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Modeling synergies in multi-criteria supplier selection and order allocation: An application to commodity trading

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ABSTRACT

We propose a novel meta-approach to support collaborative multi-objective supplier selection and order allocation (SSOA) decisions by integrating multi-criteria decision analysis and linear programming (LP). The proposed model accounts for suppliers' performance synergy effects within a hierarchical decision structure. It incorporates both heterogeneous objective data and subjective judgments of the decision makers (DMs) representing various groups with different voting powers (VPs). We maximize the total value of purchasing (TVP) by optimizing order quantity assignment to suppliers and taking into consideration their synergies encountered in different time horizons. We apply the proposed model to a contractor selection and order quantity assignment problem in an agricultural commodity trading (ACT) company. We maximize the strategic effectiveness of both the customers and the suppliers, minimize risks, increase the degree of cooperation between trading partners on all levels of supply chain integration, enhance transparent knowledge sharing and aggregation, and support collaborative decision making.

1. Introduction

Rapid globalization, economic growth and substantial scientific and technological progress have resulted in enormous competition in international trading (Engau, 2010). The gap between product quality and performance is narrowing with intensifying competition in the global market (Chang, Chang, & Wu, 2011). As business is becoming more and more competitive, purchasing and supply chain management have been increasingly recognized by top managers as key business drivers (Gunasekaran & Ngai, 2012; Van Weele, 2009). For companies who spend a high percentage of their sales revenue on supplies, savings from suppliers are of particular importance (Karpak, Kumcu, & Kasuganti, 2001). Thus, a great deal of the research has been aiming at defining supplier evaluation and selection methodologies that, despite being simple to use and easy to understand, are able to produce reasonably accurate results (Ha & Krishnan, 2008). In particular, the need for a systematic approach to purchasing decisions related to the supplier selection and order allocation has been amply declared through the last decades (Aissaoui, Haouari, & Hassini, 2007; Tempelmeier, 2002; Vonderembse & Tracey, 1999; Weber, Current, & Benton, 1991).

The use of supplier selection and order allocation (SSOA) by trading companies is complicated for several reasons: (1) suppliers may be interdependent in terms of resource sharing or synergistic performance; (2) decisions must take into account multiple objectives and opinions of different supply chain participants; (3) the objectives are often conflicting; (4) supplier assessment criteria can result from decision makers' (DMs') value-focused thinking (VFT), or be based upon a simple comparison of suppliers using alternative-focused thinking (AFT); (5) decision criteria can be quantitative and qualitative; (6) criteria may characterize suppliers indirectly, via intermediate objects, such as external facilities or third-party service providers; (7) decisions are made on a regular base and rely upon suppliers' performance history, measure of their strategic value, and operational characteristics; (8) in the case of multiple sourcing the set of suppliers needs to be balanced in terms of criteria weights; (9) the number of feasible solutions is often very large; and (10) uncertainties can affect the decision outcome.

More in general, the goal is to choose the most effective set of suppliers at the minimum costs subject to demand restrictions and

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additional requirements imposed by the single suppliers on the buyers or vice versa. At the same time, an order allocation problem must be solved, that is, the demanded quantity must be distributed among the selected suppliers so as to maximize the overall value of the purchase. This goal can be achieved using integrated multi-criteria decision analysis and optimization approaches. Suppliers' individual priorities can be calculated using multi-criteria analysis tools, and an optimization procedure can be utilized to find optimal order quantities for all feasible sets of suppliers from which the final choice can be made.

Constraints can be dictated by buyers' or customers' needs, as well as by suppliers' offers. For example, suppliers' interdependency based on resource sharing must be considered when several bidders offer a commodity from the same stock of limited capacity and the sum of the maximum offered quantities of the individual suppliers exceeds the quantity available in stock. However, the suppliers' interaction cannot always be expressed by a constraint. Positive or negative synergies of the suppliers must be explicitly considered when the joint performance of several suppliers according to a certain criterion differs from their individual performances with respect to the same criterion.

Thus, while, supplier selection and order quantity assignment decisions are fairly structured when the decision criteria concern only independent characteristics of the different suppliers, accounting for the interdependencies among criteria and alternatives make the problem much more complex and requires a much more involved use of multi-criteria decision making tools.

Sanathanam and Kyparisis (1996) classified interdependencies among information system projects into resource, benefit and technical interdependencies. Later, Lee and Kim (2001) advocated the necessity to consider interdependencies among criteria and alternatives in information system project selection. Jointly selected suppliers can offer additional benefits or opportunities for the trading firm and its customers, or conversely, cause larger losses or sharper risks. For example, cost savings can be achieved by coordinating the transportation of commodities purchased from several suppliers in a given period. On the contrary, bigger risks may be associated with selecting contractors who purchase from the same source, particularly in the cases of stock-out or delivery difficulties. In complex supply chains, multiple positive and negative synergies of suppliers' performance can emerge simultaneously.

The existing multi-objective SSOA methods fail to take into consideration positive or negative performance synergies. New models and trade-off mechanisms are needed to synthesize all suppliers' individual non-synergistic and group *synergistic* performance characteristics.

We propose a new process that facilitates a simultaneous trade-off between the synergistic and non-synergistic supplier characteristics. First, all the relevant combinations of suppliers have been identified. Then, each combination is assessed with respect to synergistic criteria and each single supplier is assessed with respect to non-synergistic criteria. Finally, the assessed suppliers are aggregated within each combination to compute their total value of purchasing (TVP) and achieve a final ranking of all feasible alternatives.

We pursue two main objectives: (1) to develop a structural collaborative approach for the support of complex multi-objective SSOA decisions involving suppliers' synergism; (2) to demonstrate the application of this methodology to SSOA in ACT companies.

More specifically, the first objective in this study is to present an integrated empirical and technical framework for multi-objective SSOA decision support in complex collaborative environments with the following five key characteristics: (a) a flexible structure of decision criteria based on the compound value system of different decision making and interest groups utilizing both the AFT and VFT approaches for criteria identification; (b) a comprehensive framework where all relevant objective data and subjective judgments regarding the weight of decision factors and performance values of the discrete alternatives on intangible strategic and operational criteria must be incorporated; (c) a framework allowing for decision options constructed by taking into consideration possible effects of suppliers' synergism in case of multiple sourcing; (d) an optimal order quantity allocation process aiming at maximizing the TVP of feasible discrete sets of potential suppliers; and (e) a clearly delineated decision committee providing proper feedbacks.

The second objective of this study is fourfold: (a) to reveal the variables necessary to measure the performance of agricultural commodity suppliers taking into account possible suppliers' synergisms; (b) to generate feasible combinations of commodity suppliers and evaluate them; (c) to optimize order quotes to be assigned to suppliers within each feasible combination; and (d) to select the best set of suppliers with optimally distributed order quantities.

The proposed method was implemented to solve a SSOA problem in one of the largest agricultural corporations in Germany. The results obtained in the case study show the applicability of the proposed method and the efficacy of the designed procedures.

The remainder of this paper is organized as follows. The next section presents the motivation and background for the proposed collaborative decision support framework and its application to SSOA in the commodity trading industry. Section 3 illustrates the formal framework of the proposed multi-objective SSOA model. Section 4 discusses some axiomatic issues and practical implications of the model. Section 5 presents the case study. Section 6 concludes outlining some future research directions.

2. Motivation and background

This section outlines the main trends in purchasing management, the key features and drawbacks of collaborative decision making and the most used SSOA methods in the contemporary literature.

2.1. Trends in purchasing management

Traditionally, companies focus on short-term transactional purchases primarily based on cost considerations where supplier assessment is used to eliminate the unwanted suppliers rather than developing reliable and acceptable suppliers (Karpak et al., 2001; Lamming, 1996). However, recognizing the need for developing sustainable long-term relations with suppliers and focusing on customer needs, two concepts belonging to supplier relationship management (SRM) and customer relationship management (CRM), have recently become the crucial indicators for successful purchasing activities. In particular, Sheth et al. (2009) argued that the integration between purchasing and marketing should be taken into consideration when choosing suppliers. The use of market intelligence creates superior value for the customers and promotes both superior company performances and sustainable competitive advantages in several sectors (Day, 1994; Gatignon & Xuereb, 1997; Hätönen & Ruokonen, 2010; Li et al., 2010; Narver & Slater, 1990).

The degree of market-oriented activities may vary within different value chains and depend on the managerial decision making activities undertaken by an organization (Grunert, Trondsen, Campos, & Young, 2010). Market orientation predetermines supply chain integration (SCI) strategies (Li, Chau, & Lai, 2010; Zhao, 2011). External SCI focuses on a customer-oriented supplier selection decisions optimizing the trade-off between the total costs of a supplier for the buying firm and the revenues generated by the supplier (Wouters, Anderson, & Wynstra, 2005). Internal SCI includes all the internal activities needed to align purchasing strategies with the development of synchronized processes aiming at improving and sustaining competitiveness and satisfying customer needs (Flynn, Huo, & Zhao, 2009; Hayes & Wheelwright, 1984; Pagell, 2004). Purchasing and supplier selection issues are due not only to structural complexity but also to multiple conflicting viewpoints and objectives that can be identified both in external and internal SCI.

