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SUPPLIER EVALUATION AND SELECTION: A FUZZY NOVEL MULTI-CRITERIA GROUP DECISION-MAKING APPROACH

Abstract: *Supplier selection problem is a multi-criteria decision-making problem that involves both quantitative and qualitative criteria. Typically, supplier selection decisions require a preliminary stage where pool of suppliers are initially screened to select potential set of suppliers for further evaluation and select the optimal supplier. This preliminary stage is heavily dependent on non-scientific approaches and do not consider any criteria during the screening process. Furthermore, quantifying the qualitative criteria has always relied quite considerably on subjective judgments, which render the supplier selection process ineffective. Therefore, this paper addresses these problems by proposing an easy going two-phase supplier selection decision model, based on fuzzy set theory that uses a scientific approach and incorporates performance criteria in screening and selecting the potential suppliers for further optimal supplier selection. To illustrate the applicability and validate the proposed model, a case study of a beverage producing company located in Ghana, the Sub-Saharan Africa is proposed.*
Keywords: *Supply Management, Supplier Screening, Supplier Evaluation and Selection, Fuzzy Logic, Group Multi-Criteria Decision-Making*

1. Introduction

The cost of raw materials and component parts contribute about 70% of the total cost of a product (Ghodsypour & O’brien, 2001; Şen et al., 2008). Therefore companies are required to strategically partnership/align and maintain long-term relationship with their strategic and efficient suppliers (Sarkar & Mohapatra, 2006; Chan et al., 2008; Ho et al., 2010) to reduce the total cost of ownership drastically. Prior to forging a long-term strategic supplier partnership requires a small supply-base to manage (Sarkar & Mohapatra, 2006). Since selecting the optimal supplier for corporation has a greater repercussion on the total purchasing cost and corporate competiveness, the purchasing department which is responsible for suppliers selection and acquisition of materials, services and equipment can play a tremendous role in this regard (Chen et al., 2006; De Boer et al., 2001; Golmohammadi & Mellat-Parast, 2012).

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However, choosing amongst these suppliers for strategic partnership by the purchasing managers or decision-makers in the purchasing department is always a difficult and risk prone task (Chan et al., 2008; Şen et al., 2008). These decisions are typically very complicated, critical and multi-criteria decision-making (MCDM) problem that involves both qualitative and quantitative criteria (Chai & Ngai, 2015). Decision-makers and analyst are expected to trade-off amongst these multiple criteria in their decisions (Ngan, 2015). Partaking in these decisions is multi-dimensional requiring the support of decision support tools.

This has subsequently raised tremendous attention in the academic literature in the development of a more systematic and efficient supplier selection decision-making processes and tools over the last couple of years (Badri Ahmadi et al., 2016; Bruno et al. 2016; Dweiri et al., 2016; Gold & Awasthi, 2015; Heidarzade et al., 2016; Karsak & Dursun, 2015; Wan et al., 2017; You et al., 2015; Zhou et al., 2016). Many methods and techniques (e.g. multi-criteria decision-making aids (Mardani, 2015)) have been proposed in literature to support purchasing decision-makers to deal with the importance and complexity in the decision-making process.

The purchasing decision (supplier selection and evaluation problem) processes typically involves four main phases according to De Boer et al., (2001) and are listed below:

1) Problem description
2) Formulation of Criteria
3) **Qualification of potential suppliers**
4) Final selection of the optimal supplier

Prior to selecting the optimal supplier for corporation, there is the need to screen pool of suppliers against some basic requirements of the specific need to select the potential suppliers to narrow down the number of suppliers for evaluation. However, this qualification screening phase of the supplier selection process has seen limited attention in literature (Choi & Kim, 2008). Again, a few if not any of these limited attempts have considered scientific approach in selecting potential suppliers from the pool of suppliers and consider evaluation criteria in the selection process (see Sarkar & Mohapatra, 2006). Most purchasing managers heavily rely on non-scientific approaches such as introduction of potential suppliers from friends, previous customers, engineering managers, production managers, etc. Some of the reference checks include supplier's delivery performance, adherence to contract terms, without critically investigating these suppliers pool against certain basic criteria using a more scientific approach.

The preliminary selection of the potential supplier is considered equally imperative and nearly the same as the optimal supplier selection since the optimal supplier is selected from amongst the limited potential supplier list and therefore requires to be completed with greater precision. The overall objective of the preliminary supplier selection phase is to identify potential suppliers who can stand the decision criteria. Furthermore, the quantification of the qualitative criteria has considerably relied on subjectivity making the optimal supplier selection process ineffective. Yet, in dealing with criteria such as suppliers' product technological level, suppliers' production systems flexibility and suppliers' products quality standards, the subjectivity and qualitative aspect of the optimal supplier selection process becomes increasingly paramount. This therefore requires a supplier selection model that is capable of dealing with these inherent complexities (Chan et al., 2008).

The objective of this paper is to propose an easy going two-phase supplier selection and evaluation decision support model that uses a scientific approach and incorporates performance evaluation criteria into the preliminary supplier screening and selection of optimal supplier involving both qualitative and quantitative criteria under uncertainty. The first phase of the model determines both the performance of the supplier on quantitative and qualitative criteria and the relative importance weights of the criteria. Fuzzy logic is then adopted and utilized to deal with the imprecision and vagueness with the subjective evaluation of both the qualitative data of the decision- matrix and the weights of the criteria. In addition, the preliminary supplier selection is conducted to screen the suppliers' pool using suppliers' efficiencies and an agreed threshold to determine the potential suppliers. In the second phase, the potential suppliers identified in the first phase are subjected to a second round of evaluation to obtain the optimal supplier to be awarded the contract. To illustrate the applicability and validate the proposed model, a case study of a beverage producing company located in Ghana, the Sub-Saharan Africa is proposed.

The rest of the paper is organized as follows. Section 2 reviews previous related works on supplier selection models and the fuzzy group decision-making and proposed two-phase model is presented in section 3. A case study is utilized to illustrate the applicability and validate the proposed model and discussion of the results in section 4. Managerial implications are presented in section 5 and section 6 concludes by presenting limitations of the study and future research direction.

2. Review of related works

In contemporary supply chain management system, selection of optimal supplier for corporation is based on potential suppliers' performance evaluation against multiple criteria contrary to the single cost criterion consideration. This has shifted the attention from a single cost criterion approach used to evaluate potential suppliers' performance to a multiple criteria evaluation. The shift has subsequently made supplier selection and evaluation receive much more attention in the academic literature. Many tools to support these decisions have been proposed and utilized in literature. The rest of the section looks into the trend of related works on the multiple criteria decision support tools proposed and utilized in supplier selection and evaluation in literature.

2.1. MCDM methods for supplier selection and evaluation

To support multiple criteria supplier selection and evaluation decision-making problem, various researchers have proposed the use of many decision-making approaches. The multiple criteria conflicting choices evaluation approaches such as data envelopment analysis (DEA) has been used to evaluate and select the optimal supplier based on potential suppliers efficiency performances (Ahmady et al., 2013; Rose et al., 2006; Toloo & Nalchigar, 2011). Analytic hierarchy process (AHP) has also been used to generate overall score of potential suppliers based on relative importance ratings for supplier selection and evaluation (Deng et al., 2014; Dweiri et al., 2016; Gürcan et al., 2016; Mani et al., 2014). Fuzzy logic has also been used either alone or in combination with other models to address the linguistic ratings in the qualitative criteria for supplier selection (for example fuzzy-AHP (Chan et al., 2008; Gold & Awasthi, 2015)); Heidarzade et al., 2016; Pitchipoo et al., 2013))). Analytic network process (ANP) has been utilized to evaluate potential supplier considering both the interrelationship between and within the clusters of the criteria to derive the importance weightings to select the best supplier (Büyüközkan, & Güleryüz, 2016; Dargi et al., 2014; Vinodh et al., 2011).

