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Application of a hybrid Goal Programming and SMAA-PROMETHEE approach to rank suppliers

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In different industries whenever the demands of end customers for faster and more reliable deliveries, better quality and lower prices increase, success strongly relies on the competitiveness of the supplier base. This involves all activities, practices and efforts undertaken by buyer firms to improve their suppliers' capabilities and performance, but first it consists of answering the question: What are the suppliers to develop? In this article we formulate this as a MCDA problem and, because of the uncertainty and imprecision resulting from the way that supplier-evaluation data is usually collected in these industries, we propose that SMAA-PROMETHEE is helpful in this context to rank suppliers. Given that PROMETHEE needs to set the indifference and preference parameters, a Goal Programming approach is proposed to inferring these values. We illustrate usage of this method by applying it on data coming from three Mexican industries: aerospace, automotive and electronics. It is shown that this approach provides much richer information which enables more complete recommendations to be made.

Keywords: Multiple criteria analysis; SMAA-PROMETHEE; supplier development

1. Introduction

Supply chain performance is becoming increasingly important as demands of customers for faster and more reliable deliveries, better quality and lower prices increase. To keep pace with these demands it is critical to compile and maintain a register of suppliers who meet the buyer's criteria for inclusion in this file. But finding competent suppliers that satisfy all the critical requirements could be difficult. The problem of finding adequate suppliers that satisfy such critical requirements is called the *supplier evaluation and selection problem* (SESP). The main issues addressed in this problem are: which approaches for supplier evaluation and selection should be applied; which evaluation criteria should be used; and which approach is the most adequate in a given situation. The evaluation and selection of suppliers has been extensively studied and formulated as a multi-criteria decision problem and several multi-criteria methods have been used to solve it. Ho et al. (2010) give an excellent panorama of methods available for this.

Once a base of suppliers is selected, the problem consists of finding which suppliers to improve, which we identify as a *supplier development problem* (SDP) (Hartley and Choi 1996; Krause et al. 1998). Supplier development involves considering all activities, practices and efforts undertaken by buyers in support of which suppliers need to improve their capabilities and performance (Krause and Ellram 1997). These efforts include projects that seek to improve the design and quality of products and issues related to how they are processed, delivered and costed (Rezaei et al. 2015; Lukhoba and Muturi 2015; Onesime et al. 2004). Usually, the SDP comprises defining a quality development

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strategy and establishing evaluation measures. The quality development strategy looks for activities that may improve supplier performance, while evaluation includes identifying measurable criteria to evaluate how suppliers have progressed in fulfilling the buyer's quality expectations (Noshad 2013).

Leading companies, for example, in the automotive and aerospace sectors, are investing a significant amount of resources in the design of systems and processes to develop supplier capabilities as a means of guaranteeing the competitiveness of their supplier base (Abdullah et al. 2008; Hartley and Choi 1996). Recently, Ahmed and Hendry (2012) identified a lack of research regarding how to measure the effectiveness of SDP actions in overcoming the negative effects that factors such as lack of interest, commitment and poor communication have on the success of SDP programs and in systematically selecting the most appropriate activities needed to achieve the objectives of buyers and their suppliers. Thus, the SDP problem addresses the following questions: What are the suppliers to develop? What are the development activities that need to be implemented to guarantee an improvement in suppliers' performance? and How can development activities be allocated to suppliers in accordance with multiple criteria such as cost, improvement and time? This article sets out to provide answers to the first question by introducing a formulation that is essentially an MCDA problem.

Most decision-making techniques have been applied to solve the SESP (Chai et al. 2013). Recently, Yildiz and Yayla (2015) reviewed literature on MCDA methods published between 2001 and 2014. They found that the methods most used were AHP/ANP and TOPSIS (both in their standard and fuzzy versions). Equally, hybrid methods have become widespread in the last 10 years. Essentially, using multicriteria methods for SESP involves ordering, that is, defining a set of criteria and a specific MCDA method in order to rank suppliers. Instead, the issue in SDP includes evaluating quality or measuring performance in order to sort and/or categorize suppliers, with a view to identifying opportunities for improvement (Omurca 2013; Osiro et al. 2014). Thus, Noshad (2013) proposes an approach to evaluate and rank different supplier quality development programs using TOPSIS. Recently, Rezaei and Ortt (2013) have proposed a method using fuzzy AHP for segmenting suppliers, defining classes that aid the decision maker (DM) to negotiate with suppliers in different ways. Rezaei et al. (2015) introduce capabilities and willingness as dimensions for evaluating suppliers; next, they apply the Best-Worst-Method to segment suppliers and a conceptual model is proposed as an approach to identifying candidate suppliers for different segments.

PROMETHEE (Brans 1982), has been applied in several cases of SESP (Dulmin and Mininno 2003; Araz et al. 2007; Tuzkaya et al. 2009; Chen et al. 2010; Shirinfar and Haleh 2011; Chen et al. 2011; Chai et al. 2013; Araújo et al. 2015; Yildiz and Yayla 2015). However, its use in SDP is rather scarce, mainly with regard to sorting suppliers in order to identify potential improvement. For instance, Araz and Ozkarahan (2007) propose a supplier segmentation process using PROMSORT, a multi-criteria sorting method based on PROMETHEE, for identifying groups of suppliers where performance could be improved by development programs. Sepúlveda et al. (2014) propose FlowSort, a sorting method based on PROMETHEE, to classify suppliers according to a set of criteria. Tsui et al. (2015) develop a hybrid method where the PROMETHEE's preference function is modified to include the concepts of "positive ideal point" (aspiration level) and "negative ideal point". Based on this modelling approach, gaps between the evaluation of a current supplier and its aspiration level are calculated, which helps to identify potential improvement zones.

Integration of MCDA techniques in structuring decision models for SESP or SDP is a complex task, mainly due to multiple uncertainty factors (Ahmed and Hendry 2012) that shape risks in the firm-supplier relation. Uncertainty is present in demand requirements, capacity, delivery time, manufacturing time and costs (**?**).

In a previous study, data about the effectiveness of several supplier development activities in three strategic industries were collected in Mexico: aerospace, electronics and automotive (Ramos-Rangel 2015). Essentially, a multi-dimensional approach was taken for the purposes of identifying suppliers with potential for development, evaluated in terms of nine criteria. In the present paper, data collected in the Mexican case study are used to rank suppliers and to identify which ones merit being selected for improvement. SMAA-PROMETHEE is used as a multi-criteria decision analysis method since the original data are imprecise and uncertain. Based on former rankings obtained from the Multi-Dimensional Scaling technique, we use the Goal Programming method proposed by Frikha et al. (2011) to infer the PROMETHEE's indifference and preference thresholds, to be used in each industry. Next, stochastic variables are defined for weights of criteria and evaluations. Simulations are used to find the final rankings by using SMAA-PROMETHEE.

This article makes three main contributions. First, the use of PROMETHEE in the Mexican case has not been done before. Second, to the best of our knowledge this is the first application of SMAA-PROMETHEE within SDP. Third, we propose that such a method is appropriate for this kind of problem due to the nature of original data available for supplier evaluations.

The article is organized as follows. In Section 2, the SMAA-PROMETHEE method is presented. The technique for discoverying PROMETHEE II's indifference and preference thresholds is described. The application to SDP, using data from three Mexican industries, is presented in Section 3. Results are discussed in Section 4. Finally, some conclusions and some suggestions for future research are presented in Section 5.

