peaked one.

Let $k = \frac{1}{\ln n}$, where " in" denotes the natural logarithm to the base 'e'. Deng *et al*. (2000) define the entropy measure as:

$$e_j = -k\sum_{i=1}^{n} p_{ij} \ln p_{ij},\ j = 1, 2, \dots ,$$

The next three results show that the properties of the weights being between 0 and 1 and adding up to 1 are satisfied.

Result 1:

$$0 \le e_j \le 1$$

Proof:

Since,

$$0 \le p_{ij} \le 1$$

Then,

$$\ln p_{ij} \le 0$$

Furthe,

$$k \ln p_{ij} = \frac{\ln p_{ij}}{\ln n} \le 0$$

Thus,

$$e_j = -k\sum_{i=1}^{n} p_{ij} \ln p_{ij} \ge 0$$

It is left to show that e_s is <1 since:

$$p_{ij} \le n$$

Then,

$$-k \ln p_{ij} = -\frac{\ln p_{ij}}{\ln n} \le 1$$

Also, there is the property that:

$$\sum_{i,j} p_{ij} = 1$$

Then:

$$e_j = -k\sum_{i=1}^{n} p_{ij} \ln p_{ij} = \sum_{i=1}^{n} p_{ij}\left(-\frac{\ln p_{ij}}{\ln n}\right)$$

$$\le \sum_{i=1}^{n} p_{ij}(1) = \sum_{i=1}^{n} p_{ij} = 1$$

Degree of divergence: The degree of divergence (d_j) is the inherent contrast of the attribute X_j (Deng *et al*., 2000). It is defined (and thus calculated) as:

$$d_j = 1 - e_j,\ j = 1, 2, \dots , m$$

When performance ratings diverge more for the attribute x_j then d_j becomes larger. Then is more important for the problem at hand (Spath, 1992). By using the definition of entropy and Eq. 4, the degree of divergence is the measure of the amount of order of an attribute:

Result 2:

$$0 \le d_j \le 1$$

Proof:

Consider:

$$0 \le e_j \le 1$$

Then:

$$0 \ge -e_j \ge -1$$

Reorderng this inequality leads to:

$$-1 \le -e_j \le 0$$

Adding 1 to the terms of the inequality gives:

$$0 \le 1 - e_j \le 1$$

Now, since:

$$d_j = 1 - e_j$$

The result of the theorem is obtained which is that:

$$0 \le d_j \le 1$$

Further logic about d_j is that an attribute is not important for a specific problem if in that problem all the alternatives have identical performance ratings for that attribute. Then, if all performance ratings for that attribute are the same, the attribute can be eliminated for the situation on which a decision is based as it transmits no information to the decision maker.

Weights: The weights derived from entropy (through the degree of divergence) for each attribute are given by Deng *et al*. (2000) as:

$$w_j = \frac{d_j}{\sum_{k=1}^{n} d_k},\ j = 1, 2, \ldots, m \tag{5}$$

Result 3:

$$0 \le w_j \le 1$$

Proof:

Consider,

$$0 \le d_j \le 1$$

Then:

$$0 \le d_j \le \sum_{i=0}^{n} d_i$$

This leads to:

$$0 \le \frac{d_j}{\sum_{i=0}^{n} d_i} \le 1$$

The middle term is the weight being proved. Hence:

$$0 \le w_j \le 1$$

Measuring with SAW approach: Simple Additive Weighting (SAW), also known as weighted linear combination or scoring method is a user-friendly mathematical method to perform pragmatic operations that demonstrate systematic appeal and applicable to many multivariate settings. It is most often used respected but not complicated MADM technique. It depends on the weighted average. Attributes are given some level of importance. Weights of relative worth are then directly assigned by the decision maker using a predetermined rule to reflect the level of importance for each attribute. In order to compare competitors, an evaluation score is calculated for each alternative by multiplying the scaled value given to the alternative of that attribute with the weights assigned followed by adding the products for all criteria.