Other integrated approaches have also been proposed and utilized by many researchers in an attempt to improve the multiple criteria supplier selection process such as AHP-based DEA model which deploys AHP to determine the relative importance (local) weights of all potential suppliers and utilize these weights as input to the DEA to compute the efficiency score for optimal supplier selection (Dobos & Vörösmarty, 2014; Kuo et al., 2010; Zhou et al., 2016). AHP-based Goal Programming (GP) model also uses the AHP to determine the weights of the criteria as input to the GP to evaluate and select the best supplier/set of suppliers (Kull & Talluri, 2008; Liao & Kao, 2010). AHP/ANP-based GRA (grey relational analysis) equally utilized the AHP/ANP to acquire the local weightings of the qualitative criteria and used these weightings as coefficients for the qualitative criteria in combination with the quantitative data in the GRA to determine the best supplier (Badri Ahmadi et al., 2016; Hashemi et al., 2015).

The reviewed literature depicts there are many models that have been utilized in the multiple criteria supplier selection and evaluation decision-making process. However, few of the models and studies have placed much attention on scientific preliminary screening (pre-qualification phase) to identify the potential suppliers and also uses both cost and benefits criteria in supporting the decision. Even with those attempts, their proposed approaches are difficult for decision-makers to handle or implement. It must be emphasized that, the screening and selection of potential supplier from pool of suppliers is equally important as the optimal supplier selection. This is because the optimal supplier is selected from amongst the potential suppliers list, therefore the process in selecting the potential suppliers ought to be precision as that of the optimal supplier selection process.

This study therefore as part of its contribution to decision-making theory, proposes an easy going two-phase supplier selection decision support tool that uses a more scientific approach and incorporates cost and benefits evaluation criteria into the supplier pre-qualification/preliminary selection process/stage. The model also uses fuzzy logic to address the subjectivity and vagueness involved with both the supplier qualitative criteria and the criteria weights evaluation. The identified limited sets of potential suppliers are further evaluated to identify the optimal supplier.

3. Fuzzy group decision-making and proposed model

3.1. Fuzzy group decision-making

Decision-making involves the process of identifying the best option from all possible alternatives (Chen, 2000). Group decision making (also known as collaborative decision-making) is a situation where multiple individuals acting collectively make a choice from feasible alternatives beforehand with the final decision not attributed to a single individual member within the group but to the group generically (consensus) (Lin & Wu, 2008; Pérez et al., 2014). Within this context, decision-makers tend to provide assessment of the alternatives based on their past experiences and knowledge, expressing their estimations in equivocal linguistic terms (Boran et al., 2009; Wang et al., 2014). To address the subjectivity and vagueness in the human thought and expression during group decision-making, fuzzy set theory is known to be extremely suitable and powerful. More importantly, to deal with the uncertainties involved in the process of linguistic estimations, it is better to introduce fuzzy number to convert the linguistic data into fuzzy data (Chen, T. Y. (2014; Wan & Dong, 2014). Thus, the problems involved in group decision-making in real-life situation where decision data of human judgments with preference are often vague have resulted in the need to employ fuzzy logic.

3.2. Proposed model's problem formulation

Let us consider a situation where a set of I suppliers are evaluated based on J criteria by a Purchasing Manager of a company for a critical product N on a long-term supply contract (strategic partnership). Supplier i $(i = 1,2,3 \ldots I)$ is evaluated by converting multiple measures under all criteria into a single score S_i. The measure of supplier i with respect to criteria j is denoted by x_{ij} $(i =$

$1,2,3, \dots I, j = 1,2,3, \dots J$). The optimal supplier D_o can be obtained based on the multiple measures under all criteria. To arrive at consensus leading to an acceptable judgment, management of the company asked the Purchasing Manager to initiate group decision-making involving the departmental heads $k (k = 1,2,3, \dots K)$ of the company that really influence the decision at hand to rate the influence of each supplier with respect to each qualitative criterion and the criteria importance weights. The quantitative data for each quantitative criterion of each supplier are collated through request-for-quote (RFQ) from the suppliers for the critical product N. The goal is first to generate and screen a pool of suppliers of a newly installed product N and select the limited potential suppliers list for further evaluation to obtain the optimal supplier for a long-term strategic partnership and competitiveness.

3.3. Proposed model's computational steps

In this study, a two-phase decision support tool for group multi-criteria decision-making (MCDM) problems is proposed. The proposed model incorporates and considers both qualitative and quantitative criteria characteristics in dealing with the suppliers' pre-qualification/screening, potential supplier selection and evaluation problem. The group decision-making processes and mathematical formulae are detailed below.

PHASE 1: Data pre-processing

Stage 1. *Populate Original Decision-Matrix (Table) and Obtain Important Weights of the Criteria*

<u>Step 1.1</u>: *Populate Original Decision-Matrix (Table*).

A decision-matrix (table) of criteria and suppliers for the newly installed product N is first populated. The decision table is divided into two halves. One half is used to populate the qualitative measures whilst the other half is for the quantitative measures/data. The decision-makers are asked to rate the performance of each supplier based on their previous performances on each qualitative criterion using a five-point linguistic scale (See Table 3 under linguistics terms) ranging from Very Low Performance (VL) to Very High Performance (VH) whilst the quantitative criteria data for each supplier are collated and aggregated from the request-for-quote (RFQ). Table 1 depicts an example of an original decision-matrix with both linguistic qualitative data and quantitative RFQ data.

Table 1. Original decision-matrix

	Qualitative Criteria					**Quantitative Criteria**				
	C_1	C_2	C_3	**….**	C_n	R_1	R_2	R_3	**….**	R_n
A_1	M	M	H	**….**	H	20	18	2.2	**….**	0.25
A_2	M	H	M	**….**	M	23	15	2.5	**….**	0.30
A_3	H	L	VH	**….**	M	19	17	2.9	**….**	0.31
…..	**…..**	**…..**	**…..**	**…..**	**…..**	**…..**	**…..**	**…..**	**….**	**…..**
A_n	VH	H	M	**….**	VH	25	20	3.1	**….**	0.27

<u>Step 1.2</u>: *Obtain Weights of the Criteria*

In this stage, the decision-makers are asked to determine the weights (or complete with actual data) of each evaluation criterion using a five-point linguistic scale (see Table 5 under linguistics terms) ranging from Extremely Very Low Importance (EL) to Very High Importance (VH). Alternatively, if the decision-makers consider the criteria to have equal importance then each criterion importance weights can be considered as $1/n$, n is the number of criteria under consideration. Table 2 depicts an example of the importance weights of the criteria with linguistic data.

Table 2 Importance weights of the criteria

	Qualitative Criteria					Quantitative Criteria				
Criteria	C_1	C_2	C_3	**….**	C_n	R_1	R_2	R_3	**….**	R_n
Weights	VH	L	H	**….**	VH	VL	L	VH	**….**	H

Stage 2. *Convert Linguistic Variables into Triangular Fuzzy numbers*

Since the scoring of each supplier of the product N performance on each qualitative criterion and weights of each evaluation criterion are given in linguistic variables and considered vague and subjective (non-statistical) (Zeng and Zhou, 2001), fuzzy number are introduced and used to convert the linguistic data into fuzzy data.

Fuzzy numbers are convex fuzzy set characterized by a given interval of real numbers, with their grade of membership between 0 and 1(Zadeh, 1965). This study adopts triangular fuzzy numbers (TFN) to obtain the ideal solutions from each of the K experts (department heads). TFN uses three-value basis: the lowest possible value l, the most promising value m and the upper possible value u to describes a fuzzy event. Then, TFN Ã can be defined by a triplet $(l, m, u)$with a membership function $\mu_{\tilde{A}}(x)$ defined as equation (1), and depicted in Figure 1.