2. Materials and methods

2.1 *PROMETHEE II*

The PROMETHEE (Preference Ranking Organisation Method for Enrichment Evaluations) method was initially introduced by Brans (1982). This is a discrete multicriteria decision analysis method that models the DM's preferences in terms of a binary aggregated relation called "outranking": for any pair of alternatives (a, b), a outranks b if a is indifferent, weakly preferred, or strictly preferred to b. Initially, PROMETHEE I was proposed to provide a partial ranking of alternatives. PROMETHEE II was then developed for whenever the decision maker (DM) asked for a complete preorder. Other versions have been developed (Brans and Mareschal 2005): PROMETHEE III generates a ranking based on intervals, PROMETHEE IV is developed to deal with a continuous set of alternatives, PROMETHEE V includes segmentation contraints and PROMETHEE VI provides a procedure for sensitivity analysis which simulates how the human brain tackles this.

Let us consider $A = \{a_1, \ldots, a_n\}$ a set of alternatives, or actions, to be compared in terms of preferences and $G = \{g_1, \ldots, g_m\}$ a set of m quantitative or qualitative criteria. In general, each criterion g_c is defined as an elaborated point of view which helps to model the DM's preferences. Thus, given a criterion $g_c \in G \quad (c \in M = \{1, \ldots, m\})$ and two alternatives a_i and $a_j \quad (i, j \in N = \{1, \ldots, n\})$, a rationality hypothesis may be assumed underlying the DM's preference model (Pomerol and Barba-Romero 2000).

Brans and Vincke (1985) proposed six different types of criterion functions, depending on the DM's preference model assumed in the process of analyzing a specific decision. In particular, the preference function of Type V, with linear preference and indifference area, enables the outranking relation to be modeled. This requires the indifference and preference thresholds q_c and p_c $(p > q)$, respectively, to be identified. If two asymmetric, irreflexive, and transitive preference relations P_c and Q_c, and a symmetric, reflexive, and non-transitive indifference relation I_c are considered, the following structure represents a pseudo-criterion (Roy 1996):

$$
\begin{aligned}
a_i I_c a_j &\Leftrightarrow |g_{ic} - g_{jc}| \leq q_c, \\
a_i Q_c a_j &\Leftrightarrow q < g_{ic} - g_{jc} \leq p_c, \\
a_i P_c a_j &\Leftrightarrow g_{ic} - g_{jc} > p_c,
\end{aligned}
\tag{1}
$$

where I_c, P_c, Q_c correspond to the indifference, strong preference and weak preference, respectively, of a_i with regard to a_j. The linear representation of this preference structure is defined in PROMETHEE as a valued outranking relation:

$$F_c(a_i, a_j) = \begin{cases} 1 & \text{if } (g_{ic} - g_{jc}) > p_c, \\ 0 & \text{if } (g_{ic} - g_{jc}) \leq q_c, \\ (g_{ic} - g_{jc} - q_c)/(p_c - q_c) & \text{otherwise.} \end{cases} \quad (2)$$

In Figure 1 this function is shown for the case where $q = 0.1$ and $p = 0.5$. Notice that any deviaton $(g_{ic} - g_{jc}) \leq q$ is evaluated as zero, which means that there is a null intensity of preference in favour of a_i, when compared to a_j in the criterion c.

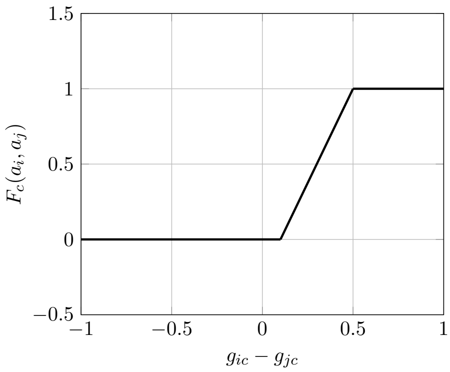

Figure 1.: PROMETHEE's preference function F_c $(q = 0.1, p = 0.5)$

In PROMETHEE, the global intensity of preference of a_i with regard to a_j, when the set of m criteria is considered, is measured by the following preference index:

$$\pi(a_i, a_j) = \sum_{c=1}^{m} w_c F_c(a_i, a_j), \quad (3)$$

where w_c is the weight of criterion c. The *outgoing flow* $\Phi^+(a_i)$ is the intensity with which a_i outranks the other alternatives at hand, whereas the *incoming flow* $\Phi^-(a_i)$ represents the intensity of outranking from other actions towards a_i. Therefore, we have

$$\Phi^+(a_i) = \sum_j \pi(a_i, a_j), \quad (4)$$

$$\Phi^-(a_i) = \sum_j \pi(a_j, a_i). \quad (5)$$

Both (4) and (5) enable the outranking relation on A to be exploited (Brans and Vincke 1985). In the case of PROMETHEE II, this leads to a global net flow defined as:

$$\Phi(a_i) = \Phi^+(a_i) - \Phi^-(a_i), \quad (6)$$

which allows a complete pre-order of actions in A to be built.

2.2 *SMAA and PROMETHEE*

Let us consider situations where a DM has an unknown or partially known preference structure, such that both the evaluations and weights of criteria are random variables with a known probability distribution. The Stochastic Multiobjective Acceptability Analysis (SMAA) is a family of MCDA methods (Lahdelmaa and Salminen 2009) where uncertain evaluations g_{ic} can be represented by stochastic variables ξ_{ic} with density functions $f_{\chi}(\xi)$ in the space $\chi \subseteq \Re^{n\times m}$. Equally, the weight space is represented by a weight distribution with a joint density function $f_W(w)$, where $W = \{w \in \Re^m : 0 \leq w \leq 1 \wedge \sum_{c=1}^{m} w_c = 1\}$.

Let $W_i^r(\xi)$ be the set of favourable weights granting that a_i ranks r. Therefore, the *rank acceptability index* is defined as

$$b_i^r = \int_{\xi\in\chi} f_{\chi}(\xi) \int_{w\in W_i^r(\xi)} f_W(w)\mathrm{d}w\mathrm{d}\xi, \tag{7}$$

where $b_i^r \in [0, 1]$. If it equals 1 then a_i is placed in rank r whatever the weights, but 0 indicates that it never reaches this rank in the selected scenarios. Applying SMAA to the classical PROMETHEE has been proposed by Corrente et al. (2014). However, our purpose is just to compute b_i^r by using a Montecarlo Simulation and a large number of iterations, thus minimizing the error margins (Tervonen and Figueira 2008). In this paper, random values for weights and evaluations are generated by using the sampling method proposed by Tervonen and Lahdelmaa (2007) to generate uniformly distributed random weights.

2.3 *Indifference and preference thresholds calculation*

PROMETHEE's indifference and preference thresholds are difficult to determine. Usually, the analyst asks the DM to provide direct information about these thresholds. However, quantifying preferences or indifference among alternatives is not an easy task and researchers have proposed using indirect methods to infer the parameter values from global information provided by the DM. Roughly speaking, inferencing consists of finding the mathematical structure which best represents the global preference statements provided by the DM (Doumpos and Zopounidis 2014). The analyst needs to assume that these statements agree with an MCDA method, which is represented by an adequate mathematical model.

An approach that seeks to elicit parameter values from preference statements that DMs make is called an *aggregation/disaggregation process*: 1) the DM is asked to provide global information about his/her preferences; 2) an MCDA method is assumed to correctly represent the DM's preferences; 3) a mathematical program is proposed to model the MCDA method applied to the DM's statements - a parameter and/or an intensity of preference among pairs of alternatives are defined as decision variables; 4) resolution of the mathematical program is integrated into an interactive approach which seeks to calibrate the mathematical model to the preference statements that the DM has made. The process finishes when a consistent model is found or no satisfactory solution is found.