From a more practical viewpoint, interviews with the purchasing executives and top managers of one of the leading agricultural trading corporations in Germany revealed that DMs generally refuse to focus on either a-priori single-sourcing or multiple-sourcing strategy. They consider real-time operational capabilities (e.g., bid price, delivery capabilities), as well as strategic capabilities (i.e., management practices, reliability, relationship potential). Therefore, a practical requirement for an effective SSOA methodology is to determine an optimal sourcing strategy for an order that maximizes the TVP per transaction.

2.2. Collaborative decision making

Today's organizations operate in a value network on a global basis by partnering with suppliers, customers, and other stakeholders in pursuit of sustainable competitive advantages (Agarwal & Selen, 2009). In the related literature, "collaboration" has a twofold meaning: *structural* and *managerial*. Structural collaboration, or relationship management, is "a firm's set of relationships with other organizations" (Perez Perez & Sanchez, 2002, p. 261), including those with supply chain partners (SCPs) such as suppliers, customers, and other key stakeholders (Agarwal & Selen, 2009), The fundamental difficulties of structural SCM collaboration have been discussed by Barratt (2004). Managerial collaboration is an organized interaction between DMs representing different links in the supply chain for definition, promotion, control and improvement of collaborative activities. It is a managerial capability and a skill that largely reflects knowledge-sharing, communication, and the learning ability of the firm (Agarwal & Selen, 2009; Dyer & Singh, 1998; Slater, 1995). Despite the distinction above, structural and managerial collaborations are really non-separable. They merge together in "collaborative relationship management" and require the implementation of group decisions.

Collective decision making and learning using multiple soft sources such as information, skills, and knowledge is believed to be at the core of competitive advantage for firms (Im & Workman, 2004; Kohli & Jaworski, 1990; Narver & Slater, 1990). A team has more resources, knowledge, and political insight than any single individual working alone (Dennis, Rennecker, & Hansen, 2010; Hackman & Kaplan, 1974). Surowiecki (2004) examined dozens of practical cases in group decision making and concluded that amalgamated views of a crowd reach more accurate conclusions than each single expert, while transparent and structured procedures are needed to avoid groupthink. Zollow and Winter (2002) observed that deliberate learning efforts articulate and codify collective knowledge. To cope with the increase in information complexity, coordinated multidisciplinary and multi-stakeholders working groups can be created in order to have diverse perspectives on the problem, reveal alternative approaches for problem solving and use different individual skills and group knowledge (Beers et al., 2006; Shum, Cannavacciuolo, Liddo, Iandoli, & Quinto, 2011).

In complex decision situations it is necessary to have the participation of the decision analyst or/and facilitator to assist the decision group. Montibeller and Franco (2010) suggested a facilitated multi-criteria decision modeling approach. Success and sustainable development of the supply chain depend on structured and transparent collaborative decision making. Ordoobadi and Wang (2011) show that the entire knowledge sharing coordination for supplier selection includes: (1) standardization of supplier selection models and concepts; (2) incorporation of the supplier selection criteria; (3) inclusion of multiple perspectives; (4) coordination of the synthesis processes for the multiple perspectives; and (5) transparency of the alternative assessment process.

2.3. Review of state-of-the-art SSOA methods

A number of methods have been proposed during the last decades to support SSOA decisions. The majority of the existing analytical supplier evaluation approaches are based on functional criteria such as quality, price, and delivery time and do not consider the repercussions of the company strategy on the evaluation decisions by taking into account soft criteria such as risks, flexibility, responsiveness, innovation, motivation, and agility (Muralidharan, Anantharaman, & Deshmukh, 2002). On the contrary, most multi-criteria decision making approaches consider only DM's subjective judgments, even though the objective data can play a crucial role (Wang & Lee, 2009). The shortcomings deriving from unilateral approaches can be overcome using integrated models.

Ho, Xu, and Dey (2010) provided an extensive literature review of the existing supplier evaluation and selection methods, analyzing a wide range of individual and integrated multi-criteria decision making approaches: analytic hierarchy process (AHP), analytic network process (ANP), case-based reasoning, data envelopment analysis, fuzzy set theory, technique to order preference by similarity to ideal solution (TOPSIS), genetic algorithm, mathematical programming (i.e., integer LP and non-LP, goal programming, multi-objective programming), and simple multi-attribute rating technique (SMART).

The selection of an appropriate technique may be a challenging task when facing complex decision problems and it requires the integration of several mathematically sound methods to beneficially address the problem under analysis (Tavana, 2006). Hybrid AHP-LP and ANP-LP approaches to SSOA have been proposed, among others, by Demitras and Üstün (2009), Faez, Ghodsypour, and O'Brien (2009). Mafakheri, Breton, and Ghoniem (2011), Özgen, Önüt, Gülsün, Tuzkaya, and Tuzkaya (2008), Sanayei et al. (2008) and Rezaei and Davoodi (2011). Fuzzy-LP and fuzzy-AHP integrated frameworks have been developed by Amin et al. (2011) and Zouggari and Benyoucef (2011).

Finally, different decision support system (DSS) approaches to SSOA have also been developed. For example, Choi and Chang (2006) proposed a DSS based on a two phase optimization method that semantically builds a goal program using a set of predefined rules to screen suppliers in a business to business e-procurement environment. They only use quantitative parameters in their model. Later, Erdem and Göçen (2012) developed an improved DSS based on an integrated AHP-goal programming model that also accounted for qualitative criteria. Sodenkamp and Suhl (2012) developed a multilevel group decision approach considering auxiliary decision objects, such as external service providers associated with suppliers, and indirect criteria (both objective and subjective). Suppliers were ranked based on their Euclidean distance from an ideal reference point and order quantities distributed proportionally among the best ranked suppliers.

To the best of our knowledge, the methods and DSSs described in the contemporary SSOA literature do not generally consider synergistic supplier performances in multiple sourcing cases.

3. The proposed model

The approach proposed in this study allows to select the best set of suppliers with optimally allocated order quantities in complex multi-objective problems involving suppliers' synergy. The selection process is carried out by a group of DMs who represent different stakeholders within the supply chain being analyzed. The goal is to select the combination of available suppliers providing

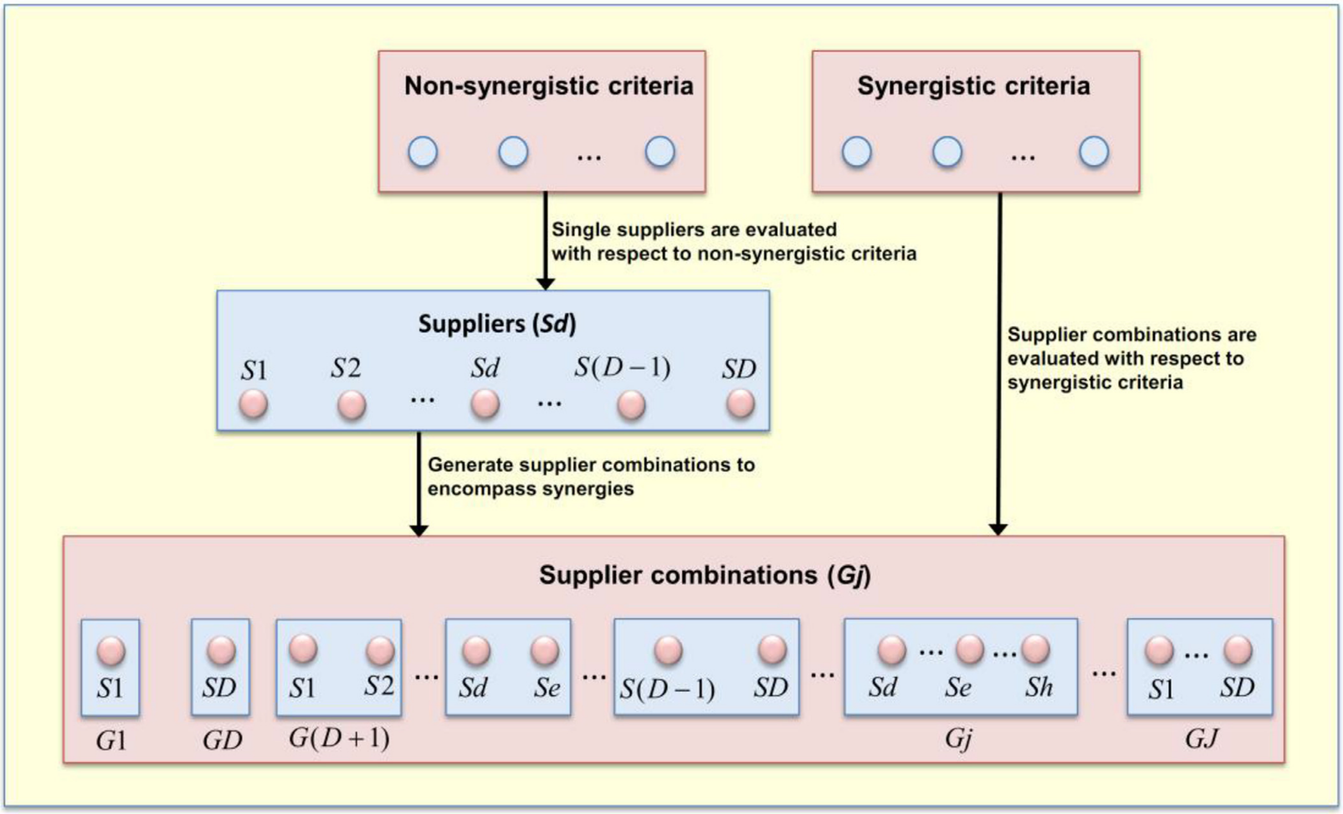

Fig. 1. Generation and evaluation of the alternatives involving suppliers' synergy.

