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Multi-Criteria Decision Making: The Case of Large and Distinct Decision Makers

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Abstract

This paper considers a multi-criteria decision making (MCDM) problem where a set of alternatives are to be evaluated or ranked. However, unlike in a traditional MCDM approach, each alternative is evaluated by a distinct group of decision makers who are different from those evaluating the other competing alternatives. In addition, the decision makers for each alternative are large (in hundreds and above). We propose a sampling based modeling technique to transform this special type of MCDM problem into a traditional MCDM format. Following this, the sampling distributions of the ranks of the alternatives are displayed with Boxplot to aid decision making. A numerical example showing the effectiveness of the proposed approach is presented.

Keywords
Decision making; Multi-criteria decision making; Large and distinct decision makers; Sampling

1. Introduction

Many important decisions in life are made through selecting from, or ranking a group of competing alternatives based on multiple and often, conflicting criteria. Problems of such nature have been studied and solved with Multi-Criteria Decision Making (MCDM) methods due to their ability to consider both qualitative and quantitative data, as well as the ability to combine multiple and often conflicting criteria. Many evaluation methods exists in the MCDM literature, including Analytic Hierarchy Process (AHP) (Saaty, 2008), Technique For Order Preference by Similarity to Ideal Solution (TOPSIS) (Hwang and Yoon, 2012; Behzadian et al, 2012), ELECTRE (Velasquez, and Hester, 2013), DEMATEL (Shieh, Wu, and Huang, 2010), and VIKOR (Opricovic and Tzeng, 2004). Several techniques have also been developed in the literature to handle different types of information or data including crisp, fuzzy, interval, intuitionistic fuzzy, and hesitant fuzzy (Aruldoss, Lakshmi, and Venkatesan, 2013; Zavadskas, Turskis, and Kildienė, 2014). This paper builds upon the growing MCDM literature, and considers a type of MCDM problem where the decision makers evaluating competing alternatives are (1) very large in number compared to those in typical MCDM applications, (2) the large decision makers are themselves a representative of an even larger body of decision makers, and (3) the decision makers differ for every alternative.

In standard MCDM approaches, a group of alternatives are each evaluated by the same group of decision makers (usually few in number) over some selected criteria (Hwang and Yoon, 2012). For example, a company might convene a number of industry experts to evaluate and select the best supplier for a particular product (see for example in Ho, Xu, and Dey, 2010; Boran, Genç, Kurt, and Akay, 2009). In this case, every supplier (i.e. alternative) would be evaluated by each of the experts. However, there exist a form of decision problems that exhibits MCDM properties but where the group of decision makers evaluating say, alternative *A* might be entirely different from those evaluating alternative *B*. That is, the decision makers are non-homogenous in relation to the competing alternatives. For example, in a survey to decide which mobile network provider has the best service performance based on the perspective of customers, it is usually the case that respondents (i.e. decision makers) on network provider *A* might be different from respondents on network provider *B* since most customers often subscribe to one network provider, and therefore can evaluate only their network provider. Therefore, the decision makers in this case are distinct for each alternative.

It is also obvious that the set of all potential 'decision makers' in the problem described above can run into thousands or even millions, and therefore one may need ratings from hundreds or even thousands of 'decision makers' to achieve credible result. In the mobile service example described above, there may be millions of customers for each competing network provider. For credible evaluation of competing alternatives in this case, a survey involving hundreds or even thousands of respondents as does, for example, in election polls (Barlett, Kotrlik, and Higgins, 2001) may be needed. However, such number of respondents will be far more than the number of decision makers in a typical MCDM problem and may lead to scalability issues (Olugbara, and Thiruthlall, 2012). Aside scalability issues, MCDM methods aggregates rating values into one whenever there are more than once decision makers (Afful-Dadzie et al, 2015; Vavrikova, 2011; Peniwati, 2007). This might work well for 4 or 5 decision makers as is the case in typical MCDM applications. For decision makers numbering hundreds and above, such as in customer satisfaction surveys, aggregating such large number of values into one to obtain one ranking for evaluation might mask the varied opinion of the decision makers and might not provide helpful information needed to guide improvement (Abulaish et al, 2009). In other words, when decision makers are large, final evaluation results should be presented in a manner that shows the variation in the varied opinion of the various decision makers. In customer satisfaction evaluation for instance, an evaluation showing the variation in customer opinions would help put into perspective, the percentage of decision makers who sees an alternative as best, and as worse. To deal with the large and distinct nature of the decision makers in the problem described above, this paper proposes a sampling based MCDM technique that is able to reduce the size of the problem as well as facilitate the presentation of final result in a manner that captures the variation in the opinion of the decision makers.