Dias et al. (2002) used this approach to define an elicitation method which helped to calculate the ELECTRE TRI parameters: the DM is asked to provide classification statements, and thus assigns a subset of the alternatives at hand into pre-defined categories; then, a non-linear mathematical program is defined such that the constraints represent the assignments; solving the program yields the parameter values. In a similar manner, Kadziński et al. (2012) proposed a linear mathematical program to represent the DM's statements in terms of outranking preference relations among alternatives. Essentially, given a pair of alternatives a, b, if a outranks b for all compatible sets of additive value functions, then it is said that "a necessarily outranks b". Otherwise, if there is at least one compatible value function agreeing with the argument, "a possibly outranks b". Compatible functions are derived from the indirect preference information provided by the DM in the form of pairwise comparisons of the reference alternatives. A good summary of disaggregation/aggregation approaches in the case of UTA methods, which model utility functions assuming the MAUT axiomatic, is provided by Siskos et al. (2005). Preference elicitation for ELECTRE TRI and the Ranking Method with multiple reference Points (RMP) are explained by Zheng (2012).

In this paper, we use the aggregation/disaggregation process proposed by Frikha et al. (2011) for inferring PROMETHEE II's indifference and preference thresholds. This consists of a Goal Programming modeling technique which is based on the global preference information: 1) the DM is asked to provide a ranking on a set of alternatives; 2) it is assumed that a PROMETHEE II model correctly represents the DM's preferences regarding the alternatives; 3) the DM's ranking is disaggregated in linear constraints representing the preference relation among every pair of alternatives; 4) providing that each constraint models a goal, deviation variables are introduced to evaluate the consistency between the MCDA model and the DM's statements; 5) the objective is to minimize a linear function of the deviation variables.

Let us define the following variables:

F_{ij}^k	intensity of preference of a_i over a_j, $F_k(a_i, a_j)$, with respect to the criterion k;
d_l^+	positive deviation from goal $l \in \{1, \ldots, p\}$;
d_l^-	negative deviation from goal $l \in \{1, \ldots, p\}$;
d_{ij}^k	difference between evaluations of a_i and a_j, $g_k(a_i) - g_k(a_j)$, with respect to the criterion k;
α_l	minimum threshold required for d_l^+.

Using the expressions (3), (4), (5) and (6), it follows that

$$\Phi(a_{i_l}) = \sum_{j \neq i_l} \sum_{k=1}^{m} w_k F_{i_l j}^k - \sum_{j \neq i_l} \sum_{k=1}^{m} w_k F_{j i_l}^k, \tag{8}$$

$$\Phi(a_{j_l}) = \sum_{i \neq j_l} \sum_{k=1}^{m} w_k F_{j_l i}^k - \sum_{i \neq j_l} \sum_{k=1}^{m} w_k F_{i j_l}^k. \tag{9}$$

Therefore, if the DM provides the information "a_{i_l} is preferred to a_{j_l}" ($a_{i_l} \succ a_{j_l}$), the constraint $(\Phi(a_{i_l}) > \Phi(a_{j_l}))$ can be set. In order to define this relation as a goal, positive and negative deviation variables can be introduced such that the following equation holds: $\Phi(a_{i_l}) - \Phi(a_{j_l}) + d_l^- - d_l^+ = 0$. If this expression is consistent with the DM's preference, then $(d_l^- - d_l^+)$ should be negative. In particular, it can be satisfied in the case $d_l^- = 0$ and $d_l^+ > \alpha_l$, where α_l is a parameter strictly greater than 0.

Thus, let us assume that the DM is asked to provide information about his/her preferences in terms of global preference or indifference statements between each pair of alternatives at hand. Let $P = \{1, \ldots, p\}$ denote the set of indices regarding the DM's comparisons (preference statements). The following Goal Programing model can be proposed to model his/her expressed preferences:

$$\min \sum_{l=1}^{p} d_l^- \tag{10}$$

subject to

$$\begin{aligned}
\Phi(a_{i_l}) - \Phi(a_{j_l}) + d_l^- - d_l^+ &= 0, & \forall l \in P \quad (11)\\
F_{ij}^k &= 0, & d_{ij}^k \leq 0, i \neq j, i, j \in N, k \in M \quad (12)\\
F_{ij}^k &\leq F_{hr}^k, & d_{ij}^k \leq d_{hr}^k, i \neq j, h \neq r, i, j, h, r \in N, k \in M \quad (13)\\
F_{ij}^k &= F_{hr}^k, & d_{ij}^k = d_{hr}^k, i \neq j, h \neq r, i, j, h, r \in N, k \in M \quad (14)\\
F_{ij}^k &= 0, & d_{ij}^k \leq q_k, i \neq j, h \neq r, i, j, h, r \in N, k \in M \quad (15)\\
F_{ij}^k &= 1, & d_{ij}^k \geq p_k, i \neq j, h \neq r, i, j, h, r \in N, k \in M \quad (16)\\
d_l^+ &\geq \alpha_l & l \in P \quad (17)\\
F_{ij}^k &\in [0,1] & i, j \in N \quad (18)\\
d_l^+, d_l^- &\geq 0 & l \in P \quad (19)
\end{aligned}$$

In the model above, the expression (10) is defined as the expectation that all the negative deviations be null. Constraint (11) models the preference or indifference relation: if $(d_l^- - d_l^+)$ is negative, then $(a_{i_l} \succ a_{j_l})$; if $(d_l^- - d_l^+)$ is null, then $(a_{i_l} \sim a_{j_l})$; otherwise, the model is not consistent with the DM's preferences. Expressions (12), (13), (14) and (18) guarantee consistency with the PROMETHEE's preference function F (defined by (2)). Constraint (17) says that the minimum threshold α_l is required to correctly model the relation $(a_{i_l} \succ a_{j_l})$. The main problem consists of how to set these values. In practice, Frikha et al. (2011) propose that α_l needs to be defined in an interactive process, which seeks the upper bounds of expression (17). If the limit $\alpha_l = 0$ is reached, for some l, then it could mean that a_{i_l} is really indifferent to a_{j_l}. In such a case, the DM is asked to verify that finding.

Constraints (15) and (16) modify the original model by Frikha et al. (2011). We introduced these restrictions to explicitly set the indifference and preference thresholds. When the mathematical program has a solution, this means that the model, using these thresholds, agrees with the DM's preferences. However, it is possible that different values of q_k and p_k yield different optimal solutions of this model. In such cases, it is worth knowing what the different values could be.

An interactive process is proposed in Figure 2, thus aiding the decision analyst to identify several pairs of thresholds. The process begins with the model resolution, using the model description and input data recorded in a database. If the goal programming model has a solution, then the values (q_k, p_k) can be used as thresholds for the SMAA-PROMETHEE application. Next, new values for (p_k, q_k, α_l) can be defined that are recorded in the database (updating the mathematical model), and a new resolution step can start. On repeating this process, the decision analyst could find several feasible indifference and preference thresholds.

Eppe et al. (2011) propose a NSGA-II evolutionary multi-objective optimization method to find a stable set of parameter values. However, they restrict their algorithm to search for the weights of criteria. In this paper, weights are pre-defined (see the example in section 3). Therefore, the problem consists of finding the possible threshold values. In addition, Frikha et al. (2011) use a two-stage process where intervals for weights are first determined by using a linear program for each criterion and thereafter they propose another model with a view to reducing violations of the DM's preferences. In our case, we inspect the threshold values using the single linear programming model (10)-(19) embedded in the interactive process depicted in Figure 2.