the maximum overall performance value while optimally adjusting the order quantities (the decision variables of the problem) within the combination so as to satisfy natural bounding constraints. The overall performance value of each supplier combination is formalized by taking into account suppliers' performance synergies. In particular, we assume the DMs to be able to identify a finite set of decision criteria to evaluate the suppliers' performance and to have different expertise and voting powers (VPs) with respect to these criteria. The objective function values are then obtained through the estimation of the criteria weights and the suppliers' performance on the bases of qualitative criteria and quantitative objective data. The nomenclature is summarized in the Online Appendix A.

3.1. Mathematical formulation of the SSOA problem

The mathematical formulation that we propose for the multi-objective SSOA problem described above is an optimization problem whose objective function expresses the TVP of the supplier combinations.

Let $S=\{S_1,\dots,S_D\}$ be the set of all available suppliers and $G=\{G_1,\dots,G_J\}$ be the set of all possible supplier combinations. G is the set of all subsets of S excluding the empty set, thus it contains $J=\sum_{d=1}^{D}\frac{D!}{(d)!(D-d)!}$ elements. DMs' final choice will have to be one of these supplier combinations.

In the case of multiple sourcing, suppliers selected to act jointly may perform better or worse than suppliers handled as independent units. Thus, the positive/negative synergy that can occur among vendors (e.g., savings on joint delivery) must be taken into consideration when defining the objective function. Fig. 1 shows the generation and evaluation of the available alternatives accounting for both the synergistic and non-synergistic criteria.

The optimization problem can be formalized as follows:

$$\begin{cases} \max\limits_{j} \quad TVP(G_j) = p^{\bar{\sigma}}(G_j) + p^{\sigma}(G_j) \\ s.t. \\ \left.\begin{aligned} & MinQ_{offered}(G_j) \le Y; \\ & \sum_{S_d\in G_j} Min\{MaxQ_{offered}(S_d), MaxQ_{CL}(S_d)\} \ge Y; \\ & MaxQ_{shared}(G_j) \ge Y \quad (if\ |G_j| \ge 2); \end{aligned}\right\} \text{feasibility constraints} \\ \left.\begin{aligned} & x_{G_j}^{S_d} \ge MinQ_{offered}(S_d); \quad x_{G_j}^{S_d} \le MaxQ_{offered}(S_d); \\ & x_{G_j}^{S_d} \le MaxQ_{CL}(S_d); \quad \sum_{S_d\in G_j} x_{G_j}^{S_d} = Y; \end{aligned}\right\} \text{sub-optimality constraints} \\ \left. x_{G_j}^{S_d} \ge 0, \quad x_{G_j}^{S_d}\,\text{integer}, \quad j=1,\dots,J,\ S_d \in G_j. \right\} \text{decision variables} \end{cases} \tag{1}$$

where: $x_{G_j}^{S_d}$ ($j=1,\dots,J$, $S_d\in G_j$) is the quantity that must be ordered to S_d; Y is the total commodity demand; $|G_j|$ is the cardinality of the set G_j; $MinQ_{offered}(S_d)$ and $MaxQ_{offered}(S_d)$ are the minimum and maximum order quantities offered by S_d, respectively; $MaxQ_{CL}(S_d)$ is the maximum order quantity offered by S_d based on the credit limit, that is:

$$MaxQ_{CL}(S_d) \overset{def}{=} \frac{CL(S_d)}{p(S_d, PricePerUnit)}, \tag{2}$$

where $CL(S_d)$ and $p(S_d, PricePerUnit)$ are the credit limit and the price per unit of measure imposed by the supplier S_d, respectively; $MinQ_{offered}(G_j) \overset{def}{=} \sum_{S_d\in G_j} MinQ_{offered}(S_d)$; $MaxQ_{shared}(G_j)$, for G_j consisting of at least two suppliers, is the maximum order quantity that the suppliers composing G_j can provide when sharing resources (i.e. by using joint transportation, joint source of goods, or, more in general, sharing logistic resources); $p^{\bar{\sigma}}(G_j)$ and $p^{\sigma}(G_j)$ stand for the overall performance value of the combination G_j with respect to all the non-synergistic and synergistic criteria, respectively.

The feasibility constraints are the constraints imposed on the buying process by the suppliers. Such constraints, generally referred to as “policy constraints” (Weber, Current, & Desai, 2000), include suppliers’ minimum or maximum order quantities based on their production capacity or their willingness to do business with a particular firm.

The first two feasibility constraints, $MinQ_{offered}(G_j) \leq Y$ and $\sum_{S_d \in G_j} Min\{MaxQ_{offered}(S_d), MaxQ_{CL}(S_d)\} \geq Y$, measure the ability of a supplier combination G_j to satisfy the demand Y under the minimum and maximum offered quantity restrictions imposed by the single suppliers. In particular, the second constraint is necessary to guarantee that a fixed feasible combination G_j is also sub-optimal, that is, the optimization problem admits a solution. See also Proposition 1 below. Finally, the third feasibility constraint, $MaxQ_{shared}(G_j) \geq Y$, accounts for the ability of a supplier combination G_j (consisting of at least two suppliers) to satisfy the demand by means of shared resources.

Proposition 1. *Let G_j be a supplier combination. If G_j satisfies the feasibility constraints of Problem (1), then there exists at least one tuple $(x_{G_j}^{S_d})_{S_d \in G_j}$ satisfying the sub-optimality constraints of Problem (1).*

Proof. The first three sub-optimality constraints are clearly satisfied. Thus, suppose, by contradiction, that there is a feasible G_j such that $\sum_{S_d \in G_j} x_{G_j}^{S_d} < Y$ for all tuples $(x_{G_j}^{S_d})_{S_d \in G_j}$ such that $\forall S_d \in G_j$, $x_{G_j}^{S_d} \geq MinQ_{offered}(S_d)$, $x_{G_j}^{S_d} \leq MaxQ_{offered}(S_d)$ and $x_{G_j}^{S_d} \leq MaxQ_{CL}(S_d)$. Then, $\sum_{S_d \in G_j} Min\{MaxQ_{offered}(S_d), MaxQ_{CL}(S_d)\} < Y$, so contradicting the feasibility of G_j. □

Problem (1) admits the following equivalent formulation:

$$\begin{cases} \underset{j}{Max} \quad TVP(G_j) = p^{\bar{\sigma}}(G_j) + p^{\sigma}(G_j) \\ s.t. \\ MinQ_{offered}(G_j) \leq Y; \quad MaxQ(G_j) \geq Y; \} \text{feasibility constraints} \\ \left. x_{G_j}^{S_d} \geq MinQ_{offered}(S_d); \quad x_{G_j}^{S_d} \leq MaxQ(S_d); \quad \sum_{S_d \in G_j} x_{G_j}^{S_d} = Y; \right\} \text{sub-optimality constraints} \\ \left. x_{G_j}^{S_d} \geq 0, \quad x_{G_j}^{S_d} \text{integer}, \quad j = 1, \ldots, J, \; S_d \in G_j. \right\} \text{decision variables} \end{cases} \tag{3}$$

where

$$MaxQ(S_d) = Min\{MaxQ_{CL}(S_d); MaxQ_{Offered}(S_d)\} \tag{4}$$

and

$$MaxQ(G_j) = \begin{cases} \sum_{S_d \in G_j} Min\{MaxQ_{Offered}(S_d), MaxQ_{CL}(S_d)\}, \text{if} \left|G_j\right| = 1 \\ Min\left\{ \sum_{S_d \in G_j} Min\{MaxQ_{Offered}(S_d), MaxQ_{CL}(S_d)\}, MaxQ_{shared}(G_j) \right\}, \text{if} \left|G_j\right| \geq 2 \end{cases} \tag{5}$$

3.1.1. A managerial remark

Formulating and structuring the objectives is a critical activity in organizational decision making (Eden et al., 1986; Franco et al., 2007; Lyles, 1981; Montibeller, Franco, Lord, & Iglesias, 2009; Nutt, 1992). Bond et al. (2008, 2010) examined DMs’ ability to generate self-relevant objectives for the decisions they face denouncing the diffuse incapacity to use personal knowledge and values in order to elicit objectives. Bond et al. (2008, 2010) identified two specific obstacles: “not thinking broadly enough about the range of relevant objectives, and not thinking deeply enough to articulate every objective within the range that is considered”. In this paper, we use a mixed AFT–VFT approach where the participation of facilitators/analysts can help the DMs, first, to explicitly articulate their individual interpretations of the problem and to jointly produce a model that adequately captures the complexity resulting from considering all their viewpoints and, secondly, to improve management conflicts within the group during the decision process (Keeney, 1992; Montibeller et al., 2009; Phillips & Phillips, 1993).