The rest of the paper is organized as follows. Section two presents the proposed model for transforming the types of problems discussed above into a standard MCDM problem. Following this, the algorithm for obtaining a ranking distribution for competing alternatives through bootstrap sampling is presented. In section three, the proposed technique is illustrated through a case study example using fuzzy TOPSIS. Section four analyze the results of the case study, and section five present the conclusions.

2. Multi-Criteria Decision Making under large and distinct decision makers

A typical MCDM problem seeks to evaluate the performance of a set of competing alternatives based on a selected set of criteria. The evaluation is normally carried out by experts usually referred to as decision makers. Formerly, consider a decision problem where $A = \{a_1, a_2, \dots, a_n\}$ is a set consisting of n alternatives to be evaluated by a group of D decision makers on a set of criteria $C = \{c_1, c_2, \dots, c_m\}$ using ratings based on q linguistic variables from the linguistic variable set $L = \{l_1, l_2, \dots, l_q\}$. For each decision maker $d = 1,2, \dots, D$, a so called decision matrix of Eq. (1) is generated, where x_d^{ij} is the linguistic rating assigned to alternative a_i under criterion c_j by a decision maker d.

$$X_d = \begin{array}{c} a_1 \\ a_2 \\ \vdots \\ a_n \end{array} \begin{bmatrix} x_d^{11} & x_d^{12} & \dots & x_d^{1m} \\ x_d^{21} & x_d^{22} & \dots & x_d^{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_d^{n1} & x_d^{n2} & \dots & x_d^{nm} \end{bmatrix} \tag{1}$$

Following this, the decision matrices from all decision makers are aggregated to form a single decision matrix similar to that of Eq. (1). At this point, two important considerations in the form of relative importance and dimensions of the criteria must be taken into account. First, the criteria must be normalized if they are of different dimensions, and second, relative importance weights must be assigned to each criterion if some of the criteria are viewed to be more important than others. Given these information, the alternatives are evaluated using specially designed composite index formula depending on whether a compromise or non-compromise ranking or evaluation is sought. Several MCDM techniques exist ranging from TOPSIS, VIKOR, ELECTRE, DEMATEL, and many more.

The challenge encountered when decision makers are distinct can be seen from a decision maker's decision matrix as shown in Eq. (1). In this case, the decision matrix has only one row since the decision maker can evaluate only one alternative. In practice, this can introduce bias in the final decision. To overcome this challenge and obtain a full decision matrix (for a decision maker) in the spirit of a typical MCDM approach, the distinctness of decision makers must be avoided. The approach adopted in this paper is to, under each criterion, determine the probability that an alternative would be rated with a particular linguistic variable. In other words, this probability would represent the chances that the alternative could be rated with a particular linguistic variable by any random decision maker under the said criterion. By the randomness assumption, hypothetical decision matrices possessing all the properties of that of Eq. (1) could be drawn from a multinomial distribution using the estimated probabilities. In practice, the probabilities can be determined from the ratings data provided by the appropriate large and distinct decision makers for each alternative. Additionally, as the data is large, the influence of outliers or extreme observations (i.e. occasional biased ratings) would be limited.

When potential decision makers are large, such as in opinion surveys, simply aggregating ratings into one value to produce one ranking might mask a lot of facts on how the alternatives compare to each other given the variation in the ratings of the decision makers. One of the reasons is that the ranking result might vary from sample to sample. Therefore, instead of a single ranking, a distribution showing the variation in possible rankings from several samples would provide better understanding of how the alternatives compare to each other. Unfortunately, it is usually difficult in practice to obtain more samples since surveys are expensive to undertake. The proposed technique make use of bootstrap sampling to generate a ranking distribution.

Similar to a typical MCDM problem, consider a decision problem where $A = \{a_1, a_2, \dots, a_n\}$ is a set consisting of n alternatives to be evaluated by a large group of decision makers under m selected criteria from the criteria set $C = \{c_1, c_2, \dots, c_m\}$ using ratings based on q linguistic variables from the linguistic variable set $L = \{l_1, l_2, \dots, l_q\}$. Let n_i, be the 'large' number of distinct 'decision makers' (e.g. survey respondents) selected to evaluate alternative a_i. By distinct, it is implied that the group of decision makers to evaluate say, alternative a_1, is different from those to evaluate say, alternative a_2. The following steps are followed to convert the problem into a typical MCDM format.

Step1: Relative Frequency Estimation.