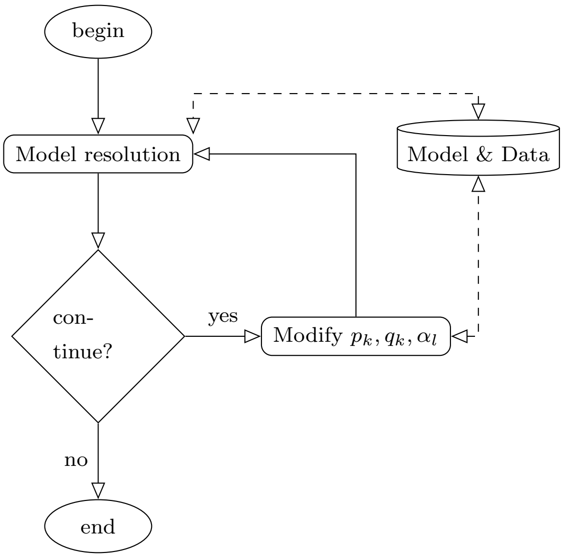

Figure 2.: Interactive process used to define q_k, p_k

3. Application

3.1 *Description of the problem*

In a previous study applied in Mexico, data were collected on the experiences with suppliers in three industries (Ramos-Rangel 2015): aerospace, electronics, automotive. The data collected were intended to provide insights about the contents of development programs for developing regional suppliers. Critical informants in each of the industries provided information about conflicting criteria used to evaluate suppliers. The criteria were validated by undertaking a literature review and confirmed by participant buyers.

Two issues can be mentioned about this data. First, a common ordinal scale from 0 ("minimum acceptable level") to 10 ("best achievable level") was used to evaluate suppliers on different dimensions. Although this is a rating scale, it is difficult to validate that a common evaluation (e.g., 7.5) could reflect the same group of reasons, objectives or values system for two different buyers. As a consequence, it seems appropriate to think that some vagueness appeared in evaluations that were very close to each other (e.g., 8.77 and 9.07 on criterion g_3 in Table 3a, below). Under these conditions, aggregating heterogeneous features should transfer imprecision from detailed to aggregated criteria.

Second, suppliers were evaluated by different buyers, in different places and at different times, and the same buyer could evaluate different suppliers. The dimensions and criteria proposed for evaluation asked the buyer to express an opinion about his/her knowledge concerning, for instance, the reliability of the supplies or post-sales service, as to whether they represent the real "future behaviour" of a supplier. In addition, different buyers needed to evaluate suppliers in terms of a complex criterion (e.g., product quality), by aggregating dimensions that included concepts which in this context could not be easily understood (e.g., quality system). Therefore, both imprecision and uncertainty were present, caused by evaluation scales, data procedures and changing evaluation conditions (Roy 1989). SMAA-PROMETHEE is a method adapted to these sort of problems and can be applied to dealing with these two types of poor information. To the best of our knowledge, this is the first time that this method is used on the SDP domain.

Let us consider $S = \{s_1, \ldots, s_n\}$ and $F = \{g_1, g_2, \ldots, g_m\}$, a set of suppliers and a family of criteria that help to evaluate every $s \in S$, respectively. The family of criteria corresponds to that defined in the original survey, which is shown in Table 1. Dimensions that help to elaborate each criterion are also mentioned in the Table.

In the former study, the criteria weights were determined by using the AHP technique (Ramos-Rangel 2015), because of the structure of dimensions and criteria is hierarchic. Punctual evaluations were considered. Here, however, we consider that weights come from uniform distributions, thereby restricting the generation of random numbers to the set of points $W = \{w \in \Re^m : 0 \leq w \leq 1 \wedge \sum_{c=1}^{m} w_c = 1\}$. It is assumed that the DM's preferences need to be considered. Therefore, the relative importance among criteria is preserved and restricted weights on the family of criteria are modeled as a set of linear constraints.

Table 1.: Family of criteria

Code	Description	Dimensions
g_1	product price	price
g_2	product quality	failures and rejections, quality system
g_3	reliability of the supplies	incompleted and delayed deliveries
g_4	technological development	product, process and supporting technology
g_5	post-sales service	product guarantees and responsiveness
g_6	organizational culture	trustness, organizational relationships and committment on changements
g_7	financial capability	assets/liabilities and sales/utilities ratios
g_8	risk management process	risk management
g_9	position in industry	client and supplier base, and credentials

In Table 2 the original weights of criteria in each industry, as obtained by Ramos-Rangel (2015), are shown. Some entries equal zero (e.g., g_6 in Electronics). This means that the respective criterion was considered unimportant by the group of decision makers (buyers) in that industry.

Table 2.: Weights of criteria in each industry

Code	Electronics	Automotive	Aerospace
g_1	0.2316	0.2154	0.1640
g_2	0.2282	0.1871	0.2800
g_3	0.1795	0.1616	0.2070
g_4	0.0803	0.0500	0.1090
g_5	0.0932	0.1113	0.1090
g_6	0.0000	0.1275	0.0000
g_7	0.1146	0.0884	0.0160
g_8	0.0726	0.0075	0.1100
g_9	0.0000	0.0514	0.0000

The supplier evaluations per industry, obtained in the previous study, are presented in Tables 3a, 3b and 3c. Notice that three fictitious suppliers appear in each industry: the ideal a_i, e_i, v_i; the anti-ideal a_a, e_a, v_a; and the one having the mean value on the scale of each criterion, a_m, e_m, v_m.

These alternatives were introduced in the original study to apply the Multi-Dimensional Scaling technique, which requires two reference points: the ideal and the anti-ideal. We preserve these fictitious actions so as not to alter the original data.

The evaluation scores are such that the best value is attained in 10 and the worst in 0. For instance, in the criterion g_1, an evaluation of 10 means that a supplier proposes a product price that is considered highly convenient by buyers in the industry. On the other hand, a supplier having a score near 0 in g_2 means that, without development, a supplier would continue to provide products of very low quality.

3.2 *Applying SMAA-PROMETHEE*

In what follows, it is assumed that evaluations and criteria weights come from independent uniform probability distributions. In order to generate random supplier evaluations (using the SMAA approach proposed in Section 2.2), on each evaluation matrix and column, the following process is applied:

- Given an industry evaluation matrix, normalize evaluations onto the interval $[0, 1]$.
- For each criterion g_j, calculate the minimum difference value between alternatives, $prec_j$.
- Let x_j denote the vector of n supplier evaluations on criterion g_j.
- Let x_j^- denote a new vector obtained as the abtement of each component of $x_{kj}(k = 1, \ldots, n)$ by the value $prec_j$.
- Generate a random vector x_k with components $x_{kj} = x_{kj}^- + e_{kj}$, where $\{e_{1j}, e_{2j}, \ldots, e_{nj}\}$ is a series of random numbers generated using Algorithm 1.

Algorithm 1 has been adapted from the one proposed by Tervonen and Lahdelmaa (2007). $RAND(0, n * prec_j)$ is a function generating a random number uniformly distributed in the interval $[0, n * prec_j]$, and $SORT(q_k)$ is a function ordering in ascending order the numbers q_k. For each criterion g_j, the proposed procedure generates random numbers satisfying the constraints $\sum_{k=1}^{n} x_{kj} = 1, x_{kj} \geq x_{kj}^-$.

for $k \leftarrow 1$ **to** $n - 1$ **do**
| $q_k \leftarrow RAND(0, n * prec_j)$;
end
$SORT(q_k)$; $q_0 \leftarrow 0$; $q_n \leftarrow 1$; **for** $k \leftarrow 1$ **to** n **do**
| $e_{kj} \leftarrow q_k - q_{k-1}$
end

Algorithm 1: Generation of uniformly distributed random numbers

This guarantees that evaluations on each criterion preserve the pre-order among alternatives, as observed in the original data on supplier evaluations, while allowing variability in scores. Notice that this procedure and Algorithm 1 can be also adapted to calculate uniformly distributed random weights.