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \\ \frac{x-l}{m-l}, & l < x \leq m \\ \frac{u-x}{u-m}, & m < x \leq u \\ 0, & x > u \end{cases} \qquad (1)$$

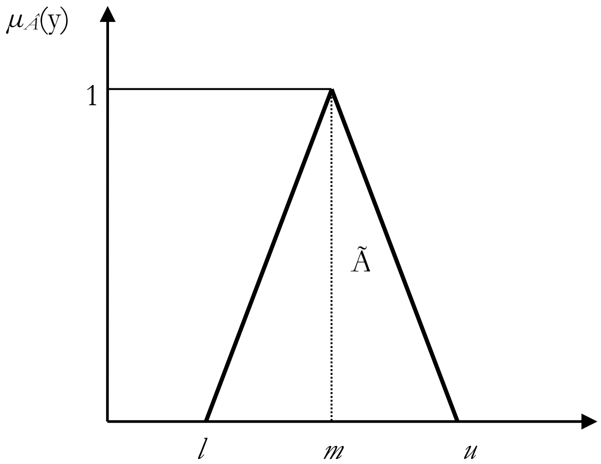

Figure 1. A triangle fuzzy numbers **Ã**.

where l, m and u are real numbers and $l \leq m \leq u$, and l, m and u are the lower, the mean and upper bounds of Ã, respectively. Thus, TFN can represent various semantics of uncertainty (Li, 2012). Then the TFN mathematical operations of two triangular fuzzy number $\tilde{A}_1 = (l_1, m_1, u_1)$ and $\tilde{A}_2 = (l_2, m_2, u_2)$ can be defined as (Yu & Hu, 2010) in expressions (2)-(6).

$$\tilde{A}_1 \oplus \tilde{A}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (2)$$
$$\tilde{A}_1 \otimes \tilde{A}_2 = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (3)$$
$$\tilde{A}_1 \Theta \tilde{A}_2 = (l_1 - l_2, m_1 - m_2, u_1 - u_2) \quad (4)$$
$$\frac{\tilde{A}_1}{\tilde{A}_2} = \left(\frac{l_1}{l_2}, \frac{m_1}{m_2}, \frac{u_1}{u_2}\right) \quad (5)$$
$$\tilde{A}_1 \otimes \lambda = (l_1\, x\, \lambda, m_1\, x\,, \lambda, u_1 x \lambda), \lambda \geq 0, \lambda \in R \quad (6)$$

Table 3 shows the linguistic variables and triangular fuzzy numbers parameters used for this conversation.

Table 3. Linguistic variables and fuzzy numbers for qualitative criteria supplier performance weighting

Linguistic Terms	Triangular Fuzzy Numbers
Very Low Performance (VL)	(0,0.1,0.3)
Low Performance (L)	(0.1,0.3,0.5)
Medium Performance (M)	(0.3,0.5,0.7)
High Performance (H)	(0.5,0.7,0.9)
Very High Performance (VH)	(0.7,0.9,1.0)

Table 4 shows the linguistic variables and triangular fuzzy numbers parameters used to convert the linguistic variables weights of both qualitative and quantitative criteria into triangular fuzzy numbers.

Table 4. Linguistic variables and fuzzy numbers for criteria importance weights

Linguistic Terms	Triangular Fuzzy Numbers
Extremely Very Low Importance (EL)	(0,0.1,0.3)
Very Low Importance (VL)	(0.1,0.3,0.5)
Low Importance (L)	(0.3,0.5,0.7)
High Importance (H)	(0.5,0.7,0.9)
Very High Importance (VH)	(0.7,0.9,1.0)

Stage 3. *Defuzzify Qualitative Criteria Data and Criteria Weights*

Defuzzifications of the triangular fuzzy numbers into crisp numbers are required and it takes into consideration the spread, height and shape of the triangular fuzzy numbers (Cheng & Lin, 2002; Chang et al., 2011). The modified-CFCS (Converting Fuzzy data into Crisp Score) defuzzification method which obtains a better crisp value (Opricovic & Tzeng, 2003; Wu & Lee, 2007) is adopted to convert the triangular fuzzy numbers of the influence measures for each supplier with respect to the qualitative criteria aspect of the decision-matrix and the criteria importance weights into crisp numbers.

Let $x_{ij} = (l_{ij}^K, m_{ij}^K, u_{ij}^K)$, which means the measure of supplier i with respect to criteria j and fuzzy questionnaire of department head $k (k = 1,2,3, \dots K)$. Then, the modified-CFCS defuzzification method involves the following four-step algorithm: Eqs. (7)-(13).

Step 3.1: *Normalize upper (xu), mean (xm) and lower (xl) fuzzy numbers*

$$xu_{ij}^k = (u_{ij}^k - minl_{ij}^k)/\Delta_{min}^{max} \quad (7)$$

$$xm_{ij}^k = (m_{ij}^k - minl_{ij}^k)/\Delta_{min}^{max} \quad (8)$$

$$xl_{ij}^{k} = \left(l_{ij}^{k} - minl_{ij}^{k}\right)/\Delta_{min}^{max} \quad (9)$$

Where $\Delta_{min}^{max} = maxu_{ij}^{k} - minl_{ij}^{k}$

$maxu_{ij}^{k}$ is the maximum upper value amongst the upper bound and $minl_{ij}^{k}$ is the minimum lower value amongst the lower bound, for all fuzzy number values for expert k.

Step 3.2: *Compute upper (xus) and lower (xls) normalized values*

$$xus_{ij}^{k} = xu_{ij}^{k}/\left(1 + xu_{ij}^{k} - xm_{ij}^{k}\right) \quad (10)$$
$$xls_{ij}^{k} = xm_{ij}^{k}/\left(1 + xm_{ij}^{k} - xl_{ij}^{k}\right) \quad (11)$$

Step 3.3: *Compute total normalized crisp values*

$$x_{ij}^{k} = \left[xls_{ij}^{k}\left(1 - xls_{ij}^{k}\right) + xus_{ij}^{k} * xus_{ij}^{k}\right]/\left[1 - xls_{ij}^{k} + xus_{ij}^{k}\right] \quad (12)$$

Step 3.4: *Compute crisp values*

$$z_{ij}^{k} = \min l_{ij}^{k} + \left(x_{ij}^{k} * \Delta_{min}^{max}\right) \quad (13)$$

Step 3.5: *Aggregate crisp values of qualitative criteria matrices and criteria weights*

All decision-makers crisp values qualitative criteria matrices and criteria weights are then aggregated into a single (average) crisp values qualitative criteria matrix and single crisp value criteria weights using Eq. (14).

$$Z_{ij} = \frac{1}{K}\left(z_{ij}^{1} + z_{ij}^{2} + \cdots + z_{ij}^{K}\right) \quad (14)$$

Stage 4: *Incorporate the aggregated qualitative criteria crisp data into the decision-matrix with importance weights*

The aggregated crisp data obtained after the defuzzification of the evaluation for all suppliers' qualitative criteria are incorporated back into the decision-matrix together with the aggregated weights of the criteria $w_j = [w_1, w_2, \ldots w_n]$ to provide a single and complete decision-matrix as shown in Table 5.

Table 5. Aggregated crisp data for qualitative and quantitative criteria and weights

	Qualitative Criteria					Quantitative Criteria				
	C_1	C_2	C_3	….	C_n	R_1	R_2	R_3	….	R_n
A_1	0.35	0.35	0.56	….	0.56	20	18	2.2	….	0.25
A_2	0.35	0.56	0.35	….	0.35	23	15	2.5	….	0.30
A_3	0.56	0.25	0.67	….	0.35	19	17	2.9	….	0.31
…..	…..	…..	…..	…..	…..	…..	…..	…..	….	…..
A_n	0.67	0.56	0.35	….	0.67	25	20	3.1	….	0.27
Importance Weights	0.67	0.35	0.56	….	0.67	0.25	0.35	0.67	….	0.56

Stage 5: *Normalize the Crisp Decision-Matrix and the Criteria Weights*

Since both qualitative and quantitative criteria in supplier performance decision-matrix has different scales and that a particular criteria measure in a large scale may dominate the score, we propose normalizing all measures x_{ij} to be within 0-1 scale. We therefore denote the normalized measures as y_{ij} and propose two liner normalization methods (Li & Zhao, 2009; Wu, 2002; Kuo et al., 2008) with both taking into consideration the characteristics of the criteria.

Step 5.1: **Option 1**: If the characteristics of the criteria are larger-the-better (e.g. quality), then the measures x_{ij} can be normalized into measures as y_{ij} using Eq. (15)

$$y_{ij} = \frac{x_{ij} - \min_j x_{ij}}{\max_j x_{ij} - \min_j x_{ij}} \quad (15)$$

Option 2: If the characteristics of the criteria are smaller-the-better (e.g. price), then, the measures x_{ij} can be normalized into measures as y_{ij} using Eq. (16).

$$y_{ij} = \frac{\max_j x_{ij} - x_{ij}}{\max_j x_{ij} - \min_j x_{ij}} \quad (16)$$

Where $\min_j x_{ij}$ and $\max_j x_{ij}$ are the minimum and the maximum measure of criteria j respectively.