To remove the distinctness of decision makers, the ratings of the alternatives are reconstructed such that it is thought to be carried out by randomly chosen decision makers. This can be done by estimating the probability that a randomly chosen decision maker would rate an alternative a_i under criterion c_j with linguistic variable l_k. For each alternative a_i, let n_k^{ij} be the frequency or counts of the k_{th} linguistic variable recorded among the n_i decision makers under criterion c_j so that Eq. (2) holds.

$$\sum_{k=1}^{q} n_k^{ij} = n_i \qquad \forall i\ , \forall j \qquad (2)$$

Given the counts of the linguistic variables under each alternative-criterion combination, the relative frequency for the k_{th} linguistic variable can be estimated using Eq. (3), which gives the probability that a random decision maker will rate alternative a_i under criterion c_j using the k_{th} linguistic variable.

$$P_k^{ij} = \frac{n_k^{ij}}{n_i} \qquad \forall j,\ \forall i\ , \forall k \qquad (3)$$

Therefore the set $P^{ij} = \{\, P_1^{ij}, P_2^{ij}, \dots, P_q^{ij} \mid \sum_{k=1}^{q} P_k^{ij} = 1\}$ gives the frequency distribution for the linguistic variables for an alternative-criterion combination. If this frequency distribution adequately reflect the wider population from which the sample was drawn, then for each alternative a_i and criterion c_j , P^{ij} gives the probabilities that alternative a_i would be rated with any of the q linguistic variables by a randomly chosen decision maker under criterion c_j. In practice, and for the type of problems considered in this paper, the number of decision makers for each alternative would be large enough such that n_i can be taken as a pseudo population for alternative a_i. Note that there will be an *nxm* number of these probability sets.

Overall, each alternative a_i should have a probability matrix as shown in Eq. (4).

$$P^i = \begin{array}{|ccccc|} \hline C_1 & C_2 & C_3 & \cdots & C_m \\ \hline P_1^{i1} & P_1^{i2} & P_1^{i3} & \cdots & P_1^{im} \\ P_2^{i1} & P_2^{i2} & P_2^{i3} & \cdots & P_2^{im} \\ P_3^{i1} & P_3^{i2} & P_3^{i3} & \cdots & P_3^{im} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ P_q^{i1} & P_q^{i2} & P_q^{i3} & \cdots & P_q^{im} \\ \hline \end{array} \qquad (4)$$

The set $P = \{P^1, P^2, P^3, \dots, P^i, \ \dots, P^n\}$ would therefore constitute knowledge on the possible alternative-criterion rating that a randomly chosen decision maker is likely to provide on the competing alternatives under evaluation. More importantly, the set P can also be used to draw samples of ratings similar to that of Eq. (1) through multinomial sampling. In practice, the probabilities capture the variation in the opinions of customers (decision makers) with respect to the ratings of the competing alternatives. For each alternative, it also captures the range of customer satisfaction under each criterion.

Once the probabilities that an alternative under a particular criterion would be rated with a certain linguistic variable are determined (.i.e. the set P), the following steps would be followed to generate decision matrices thought to come from 'non-distinct' decision makers. Doing this thus transforms the problem from distinct decision makers into a typical MCDM problem format of non-distinct decision makers.

Step2: Multinomial sampling of responses or ratings.
The next step in the modeling phase is to remove the distinctness of the decision makers by using hypothetical decision makers to evaluate the alternatives. These hypothetical decision makers could be imagined as experts in a normal multi-criteria decision making process. Suppose there are D number of hypothetical decision makers. Then for each decision maker, $d = 1,2, \dots, D$, draw a sample of decision matrix X_d, of size nxm, made up of alternative-criterion ratings from a multinomial distribution based on information in set P. The sampled decision matrix X_d for a hypothetical decision maker d will be of the same form as that of Eq. (1).

As is the case in an MCDM procedure, the decision matrices from the hypothetical decision makers would be aggregated to form a composite decision matrix. From this, an appropriate MCDM model can be used to obtain a ranking for the alternatives. For instance, the TOPSIS technique could be used to rank the alternatives. However, note that (by the proposed approach, and also in practice), this ranking result could as well come from an extreme sample by luck of a draw. To obtain a ranking result closer to the true ranking of the alternatives, it is imperative the procedure is repeated multiple times to generate a distribution of performance rankings. The next step outlines the procedure for generating such performance ranking distribution. The procedure is similar to the one proposed in Afful-Dadzie, Allen, and Raqab (2013).

Step 3: Generate Multiple MCDM-Models.
This step recognizes that in situations where large decision makers are present, such as in opinion surveys, ranking result based on just one survey sample might not provide much insight that reflect the varied opinions of the decision makers regarding the alternatives. Ideally, multiple survey samples could be obtained to generate several rankings to build a distribution. However, surveys are expensive to conduct. Following the approach by Afful-Dadzie, Allen, and Raqab (2013), the alternative-criterion probability set P can be used in a parametric bootstrap sampling procedure to resample from P, a new set of ratings from a new set of hypothetical decision makers to generate new rankings. This will require that step 2 is repeated multiple times. In each iteration of step 2, decision matrices would be generated for the assumed hypothetical decision makers using the same probability set P. The resulting aggregated decision matrix from such iteration could be considered an MCDM-Model. For each MCDM-Model, an appropriate MCDM analysis would be performed to obtain a ranking result.