3.2. Seven-step procedure to model the overall performance of supplier combinations

As stated above, the goal is to rank the supplier combinations with respect to their overall performance values. Herein, the overall performance value of a generic combination G_j is interpreted as its TVP and evaluated on the basis of all the criteria identified by the DMs.

In this section, we introduce a seven-step procedure that allows us to model the effects of synergies on the suppliers’ performance and to evaluate supplier combinations through the TVP formally defined as an additive value function within a multi-criteria approach. A small theoretical example of the proposed procedure is provided in the Online Appendix B.

Step 1. Forming the decision group: A decision group (or committee) is a team brought together to achieve a shared goal. In our framework, the decision group (DG) must be a purchasing team, that is, a committee aiming to achieve a common supply management-related goal, such as supplier selection, standardization of raw material inputs or quality improvements for purchased materials and services (Ellram & Pearson, 1993). This team consist of personnel from a variety of functional areas and may include representatives from outside the organization, such as suppliers or customers (Carter & Narasimhan, 1996; Leenders & Fearon, 1997; Trent & Monczka, 1998).

We assume the DMs of the decision group DG to be arranged into M divisions, $\langle 1\rangle, \ldots, \langle M\rangle$. Each division $\langle m\rangle$ ($m = 1, \ldots, M$) is composed of N^m clusters, $\langle m, 1\rangle, \ldots, \langle m, N^m\rangle$. Each cluster $\langle m, n\rangle$ ($n = 1, \ldots, N^m$) refers to an area of expertise to which the DMs can belong, such as political, economical, social, technological and legal (PESTL). We denote by A^{mn} the cardinality of the cluster $\langle m, n\rangle$ and by $\langle m, n, a\rangle$ the ath DM ($a = 1, \ldots, A^{mn}$) in the cluster $\langle m, n\rangle$. Each DM belongs to only one division and only one cluster. Hence, the total number of DMs in DG is $|DG| = \sum_{m=1}^{M} \sum_{n^m=1}^{N^m} A^{mn}$.

Step 2. Identifying decision criteria: A decision cannot be appropriately made without fully considering its context and all criteria (Tavana & Zandi, 2012). The criteria in a given problem must encompass all the relevant areas of concern (i.e., operational strengths and weaknesses as well as strategic opportunities and risks) to work as decision factors thoroughly. As mentioned above, we follow an AFT–VFT approach to identify and structure the selection criteria (Keeney, 1992). That is, with the help of

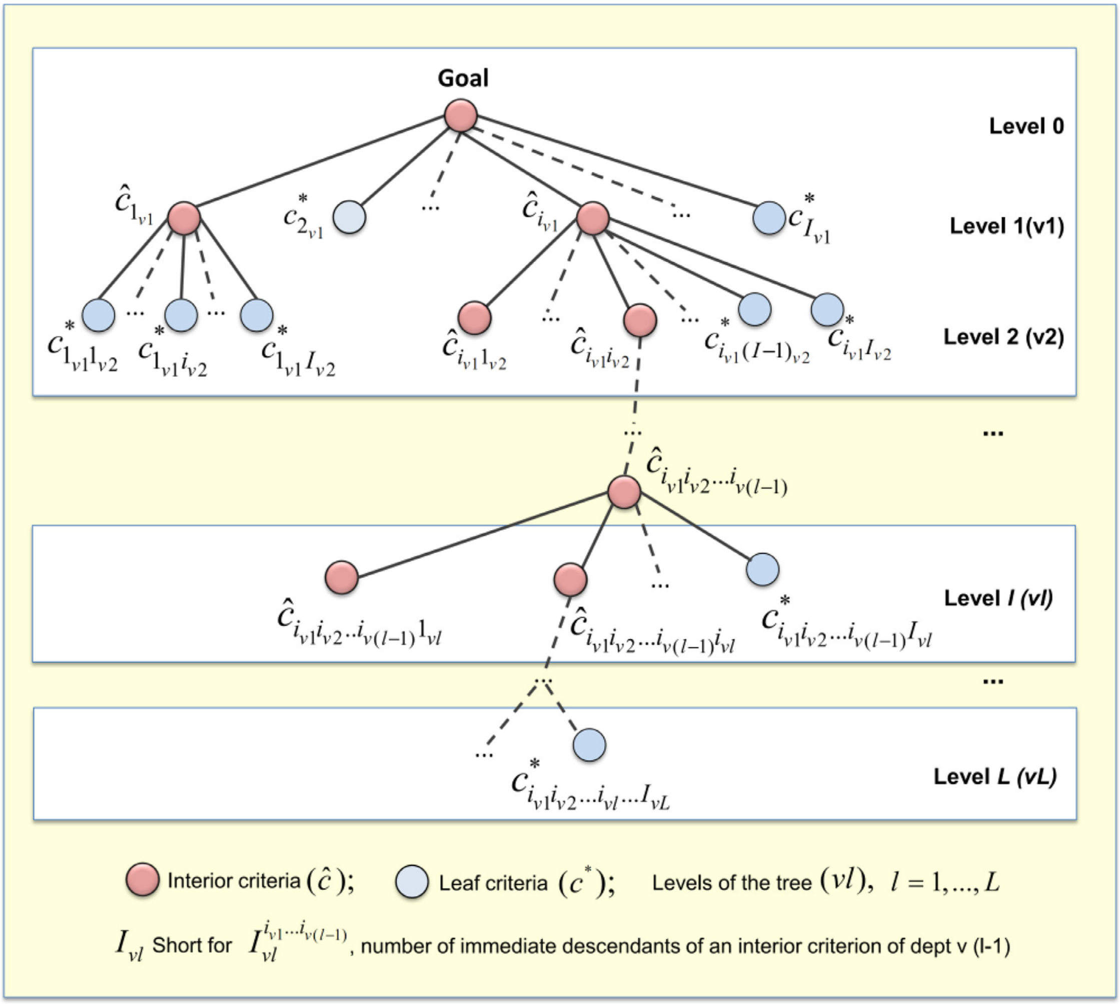

Fig. 2. *L*-level tree of decision criteria.

facilitators/analysts, an analysis of both the characteristics allowing to distinguish the available alternatives (AFT approach) and the company objectives and values (VFT approach) must be considered when formulating the decision criteria.

Step 3. Structuring decision criteria: The identified criteria must be logically arranged and thoroughly classified in order to provide a comprehensive analysis of all the relevant aspects.

Hierarchies of criteria can be formally defined using graph theory as *ordered rooted trees*. See, among others, Gossett (2009), Knuth (1997), Knuth (2006), Lu (1984) and Valiente (2002). Generally speaking, a hierarchy is a tree structure with nodes, leaves and a root satisfying the assumption that there exists a unique path from the root to any other node (Chidamber & Kemerer, 1994; Valiente, 2002). An efficient method to represent ordered trees of large complexity is the Dewey decimal notation, or *D*-notation (Knuth, 1997; Lu, 1984). A hierarchy of criteria with *L* levels can be formally represented as follows.

Let *T* be a tree of decision criteria. The root node of this tree is the decision goal, $Goal_{v0}$. The number of *levels*, vL, in the hierarchy of criteria corresponds to the *depth* of the tree. The *degree* of a criterion in the hierarchy is given by the number of sub-criteria that this criterion includes. A criterion is a *leaf* of the tree (or a *leaf criterion*) if it is not divided into sub-criteria, and its degree is "0". A criterion that includes sub-criteria is called an *interior criterion*, and its degree is greater than or equal to "2". The decision goal, $Goal_{v0}$, has depth 0 and is always connected to several criteria, therefore it is an interior criterion.

The symbols $\hat{c}$ and c^* will denote a generic interior and leaf criterion, respectively, while $sub(\hat{c})$ will stand for the set of all sub-criteria of $\hat{c}$.

Sub-criteria belonging to the same criterion are ordered lexicographically according to their *D*-notation. Thus, if $\hat{c}_{i_{v1}\ldots i_{vl}}$ is an interior criterion of *T* with depth vl and $I^{i_{v1}\ldots i_{vl}}$ immediate descendants (sub-criteria), its sub-criteria have the following *D*-notation:

$$i_{v1}\ldots i_{vl}1_{v(l+1)},\quad i_{v1}\ldots i_{vl}2_{v(l+1)},\ldots,i_{v1}\ldots i_{vl}I_{v(l+1)}^{i_{v1}\ldots i_{vl}} \tag{6}$$

The *D*-notation of $Goal_{v0}$ is "0". Fig. 2 provides a general representation of a tree of criteria with *L* levels whose nodes are described using the Dewey indexation system.