Step 5.2: Since the criteria weights must meet the condition $\sum_{j=1}^{n} w_j = 1$, therefore the criteria weights are further normalized using Eq. (17).

$$w_j^* = \frac{w_j}{\sum_{j=1}^{n} w_j} \quad (17)$$

Where w_j^* is the normalized weight of the criteria and w_j are the original weights of the criteria.

PHASE 2: Screening, Selection and Evaluation of Potential Suppliers

Stage 6: *Screening of Potential Suppliers*

Step 6.1*: Weighted Decision-Matrix and Suppliers Efficiencies Computation*

A weighted decision-matrix is obtained by multiplying the normalized weights of the criteria in Step 5.2 and the normalized decision-matrix for all suppliers obtained from step 5.1. Then, the efficiencies of the supplier E_i are computed based on the groupings of the criteria (into input and output). This study uses resources criteria (cost of using the supplier) as input items while using revenues criteria (performance of the supplier) as output items (De Boer et al., 2001; Ma & Liu, 2011; Wu et al., 2012). The efficiencies of the supplier are computed as the sum of the weighted output divided by the sum of the weighted input and usually constrained as [0, 1] (Kuo et al., 2008) using Eq. (18)

$$E_i = \frac{\sum_{r=1}^{s} w_r^* y_{rj}}{\sum_{k=1}^{m} w_k^* y_{kj}} \quad (18)$$

where E_i is the efficiency score of the ith supplier, s is the number of criteria of larger-the-better, m is the number of criteria of smaller-the-better, y_{rj} is the performance evaluation criteria for the ith supplier of larger-the-better (revenue criteria), y_{kj} is the performance evaluation criteria for the ith supplier of smaller-the-better(resource criteria), w_r^* is the normalized weight of y_r and w_k^* is the normalized weight of y_k.

Since Eq. (18) is sensitive to the zero values, it is recommended that, before applying this equation a transformation or reasonable adjustment of the dataset is completed should there be a zero value in the dataset. If for example a zero value is identified under any of the supplier's evaluation criterion, then the entire weights of the decision-matrix for all suppliers should be transformed. The data are transformed using the weights as an exponent for an exponential function to make a reasonable adjustment that does not overestimate the evaluation criteria using Eq. (19).

$$k_{ij} = e^{y_{ij}} \tag{19}$$

Where k_{ij} is the transformed weights, e is exponential base and y_{ij} is normalized criteria weights.

Once the efficiencies of the suppliers have been computed, a threshold is computed (or agreed) to screen the suppliers. This can be achieved by using the averages of the efficiencies to select the potential suppliers with efficiencies above the threshold.

Step 6.2*: Form Sub Decision-Matrix of Potential Suppliers*

The selected potential suppliers and their associated dataset are then retrieved from the decision- matrix (Table 7) to form a sub decision- matrix.

Stage 7: *Normalization of (sub) decision-matrix and criteria importance sequence ranking*

In this stage, the sub decision-matrix obtained in step 6.2 after screening and selecting the potential suppliers is first normalized following the two normalization options in step 5.1. Then, the Purchasing Manager ranks the criteria importance in sequence (based on the company's criteria importance rankings) rather than specifying the exact weight values as done in step 1.2. In this model development, we assumed that the criteria importance is arranged in descending order and in the format as $w_{i1} \geq w_{i2} \geq w_{i3} .... w_{iJ}$.

Stage 8: *Rearranging the sub decision-matrix criteria sequence and compute partial averages*

Once the normalized sub decision-matrix measures/criteria are listed or rearranged in the same sequence as the importance of measures/criteria ranked by the Purchasing Manager based on the company's criteria importance rankings is completed (refer to stage 7), the partial averages (Ng, 2008) for each supplier's measures/criteria are then computed using Eq. (20).

$$PA_m = \frac{1}{J}\sum_{m=1}^{J} z_{ijm} \tag{20}$$

Where J is the number of measures/criteria, z_{ij} is the normalized performance evaluation measures/criteria value at the intersection of row i and column j from the rearranged sub-decision matrix, $m = 1,2,........ J$ and $j \neq m$. PA_m , is the partial averages of the evaluation measures/criteria and $0 \leq PA_m \leq 1$.

Stage 9: *Identify the optimal supplier/decision*

Step 9.1: *Compute the global utility of each potential supplier from the PA*

Since a single criterion only provides the performance attributes of a potential supplier based on a single criteria evaluation, we consider a more comprehensive aggregation operator that considers all the criteria in the decision-making processes. The two most popular aggregation techniques include multiplicative and additive models and are used in this work. In the multiplicative aggregation model, a poor or low value in any evaluating criterion is reflected in the global utility of suppliers while a good global utility would depend on higher values in all evaluating criteria (Natoli and Zuhair, 2011). The additive aggregation model allows full compensation of poor or lower value of the individual evaluating criterion to be offset by good or higher values in the other evaluating criteria when determining the global utility of suppliers (Munda & Nardo, 2005; Nardo et al., 2005).

Considering the strengths and weaknesses of these two popular aggregation options, we proposed the use of both aggregation techniques to compute the global utility of each potential supplier using the PA scores of all evaluation criteria for each supplier and representing the results as S_i. The additive (weighted sum) aggregation techniques (SA_i) for the computation of the global utility of each potential supplier uses Eq. (21) and the multiplicative aggregation (SM_i) uses Eq. (22).

$$SA_i = \sum_{j=1}^{n} PA_j \tag{21}$$

$$SM_i = PA_1 x PA_2 x \ldots PA_j x \ldots PA_n \tag{22}$$

Where x in Eq. (22) is not a variable but an operator meaning multiplication and n is the last PA entry/score in the jth column.

Since the aggregation technique Eq. (22) is sensitive to the zero values, it is recommended that, before applying any of the two techniques a transformation or reasonable adjustment of the dataset be completed should there be a zero value in the dataset. The data are transformed using the weights as an exponent for an exponential function to make a reasonable adjustment to weights using Eq. (19) and replacing y_{ij} in the formula with PA_j .

Step 9.2: *Compute resultant predictive score for each potential supplier and select optimal supplier/decision D_o*

In this stage, the resultant predictive score for each potential supplier can be computed by subtracting the multiplicative global utility function scores from the additive global utility function scores or vice versa and the scores S_i are sorted in descending order with the corresponding maximum S_i score identified as the optimal supplier/decision D_o as per Eq. (24) and (25).

$$S_i = \left| SA_j - SM_j \right| = \left| SM_j - SA_j \right| \tag{24}$$

$$D_o = \max_i (S_i) \tag{25}$$

4. Numerical illustration - real world case study

4.1. Specific case problem description and solution

A beverage producing company located in Ghana and provide beverages to it consumers in Sub-Saharan Africa intends to select an optimal supplier for a long-term supplier contract (consignment stock/vendor managed inventory) for one of its newly installed electrical critical spare. Management first wants to generate and screen a pool of suppliers to obtain some limited set of potential suppliers, then undertake a second round of evaluation and select the optimal supplier amongst these limited set of potential suppliers for the corporation. As a result, the Procurement Category Manager (Technical) is tasked by management to generate and preliminary screen a pool of suppliers for the newly installed electrical critical spare to select some limited set of potential suppliers for further evaluation. Additionally, since the newly installed electrical critical spare that management plan to have it on consignment stock relates to production, the Procurement Category Manager set a committee of four decision-makers (Managers) involving Utilities Engineering Manager, Shift Packaging Manager, Supplier Performance Manager and himself for the evaluation process.

Six criteria were considered necessary by management in this exercise and include: price/unit (US Dollars) (**C1**), transportation cost/unit (US Dollars) (**C2**), delivery (Weeks) (**C3**), quality (**C4**), technology level (**C5**), and production systems flexibility (**C6**) (Golmohammadi & Mellat-Parast, 2012). The Procurement Category Manager with these criteria then sent out a request-for-quotation (RFQ) for the newly installed electrical critical spare to all their registered electrical spares suppliers (twenty-five in numbers) and asked them to quote their best offer. However, only fifteen out of the twenty-five suppliers responded to the RFQ with their quotation and were all able to quote for price (**C1**), transportation cost (**C2**) and delivery (Weeks) (**C3**). Management then asked each of the committee members to assign textual perception scores (since there were no historical data) to the fifteen suppliers' qualitative criteria based on the suppliers three years perceived performance and determine the weights of the criteria.