Step 4: Fit a distribution to the Multiple MCDM-Model Rankings.
Differences might be present in the ranking results from the multiple MCDM-Models. The distribution of the multiple rankings for each alternative can be displayed with a boxplot to provide better insight into how the alternatives compare. In effect, two variations can be observed. The within variation will show how the performance of an alternative vary given the varied opinions of the decision makers. The between variation can be observed by the side-by-side visualization of the boxplots for the alternatives and can put into perspective the gap between the ranking performances of competing alternatives.

3. Case Study: Service Performance of Mobile Phone Providers in Ghana with Fuzzy TOPSIS.

3.1 Problem Description

The mobile telecommunication industry in Ghana comprises of five main players namely MTN, VODAFONE, TIGO, AIRTEL, and GLO with respective market share as shown in Table 1. The companies provide mainly voice and internet services to Ghanaian customers. Each year, these companies are evaluated and awarded top prizes in many categories including Service Provider of the Year, Internet Provider of the Year, Telecom Brand of the Year, Mobile Money Service of the Year, and Best Corporate Social Responsibility. Despite these awards portraying great strides in the industry, there has been many complaint from customers regarding the service provision of the operators. Many customers wonder at the usefulness of the many national awards dished out to the operators since they feel their services are poor. In fact in 2013, the National Communication Authority (NCA), imposed heavy fines on 5 of the 6 major network providers in the country for poor service delivery. The clarion call from customers has been that they should have a major say in the data used for determining the awards. This case study therefore seeks to evaluate the service performance of mobile network providers in Ghana from the perspective of customers.

In the MCDM literature, the mobile subscribers are essentially the decision makers, which in this case numbers into millions for each provider. In addition, each subscriber or a decision maker can only evaluate one alternative (in this case, its network provider). These two features of the problem at hand is a departure from conventional MCDM problem set up and would require new ways to ensure credible evaluation. The next section detail how the proposed method was applied to evaluate the services of mobile network providers from the perspective of customers.

Table 1: Market share distribution of the major mobile phone providers in Ghana in 2015.

Mobile Provider	Market Share(%)
MTN	42.24
VODAFONE	21.92
TIGO	14.32
AIRTEL	13.58
GLO	2.64

Table 2: Criteria for assessing customer satisfaction in the Ghanaian mobile phone industry and their related importance weights.

Criteria	Abbreviation	Fuzzy Triangular Weights			BNP
		TF1	TF2	TF3	
Network Quality	NQ	0.175	0.260	0.376	0.270
Service Charges	SC	0.116	0.173	0.256	0.182
Internet Access	IA	0.132	0.197	0.291	0.206
Social Responsibility	SR	0.052	0.079	0.123	0.085
Product Innovations	PV	0.062	0.093	0.144	0.100
Customer Relations	CR	0.086	0.129	0.196	0.137
Company Brand	CB	0.020	0.028	0.044	0.031
Product Advertisement	PA	0.027	0.041	0.064	0.044

3.2 Criteria and Criteria Weights

Before a questionnaire was sent to customers for their opinion on services provided by their respective network providers, a fuzzy AHP analysis was carried out to determine the important determinants of customer satisfaction in the mobile telecommunication industry in Ghana. To do this, several relevant criteria were given to industry experts and customers for their opinion on its relevance to customer satisfaction in the mobile network industry in Ghana. Out of the several criteria posed to industry experts and customers, the eight criteria shown in the first column of Table 2 were found to be the major determinant of customer satisfaction from the perspective of customers. The corresponding fuzzy triangular weights of the criteria as well as their Best Non-Fuzzy Performance (BNP) score are shown in Table 2. From the BNP scores, it is clear customers sees Network Quality as the most important determinant of customer satisfaction, followed by Internet Access, Service Charges, Customer Relations, Product Innovations, Social Responsibility, Product Advertisement, and Company Brand, in that order.

3.3 Service Performance Evaluation

To evaluate the mobile network providers from the perspective of customers, a questionnaire was given to potential customers for their opinion on the services they receive from their providers with regards to the criteria listed in Table 2. Customers were asked to rate their providers using the linguistic variable ratings shown in Table 3. The imprecision and vagueness in the linguistic variable rating responses of decision makers are captured in the proposed model with fuzzy scale as shown in Table 3. Care was taken to ensure the number of respondents for each provider reflected its market share proportion. Data from Table 4 gives a record of the number of respondents who rated their providers based on the criteria list from Table 2. To avoid bias in responses for an alternative, respondents were not told that the results would be used for comparative study.