Step 4. Defining DMs' α-VP: Following Sodenkamp and Suhl (2012), we can assign to every DM in DG, and for every criterion identified in *Step 3*, a value describing the DM's relative ability to estimate the weight of the criterion. This value is called α-*VP*. Moreover, we extend this assumption to every cluster and every division composing DG as follows.

Definition. For every $c \in T$, $m = 1, \ldots, M$, $n = 1, \ldots, N^m$ and $a = 1, \ldots, A^{mn}$,

- the *α-VP of $\langle m, n, a\rangle$ relative to c*, denoted by $w^{\alpha}(mna, c)$, describes the DM's relative ability to estimate the weight of criterion *c*;
- the *α-VP of $\langle m, n\rangle$ relative to c*, denoted by $w^{\alpha}(mn, c)$, describes the relative impact of the *n*th cluster within the *m*th division when estimating the weight of criterion *c*;

- the *α-VP of $\langle m\rangle$ relative to c*, denoted by $w^{\alpha}(m,c)$, expresses the impact that the mth division's evaluation of criterion c has on the decision group DG.

The VPs described above are all "local" VPs since they reflect the relative credibility of a DM within the cluster or division that he/she belongs to. Thus, we also need to introduce the global VP of a DM, that is, his/her relative influence within DG.

Definition. For every $c\in T$, $m=1,\ \dots,\ M$, $n=1,\ \dots,\ N^m$ and $a=1,\ \dots,\ A^{mn}$, the *global VP* of $\langle m,n,a\rangle$ *relative to* c is given by:

$$w^{\alpha}{}_G(mna,c)=w^{\alpha}(m,c)\cdot w^{\alpha}(mn,c)\cdot w^{\alpha}(mna,c), \tag{7}$$

where

$$w^{\alpha}{}_G(mna,c), w^{\alpha}(m,c), w^{\alpha}(mn,c), w^{\alpha}(mna,c)\in[0,1], \tag{8}$$

$$\sum_{m=1}^{M}w^{\alpha}(m,c)=1,\quad \sum_{n=1}^{N^m}w^{\alpha}(mn,c)=1,\quad \sum_{a=1}^{A^{mn}}w^{\alpha}(mna,c)=1,$$
$$\sum_{m=1}^{M}\sum_{n=1}^{N^m}\sum_{a=1}^{A^{mn}}w^{\alpha}{}_G(mna,c)=1 \tag{9}$$

Definition. A cluster $\langle m,n\rangle$ is called *homogeneous* if:

$$\forall\langle m,n,a\rangle\in\langle m,n\rangle,\quad \forall c\in T,\quad w^{\alpha}(mna,c)=\frac{1}{A^{mn}}. \tag{10}$$

Step 5. Setting criteria weights: In commodity trade SSOA, criteria weighting methods include indifference (Delforce & Hardaker, 1985; Rausser & Yassour, 1981), simple multi-attribute rating technique (SMART) (Edwards, 1977; Mustajoki, Hämälainen, & Salo, 2005; von Winterfeldt & Edwards, 1986), preference programming (Liesiö, Mild, & Salo, 2007), SWING (Mustajoki et al., 2005; von Winterfeldt & Edwards, 1986), and AHP (Saaty & Sodenkamp, 2010), among others. Hayashi (2000) pointed out that the weight assessment procedure should be chosen considering how the weights are interpreted in the problem at hand.

In our framework, the weight of a criterion is estimated only by the DMs that have α-VP with respect to this criterion. These DMs are called α-level DMs. The reason to prefer VP-based weights to other weighting method is further discussed in Section 4.

Definition. For every $c\in T$, $m=1,\ \dots,\ M$, $n=1,\ \dots,\ N^m$ and $a=1,\ \dots,\ A^{mn}$, $\langle m,n,a\rangle$ is an *α-level DM for c* if $w^{\alpha}{}_G(mna,c)>0$.

Henceforth, $\forall c\in T$, let

$$\Gamma^{\alpha}(c)\overset{def}{=}\{mna: w^{\alpha}_G(mna,c)>0\}$$

$w^{mna}(c)\overset{def}{=}$ weight that $\langle m,n,a\rangle$ assigns to the criterion c.

We assume that each DM normalizes the weights assigned to the sub-criteria of each interior criterion $\hat{c}\in T$. That is, after assigning a weight to each of the sub-criteria in $sub(\hat{c})$, $\langle m,n,a\rangle$ normalizes such weights as follows:

$$\forall c\in sub(\hat{c}),\quad w^{mna\prime}(c)=\frac{w^{mna}(c)}{\sum_{c\in sub(\hat{c})}w^{mna}(c)}. \tag{11}$$

Thus, without loss of generality, we assume:

$$\forall\langle m,n,a\rangle\in\langle m,n\rangle,\quad \forall\hat{c}\in T,\quad \forall c\in sub(\hat{c}),\quad \sum_{c\in sub(\hat{c})}w^{mna}(c)=1. \tag{12}$$

The collective weight assigned to any criterion by the set of all the α-level DMs is obtained using the following equation:

$$w(c)=\sum_{mna\in\Gamma^{\alpha}(c)}w^{mna}(c)\cdot w^{\alpha}{}_G(mna,c). \tag{13}$$

Finally, the global weight of a leaf criterion is calculated multiplying the collective weights of all the interior criteria that precede the criterion itself. That is, using the D-notation:

$$w_G(c*_{i_{v1}\dots i_{vl}})=\prod_{\delta=i_{v1}}^{i_{v1}\dots i_{vl}}w(c_\delta)=w(\hat{c}_{i_{v1}})\cdot w(\hat{c}_{i_{v1}i_{v2}})\cdot\ldots\cdot w(c*_{i_{v1}\dots i_{vl}}) \tag{14}$$

$w_G(c*_{i_{v1}\dots i_{vl}})$ can be interpreted as the criterion weight within the whole value system.

Step 6. Defining DMs' β-VP: Building on Sodenkamp and Suhl (2012), we assign to every DM a value describing his/her level of expertise in estimating the performance of the alternatives based on the subjective criteria. This value is called *β-VP*.

Definition. Let $c*^{Sbj,\sigma}$ and $c*^{Sbj,\bar{\sigma}}$ be a subjective synergistic and non-synergistic leaf criterion, respectively. For every $m=1,\ \dots,\ M$, $n=1,\ \dots,\ N^m$, $a=1,\ \dots,\ A^{mn}$, $d=1,\ \dots,\ D$ and $j=1,\ \dots,\ J$,

- the *β-VP of $\langle m,n,a\rangle$ relative to* $c*^{Sbj,\bar{\sigma}}$ and S_d, denoted by $w^{\beta}(mna,\ c*^{Sbj,\bar{\sigma}},\ S_d)$, describes the DM's relative ability to estimate S_d' performance using $c*^{Sbj,\bar{\sigma}}$;
- the *β-VP of $\langle m,n,a\rangle$ relative to* $c*^{Sbj,\sigma}$ and G_j, denoted by $w^{\beta}(mna,\ c*^{Sbj,\sigma},\ G_j)$, describes the DM's relative ability to estimate the supplier combination G_j' performance using $c*^{Sbj,\sigma}$.

In particular, $w^{\beta}(mna,\ c*^{Sbj,\bar{\sigma}},\ S_d)=0$ means that $\langle m,n,a\rangle$ is unable to estimate S_d with respect to $c*^{Sbj,\bar{\sigma}}$. Similarly, $w^{\beta}(mna,\ c*^{Sbj,\sigma},\ G_j)=0$ means that $\langle m,n,a\rangle$ cannot estimate G_j with respect to $c*^{Sbj,\sigma}$.

Remark. Note that the β-VP of a DM is assigned only relative to subjective leaf criteria. This is due to both the tree structure for the criteria classification and the weight assignment procedure implemented in *Steps 3–5*.

Definition. Let $c*^{Sbj,\sigma}$ and $c*^{Sbj,\bar{\sigma}}$ be a subjective synergistic and non-synergistic leaf criterion, respectively. For every $m=1,\ \dots,\ M$, $n=1,\ \dots,\ N^m$, $a=1,\ \dots,\ A^{mn}$, $d=1,\ \dots,\ D$ and $j=1,\ \dots,\ J$,

- $\langle m,n,a\rangle$ is a *β-level DM for* $c*^{Sbj,\bar{\sigma}}$ and S_d if $w^{\beta}(mna,\ c*^{Sbj,\bar{\sigma}},\ S_d)>0$;
- $\langle m,n,a\rangle$ is a *β-level DM for* $c*^{Sbj,\sigma}$ and G_j if $w^{\beta}(mna,\ c*^{Sbj,\sigma},\ G_j)>0$.