Next, in order to apply SMAA-PROMETHEE the indifference and preference thresholds must be defined with the help of a decision maker. However, the DMs that participated in the original study are no longer available. Instead, we have a global preference relation for each industry, expressed as a pre-order obtained by applying the Multi-Dimensional Scaling (MDS) technique. This is a dimension-reduction technique that allows the generation of a perceptual map that describes the competitive position of each supplier graphically. Indeed, MDS starts with a $n \times n$ matrix of dissimilarities between each pair of vectors (rows in the respective evaluation matrix). Next, the purpose consists of finding n points in the lowest dimensional coordinate system (typically from 1 to 3 dimensions), such that the distances (usually Euclidean) between the points in the low-dimensional space closely match the original distances.

Table 3.: Evaluations of suppliers in three Mexican industries (source: (Ramos-Rangel 2015))

(a) Aerospace

Supplier	g_1	g_2	g_3	g_4	g_5	g_7	g_8
s_1	8.00	8.82	4.00	9.68	0.00	9.36	3.75
s_2	8.00	10.00	8.46	9.84	8.81	8.64	8.00
s_3	8.00	10.00	10.00	9.84	8.81	7.27	7.51
s_4	4.00	6.94	8.46	8.38	5.19	10.00	6.00
s_5	8.00	9.18	10.00	9.00	10.00	10.00	8.00
s_6	7.50	8.29	9.07	9.47	9.19	10.00	8.00
s_7	7.00	9.41	10.00	10.00	10.00	10.00	10.00
s_8	7.50	9.41	10.00	9.84	10.00	10.00	10.00
s_9	8.00	9.41	5.37	9.68	9.19	8.00	9.75
s_{10}	8.00	8.00	9.00	8.54	6.38	8.64	6.00
s_{11}	8.00	10.00	10.00	10.00	8.81	8.00	8.00
s_{12}	6.00	8.00	8.77	7.84	7.19	8.64	6.00
s_i	10.00	10.00	10.00	10.00	10.00	10.00	10.00
s_a	0.00	0.00	0.00	0.00	0.00	0.00	0.00
s_m	5.00	5.00	5.00	5.00	5.00	5.00	5.00

(b) Electronics

Supplier	g_1	g_2	g_3	g_4	g_5	g_7	g_8
e_1	10.00	10.00	10.00	10.00	10.00	10.00	10.00
e_2	10.00	6.55	10.00	8.53	8.86	8.94	8.00
e_3	6.00	2.55	5.64	8.13	4.56	6.82	2.00
e_4	4.00	8.55	6.55	3.20	10.00	8.94	8.00
e_5	6.00	10.00	8.55	4.95	10.00	10.00	8.00
e_6	10.00	8.55	8.55	8.80	9.14	8.94	10.00
e_7	8.00	6.55	7.09	8.00	7.14	8.94	8.00
e_8	8.00	8.00	8.55	8.00	8.00	8.94	8.00
e_9	8.00	6.00	8.55	7.33	8.00	8.94	6.00
e_i	10.00	10.00	10.00	10.00	10.00	10.00	10.00
e_a	0.00	0.00	0.00	0.00	0.00	0.00	0.00
e_m	5.00	5.00	5.00	5.00	5.00	5.00	5.00

(c) Automotive

Supplier	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9
v_1	8.00	6.00	8.00	7.70	9.05	10.00	8.00	8.00	6.57
v_2	10.00	6.00	9.16	7.70	8.00	8.00	7.11	8.00	8.00
v_3	10.00	9.48	7.58	10.00	10.00	10.00	10.00	10.00	10.00
v_4	4.00	8.52	8.00	9.50	8.00	8.59	8.89	10.00	8.79
v_5	8.00	8.52	7.58	6.81	6.00	8.79	8.00	6.00	8.79
v_6	6.00	8.52	9.58	10.00	7.90	8.08	8.89	6.00	8.79
v_7	10.00	10.00	8.00	7.50	10.00	10.00	10.00	8.97	10.00
v_8	8.00	6.00	6.00	6.30	8.95	8.79	6.00	6.00	6.79
v_9	8.00	10.00	7.58	8.69	10.00	10.00	10.00	8.97	10.00
v_{10}	8.00	8.52	10.00	9.19	10.00	9.49	8.89	8.00	8.79
v_{11}	4.00	6.00	7.58	6.89	6.95	8.28	7.78	6.00	5.43
v_{12}	8.00	8.52	10.00	9.70	10.00	9.49	8.89	10.00	8.79
v_{13}	8.00	8.52	9.58	8.81	8.95	8.79	10.00	6.00	10.00
v_{14}	10.00	10.00	10.00	8.81	8.95	8.79	10.00	6.00	8.00
v_{15}	8.00	10.00	10.00	8.30	10.00	8.79	10.00	6.00	8.00
v_i	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
v_a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
v_m	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00

In Table 4 the three rankings obtained with MDS, which does not take either imprecision or uncertainty into account, are shown.

Following the process described in Section 2.3, each one of these rankings has been modeled as a mathematical program. A systematic procedure for finding the threshold values that agree with the respective initial rankings has been defined as follows:

Table 4.: Rankings on the three industries, obtained by Ramos-Rangel (2015)

Industry	MDS ranking
Aerospace	$s_i \succ s_{11} \succ s_3 \succ s_8 \succ s_7 \succ s_2 \succ s_5 \succ s_6 \succ s_9 \succ s_{10} \succ s_4 \succ s_1 \succ s_m \succ s_a$
Electronics	$e_i \succ e_1 \succ e_6 \succ e_2 \succ e_8 \succ e_5 \succ e_9 \succ e_7 \succ e_4 \succ e_3 \succ e_m \succ e_a$
Automotive	$v_i \succ v_{14} \succ v_7 \succ v_3 \succ s_{15} \succ v_{12} \succ v_{10} \succ v_9 \succ v_{13} \succ v_5 \succ v_2 \succ v_1 \succ v_6 \succ v_8 \succ v_4 \succ v_{11} \succ v_m \succ v_a$

(1) Model an MDS ranking as a mathematical program, using equations (10)-(19).
(2) For each $q_k = \{0, 1, 2, 3\}$:
   (a) Search for the minimum p_k such that (10) is minimized, i.e., $d_l^- = 0, \forall l \in P$.
   (b) If $(\exists l | d_l^+ = \alpha_l)$ and Equation l represents a preference relation ($\succ$), reduce α_l and go to Step 2a.

Step 2 in this procedure searches for a p_k value taking into account the fact that some d_l^+ could really be less than α_l. Providing that the mathematical program has a solution, this means that if $\alpha_l = 0$ the DM's preference statement from type $\succ$, modeled by Equation l, could be violated. In practice, this occurs and can be interpreted as meaning that the original ranking obtained by using MDS is not necessarily consistent with the PROMETHEE II method. We discuss this below.

Given that the evaluation scale is defined as $[0, 10]$, it has been considered that an indifference threshold cannot be greater than or equal to 3, approximately 30% of the scale interval (Eppe et al. (2011) chose a maximum preference threshold of 10%). Values of indifference are arbitrarily chosen in the set $\{0, 1, 2, 3\}$, but experiments with these models show that there is not a great difference when intermediate values (e.g., 0.5 or 2.3) are defined.

In order to find the preference thresholds, given the q_k values, the model resolution process were run iteratively. Results show that q_k and p_k vary slightly among criteria, when an MDS model is solved. Consequently, a set of single pairs of threshold values was defined to run SMAA-PROMETHEE. In Table 5 each pair (q_k, p_k) allows the resolution of its respective model, with the result $d_l^- = 0, \forall l \in P$.