Table 3: Linguistic variable ratings and their related fuzzy scale for evaluating mobile phone providers.

Rating	Fuzzy Scale		
Very Dissatisfied (VD)	0	1	3
Dissatisfied (D)	1	3	5
Neutral (N)	3	5	7
Satisfied (S)	5	7	9
Very Satisfied (VS)	7	9	10

Table 4: Number of respondents and relative percentage of respondents in a service performance evaluation survey on the major mobile phone providers in Ghana.

OPERATOR	No. of Respondents	Relative Percent of Respondents
MTN	572	41.33%
VODAFONE	319	23.05%
AIRTEL	213	15.39%
TIGO	230	16.62%
GLO	48	3.47%

As can be seen from Table 4, the number of respondents (in this case, decision makers) are in the hundredths which is quite large for a typical MCDM problem. Even then, this number is just a sample of the potential millions of customers for each mobile phone provider. Also note that the 572 respondents for the mobile network provider MTN for instance, are different from the 319 respondents for the provider, VODAFONE. Thus, decision makers for each provider are not only large, but are distinct from those of its competitors.

Data in Table 5 gives a breakdown summary of the total number of each linguistic variable rating assigned to the mobile network providers under each criterion from respondents. For instance, under the criterion Network Quality (NQ), out of the 562 respondents who rated MTN, 8 felt very dissatisfied (VD), 18 were dissatisfied (D), 115 were O.K (N), 336 were Satisfied (S), 85 were Very Satisfied (VS). Based on data from Table 5, Table 6 provides relative frequency estimates or probabilities that a randomly selected respondent would rate an alternative under a selected criterion with a particular linguistic variable. Data from Table 6 is important because, it allows the modeler to abstract the evaluation of competing alternatives to hypothetical (randomly chosen) decision makers. For each criterion, and with the respective probabilities for each linguistic variable for each alternative, the hypothetical decision makers would be able to provide ratings for each alternative as required in a typical MCDM approach by drawing samples of linguistic variables using the probabilities. The outcome of the draw would lead to a decision matrix similar to that of Eq. (1).

Table 5: Summary Breakdown of linguistic variable ratings from survey respondents for the mobile phone providers under each criterion.

	Linguistic variable	NQ	SC	IA	SR	PI	CR	CB	PA
MTN	VD	8	226	117	11	12	53	10	21
	D	18	69	73	70	44	162	20	44
	N	115	185	58	191	201	185	155	144
	S	336	29	247	215	221	126	259	228
	VS	85	53	67	74	84	36	118	125
VODA	VD	22	2	12	7	2	13	2	5
	D	71	25	34	42	16	54	8	23
	N	55	36	45	89	83	101	92	68
	S	125	140	171	136	148	119	148	157
	VS	46	116	57	45	70	32	69	66
TIGO	VD	7	3	17	7	3	8	3	5
	D	61	22	26	23	10	20	12	18
	N	74	77	65	82	75	69	61	52
	S	48	97	83	96	103	100	115	104
	VS	40	31	39	22	39	33	39	51
AIRTEL	VD	10	3	30	7	3	9	2	14
	D	57	8	12	18	16	28	12	11
	N	73	75	83	84	86	82	49	47
	S	37	96	46	68	66	72	98	102
	VS	36	31	42	36	42	22	52	39
GLO	VD	1	2	12	10	5	3	1	1
	D	8	8	5	12	12	7	1	8
	N	13	16	7	10	20	19	11	15
	S	21	20	19	15	10	15	26	17
	VS	6	3	6	2	2	5	10	8

Table 6: Probabilities that a randomly selected decision maker would rate a mobile phone provider with a certain linguistic variable for each criterion. The probabilities are based on the values in Table 5