We also let:

$$\Gamma^{\beta}(c*^{Sbj,\bar{\sigma}},d)\overset{def}{=}\{mna: w^{\beta}(mna,\ c*^{Sbj,\bar{\sigma}},\ S_d)>0\},$$
$$\Gamma^{\beta}(c*^{Sbj,\sigma},j)\overset{def}{=}\{mna: w^{\beta}(mna,\ c*^{Sbj,\sigma},\ G_j)>0\}.$$

All DMs' credibility values must be normalized in order to assure conformity of their magnitudes. Thus,

$$\forall c*^{Sbj,\bar{\sigma}},\quad \forall d=1,\ \dots,\ D,\quad w^{\beta}(mna,\ c*^{Sbj,\bar{\sigma}},\ S_d)\in[0,\ 1],$$
$$\forall c*^{Sbj,\sigma},\quad \forall j=1,\ \dots,\ J,\quad w^{\beta}(mna,\ c*^{Sbj,\sigma},\ G_j)\in[0,\ 1],$$
$$\sum_{mna\in\Gamma^{\beta}(c*^{Sbj,\bar{\sigma}},\ d)}w^{\beta}(mna,\ c*^{Sbj,\bar{\sigma}},\ S_d)=1,$$
$$\sum_{mna\in\Gamma^{\beta}(c*^{Sbj,\sigma},\ j)}w^{\beta}(mna,\ c*^{Sbj,\sigma},\ G_j)=1. \tag{15}$$

Step 7. Assessing the TVPs of suppliers' combinations: Following Hamilton and Chervany (1981), we need to design a procedure allowing us to estimate how well objectives are being achieved by each alternative listed as possible solution. Quantitative data can be used to assess alternatives on the objective criteria, but the experts' judgments are necessary in order to evaluate the alternatives on subjective criteria. Finally, suppliers' performance measures usually include heterogeneous scales and units. Thus, a normalization step is necessary in order to combine the DMs' evaluations of suppliers' performance data obtained on the basis of different criteria (i.e., evaluations expressed by different units of measure and scales).

Sub-procedure 7.1. Objective evaluations of suppliers' performance

(i) Every supplier must be evaluated individually with respect to every single objective non-synergistic criterion. This yields D values for every objective non-synergistic criterion:

$$p(S_d, c*^{Obj,\bar{\sigma}}), \quad d = 1, \ldots, D. \tag{16}$$

(ii) Every supplier combination must be evaluated with respect to every single objective synergistic criterion. This yields J values for every objective synergistic criterion:

$$p(G_j, c*^{Obj,\sigma}), \quad j = 1, \ldots, J. \tag{17}$$

Sub-procedure 7.2. Subjective evaluations of suppliers' performance

(i) Every DM must provide an evaluation of every supplier with respect to each subjective non-synergistic criterion relative to which he/she is a β-level DM. Thus, for every $c*^{Sbj,\bar{\sigma}}$ and every $mna \in \Gamma^{\beta}(c*^{Sbj,\bar{\sigma}}, d)$, we have D values:

$$p^{mna}(S_d, c*^{Sbj,\bar{\sigma}}), \quad d = 1, \ldots, D. \tag{18}$$

(ii) DMs' estimates of each supplier' performance with respect to each subjective non-synergistic criterion are to be combined together to obtain the entire group evaluation. That is, for every $c*^{Sbj,\bar{\sigma}}$ and every $d = 1, \ldots, D$, we have:

$$p(S_d, c*^{Sbj,\bar{\sigma}}) = \sum\nolimits_{\mathrm{mna}\in\Gamma^{\beta}(c*^{Sbj,\bar{\sigma}},\, d)} p^{mna}(S_d, c*^{Sbj,\bar{\sigma}}) \cdot w^{\beta}(mna,\ c*^{Sbj,\bar{\sigma}},\ S_d). \tag{19}$$

(iii) Every DM must provide an evaluation of every supplier combination with respect to each subjective synergistic criterion relative to which he/she is a β-level DM. Thus, for every $c*^{Sbj,\sigma}$ and every $mna \in \Gamma^{\beta}(c*^{Sbj,\sigma}, j)$, we have J values:

$$p^{mna}(G_j, c*^{Sbj,\sigma}), \quad j = 1, \ldots, J. \tag{20}$$

(iv) DMs' estimates of each supplier combination' performance with respect to each subjective synergistic criterion are to be combined together to obtain the entire group evaluation. That is, for every $c*^{Sbj,\sigma}$ and every $j = 1, \ldots, J$, we have:

$$p(G_j, c*^{Sbj,\sigma}) = \sum\nolimits_{\mathrm{mna}\in\Gamma^{\beta}(c*^{Sbj,\sigma},\, j)} p^{mna}(G_j, c*^{Sbj,\sigma}) \cdot w^{\beta}(mna,\ c*^{Sbj,\sigma},\ G_j). \tag{21}$$

Sub-procedure 7.3. Normalizing all evaluations of suppliers' performance

The suppliers' evaluations obtained on the basis of different criteria may not be represented in commensurate terms (i.e., different criteria may use different units of measure and/or different scales). Thus, we need to normalize the performance values of both single suppliers and supplier combinations. That is:

$\forall c*^{\bar{\sigma}}$ (Obj.orSbj.), $\quad \forall d = 1, \ldots, D$,

the normalized performance value of S_d is:

$$p'(S_d, c*^{\bar{\sigma}}) = \frac{p(S_d, c*^{\bar{\sigma}})}{\sum_{d=1}^{D} p(S_d, c*^{\bar{\sigma}})}$$

$\forall c*^{\sigma}$ (Obj.orSbj.), $\quad \forall j = 1, \ldots, J$,

the normalized performance value of G_j is:

$$p'(G_j, c*^{\sigma}) = \frac{p(G_j, c*^{\sigma})}{\sum_{j=1}^{J} p(G_j, c*^{\sigma})}$$

Clearly, we have:

$$p'(S_d, c*^{\bar{\sigma}}),\ p'(G_j, c*^{\sigma}) \in [0,\ 1], \quad \sum_{d=1}^{D} p'(S_d, c*^{\bar{\sigma}}) = 1, \quad \sum_{j=1}^{J} p'(G_j, c*^{\sigma}) = 1. \tag{22}$$

Sub-procedure 7.4. Defining the objective function TVP

The TVP of the jth alternative G_j is characterized by two components: the overall value $p^{\bar{\sigma}}(G_j)$ assigned to the suppliers on the basis of the non-synergistic criteria and overall value $p^{\sigma}(G_j)$ assigned on the basis of the synergistic criteria. That is,

$$TVP(G_j) = p^{\bar{\sigma}}(G_j) + p^{\sigma}(G_j). \tag{23}$$

We assume the value of G_j with respect to the non-synergistic criteria to be given by:

$$p^{\bar{\sigma}}(G_j) = \sum_{S_d \in G_j} p^{\bar{\sigma}}(S_d) \cdot x_{G_j}^{S_d} \tag{24}$$

where $p^{\bar{\sigma}}(S_d)$ is the value of a supplier $S_d \in G_j$. We define this value to be the difference between the sum of all the weighted positive characteristics ($c*^{Pro,\bar{\sigma}}$) and that of all the weighted negative characteristics ($c*^{Con,\bar{\sigma}}$) of S_d. In symbols:

$$\begin{aligned} p^{\bar{\sigma}}(S_d) &= p^{Pro,\bar{\sigma}}(S_d) - p^{Con,\bar{\sigma}}(S_d), \\ p^{Pro,\bar{\sigma}}(S_d) &= \sum_{c*^{Pro,\bar{\sigma}}} w_G(c*^{Pro,\bar{\sigma}}) \cdot p'(S_d, c*^{Pro,\bar{\sigma}}), \\ p^{Con,\bar{\sigma}}(S_d) &= \sum_{c*^{Con,\bar{\sigma}}} w_G(c*^{Con,\bar{\sigma}}) \cdot p'(S_d, c*^{Con,\bar{\sigma}}). \end{aligned} \tag{25}$$

At the same time, we assume the value of G_j with respect to the synergistic criteria to be given by the difference between the sum of all the weighted positive performances ($p^{Pro,\sigma}(G_j)$) and that of all the weighted negative performances ($p^{Con,\sigma}(G_j)$) of G_j. Hence:

$$p^{\sigma}(G_j) = p^{Pro,\sigma}(G_j) - p^{Con,\sigma}(G_j) \tag{26}$$

where

$$\begin{aligned} p^{Pro,\sigma}(G_j) &= \sum_{c*^{Pro,\sigma}} w_G(c*^{Pro,\sigma}) \cdot p'(G_j, c*^{Pro,\sigma}), \\ p^{Con,\sigma}(G_j) &= \sum_{c*^{Con,\sigma}} w_G(c*^{Con,\sigma}) \cdot p'(G_j, c*^{Con,\sigma}). \end{aligned} \tag{27}$$

Therefore, the TVP of the jth supplier combination is the sum of its overall normalized and weighed performance values on all non-synergistic and synergistic criteria:

$$\begin{aligned} TVP(G_j) = \sum_{S_d \in G_j} \Bigg(& \sum_{c*^{Pro,\bar{\sigma}}} w_G(c*^{Pro,\bar{\sigma}}) \cdot p'(S_d, c*^{Pro,\bar{\sigma}}) \\ & - \sum_{c*^{Con,\bar{\sigma}}} w_G(c*^{Con,\bar{\sigma}}) \cdot p'(S_d, c*^{Con,\bar{\sigma}}) \Bigg) \cdot x_{G_j}^{S_d} \\ & + \sum_{c*^{Pro,\sigma}} w_G(c*^{Pro,\sigma}) \cdot p'(G_j, c*^{Pro,\sigma}) \\ & - \sum_{c*^{Con,\sigma}} w_G(c*^{Con,\sigma}) \cdot p'(G_j, c*^{Con,\sigma}) \end{aligned} \tag{28}$$

3.3. Finding the optimal solution to the SSOA problem

One of the most commonly used approaches to solve multi-objective optimization problems such as our problem (1) is the weighting method (An, Green, & Johrendt, 2010; Weber & Current, 1993). Other methods include the ε-constraint approach, the goal-attainment method and multi-objective genetic algorithms. For a detailed discussion of multi-objective optimization techniques the interested reader is referred to Alves and Climaco (2004), Cohon (1978), and Demirtas & Ustun (2009).