Table 6 provides the committee members in the decision-making process from the beverage producing company located in Ghana. The general structure of the decision problem is shown in Figure 2.

Table 6. The four managers involved with the group decision-making

Manager	Description	Years experience
Manager1	Procurement Category Manager - Technical	12
Manager2	Utilities Engineering Manager	5
Manager3	Supplier Performance Manager - Technical	5
Manager4	Shift Packaging Manager	6

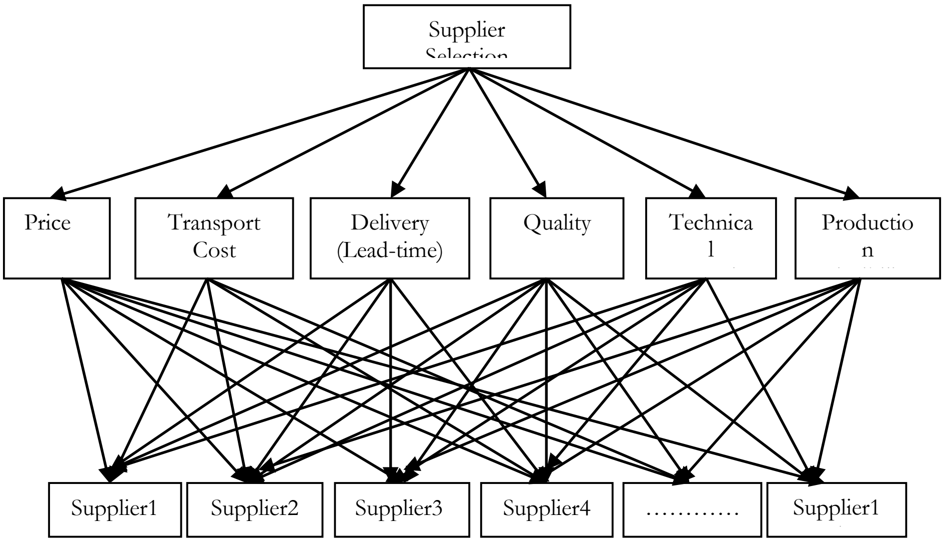

Figure. 2. The general decision structure for supplier evaluation and selection

The proposed model is then applied to solve the problem with the computational steps summarized as follows.

PHASE 1: Pool of Suppliers Screening, Evaluation and Selection of Potential Suppliers

Stage 1. *Populate Original Decision-Matrix (Table) and Obtain Weights of Criteria/Indicators*

The procurement category manager (Manager 1) first completed the quantitative aspect of the decision-matrix using the quantitative data received from each of the supplier from the RFQ responses. Then, the four decision-makers (Managers) used the linguistic variables shown in Table 3 to evaluate each supplier past performance with the company with respect to the qualitative criteria. Table 7 depicts the perceived qualitative criteria rating of each supplier's past performance with the company by manager 1 and quantitative criteria data of each supplier from the RFQ responses.

The linguistic variables shown in Table 4 were used by the four managers to assess the criteria importance weights. The criteria weights determined by manager 1 are shown in Table 8.

Table 7. Quantitative and qualitative criteria data for manager 1

	Quantitative			Qualitative		
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
Supplier1	66.367	60.80	8	VH	VH	H
Supplier2	61.993	50.40	5	VH	VH	H
Supplier3	110.657	80.26	4	H	M	M
Supplier4	74.615	70.75	6	M	M	M
Supplier5	59.934	65.66	9	H	H	H
Supplier6	68.256	74.80	8	H	H	H
Supplier7	73.121	69.25	5	H	VH	H
Supplier8	100.341	77.13	5	VH	VH	H
Supplier9	66.712	73.12	7	VH	H	H
Supplier10	88.192	78.12	6	H	H	H
Supplier11	105.112	75.31	8	VH	H	M
Supplier12	65.321	61.3	9	H	H	H
Supplier13	98.111	65.12	6	VH	VH	H
Supplier14	69.181	75.3	8	VH	M	H
Supplier15	67.512	70.56	7	H	H	M

Table 8. Linguistic variables criteria importance weights for manager 1

	C1	**C2**	**C3**	**C4**	**C5**	**C6**
Importance Weights	VH	H	VH	VH	H	H

Stage 2. *Convert Linguistic Variables into Triangular Fuzzy numbers*

Triangular fuzzy numbers were used to convert the linguistic evaluations into fuzzy decision-matrix and fuzzy criteria weights. Tables 9 and 10 depict the fuzzy data of the linguistic evaluations in Tables 7 and 8 respectively.

Table 9. Fuzzy qualitative decision-matrix for manager 1

	Qualitative		
	C4	**C5**	**C6**
Supplier1	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)
Supplier2	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
Supplier3	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
Supplier4	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
Supplier5	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
Supplier6	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)
Supplier7	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)
Supplier8	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)
Supplier9	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
Supplier10	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
Supplier11	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)
Supplier12	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
Supplier13	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)
Supplier14	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)
Supplier15	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)

Table 10. Fuzzy criteria importance weights for manager 1

	C1	C2	C3	C4	C5	C6
Importance Weights	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)

Stage 3. *Defuzzify Qualitative Criteria Data and Criteria Importance Weights*

All fuzzy qualitative criteria decision-matrix and fuzzy criteria weights for all managers were defuzzified into crisp data using Eqs. (7)-(14). Tables 11 and 12 depict the defuzzified data of the fuzzy evaluations and aggregation in Tables 9 and 10 respectively.

Table 11. Crisp data for qualitative decision-matrix for manager 1

	Qualitative		
	C4	**C5**	**C6**
Supplier1	0.872	0.872	0.872
Supplier2	0.872	0.696	0.696
Supplier3	0.696	0.696	0.696
Supplier4	0.696	0.696	0.696
Supplier5	0.696	0.696	0.696
Supplier6	0.872	0.872	0.872
Supplier7	0.696	0.872	0.696
Supplier8	0.872	0.872	0.696
Supplier9	0.872	0.696	0.696
Supplier10	0.696	0.696	0.696
Supplier11	0.872	0.696	0.512
Supplier12	0.696	0.696	0.696
Supplier13	0.872	0.872	0.696
Supplier14	0.872	0.512	0.696
Supplier15	0.696	0.696	0.512

Table 12. Crisp data for criteria importance weights for manager 1

	C1	C2	C3	C4	C5	C6
Importance Weights	0.8722	0.7063	0.8722	0.8722	0.7063	0.7063

Stage 4: *Incorporate the aggregated qualitative criteria crisp data into the decision-matrix with criteria weights*

The crisp qualitative criteria data and crisp criteria weights obtained in stage 3 for all managers and the quantitative data obtained through the RFQ are integrated to form a single decision-matrix as shown in Table 13.