	Linguistic variable	NQ	SC	IA	SR	PI	CR	CB	PA
MTN	VD	0.014	0.402	0.208	0.02	0.021	0.094	0.018	0.037
	D	0.032	0.123	0.13	0.125	0.078	0.288	0.036	0.078
	N	0.205	0.329	0.103	0.34	0.358	0.329	0.276	0.256
	S	0.598	0.052	0.44	0.383	0.393	0.224	0.461	0.406
	VS	0.151	0.094	0.119	0.132	0.149	0.064	0.21	0.222
VODA	VD	0.069	0.006	0.038	0.022	0.006	0.041	0.006	0.016
	D	0.223	0.078	0.107	0.132	0.05	0.169	0.025	0.072
	N	0.172	0.113	0.141	0.279	0.26	0.317	0.288	0.213
	S	0.392	0.439	0.536	0.426	0.464	0.373	0.464	0.492
	VS	0.144	0.364	0.179	0.141	0.219	0.1	0.216	0.207
TIGO	VD	0.03	0.013	0.074	0.03	0.013	0.035	0.013	0.022
	D	0.265	0.096	0.113	0.1	0.043	0.087	0.052	0.078
	N	0.322	0.335	0.283	0.357	0.326	0.3	0.265	0.226
	S	0.209	0.422	0.361	0.417	0.448	0.435	0.5	0.452
	VS	0.174	0.135	0.17	0.096	0.17	0.143	0.17	0.222
AIRTEL	VD	0.047	0.014	0.141	0.033	0.014	0.042	0.009	0.066
	D	0.268	0.038	0.056	0.085	0.075	0.131	0.056	0.052
	N	0.343	0.352	0.39	0.394	0.404	0.385	0.23	0.221
	S	0.174	0.451	0.216	0.319	0.31	0.338	0.46	0.479
	VS	0.169	0.146	0.197	0.169	0.197	0.103	0.244	0.183
GLO	VD	0.02	0.041	0.245	0.204	0.102	0.061	0.02	0.02
	D	0.163	0.163	0.102	0.245	0.245	0.143	0.02	0.163
	N	0.265	0.327	0.143	0.204	0.408	0.388	0.224	0.306
	S	0.429	0.408	0.388	0.306	0.204	0.306	0.531	0.347
	VS	0.122	0.061	0.122	0.041	0.041	0.102	0.204	0.163

Table 7: A sample of criteria ratings of three hypothetical decision makers for alternatives based on probabilities from Table 6.

Hypothetical Decision Maker	Alternative	Criteria ratings							
		NQ	**SC**	**IA**	**SR**	**PI**	**CR**	**CB**	**PA**
D1	MTN	VS	S	D	D	N	D	VS	D
	VODAFONE	S	VS	S	S	S	S	N	N
	TIGO	N	N	S	N	S	S	VS	VS
	AIRTEL	D	S	D	D	D	VS	VS	VS
	GLO	VD	VD	VD	N	N	N	N	N
D2	MTN	VD	VD	VD	VD	VD	N	N	N
	VODAFONE	VS	VS	S	S	VS	VS	S	S
	TIGO	N	N	S	N	S	S	VS	VS
	AIRTEL	N	N	N	VS	VS	N	N	VS
	GLO	D	N	D	D	S	S	N	N
D3	MTN	VD	VD	VD	VD	N	N	N	N
	VODAFONE	S	VS	N	D	N	D	VS	S
	TIGO	N	D	S	N	VS	VS	N	S
	AIRTEL	N	VS	VS	N	VS	VS	VS	VS
	GLO	N	N	N	S	N	N	D	N

Table 7, provides examples of such decision matrices made up of linguistic variable ratings drawn from 3 hypothetical decision makers using the probability values in Table 6.

After aggregating the decision matrices for the hypothetical decision makers based on information from Table 7, the alternatives can be ranked using a suitable MCDM technique in combination with data on relative importance weights for the criteria. For example, based on data from Table 2, Table 3, and Table 7, the ranking of the mobile phone providers using Fuzzy TOPSIS is 5, 1, 2, 3, 4. This means, from the perspective of customers, VODAFONE has the best customer service performance, followed, in order, by TIGO, AIRTEL, GLO, and MTN. However, note that Table 7 is just one sample, and therefore it is possible a different sample could yield different ranking. To observe the true ranking of an alternative given the variation in the ratings of decision makers, multiple rankings could be obtained from multiple samples to build a ranking distribution for each alternative. A side-by-side display of such distribution can also point out the variation in the opinion of decision makers both within an alternative and between the alternatives.

4. Results

1000 bootstrap samples were generated and ran to obtain 1000 rankings. As an example, Table 8 shows 15 of the 1000 rankings using the established probabilities in Table 6 using fuzzy TOPSIS. Based on the 15 rankings for instance, it will mean that the provider MTN was never ranked number 1, was ranked number 2 only once, number 3 four times, number 4 three times and number 5 seven times. Clearly, this would mean that majority of the customers feel MTN ranks no better than third among the five major mobile network providers in Ghana, although there are few who regard it as even the best alternative.

Table 8: TOPSIS rankings of alternatives from 15 out of 1000 samples of customer opinions showing the variation in how customers perceive the service performance of competing mobile phone providers.