SAW assigns scores to alternative competitors (Dawes 1971). To assign a score for an alternative, the process requires the contribution of each attribute which is obtained by multiplying the weights (signifying the level of importance) with the corresponding performance indexes. The resulting score is obtained by adding contributions from each alternative. SAW starts by considering the n×m performance matrix $P = (P_{ij})$ and the m-vector of weights given by the column vector $\omega = (w_1\ \ldots\ w_n)^T$ from $(P\omega) = (v_1\ \ldots v_n)^T$, a n column vector, where:

$$v_i = \sum_{j=1}^{m} w_j p_{ij}\ \ j = 1, 2, \ldots, n$$

These values are the SAW scores signifying the worth of alternatives that are to be compared. These scores are arranged from largest to smallest and are used to order the corresponding competitors.

Study setting: This study considers $A_1, A_2, \ldots, A_n$ a set of n alternative candidates competing for an opportunity, based on $S_1, S_2, \ldots, S_m$ a set of m attributes. The environment of the selection process consists of entries x_{ij} reflecting the occurrence for candidate A_i under attribute $|S_j$ as follows:

$$\begin{array}{c|cccc|} & S_1 & S_2 & \ldots & S_m \\ \hline A_1 & x_{11} & x_{12} & \ldots & x_{1m} \\ A_2 & x_{21} & x_{22} & \ldots & x_{2m} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ A_n & x_{n1} & x_{n2} & \ldots & x_{nm} \end{array} \tag{7}$$

To enhance mathematical manipulations the decision matrix obtained from this setting is:

$$D = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1m} \\ x_{21} & x_{22} & \ldots & x_{2m} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ x_{n1} & x_{n2} & \ldots & x_{nm} \end{bmatrix} \tag{8}$$

Model for order allocation: The model is established for candidate selection problem based on merit defined by the criteria used. The scores obtained (marks awarded to the candidates for the various criteria) are calculated using SAW to decide on the highest score given by the method. The objective function simply requires the maximum average.

MATERIALS AND METHODS

SAW is fundamentally based on the concept that the selected best alternative should have the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution in a Euclidean sense (Hwang and Yoon, 1981). Subjective views into an explicit decision process are reduced. Due to successes and robustness in different decision situations (Deng *et al*., 2000), the entropy method is suggested for achieving the task. This task is efficiently achieved using Shannon's entropy which basically considers decision matrix contents as a specific source of information emitted through criteria to the decision maker. Entropy based method in turn computes unbiased relative criteria weights and enables an application of SAW to rank scenarios appropriately. Obtained ranking is considered the final result of proposed methodology.

Data: The data were supplied from a selection committee of a suitable applicant for a job opportunity. They consist of a matrix of values which are values awarded for the various criteria. The data appear in matrix format. The rows were the candidate's identities that were hidden deliberately or changed identities while the columns were the multiple criteria that were used in the comparison and selection.

Analysis of data: SPSS was used to perform all the analyses. The data analyses consisted of calculations of the weights and the SAW measures.

Experiential exercise: A real exercise is used. Due to the ethical guidelines adhered to, the company name is concealed. The company is located in Gauteng province, South Africa. Before engaging in the exercise, we report that the winning candidate from the scientific method SAW was C_2 while the community wanted to appoint C_5. The criteria used were:

X_1 : Important qualification (s)
X_2 : Relevant experience
X_3 : Self-expression regarding suitability to position
X_4 : Capability to use to existing policies to raise standards
X_5 : Understanding of roles for the position
X_6 : Human relations with stakeholders
X_7 : Financial management skills/proficiency
X_8 : Self-sufficiency

RESULTS AND DISCUSSION

Initial data for assigning performances scores on the set criteria were generated from Curriculum Vitaes (CVs) and communicating with the candidate's referees. Each criterion was scored on a scale of 1-0 where '1' is the worst possible performance and '10' the best possible performance. Also, the scores 1 and 10 were avoided as much as possible, since, no one is completely useless while at the same time no one is fully perfect the data matrix, therefore is:

Data matrix:

$$X = \begin{bmatrix} 5 & 8 & 4 & 4 & 6 & 6 & 5 & 3 \\ 6 & 7 & 8 & 5 & 3 & 8 & 6 & 5 \\ 4 & 8 & 5 & 7 & 9 & 8 & 8 & 2 \\ 9 & 9 & 4 & 6 & 4 & 4 & 5 & 3 \\ 8 & 8 & 7 & 5 & 2 & 6 & 5 & 2 \end{bmatrix}$$