Table 13. Integrated crisp decision-matrix and criteria crisp weights for all managers

	Quantitative			Qualitative		
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
Supplier1	66.367	60.80	8	0.8282	0.8282	0.7841
Supplier2	61.993	50.40	5	0.8282	0.7841	0.7400
Supplier3	110.657	80.26	4	0.6960	0.6500	0.6040
Supplier4	74.615	70.75	6	0.6040	0.6040	0.5581
Supplier5	59.934	65.66	9	0.6960	0.6500	0.6500
Supplier6	68.256	74.80	8	0.8282	0.8282	0.8282
Supplier7	73.121	69.25	5	0.7400	0.6941	0.6500
Supplier8	100.341	77.13	5	0.7400	0.8723	0.6941

Table 13. Integrated crisp decision-matrix and criteria crisp weights for all managers (continued)

	Quantitative			Qualitative		
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
Supplier9	66.712	73.12	7	0.8282	0.7382	0.7841
Supplier10	88.192	78.12	6	0.7400	0.5581	0.5581
Supplier11	105.112	75.31	8	0.7400	0.7400	0.5581
Supplier12	65.321	61.3	9	0.7400	0.6941	0.5581
Supplier13	98.111	65.12	6	0.7400	0.7400	0.6500
Supplier14	69.181	75.3	8	0.7841	0.6500	0.6500
Supplier15	67.512	70.56	7	0.7400	0.6941	0.6040
Importance Weights	0.8722	0.6967	0.8722	0.8722	0.7426	0.6092

Stage 5: *Normalize the Decision-Matrix Dataset and the Criteria Weights*

Since the criteria quality (C4), technology level (C5) and production system flexibility (C6) are usually considered larger-the-better, we applied EQ. (15) to normalize these criteria in Table 13. Also, the criteria price (C1), delivery (Weeks) (C2) and transportation cost (C3) usually are considered smaller-the-better; we therefore applied Eq. (16) to normalize these criteria in Table 13. Furthermore, the criteria relative important weights in Table 15 were also normalized using Eq. (17). The normalized integrated decision-matrix dataset and criteria weights can be found in Table 14.

Table 14. Normalized integrated decision-matrix dataset and criteria weights

	Quantitative			Qualitative		
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
Supplier1	0.4153	0.4675	0.9625	0.8597	0.8597	0.7194
Supplier2	0.4563	0.5650	0.9906	0.8597	0.7194	0.5791
Supplier3	0.0000	0.2850	1.0000	0.4388	0.2926	0.1463
Supplier4	0.3379	0.3742	0.9812	0.1463	0.1463	0.0000
Supplier5	0.4756	0.4219	0.9531	0.4388	0.2926	0.2926
Supplier6	0.3975	0.3362	0.9625	0.8597	0.8597	0.8597
Supplier7	0.3519	0.3882	0.9906	0.5791	0.4328	0.2926
Supplier8	0.0967	0.3143	0.9906	0.5791	1.0000	0.4328
Supplier9	0.4120	0.3519	0.9719	0.8597	0.5731	0.7194
Supplier10	0.2106	0.3051	0.9812	0.5791	0.0000	0.0000
Supplier11	0.0520	0.3314	0.9625	0.5791	0.5791	0.0000
Supplier12	0.4251	0.4628	0.9531	0.5791	0.4328	0.0000
Supplier13	0.1176	0.4269	0.9812	0.5791	0.5791	0.2926
Supplier14	0.3889	0.3315	0.9625	0.7194	0.2926	0.2926
Supplier15	0.4045	0.3759	0.9719	0.5791	0.4328	0.1463
Importance Weights	0.1870	0.1493	0.1870	0.1870	0.1592	0.1306

Stage 6: *Weighted Decision-Matrix and Suppliers Efficiencies Computation*

Since there are some zero criteria values in the decision-matrix generated from the normalization approach, we applied Eq. (19) to transform and dampen the sensitivity of zero criteria values to avoid losing information from some suppliers when computing the efficiencies of the suppliers to determine a more accurate efficiencies calculation. Table 15 depicts the transformed decision-matrix dataset together with the (non-transformed) criteria weights from Table 14.

Table 15. Transformed decision matrix dataset and criteria weights

	Quantitative			Qualitative		
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
Supplier1	1.5148	1.5959	2.6182	2.3625	2.3625	2.0532
Supplier2	1.5782	1.7594	2.6929	2.3625	2.0532	1.7845
Supplier3	1.0000	1.3298	2.7183	1.5509	1.3399	1.1575
Supplier4	1.4020	1.4538	2.6678	1.1575	1.1575	1.0000
Supplier5	1.6089	1.5248	2.5938	1.5509	1.3399	1.3399
Supplier6	1.4882	1.3996	2.6182	2.3625	2.3625	2.3625
Supplier7	1.4218	1.4744	2.6929	1.7845	1.5416	1.3399
Supplier8	1.1016	1.3694	2.6929	1.7845	2.7183	1.5416
Supplier9	1.5099	1.4218	2.6429	2.3625	1.7738	2.0532
Supplier10	1.2345	1.3567	2.6678	1.7845	1.0000	1.0000
Supplier11	1.0534	1.3929	2.6182	1.7845	1.7845	1.0000
Supplier12	1.5297	1.5885	2.5938	1.7845	1.5416	1.0000
Supplier13	1.1248	1.5326	2.6678	1.7845	1.7845	1.3399
Supplier14	1.4753	1.3931	2.6182	2.0532	1.3399	1.3399
Supplier15	1.4986	1.4564	2.6429	1.7845	1.5416	1.1575
Importance Weights	0.1870	0.1493	0.1870	0.1870	0.1592	0.1306

The weighted decision-matrix was then achieved by multiplying through the transformed decision- matrix criteria dataset with the equivalent criteria weights in Table 14 to obtain Table 15.

Eq. (18) was applied to compute all suppliers' efficiencies and shown in column 8 of Table 16. A threshold of 0.8349 (0.2087) was set using the averages of the efficiencies to select the potential supplier list above the threshold. Since the efficiencies are more than 1 as a result of the exponential transformation, we therefore adjusted the efficiencies values to meet the condition being within the intervals [0, 1] by dividing through by n =4, where n is the number of managers involved in the decision-making. Suppliers 1, 2, 6, 8, 9, 11 and 13 were selected as potential supplier set for the next stage of the evaluation.

Table 16. Weighted decision matrix dataset and efficiencies of suppliers

	Quantitative			Qualitative					
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	E_i	E_i / n	**Decision**
Supplier1	0.2832	0.2383	0.4895	0.4417	0.3761	0.2681	**1.0740**	**0.2685**	**Selected**
Supplier2	0.2951	0.2627	0.5035	0.4417	0.3268	0.2330	**0.9438**	**0.2359**	**Selected**
Supplier3	0.1870	0.1986	0.5082	0.2900	0.2133	0.1512	0.7322	0.1830	Rejected
Supplier4	0.2621	0.2171	0.4988	0.2164	0.1843	0.1306	0.5432	0.1358	Rejected
Supplier5	0.3008	0.2277	0.4849	0.2900	0.2133	0.1750	0.6692	0.1673	Rejected
Supplier6	0.2782	0.2090	0.4895	0.4417	0.3761	0.3085	**1.1531**	**0.2883**	**Selected**
Supplier7	0.2658	0.2202	0.5035	0.3336	0.2454	0.1750	0.7620	0.1905	Rejected
Supplier8	0.2060	0.2045	0.5035	0.3336	0.4327	0.2013	**1.0588**	**0.2647**	**Selected**
Supplier9	0.2823	0.2123	0.4941	0.4417	0.2824	0.2681	**1.0035**	**0.2509**	**Selected**
Supplier10	0.2308	0.2026	0.4988	0.3336	0.1592	0.1306	0.6688	0.1672	Rejected
Supplier11	0.1969	0.2080	0.4895	0.3336	0.2841	0.1306	**0.8366**	**0.2091**	**Selected**
Supplier12	0.2860	0.2372	0.4849	0.3336	0.2454	0.1306	0.7039	0.1760	Rejected
Supplier13	0.2103	0.2289	0.4988	0.3336	0.2841	0.1750	**0.8451**	**0.2113**	**Selected**
Supplier14	0.2758	0.2080	0.4895	0.3839	0.2133	0.1750	0.7933	0.1983	Rejected
Supplier15	0.2802	0.2175	0.4941	0.3336	0.2454	0.1512	0.7362	0.1841	Rejected

PHASE 2: Potential Suppliers Evaluation and Selection of Optimal Supplier

Step 7: *Form Sub Decision-Matrix for Potential Suppliers*

The seven potential suppliers selected from Table 16 (phase 1 stage 6) were then retrieved from Table 13 with their dataset to form a sub decision-matrix in Table 17.