Table 5.: Pairs of threshold values chosen for running SMAA-PROMETHEE

Industry	(q_k, p_k)
Aerospace	$\{(0, 2.1), (1, 2.5), (2, 3.7), (3, 4.1)\}$
Electronics	$\{(0, 2.9), (1, 2.9), (2, 4.1), (3, 5.1)\}$
Automotive	$\{(0, 1.2), (1, 1.8), (2, 3.1), (3, 3.2)\}$

4. Results

Tables 6a, 6b and 6c show the results of simulations after calculating the acceptability index for each supplier (see Section 2.2) and assigning a rank position; 100.000 iterations are run for each case (industry) and pair of thresholds. In these Tables, the 0 code represents the best position. Thus, the higher the rank, the worse an alternative. The rank position obtained by a supplier, according to the MDS, is also shown.

To construct each pre-order, the following rule is considered: if the acceptability index for a given rank is greater than or equal to the lower threshold of 70%, that position is reported; if not, the most probable rank positions are obtained by adding up the adjacent acceptability indices until the lower threshold has been exceeded. In such cases, two or more probable rank positions are reported. For instance, in Table 6a, when $(q_k, p_k) = (0, 2.1)$, supplier s_1 probably has the rank positions 10 or 11. Instead, if $(q_k, p_k) = (1, 2.5)$, this supplier has rank 11. Although the ideal supplier (s_i, e_i, v_i) appears in first place and the anti-ideal (s_a, e_a, v_a) in the last position, in the Electronics industry, the ideal appears in first or second position because supplier e_1 has the highest evaluations (see

Table 6.: Ranking of suppliers using SMAA-PROMETHEE

(a) Aerospace

Supplier	$(0, 2.1)$	$(1, 2.5)$	$(2, 3.7)$	$(3, 4.1)$	MDS
s_1	10,11	11	12	12	12
s_2	6	5,6	4,5	6	5
s_3	3,4,5	4,5,6	6,7	4,5	2
s_4	12	12	11	11	11
s_5	5,6	4,5,6	3,4,5	4,5	6
s_6	8	7	6,7	7	7
s_7	2,3,4	1,2,3	1,2,3	1,2	4
s_8	1,2	1,2	1,2	1,2	3
s_9	7	8	10	9,10	8
s_{10}	9	9	8	8	9
s_{11}	1,2,3	2,3,4	3,4,5	3,4	1
s_{12}	10,11	10	9,10	9,10	10
s_i	0	0	0	0	0
s_a	14	14	14	14	14
s_m	13	13	13	13	13

(b) Electronics

Supplier	$(0, 1.2)$	$(1, 1.8)$	$(2, 3.1)$	$(3, 3.2)$	MDS
e_1	0,1	0,1	0,1	0,1	1
e_2	2,3	3	3,4	3,4	3
e_3	9	9	9	9	9
e_4	7,8	8	8	8	8
e_5	3,4	5,6	5,6	5,6	5
e_6	2	2	2	2	2
e_7	6,7	6,7	6,7	6,7	7
e_8	5	4,5	3,4	3,4	4
e_9	6,7	6,7	6,7	6,7	6
e_i	0,1	0,1	0,1	0,1	0
e_a	11	11	11	11	11
e_m	10	10	10	9,10	10

(c) Automotive

Supplier	$(0, 2.9)$	$(1, 2.9)$	$(2, 4.1)$	$(3, 5.1)$	MDS
v_1	11,12	12,13	11,12	11,12	11
v_2	9,10	9,10	9,10	9,10	10
v_3	1,2,3	2,3,4	2,3,4	1,2,3,4	3
v_4	12,13	12,13	13	14	14
v_5	11,12,13	10,11,12	10,11,12	10,11	9
v_6	9,10	9,10	9,10	11,12	12
v_7	1,2,3	2,3,4	1,2,3	1,2,3	2
v_8	14	14	14	13	13
v_9	5,6,7	6,7,8	6,7,8	4,5,6	7
v_{10}	5,6,7,8	5,6,7,8	6,7,8	6,7,8	6
v_{11}	15	15	15	15	15
v_{12}	5,6,7	4,5,6,7	5,6,7	6,7,8	5
v_{13}	7,8	6,7,8	6,7,8	6,7,8	8
v_{14}	1,2,3	1,2	1,2	1,2,3	1
v_{15}	4,5,6	3,4,5,6	3,4,5,6	4,5,6	4
v_i	0	0	0	0,1	0
v_a	17	17	17	17	17
v_m	16	16	16	16	16

Table 3b).

The average ranking for each industry and pair (q_k, p_k) is presented in Tables 8a, 8b and 8c. It is calculated as follows: given a pair (q_k, p_k), the average ranking is defined as $\sum_{t=1}^{\rho} r_{it}/\rho$, where r_{it} is the rank position of the alternative i in the t-th ranking and ρ is the number of different rank positions obtained by the alternative. For instance, when considering the Aerospace results and $(0, 2.1)$, the average ranking of s_3 is given by $(3 + 4 + 5)/3 = 4$.

Computing Spearman's rank correlation coefficient shows that a monotonic relationship exists between every PROMETHEE average ranking and its respective MDS pre-order (see tables (7a), (7b) and (7c)). Only the upper triangular part of the correlation matrix is shown, because of symmetry. All correlation coefficients are highly significant (.01% bilateral significance level).

Table 7.: Spearman's Rank-Order correlation between rankings

(a) Aerospace

Supplier	$(0, 2.1)$	$(1, 2.5)$	$(2, 3.7)$	$(3, 4.1)$	MDS
$(0, 2.1)$	1.000	.991	.945	.970	.969
$(1, 2.5)$		1.000	.974	.989	.958
$(2, 3.7)$			1.000	.987	.916
$(3, 4.1)$				1.000	.954

(b) Electronics

Supplier	$(0, 1.2)$	$(1, 1.8)$	$(2, 3.1)$	$(3, 3.2)$	MDS
$(0, 1.2)$	1.000	.993	.988	.988	.989
$(1, 1.8)$		1.000	.998	.998	.996
$(2, 3.1)$			1.000	1.000	.995
$(3, 3.2)$				1.000	.995

(c) Automotive

Supplier	$(0, 2.9)$	$(1, 2.9)$	$(2, 4.1)$	$(3, 5.1)$	MDS
$(0, 2.9)$	1.000	.989	.992	.983	.976
$(1, 2.9)$		1.000	.997	.974	.982
$(2, 4.1)$			1.000	.981	.984
$(3, 5.1)$				1.000	.984

Although the average rankings of SMAA-PROMETHEE are strongly correlated with the MDS rankings, recommendations to the DMs could be different in each case. Ramos-Rangel (2015) proposed an approach to identify suppliers who merited being developed, based on the ranking result produced by the MDS. The main idea was that best suppliers have their own tools and are able to improve themselves, while a lot of financial resources and time would need to be set aside to develop the worst suppliers. In order to define these groups, a competitiveness level was defined as the inverse of the relative distance from a supplier to the ideal. Thus, suppliers at or above the 85% level of competitiveness were defined as the best ones and those under a level of 70% were discarded.

The ranking positions selected for development in the three industries were as follows: Aerospace (ranks 7 to 10), Electronics (ranks 3 to 7) and Automotive (ranks 10 to 13). If we compare these limits with the SMAA-PROMETHEE results, the following is observed:

- In Table 6a, alternatives s_1 and s_3 appear once in position 10 and 7, respectively. Supplier s_{12} appears once in position 11.
- In Table 6b, e_2 and e_4 appear in position 2 and 7, respectively.
- In Table 6c, v_2 and v_6 appear four and three times, respectively, in position 9. Suppliers v_4 and v_8 appear once and three times, respectively, in position 14.

Given that development activities involve a lot of economic and time resources, which of these suppliers should be included in the group to be selected should be reviewed before the final selection is made. Notice that by analyzing these cases, the limits that help to distinguish the three alternative classes (best suppliers, the ones meriting development and the worst suppliers) could also be reviewed.