Deriving matrix of performance: The performances are calculated using:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{m} x_{ij}}$$

Then the performance matrix is:

Performance matrix:

$$P = \begin{matrix} 0.022 & 0.035 & 0.018 & 0.026 & 0.022 & 0.013 \\ 0.024 & 0.031 & 0.035 & 0.013 & 0.026 & 0.022 \\ 0.018 & 0.035 & 0.022 & 0.040 & 0.035 & 0.009 \\ 0.040 & 0.040 & 0.018 & 0.018 & 0.033 & 0.013 \\ 0.035 & 0.035 & 0.031 & 0.026 & 0.022 & 0.009 \end{matrix}$$

Calculating weights: Deng *et al*. (2000) propose using entropy to derive the attribute weights. Entropy depends on 'facts' in the data. The degree of divergence (d_j) is calculated from the entropies. Weights are then calculated from the d_j. Hence, these weights are free from human bias.

Entropy arrangement: Entropy is an objective method for determining the attribute weights. Its values are given by the formula $e_j = -k\sum_{i=1}^{n} p_{ij} \ln p_{ij}$:

Entropy weights: The entropy derived weights $w_j = \frac{d_j}{\sum_{k=1}^{n} d_k}$ are:

Table 1: Scores obtained

	Criteria							
Variables	X_1	X_2	X_2	X_4	X_5	X_6	C_7	X_8
Candidates								
C_1	5	8	4	4	6	6	5	3
C_2	6	7	8	5	3	8	6	5
C_3	4	8	5	7	9	8	8	2
C_4	9	9	4	6	4	4	5	3
C_5	8	8	7	5	2	6	5	2

Table 2: Entropy values

j	1	2	3	4	5	6	7	8
e_j	0.69	0.63	0.72	0.73	0.76	0.69	0.71	0.82

Table 3: Degrees of divergence

j	1	2	3	4	5	6	7	8
e_j	0.12	0.11	0.13	0.13	0.13	0.12	0.12	0.14

Table 4: Entropy weights

Competitor	C1	C2	C3	C4	C5
SAW	0.0222	0.0048	0.0059	0.0055	0.0051

Table 5: Entropy values

Competitor	1	2	3	4	5	6	7	8
SAW	0.31	0.37	0.28	0.26	0.25	0.31	0.29	0.18

SAW scores: The SAW scores $v_i = \sum_{j=1}^{m} w_j p_{ij}$ are:

Table 1 presents raw data from the scoring after the interviews. It is converted to which is the data matrix required by the SAW methodology. The formula for performances is used on values to derive the performance matrix. Table 2 presents entropy values. It leads to Table 3 by calculating the degrees of divergence. Then Table 4 presents the weights from the entropy formula. Table 5 are the SAW scores calculated from weights and the performance matrix.

Order of preference: The SAW scores give the order of preference:

C_3 C_2 C_4 C_5 C_1

The conflict between human preference and scientific method existed. The difference was that SAW use could demonstrate transparency in the selection while it was not possible with the subjective approach. Logical steps were clear with SAW application. On the other hand, no reasoning was possible from subjective methods. The integrity of scientific approaches is also that the selection can be confirmed by a different panel.

CONCLUSION

SAW was used to select a candidate in the selection process. This offsets the issue of selecting a candidate and not be able to corroborate the selection. Each of the three methods is a scientific method in its own right that can also be used alone in many selection processes. In this instance one was used to select the preferred candidate and the other two were used to validate or improve on the choice made by the first one. Any of the methods can be used as the starting method and the remaining two serving to support the first one. Care has been taken by an explanation of additional tasks to undertake to offset rare situations where the methods are not able to effect the final choice.

RECOMMENDATIONS

It is recommended that:

- Scientific methods such as SAW should be used in the place of normal averages or human subjective approaches to delete prejudice
- Entropy should be used to derive weights of relative importance because they lack bias

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