Table 17. Sub decision-matrix for potential suppliers

	Quantitative			**Qualitative**		
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
Supplier1	66.367	60.8	8	0.8282	0.8282	0.7841
Supplier2	61.993	50.4	5	0.8282	0.7841	0.7400
Supplier6	68.256	74.8	8	0.8282	0.8282	0.8282
Supplier8	100.341	77.13	5	0.7400	0.8723	0.6941
Supplier9	66.712	73.12	7	0.8282	0.7382	0.7841
Supplier11	105.112	75.31	8	0.7400	0.7400	0.5581
Supplier13	98.111	65.12	6	0.7400	0.7400	0.6500

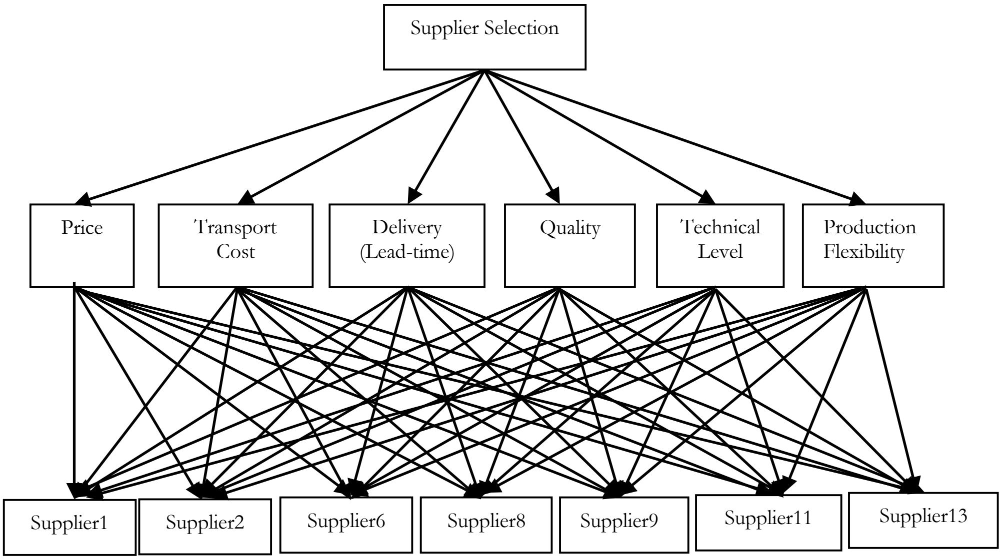

Figure 3. The sub-decision structure for potential supplier evaluation and selection problem

Stage 8: *Normalization of (sub) decision-matrix and criteria importance sequence ranking*

The normalization operations conducted in Stage 5 for the decision-matrix dataset was repeated at this stage to normalize the potential suppliers' sub decision-matrix and is shown in Table 18.

Again since the multiplicative operator is sensitive to the zero values in the sub decision-matrix data generated from the two normalization approaches, Eq. (19) was applied to Table 18 to dampen the zero values in the data. Also criteria importance sequence ranking of descending order $C4 \geq C1 \geq C3 \geq C2 \geq C5 \geq C6$ was provided by the Procurement Category Manager based on management decision. The outputs from the two operations are simultaneously depicted in Table 19.

Table 18. Normalized sub decision-matrix for potential suppliers

	Quantitative			Qualitative		
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
Supplier1	0.3870	0.4426	0.9700	0.8597	0.8597	0.7194
Supplier2	0.4307	0.5465	1.0000	0.8597	0.7194	0.5791
Supplier6	0.3681	0.3028	0.9700	0.8597	0.8597	0.8597
Supplier8	0.0477	0.2795	1.0000	0.5791	1.0000	0.4328
Supplier9	0.3836	0.3196	0.9800	0.8597	0.5731	0.7194
Supplier11	0.0000	0.2977	0.9700	0.5791	0.5791	0.0000
Supplier13	0.0699	0.3995	0.9900	0.5791	0.5791	0.2926

Table 19. Transformed sub decision-matrix for potential suppliers and criteria importance ranking

	C4	**C1**	**C3**	**C2**	**C5**	**C6**
Supplier1	2.362	1.473	2.638	1.557	2.362	2.053
Supplier2	2.362	1.538	2.718	1.727	2.053	1.784
Supplier6	2.362	1.445	2.638	1.354	2.362	2.362
Supplier8	1.784	1.049	2.718	1.322	2.718	1.542
Supplier9	2.362	1.468	2.665	1.377	1.774	2.053
Supplier11	1.784	1.000	2.638	1.347	1.784	1.000
Supplier13	1.784	1.072	2.691	1.491	1.784	1.340

Stage 9: *Compute partial averages of the transformed decision matrix*

The partial averages for each potential supplier transformed database in Table 19 are computed using Eq. (20) and are shown in columns 2-7 of Table 20.

Stage 10: *Identify the optimal supplier/decision*

Step 10.1 *Compute the global utility of each potential supplier from the PA*

Two global utility results are obtained in this stage using the additive approach Eq. (21) and multiplicative approach Eq. (22). Applying these equations to Table 20 for all potential suppliers provides the two results shown in columns 8 & 9 of Table 20.

Step 10.2: *Compute resultant predictive score for each potential supplier and select optimal supplier/decision* D_o

The resultant predictive scores for each potential supplier were computed using Eq. (24) and are shown in column 10 and ranked in column 11 of Table 20. Eq. (25) is used to identify the optimal supplier and is considered the most preferred supplier for the long-term contract.

Table 20. Global utility and resultant predictive score with rankings for each potential supplier

	C4	**C1**	**C3**	**C2**	**C5**	**C6**	SA_i	SM_i	S_i	**Rank**
Supplier1	2.362	1.918	2.158	2.007	2.078	2.074	12.598	84.597	71.999	**2**
Supplier2	*2.362*	*1.950*	*2.206*	*2.087*	*2.080*	*2.031*	*12.716*	*89.596*	*76.880*	***1***
Supplier6	2.362	1.904	2.149	1.950	2.032	2.087	12.484	79.928	67.444	**3**
Supplier8	1.784	1.417	1.851	1.719	1.918	1.856	10.544	28.620	18.076	**5**
Supplier9	2.362	1.915	2.165	1.968	1.929	1.950	12.289	72.481	60.192	**4**
Supplier11	1.784	1.392	1.808	1.692	1.711	1.592	9.980	20.701	10.722	**7**
Supplier13	1.784	1.428	1.849	1.760	1.765	1.694	10.281	24.800	14.519	**6**

4.2. Discussion of results

Selecting an optimal supplier from a list of potential suppliers considering multiple performance criteria is extremely imperative. Various methods including technique for order preference by similarity to ideal solution (TOPSIS), analytic hierarchy process (AHP), grey relational analysis (GRA) etc, are often used in dealing with these kinds of problems. Yet, few if not any of these approaches deal with the pre-qualification screening stage. To advance the understanding of this subject matter, this work has proposed an easy going and investigated suppliers' selection involving two-stages, including the pre-qualification screening of potential suppliers and final selection of optimal supplier.

The empirical result in Table 20 depicts the final evaluation results of the potential suppliers and their respective rankings from the proposed supplier selection and evaluation model. From Table 20, supplier 2 is ranked the topmost supplier and is recommended to management as the optimal supplier for the long-term supplier contract of the newly installed electrical critical spare. Even though supplier 2 is considered the optimal supplier from the final evaluation result, there are some performance criteria that supplier 2 was not rated topmost amongst others hence may require specific negotiations for improvements or better deal.

For example from Table 13, supplier 2 had 5 weeks for delivery (C3) and 61.933US Dollar unit price (C1), which are both the second best. The procurement category manager can as part of the post-optimal supplier selection process, negotiate with suppliers 2 to possibly shorten/reduce it delivery period to at least 4 weeks (*best delivery period as baseline measurement*) and reduce the unit price to at least 59.934 (*best unit price as baseline measurement*) but this should be carefully done not to compromise the overall performance of this supplier. Same negotiations steps can be initiated by the procurement category manager with supplier 2 to at least agree to improve it technology level (C5) performance to 0.8723 (*best technology level performance as baseline measurement*) and production systems flexibility (C6) performance to 0.8282 (*best production systems flexibility performance as baseline measurement*) over a period of time once these information are translated into formal contract for better return on investment.

5. Managerial input

A small survey with some mathematical background associated with the technique was sent to the decision-makers (managers) asking them about the usefulness of the model in a form of post hoc analysis. This was presented to them to show transparency and robustness of the model for them to have the feeling that the model is scientific and mathematical principled and logic-based. All four managers replied. Although they understood the usefulness of the model and they agreed that the issue addressed by the model is encountered, the mathematical descriptions and process was very complicated to them.