We look at obtaining the optimal solution to the SSOA problem (1) as a three-stage routine:

Stage 1: Identify all the feasible supplier combinations, that is, all the supplier combinations satisfying the feasibility constraints.

Stage 2: Find all the sub-optimal solutions relative to the feasible combinations, that is, for each feasible combination G_j, compute the optimal values of the variables $x_{G_j}^{S_d}$, where S_d is a supplier in G_j, and the corresponding optimal objective value $TVP(G_j)$. In other words, for every feasible G_j, an integer linear programming problem must be solved.

Stage 3: Find the optimal final solution, that is, the supplier combination $G*$ delivering the highest value for TVP among all feasible supplier combinations. Having computed the optimal objective value relative to each feasible G_j in Stage 2, deciding which supplier combination is the optimal one is just matter of ordering all the objective values obtained.

This three-stage routine allows us to implement any commonly used software endowed with an optimization toolbox such as Excel or MatLab. In the case study, the optimal solutions of integer linear programming problems of Stage 2 have been found by using Excel Solver. The Excel Solver spreadsheets are available from the authors upon request.

4. VPs and weights: axiomatic issues and practical implications

4.1. Assessing DMs' VPs

Both definitions of α-VP and β-VP are justified by the fact that the decision committee is composed of several experts with different backgrounds and, hence, different *authority, expertise, knowledge and skills*. Due to these differences, not all the DMs are given the power to decide on every criterion or every supplier' performance. For example, engineers should be assigned the power to evaluate the technical performance of different stages of a production process, managers the power to evaluate the efficiency of the whole process or whether or not the different stages are efficiently connected, consumers the power to evaluate the quality of a product based on their expectations, which, at the same time, are built on the characteristics of the product, etc.

Ideally, in order to assign VPs to the DMs, we should be able to evaluate their performance with respect to a set of real data. That is, given a set of data on previous evaluations/forecasts given by the DMs and the actual results produced by the decision process, it should be possible to provide a more objective measure of each DM's ability to evaluate criteria and suppliers.

In this sense, a scoring rule could be used to define a continuous probability distribution allowing to compare deterministic forecasts, discrete forecast ensembles, and post-processed forecast ensembles (see, for example, Matheson & Winkler, 1976).

Unfortunately, this not always possible: previous data may not be available or not be complete enough for a purely objective calibration procedure. An alternative approach is the one proposed, among others, by Bodily (1979) who suggested these sort of powers/weights to be assigned either through mutual agreement of the decision team members or by a "super decision maker" (benevolent dictator). We follow this approach in the case study (see Section 5). It must be underlined that the procedures developed in this paper apply regardless of the methods used to weight the power of the different decision makers.

4.2. Weighting criteria and suppliers

The use of weights as measures of importance is always problematic. In particular, there is behavioral evidence that such conceptualization is misleading (Keeney, See, & Von Winterfeldt, 2006; von Nitzsch & Weber, 1993). Besides, weights are by definition always subjective, as they represent value trade-offs (Keeney, 2002).

In our approach, the choice of letting the DMs assign the weights to criteria as well as the evaluations to the suppliers' performance is corroborated by the α- and β-VPs assigned to the DMs. That is, even though the weights remain subjectively assigned, an a priori correct evaluation of the expertise of all the DMs should provide a reliable enough assessment of both criteria weights and performance values.

However, as discussed by Montibeller and von Winterfeldt (2015), cognitive and motivational biases are always present, even in the evaluation of the analysts, who are often affected by the same biases they are trying to help to overcome. Thus, biases are unavoidably present also in our weighting method and suitable debiasing routines should be implemented in parallel with the weighting method. In particular, our weighting method is prone to the splitting biases (Weber, Eisenfuhr, & von Winterfeldt, 1988) that occur when the way the objectives are grouped in a value tree affects their weights. These types of biases can be corrected by avoiding splits with large probability or weight ratios, using hierarchical estimation of weights or probabilities, and using ratio judgments instead of direct estimation or distribution of points. See Montibeller and von Winterfeldt (2015) for more details on how to identify several biases relevant to decision and risk analyses and correct them on the basis of the existing debiasing techniques.

In the case study, we kept the splitting bias to a minimum by diversifying the set of analysts in terms of expertise and providing a well-balanced description of all the objectives and the criteria on the same level so as not to induce the DMs to overweight some criteria with respect to others. That is, we have used the hierarchical structure of criteria and ratio judgments as debiasing techniques for the elicitation of the criteria weights.

A more modern treatment to the issue of calibration of expert judgments has been recently offered by Bolger and Rowe (2015).

4.3. Fundamental criteria and preferential independence

In the hierarchy of criteria that the DMs define in *Steps 2* and *3*, the fundamental criteria are the top level ones. All the sub-criteria are to be interpreted as lower-level values, with the leaf sub-criteria being key performance indicators (KPIs) that operationalize the values making them measurable and/or quantifiable.

This fact is reflected in the way the leaf criteria are assigned a global weight (i.e. by multiplying the group weights of all the interior super-criteria) and the way the TVP of a supplier combination G_j is defined (i.e. as the sum of the performances of the suppliers in G_j multiplied by the global weights of the leaf criteria). Furthermore, this fact also rises the problem of whether or not it is necessary to assume some sort of mutual preferential independence for the leaf criteria.

In our framework, the leaf criteria can be either synergistic or non-synergistic. While non-synergistic criteria can be easily assumed to be mutually preferentially independent, the synergistic ones make impossible to define an additive value function representing the DMs' preferences over the set of suppliers.

We overcome this obstacle by generating all possible supplier combinations and considering them as distinctive decision alternatives to be evaluated independently from the others. That is, the supplier combinations are regarded as additional suppliers and evaluated only with respect to the synergistic criteria. This is reflected by the algebraic form proposed for the TVP function (see

Eq. (28)), which is, therefore, guaranteed to represent linear preferences for the DMs.

In the case study, DMs identified six fundamental criteria (Product, Service, Delivery, Relationship, Reputation and Financial) operationalized by 31 leaf criteria working as KPIs. Only one of the leaf criteria was synergistic (transportation costs). See Section 5 for further comments.

5. Case study

In this section, we present an application of the proposed SSOA solution method to a real-life case study for grain supplier selection in one of the largest ACT companies in Germany.

ACT companies use two main approaches in supplier selection. Single-sourcing: looking for the best single supplier that meets the demand and satisfies all the requirements. Multiple-sourcing: determining the best supplier combination meeting the demand quantity and splitting the total order quantity among the suppliers in the combination.

Thus, the goal of the proposed case study is to evaluate all single- and multiple-sourcing purchasing alternatives according to a large number of conflicting synergistic and non-synergistic criteria, optimize the distribution of the demand quantity among the suppliers, and choose the best supplier combination with respect to the objectives and the values provided by firm representatives and customers.

Formally speaking, the problem is an instance of the SSOA problem (1). Hence, we implemented the seven-step procedure described in Section 3 to be able to evaluate the TVP of each supplier combinations.

In the case study, the available suppliers were three, S_1, S_2 and S_3, for a total of seven possible solutions: $G_1 = \{S_1\}$, $G_2 = \{S_2\}$, $G_3 = \{S_3\}$, $G_4 = \{S_1, S_2\}$, $G_5 = \{S_1, S_3\}$, $G_6 = \{S_2, S_3\}$, $G_7 = \{S_1, S_2, S_3\}$.

Following Keeney (1992), the facilitators used several tools to support the DMs in formulating objectives, including writing a wish list, discussing problems and shortcomings, imagining consequences of actions, considering goals and constraints, and adopting perspectives of other members. This was probably the most challenging part of the project.

The decision committee was composed of two company representatives, a top manager and a purchasing manager, and two costumers. DMs' VPs were assigned by a group of three "supra decision makers", the headquarter managers, using the method described by Keeney and von Winterfeldt (1991). The customers were not informed about their VPs, as the final decision is part of the company's internal decision/ policy procedure. The customers' β-VPs were considered to be constant across the criteria, based on the purchases of the last 3 years.