	R1	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**	**R8**	**R9**	**R10**	**R11**	**R12**	**R13**	**R14**	**R15**
MTN	2	4	5	5	3	3	5	5	5	4	5	3	5	3	4
VODA	1	3	1	2	2	5	1	1	2	2	2	1	1	1	2
TIGO	3	2	3	3	4	2	2	2	1	3	1	2	3	2	1
AIRTEL	5	1	2	1	1	1	3	3	4	1	3	4	2	4	5
GLO	4	5	4	4	5	4	4	4	3	5	4	5	4	5	3

Table 9 presents summary ranking results based on 1000 bootstrap samples drawn from the probability distributions in Table 6. The ranking results are also displayed in Figure 1 with a box plot to help visualize the variation in the opinions of decision makers. It can be observed from the boxplot that the 25th percentile rank for MTN and GLO is 3 and 4 respectively. This means at least 75% of the 1000 sample rankings for MTN and GLO led to a respective ranking of at least 3 and 4. MTN appears to be doing better overall than GLO. Overall, MTN has a mean ranking of 3.89 as against 4.36 for GLO. The 25th and 75th percentile rank for VODAFONE are a rank of 1 and 2 respectively. This means, at least 75% of the 1000 samples led to a ranking of at most 2 for Vodafone. On the other hand, TIGO had a 25th and 75th percentile rank of 2 and 3 respectively, putting it somewhat second to Vodafone. Intuitively, majority of the customers of VODAFONE and TIGO overall have a good impression about the level of services rendered by their providers. It is the opposite for MTN and GLO. In summary, it can be observed from the side-by-side comparison of the boxplots in Figure 1 that VODAFONE ranks number 1, followed in order by TIGO, AIRTEL, MTN, and GLO.

The ranking result from several samples in Table 9 and Figure 1 is also a reflection of what occurs in practice. It is not surprising that although majority of Ghanaian mobile phone users put MTN and GLO respectively at the rank of 4 and 5, there are still some users who rank them better than the other competitors. The box plot representation is better than the case where the alternatives are evaluated based on only one ranking from an aggregated dataset. For example, although TIGO may appear to perform better than AIRTEL overall, the side-by-side comparison reveals somewhat closer performances than can be understood with a single ranking. Likewise, VODAFONE's overall service performance appears to be far better appreciated than its competitors.

Table 9: Summary of the number of rank types achieved by the competing alternatives from 1000 samples.

	No. of Rank 1	No. of Rank 2	No. of Rank 3	No. of Rank 4	No. of Rank 5
MTN	32	96	187	313	372
VODA	661	228	84	25	2
TIGO	198	380	291	106	25
AIRTEL	104	275	338	204	79
GLO	5	21	100	352	522

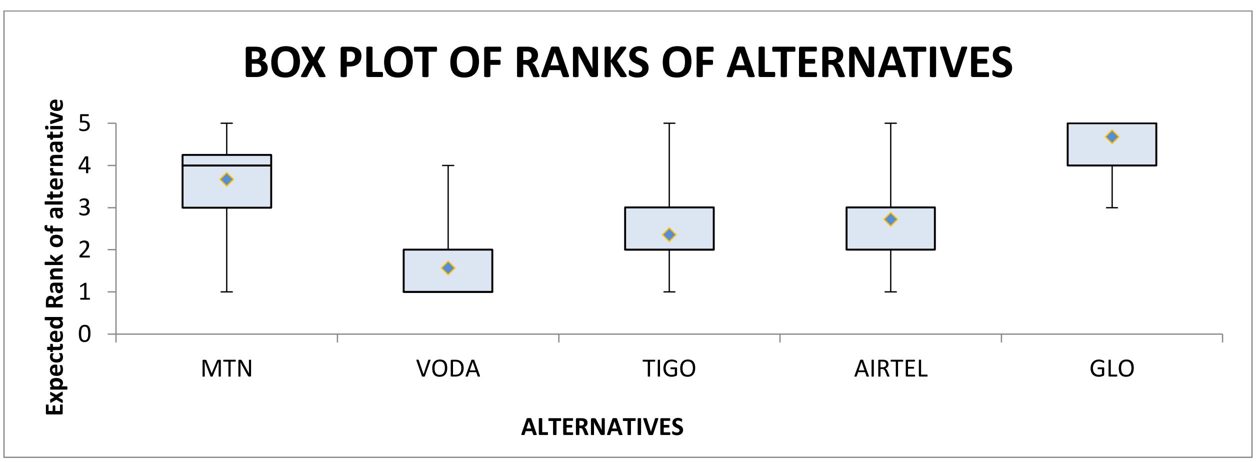

Figure 1: Box plot of rank distribution of service performance from the perspective of customers of mobile service providers in Ghana.