In response to this, we developed a more simplified step-by-step description with absolutely minimal mathematical description to explain the overall process (See appendix A- Table A1). We believe this step-by-step description will make the model easy to understand and accessible to management and practitioners. Clearly, the technique and methodology would best be framed as a model in a decision support system using spreadsheet package with a practitioner friendly user interface.

Another important issue we tried to seek manager's feedback was the validity and confidence in the final results. Even though the processes followed in achieving these results may have been very complicated to them, the managers believe the final result was what they expected and what they wished to communicate. Thus, the final result could be viewed as managerially valid and reliable.

6. Conclusion remarks and future research directions

Supplier selection and evaluation is a decision-making problem that requires decision-makers to determine a solution based on multiple criteria with some level of input and decisions uncertainty. These decisions are characterized by the conflicting trade-offs amongst the multiple criteria to select an optimal solution requiring the support of multi-criteria decision-making (MCDM) systems. Notwithstanding the heavy development of MCDM tools, methods and approaches to support suppliers selection and evaluation, most of these decision support systems are limited to just the final optimal supplier selection. However, the few that have attempted prescreening suppliers have also proposed approaches that are difficult to handle or implement by decision-makers.

This paper has explicitly modeled and proposed an easy going two-phase supplier selection and evaluation model that combines both pre-qualification (screening of supplier pool for potential suppliers) stage and evaluate the potential suppliers for optimal supplier selection. The model combines both qualitative (decision-makers linguistic evaluations for supplier influence on criteria and criteria important) and quantitative (from RFQ of suppliers) criteria and utilized fuzzy set theory to covert the linguistic evaluations to fuzzy evaluations. The proposed model was applied to a real case in a beverage producing company located in Ghana, Sub-Saharan Africa with it customer-base across the Africa continent and beyond. The company intended to select an optimal supplier for a long-term supplier contract. Fifteen suppliers were prescreened to obtain seven potential suppliers. These seven potential suppliers were further evaluated to recommend an optimal supplier to management based on the final score. Based on our proposed model, supplier 2 was ranked the topmost hence considered the optimal supplier for the newly installed electrical critical spare consignment stock contract. The proposed model for multiple criteria supplier selection and evaluation decision problem can be implemented using a spreadsheet package making it cheaper and easier to implement with simple user interface and promotes information sharing with other excel users.

This study, thus do provide some contributes to decision-making theory and practice. The results from the study can provide valuable clues and guidelines to decision-makers and analyst in establishing systematic approach to prescreening, evaluation and selecting optimal supplier for corporation. Since contract negotiation strategy is an important post supplier selection stage, the results attained from this study can assist management of the beverage producing company to effectively negotiate with the selected optimal supplier to achieve win-win situation in terms of reduced resources and improved benefit criteria. Also the proposed model will assist practicing managers to effectively reduce their supply-base or potential suppliers for detailed evaluation and efficiently select the optimal supplier for corporation or order allocation.

Notwithstanding these promising aspects, this paper still has some limitations. One of the primary limitations is the small/limited number of respondents (managers) involved with the decision-making process. Future studies could extend the coverage of respondents to ensure the validity of the research. Another limitation is the lack of proposed supplier selection and evaluation decision framework (criteria and indicators) in this study to guide the evaluation and selection of the suppliers. The study instead, adopted a proposed supplier selection and evaluation decision framework from previous study. A more rigorous and scientific approach for developing a supplier selection and evaluation decision framework could add some insights to framework developments in literature.

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Appendix A:

Table A1. Overview of the Two-Phase Simplified and Efficient Supplier Selection Methodology

No	Activity	Activity description
PHASE 1: Data Pre-Processing		
Stage 1: Populate Original Decision Matrix and Obtain Important Weights of the Criteria		
Step 1.1	**Populate Original Decision Matrix**	The decision matrix comprises a number of alternatives (suppliers) in the row and criteria (both quantitative and qualitative) in the column to be used in evaluating the alternatives. Quantitative criteria data are obtained through request-for-quotation (RFQ) and are aggregated. Qualitative criteria data are obtained by decision makers assigning textual perception based on suppliers past performance on those qualitative criteria using linguistic scale ranging from Very Low Performance (VL) to Very High Performance (VH).
Step 1.2	**Obtain importance weights of criteria**	Criteria importance weights are obtained by decision makers assigning textual perception using linguistic scale ranging from Extremely Very Low Importance (EL) to Very High Importance (VH).
Stage 2	**Converting Linguistic Evaluations into Triangular Fuzzy Numbers**	The linguistic evaluation of each supplier performance on the qualitative criterion and the importance weights of each evaluation criterion by each decision maker are replaced/reassigned corresponding triangular fuzzy number
Stage 3	**Defuzzify Qualitative Criteria Data and Criteria Importance Weights**	The modified-CFCS (Converting Fuzzy data into Crisp Score) defuzzification method, Eq. (7)-(13) is used to transform all the triangular fuzzy numbers of both the qualitative criteria data and criteria importance weights into crisp numbers
Step 3.5	**Aggregate crisp values of qualitative criteria matrices and criteria importance weights**	All qualitative criteria crisp value matrices and criteria importance crisp weights are then aggregated into a single (average) qualitative criteria crisp values matrix and a single criteria importance crisp value weights using Eq. (14).
Stage 4	**Incorporate the aggregated qualitative criteria crisp data into the decision matrix with importance weights**	The aggregated qualitative criteria crisp matrix and criteria importance crisp weights are then integrated into the original decision matrix to form a complete decision crisp matrix with criteria importance crisp weights
Stage 5	**Normalize the Crisp Decision Matrix and the Criteria Important Weights**	The decision-matrix comprising of both qualitative and quantitative criteria is normalize to keep the data free from any criteria measurement scale dominance using bigger-the-better (e.g. quality) Eq. (15) or smaller-the-better (e.g. price) Eq. (16). Then the criteria importance weights are also normalize using Eq. (17).

Table A1. Overview of the Two-Phase Simplified and Efficient Supplier Selection Methodology (continued)

No	Activity	Activity description
PHASE 2: Screening, Selection and Evaluation of Potential Suppliers		
Stage 6: Screening of Potential Suppliers		
Step 6.1	**Weighted Decision Matrix and Suppliers Efficiencies Computation**	The weighted decision matrix is obtained by multiplying the normalized criteria important weights through the normalized decision matrix for all suppliers. Then, the efficiencies of the supplier are computed as the sum of the weighted output divided by the sum of the weighted input using Eq. (18). Prior to that, we address the zero outliner in the data using Eq. (19). A threshold is then determined to screen the suppliers.
Step 6.2	**Form Sub-Decision Matrix of Potential Suppliers**	The selected potential suppliers and their associated dataset are then retrieved from the crisp data decision matrix (Table 7) to form a sub-decision matrix.
Stage 7	**Normalization of (sub) decision matrix and criteria importance sequence ranking**	The crisp sub-decision matrix is first normalized and then, the lead decision-maker (purchasing manager in this case) ranks the criteria importance in sequence based on the company's criteria importance rankings rather than specifying the exact weight values.
Stage 8	**Rearranging the sub-decision matrix criteria sequence and compute partial averages**	After the normalized sub-decision matrix criteria are listed or rearranged in the sequential ranking order, the partial averages for each supplier's criteria are then computed using Eq. (20).
Stage 9: Identify the optimal supplier/decision		
Step 9.1	**Compute the global utility of each potential supplier from the PA**	Two popular aggregation techniques are used for the computation of the global utility of each potential supplier including the additive (weighted sum) aggregation techniques (SA_i) Eq. (21) and the multiplicative aggregation (SM_i) Eq. (22). Prior to that, we address the zero outliner in the data using Eq. (19).
Step 9.2	**Compute resultant predictive score for each potential supplier and select optimal supplier/decision D_o**	The resultant predictive score for each potential supplier can be computed by subtracting the multiplicative global utility function scores from the additive global utility function scores or vice versa and the scores S_i are sorted in descending order with the corresponding maximum S_i score identified as the optimal supplier/decision D_o as per Eq. (24) and (25).