From another point of view, it is interesting to observe how the ranking positions vary among methods. For instance, in Table 8a, MDS and SMAA-PROMETHEE give different positions for $s_2, s_3, s_5, s_7, s_8, s_{11}$. A similar fact is observed in Table 6c where two or more SMAA-PROMETHEE

Table 8.: Average ranking of suppliers

(a) Aerospace

Supplier	$(0, 2.1)$	$(1, 2.5)$	$(2, 3.7)$	$(3, 4.1)$	MDS
s_1	10.5	11	12	12	12
s_2	6	5.5	4.5	6	5
s_3	4	5	6.5	4.5	2
s_4	12	12	11	11	11
s_5	5.5	5	4	4.5	6
s_6	8	7	6.5	7	7
s_7	3	2	2	1.5	4
s_8	1.5	1.5	1.5	1.5	3
s_9	7	8	10	9.5	8
s_{10}	9	9	8	8	9
s_{11}	2	3	4	3.5	1
s_{12}	10.5	10	9.5	9.5	10
s_i	0	0	0	0	0
s_a	14	14	14	14	14
s_m	13	13	13	13	13

(b) Electronics

Supplier	$(0, 1.2)$	$(1, 1.8)$	$(2, 3.1)$	$(3, 3.2)$	MDS
e_1	0.5	0.5	0.5	0.5	1
e_2	2.5	3	3.5	3.5	3
e_3	9	9	9	9	9
e_4	7.5	8	8	8	8
e_5	3.5	5.5	5.5	5.5	5
e_6	2	2	2	2	2
e_7	6.5	6.5	6.5	6.5	7
e_8	5	4.5	3.5	3.5	4
e_9	6.5	6.5	6.5	6.5	6
e_i	0.5	0.5	0.5	0.5	0
e_a	11	11	11	11	11
e_m	10	10	10	9.5	10

(c) Automotive

Supplier	$(0, 2.9)$	$(1, 2.9)$	$(2, 4.1)$	$(3, 5.1)$	MDS
v_1	11.5	12.5	11.5	11.5	11
v_2	9.5	9.5	9.5	9.5	10
v_3	2	3	3	2.5	3
v_4	12.5	12.5	13	14	14
v_5	12	11	11	10.5	9
v_6	9.5	9.5	9.5	11.5	12
v_7	2	3	2	2	2
v_8	14	14	14	13	13
v_9	6	7	7	5	7
v_{10}	6.5	6.5	7	7	6
v_{11}	15	15	15	15	15
v_{12}	6	5.5	6	7	5
v_{13}	7.5	7	7	7	8
v_{14}	2	1.5	1.5	2	1
v_{15}	5	4.5	4.5	5	4
v_i	0	0	0	0.5	0
v_a	17	17	17	17	17
v_m	16	16	16	16	16

rankings differ from the MDS result: $v_2, v_4, v_5, v_6, v_8, v_9, v_{10}, v_{12}, v_{14}$ and v_{15}. In addition, on observing the average rankings, note that there are several ties, depending on the pair (q_k, p_k):

- Aerospace:
  $(0, 2.1)$: (s_1, s_{12}),
  $(1, 2.5)$: (s_3, s_5),

$(2, 3.7)$: (s_3, s_6), (s_5, s_{11}),
$(3, 4.1)$: (s_3, s_5), (s_7, s_8), (s_9, s_{12}).

- Electronics:
  $(0, 1.2)$: (e_1, e_i), (e_7, e_9),
  $(1, 1.8)$: (e_1, e_i), (e_7, e_9),
  $(2, 3.1)$: (e_1, e_i), (e_2, e_8), (e_7, e_9),
  $(3, 3.2)$: (e_1, e_i), (e_2, e_8), (e_7, e_9).
- Automotive:
  $(0, 2.9)$: (v_2, v_6), (v_3, v_7, v_{14}), (v_9, v_{12}),
  $(1, 2.9)$: (v_1, v_4), (v_2, v_6), (v_3, v_7), (v_9, v_{13}),
  $(2, 4.1)$: (v_2, v_6), (v_9, v_{10}, v_{13}),
  $(3, 5.1)$: (v_1, v_6), (v_7, v_{14}), (v_9, v_{15}), (v_{10}, v_{12}, v_{13}).

This information is valuable. Ties, for example, could help to identify groups of suppliers meriting the same kind of development activities. Difficult or imprecise assignments into the "development" class could be analyzed and solved by showing more detailed and precise information (e.g., detailed evaluations on specific criteria). Imprecise ranking could also help to identify what criteria make a supplier appear in different ranking positions. New recommendations can emerge from richer information, which could indicate to DMs whether or not to analyze different situations in more detail.

5. Conclusions

In different industries, success strongly relies on supplier development. Once a base of suppliers is selected, buyers need which suppliers to improve, which we call here the *supplier development problem* (SDP). In this article we have formulated the SDP as an MCDA problem and applied SMAA-PROMETHEE to rank a set of suppliers for development, based on data collected on three Mexican industries: aerospace, automotive and electronics.

In the application, PROMETHEE's indifference and preference parameters have been inferred by using a Goal Programming approach, based on the ranking information provided by a previous deterministic analysis, and four pairs of values have been selected in each industry. Accordingly, four rankings have been produced and compared to the former result, in each case. Results show that SMAA-PROMETHEE rankings are strongly correlated with the respective deterministic ranking. However, when detailed analysis is done, new information is provided by our approach, which could help DMs to better exploit the available outcomes.

Actually, SMAA-PROMETHEE is justified when both imprecision and uncertainty are present in a domain. In the context of this paper, we have verified these conditions, which are caused because use is made of evaluation scales, data procedures and the DM's preferences unconscious misinterpretation of the meaning and importance of each criterion. Although it could be argued that this is a consequence of the data collection methodology, we think that the information elicited from buyers is rarely precise and certain. Taking this situation into account helps to identify conclusions that could be weakly sustained, thereby encouraging the decision analyst and the DMs to jointly explore the reasons for this. In this application, we have shown that SMAA-PROMETHEE revealed that some preference relations, found by using a deterministic procedure, need to be reviewed.

Usage of SMAA-PROMETHEE in the SDP domain (and similarly in the SESP problem) brings different challenges for future research and applications. First, as presented in the literature review, most applications use AHP/ANP and TOPSIS for selecting or classifying suppliers. We think that this is due to the fact that implementation of these techniques is straighforward and because the respective softwares already exist. As part of our research, an SMAA-PROMETHEE prototype software has been developed, which helps to generate random evaluations and criteria weights by considering uniformly distributed random variables. Indeed, future work is needed to provide other probability distributions. Second, the indifference and preference thresholds in PROMETHEE are difficult to elicit from DMs. We have implemented a modified version of the Frikha et al. (2011) procedure to tackle this problem. However, additional research is intended in order to simplify and automatize this process. Third, most real problems in SDP regard sorting processes that help to identify suppliers who merit different improvement treatments. Given that information in this domain can be imprecise and uncertain, MCDA strategies considering SMAA and sorting methods (e.g., PROMSORT) should be very promising.

References

References

Abdullah, R., M. Keshavlall, and K. Tatsuo (2008). Supplier development framework in the Malaysian automotive industry: Proton's experience. *International Journal of Economics and Management 2*(1), 29–58.

Ahmed, M. and L. Hendry (2012). Supplier development literature review and key future research areas. *International Journal of Engineering and Technology Innovation 2*(4), 293–303.

Araújo, M., L. Alencar, and J. Viana (2015). Structuring a model for supplier selection. *Management Research Review 38*(11), 1213–1232.