5. Conclusion

In this paper, a new technique that extends the traditional MCDM approach to decision making was developed to handle ranking and selection decision making problems with large and distinct decision makers. The approach provides a new way of analyzing ranking and selection problems where opinions are elicited from a large populace such as customer service evaluation of competing companies, and product selection based on online customer reviews. A characteristic of such problems is that, often surveyed respondents have an experience with only one alternative making them unable to comment on other alternatives. This character of distinctness of the decision makers render the traditional MCDM ranking/selection techniques not useful since general MCDM approaches require that each decision maker evaluate every alternative. The proposed approach transforms this unique problem onto the traditional MCDM format for easier analysis and interpretation by imagining the ranking performed by a randomly chosen decision maker. This approach therefore makes it possible to apply MCDM methods to problems where competing alternatives are evaluated by the larger public, such as in market surveys and product reviews by customers. To most organizations and industries, the proposed technique offers a convenient tool to analyze surveys on customer satisfaction and product performance in relation to their competitors. More so, the bootstrap sampling method underpinning the proposed technique helps ensure the final result is a true reflection of the larger customer population. The applicability of the proposed technique was demonstrated using a real-world data on service performance of mobile network providers in Ghana from the perspective of customers. The example demonstrate the capability of the proposed technique to generate ordinal ranking for the alternatives, as well as put into perspective the real gap in performance between competing alternatives.

On the overall service performance of mobile network providers in Ghana from the perspective of customers, it is seen that VODAFONE ranks number 1, followed by TIGO, which is closely followed by AIRTEL. MTN and GLO come number 4 and 5 respectively. Given the competitive and fast changing nature of the industry in terms of market share, the result therefore is an indication that MTN and GLO need to improve upon their service performances.

References

Abulaish, M., Jahiruddin and Doja, M. N., Feature and opinion mining for customer review summarization. *Lectures Notes in Computer Science*, 5909, 219–224, 2009.

Afful-Dadzie, E., Nabareseh, S., Afful-Dadzie, A., and Oplatková, Z. K., A fuzzy TOPSIS framework for selecting fragile states for support facility. *Quality & Quantity*, 49(5), 1835-1855, 2015.

Afful-Dadzie, A., Allen, T. T., Raqab, A., and Li, J., Sufficiency model-action clarification for simulation optimization applied to an election system. *In Proceedings of the Winter Simulations Conference*, Washington D.C., U.S.A. pp. 1079-1088, December, 2013.

Aruldoss, M., Lakshmi, T. M., and Venkatesan, V. P., A survey on multi criteria decision making methods and its applications. *American Journal of Information Systems*, 1(1), 31-43, 2013.

Barlett, J. E., Kotrlik, J. W., and Higgins, C. C., Organizational research: Determining appropriate sample size in survey research. *Information technology, learning, and performance journal*, 19(1), 43, 2001.

Behzadian, M., Otaghsara, S. K., Yazdani, M., and Ignatius, J., A state-of the-art survey of TOPSIS applications. *Expert Systems with Applications*, 39(17), 13051-13069, 2012.

Boran, F. E., Genç, S., Kurt, M., and Akay, D., A multi-criteria intuitionistic fuzzy group decision making for supplier selection with TOPSIS method. *Expert Systems with Applications*, 36(8), 11363-11368, 2009.

Ho, W., Xu, X., and Dey, P. K., Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of operational research*, 202(1), 16-24, 2010.

Hwang, C. L., and Yoon, K., *Multiple attribute decision making: methods and applications a state-of-the-art survey* (Vol. 186). Springer Science & Business Media, 2012.

Olugbara, O. O., and Thiruthlall, N., Exploring TOPSIS based algorithm for non-homogeneous alternatives in group decision making. *Proceedings of the World Congress on Engineering and Computer Science* 2012 Vol II WCECS 2012, October, 24-26, San Francisco, USA, 2012

Opricovic, S.,and Tzeng, G.H., Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Re- search, 156, 445–455, 2004.

Peniwati, K., Criteria for evaluating group decision-making methods. *Mathematical and Computer Modelling*, 46(7), 935-947, 2007.

Saaty, T. L., Decision making with the analytic hierarchy process. *International journal of services sciences* 1(1), 83-98, 2008.

Shieh, J. I., Wu, H. H., and Huang, K. K., A DEMATEL method in identifying key success factors of hospital service quality. *Knowledge-Based Systems*, 23(3), 277-282, 2010.

Vavrikova, L., Multicriteria Decision Making and Rankings Based on Aggregation Operators (Application on Assessment of Public Universities and Their Faculties). *ACTA POLYTECHNICA HUNGARICA*, 8(3), 79-90, 2011.

Velasquez, M., and Hester, P. T.,An analysis of multi-criteria decision making methods. *International Journal of Operations Research*, 10(2), 56-66, 2013.

Zavadskas, E. K., Turskis, Z., and Kildienė, S., State of art surveys of overviews on MCDM/MADM methods. Technological and economic development of economy, 20(1), 165-179, 2014.

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