Araz, C., P. Ozfirat, and I. Ozkarahan (2007). An integrated multicriteria decision-making methodology for outsourcing management. *Computers & Operations Research* (34), 3738–3756.

Araz, C. and I. Ozkarahan (2007). Supplier evaluation and management system for strategic sourcing based on a new multicriteria sorting procedure. *International Journal of Production Economics* (106), 585–606.

Brans, J. (1982). *L'ingénierie de la décision: élaboration d'instruments d'aide à la décision. La méthode PROMETHÉE.* Presses de l'Université Laval.

Brans, J. and B. Mareschal (2005). *Multiple Criteria Decision Analysis: State of the Art Surveys*, Volume 78 of *International Series in Operations Research & Management Science*, Chapter PROMETHEE Methods, pp. 163–196. New York: Springer.

Brans, J. and P. Vincke (1985). A preference ranking organisation method: (the PROMETHEE method for multiple criteria decision-making). *Management Science 31*(6), 647–656.

Chai, J., J. Liu, and E. Ngai (2013). Application of decision-making techniques in supplier selection: A systematic review of literature. *Expert Systems with Applications* (40), 3872–3885.

Chen, C., P.-F. Pai, and W.-Z. Hung (2010). An integrated methodology using linguistic PROMETHEE and Maximum Deviation Method for third-party logistics supplier selection. *International Journal of Computational Intelligence Systems 3*(4), 438–451.

Chen, Y., T. Wang, and C. Wu (2011). Strategic decisions using the fuzzy PROMETHEE for IS outsourcing. *Expert Systems with Applications 38*(10), 13216–13222.

Corrente, S., J. Figueira, and S. Greco (2014). The SMAA-PROMETHEE method. *European Journal of Operational Research 239*(2), 514–522.

Dias, L., V. Mousseau, J. Figueira, and J. Clímaco (2002). An aggregation/disaggregation approach to obtain robust conclusions with ELECTRE TRI. *European Journal of Operational Research 138*(2), 332–348.

Doumpos, M. and C. Zopounidis (2014). *Optimization in Science and Engineering: In Honor of the 60th Birthday of Panos M. Pardalos*, Chapter The Robustness Concern in Preference Disaggregation Approaches for Decision Aiding: An Overview, pp. 157–177. Springer.

Dulmin, R. and V. Mininno (2003). Supplier selection using a multi-criteria decision aid method. *Journal of Purchasing & Supply Management* (9), 177–187.

Eppe, S., Y. De Smet, and T. Stützle (2011). A bi-objective optimization model to eliciting decision maker's preferences for the PROMETHEE II method. In R. Brafman, F. Roberts, and A. Tsoukias (Eds.), *ADT'11 Proceedings of the Second international conference on Algorithmic Decision Theory*, Volume 6992 of *Lecture Notes in Computer Science*, pp. 56–66.

Frikha, H., H. Chabchoub, and J.-M. Martel (2011). An interactive disaggregation approach inferring the indifference and the preference thresholds of PROMETHEE II. *International Journal of Multicriteria*

Decision Making 1(4), 365–393.
Hartley, J. and T. Choi (1996). Supplier development: Customers as a catalyst of process change. *Business Horizons July-August*, 37–44.
Ho, W., X. Xu, and P. Dey (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research* (202), 16–24.
Kadziński, M., S. Grecco, and R. Slowinski (2012). Selection of a representative set of parameters for robust ordinal regression outranking methods. *Computers & Operations Research* (39), 2500–2519.
Krause, D. and L. Ellram (1997). Success factors in supplier development. *International Journal of Physical Distribution & Logistics Manageme nt 27*(1), 39–52.
Krause, D., R. Handfield, and T. Scanell (1998). An empirical investigation of supplier development: reactive and strategic processes. *Journal of Operations Management* (17), 39–58.
Lahdelmaa, R. and P. Salminen (2009). Prospect Theory and Stochastic Multicriteria Acceptability Analysis (SMAA). *Omega* (37), 961–971.
Lukhoba, E. and W. Muturi (2015). Effect of supplier development on supplier performance: a survey of food manufacturing companies in Kisumu county. *International Journal of Economics, Commerce and Management III*(11), 1146–1159.
Noshad, K. (2013). *A multi - criteria framework for Supplier Quality Development.* Ph. D. thesis, Concordia Institute for Information Systems Engineering (CIISE), Concordia University.
Omurca, S. (2013). An intelligent supplier evaluation, selection and development system. *Applied Soft Computing* (13), 690–697.
Onesime, O., X. Xu, and D. Zhan (2004). A decision support system for supplier selection process. *International Journal of Information Technology & Decision Making 3*(3), 453–470.
Osiro, L., F. Lima-Junior, and L. Carpinetti (2014). A fuzzy logic approach to supplier evaluation for development. *International Journal of Production Economics* (153), 95–112.
Pomerol, J.-C. and S. Barba-Romero (2000). *Multicriterion Decision in Management: principles and practices.* Boston: Kluwer.
Ramos-Rangel, J. A. (2015). *Evaluation of strategic suppliers in Mexico.* PhD Thesis, industrial Engineering Graduate Program, Tecnologico de Monterrey, Campus Toluca.
Rezaei, J. and R. Ortt (2013). Multi-criteria supplier segmentation using a fuzzy preference relations based on AHP. *European Journal of Operational Research* (225), 75–84.
Rezaei, J., J. Wang, and L. Tavasszy (2015). Linking supplier development to supplier segmentation using Best Worst Method. *Expert Systems With Applications* (42), 9152–9164.
Roy, B. (1989). Main sources of inaccurate determination, uncertainty and imprecision in decision models. *Mathematical and Computer Modelling 12*(10-11), 1245–1254.
Roy, B. (1996). *Multicriteria methodology for decision aiding.* Dordrecht: Kluwer Academic Publishers.
Sepúlveda, J., I. Derpich, and J. Bull (2014, November). Determining supplier management strategy by multicriteria analysis. In *10th International Conference on Modeling, Optimization and Simulation*, Nancy, France.
Shirinfar, M. and H. Haleh (2011). Supplier selection and evaluation by fuzzy multi-criteria decision making methodology. *International Journal of Industrial Engineering & Production Research 22*(4), 271–280.
Siskos, Y., E. Grigoroudis, and N. Matsatsinis (2005). *Multiple Criteria Decision Analysis: State of the Art Surveys*, Volume 78 of *International Series in Operations Research & Management Science*, Chapter UTA methods, pp. 297–334. Springer.
Tervonen, T. and J. Figueira (2008). A survey on Stochastic Multicriteria Acceptability Analysis Methods. *Journal of Multi-Criteria Decision Analysis* (15), 1–14.
Tervonen, T. and R. Lahdelmaa (2007). Implementing Stochastic Multicriteria Acceptability Analysis. *European Journal of Operational Research* (178), 500–513.
Tsui, C.-W., G. Tzeng, and U.-P. Wen (2015). A hybrid MCDM approach for improving the performance of green suppliers in the TFT-LCD industry. *International Journal of Production Research 53*(21), 6436–6454.
Tuzkaya, G., D. Ozgen, A. amd Ozgen, and U. Tuzkaya (2009). Environmental performance evaluation of suppliers: A hybrid fuzzy multi-criteria decision approach. *International Journal of Environmental Science and Technology 6*(3), 477–490.
Yildiz, A. and Y. Yayla (2015). Multi-criteria decision-making methods for supplier selection: A literature review. *South African Journal of Industrial Engineering 26*(2).

Zheng, J. (2012). *Élicitation des Préférences pour des Modèles d'Agregation basés s ur des Points de Référence: Algorithmes et Procédures.* Ph. D. thesis, École Centrale de Paris.