By the direct observation of the real purchasing decision processes and the interviews with purchasing managers, it was clear that their decisions were often biased. Purchasing managers would take dozens of decisions every day without any protocol so that the correctness of their decisions cannot be traced by the management. For example, one manager did not purchase anything from one supplier for some days, because it was unfriendly on the phone, although this supplier was good in terms of other criteria (desirability bias). This was one of the reasons to include a purchasing manager in the decision committee.

The top manager was involved only into the weighting of criteria and assessment of the alternatives with respect to strategic criteria (the suppliers' performance on strategic criteria is reassessed every 6 months or in the case of obvious performance changes), but not into the assessment of suppliers on operational criteria – this was the task of purchasing managers. The top manager was assigned a higher α-VP due to a better vision of the company's values. The managers' β-VPs were assigned considering their experience with the individual suppliers. Supra DMs also participated in the formulation of the objectives and approved the weight assessment of the criteria determined by the decision group.

Implementing the proposed seven-step procedure

Step 1: In the case study, DG was composed of $\Lambda = 4$ DMs divided in two divisions ($M = 2$). The first division $\langle 1 \rangle$ included two clusters of experts ($N^{m=1} = 2$): a cluster of top managers represented by only one person ($A^{m=1,n=1} = 1$ and $\langle 1, 1 \rangle = \{\langle 1, 1, 1 \rangle\}$) and a cluster of purchasing executives, also represented by a single member ($A^{m=1,n=2} = 1$ and $\langle 1, 2 \rangle = \{\langle 1, 2, 1 \rangle\}$). The second division $\langle 2 \rangle$ was composed of two clusters of customers ($N^{m=2} = 2$), each one represented by a single member ($A^{m=2,n=1} = 1$, $A^{m=2,n=2} = 1$, $\langle 2, 1 \rangle = \{\langle 2, 1, 1 \rangle\}$ and $\langle 2, 2 \rangle = \{\langle 2, 2, 1 \rangle\}$).

To simplify the presentation, we use M_1, M_2, C_1 and C_2 to denote $\langle 1, 1, 1 \rangle$ (top manager), $\langle 1, 2, 1 \rangle$ (purchasing manager), $\langle 2, 1, 1 \rangle$ (customer) and $\langle 2, 2, 1 \rangle$ (costumer), respectively.

Step 2: With the help of facilitators and based on interviews with representatives of the investigated commodity trading company in Germany, a large number of conflicting views was generated, summarized and translated into a common value system for the company representatives and their customers. Six fundamental criteria (Product, Service, Delivery, Relationship, Reputation and Financial) were identified and operationalized by 31 leaf criteria. These leaf criteria are listed in Table 1.

All of the leaf criteria, except "Financial costs", characterize the suppliers' individual performance in both single and multiple sourcing cases and are non-synergistic criteria. "Financial costs" is the only synergistic criterion. Financial costs are not linear due to the transportation cost component. For an optimal delivery of the purchased commodities several suppliers' logistics centers have to be covered by the vehicles. Joint transportation from multiple suppliers is usually cheaper than independent delivery from single suppliers. For example, given two suppliers, the transportation route "company→ S_1 → S_2 →company" may be cheaper than "(company→ S_1 →company) + (company→ S_2 →company)". In order to guarantee an additive value function representation of all alternatives, every supplier combination was evaluated with respected to its distinctive transportation costs and independently from the costs of the other combinations.

Finally, note that the criteria units in the SSOA case study were different. They are shown in Table 1, under the column "Units".

Step 3: The tree of criteria used to evaluate the grain suppliers in the investigated case study is exhibited in Fig. 3. All the criteria are indexed using the D-notation. The criteria include not only suppliers' operational strengths and weaknesses (e.g., discount, delivery difficulties), but also strategic opportunities and risks (e.g., desire to cooperate, product recalls).

Step 4: The decision committee in the case study was heterogeneous. The relative α-VPs assigned to the two divisions and their corresponding clusters are shown in Table 2.

These weights were assumed constant with respect to the different criteria. Thus, being each cluster $\langle m, n \rangle$ composed of a single DM, $w^{\alpha}(mna, c) = 1$ $\forall m, n, a$ and $\forall c$. The global α-VPs were derived using Eq. (7) and are given in Table 3.

Step 5: Table 4 presents the weights of the six top-level decision criteria estimated by the four α-level DMs composing the decision committee.

Step 6: Table 5 shows the DMs' β-VPs for assessing suppliers S_1, S_2 and S_3 assigned relative to three subjective non-synergistic criteria: "Sustainability", "Country of Origin" and "Product Recalls". "Sustainability", C_1 and C_2 are the final buyers (usually farmers). Thus, they do not have any business relations with the supplier, nor generally know who the suppliers are. Therefore, C_1 and C_2 were given a null β-VP with respect to "Sustainability". At the same time, the β-VPs of M_1 and M_2 were assigned on the basis of

Table 1
Leaf criteria for evaluating single wheat suppliers.

No.	Criteria description	Units	Criteria	Concerned DMs: Buyer	Concerned DMs: Customers
1	Number of business hours the loading terminals are open, per day	Hours	Loading Hours	•	
2	Other companies' bad experience with the supplier, including breaches of contracts through the supplier's fault	Scores	Bad Experience (E)	•	
3	Closeness of relationship with the supplier within and beyond the business	Scores	Closeness	•	
4	Category of the offered commodity according to the given standard	Rating scale	Product Category	•	•
5	Supplier's product recalls in the past	Scores	Recalls	•	•
6	Bad experience with the supplier in the past, except the items No. 2, 5, 10, 21	Scores	Bad Experience (I)	•	•
7	Conventional/Organic product	Rating scale	Production Method	•	•
8	Country of commodity origin	Rating scale	Country of Origin		•
9	Financial costs associated with the purchase	Euros	Financial Costs	•	•
10	Late available orders in the past	Integer number	Delays	•	•
11	Not transparent inspection of the offered product	Scores	Improper Inspection	•	•
12	Number of logistics centers related to the supplier	Integer number	Number of LCs	•	
13	Number of other commodity categories purchased from the supplier during the reference period	Integer number	Number of Items	•	
14	Number of producers that compound the offered lot of commodity	Integer number	Composition		•
15	Number of contact persons authorized to take orders and reply to inquiries	Integer number	Contact Persons	•	
16	Orders per internet, phone, fax	Scores	Multimedia	•	
17	Quantities of other commodities purchased from the supplier during the reference period	Euro	Past Businesses II	•	
18	Quantities of the product at hand purchased from the supplier during the reference period	Euro	Past Businesses I	•	•
19	Maximum allowed payment period	Days	Terms of Payment	•	
20	Probability of delivery difficulties	Subjective probability	Delivery Difficulties	•	•
21	Orders rejected by the supplier in the past	Integer number	Rejected Orders	•	•
22	Rush order processing and supply on order capabilities	Scores	Order Processing	•	•
23	Slow speed of inquiry processing	Scores	Inquiry Processing	•	
24	Friendly and individual treatment by the supplier's contact persons	Scores	Attitude	•	
25	Supplier's desire and attempts to build a sustainable partnership based on trust and commitment	Scores	Desire to Cooperate	•	
26	Supplier's attempts to contribute to environmental protection	Scores	Environmental Management		•
27	Supplier's honesty, fairness and equity in professional and interpersonal relationships	Scores	Ethical Behavior	•	•
28	Well organized loading process, modern equipment and logistics training programs	Scores	Logistics Facilities	•	
29	Supplier's office hours, per week	Hours	Office Hours	•	
30	Supplier's acting in advance	Scores	Proactiveness	•	
31	Sustainable relations with the supplier	Scores	Sustainability	•	

Table 2
α-voting powers of divisions and corresponding clusters in the case study.

Weights of α-level DMs (locally normalized)	Division 1—Buying firm representatives		Division 2—Customers	
	$w^\alpha(1) = 0.80$		$w^\alpha(2) = 0.20$	
	Cluster $\langle 1,1\rangle = \{M_1\}$	Cluster $\langle 1,2\rangle = \{M_2\}$	Cluster $\langle 2,1\rangle = \{C_1\}$	Cluster $\langle 2,2\rangle = \{C_2\}$
	$w^\alpha(1,1) = 0.75$	$w^\alpha(1,2) = 0.25$	$w^\alpha(2,1) = 0.60$	$w^\alpha(2,2) = 0.40$

Table 3
Global α-voting power of the DMs.

Decision maker$\langle m, n, a\rangle$	Top managerM_1	Purchasing managerM_2	Customer 1 C_1	Customer 2 C_2
Global α-voting power, $w_G^\alpha(mna, c)$	0.60	0.20	0.12	0.08

their experience with the individual suppliers. M_1 (top manager) was assigned a higher beta-priority than M_2 (purchasing manager) to assess S_1 and S_3. M_1 had experienced a long relationship with S_1 and S_3, while supplier S_2 was relatively new to the company. M_2 had joined our company recently and had previous experiences with S_2. “Country of origin”: all DMs were considered equally capable to assess suppliers with respect to this criterion. “Product recalls”: M_2 was generally better informed about this criterion, so his beta-weights were higher, except for S_3 with whom he had not had much experience.

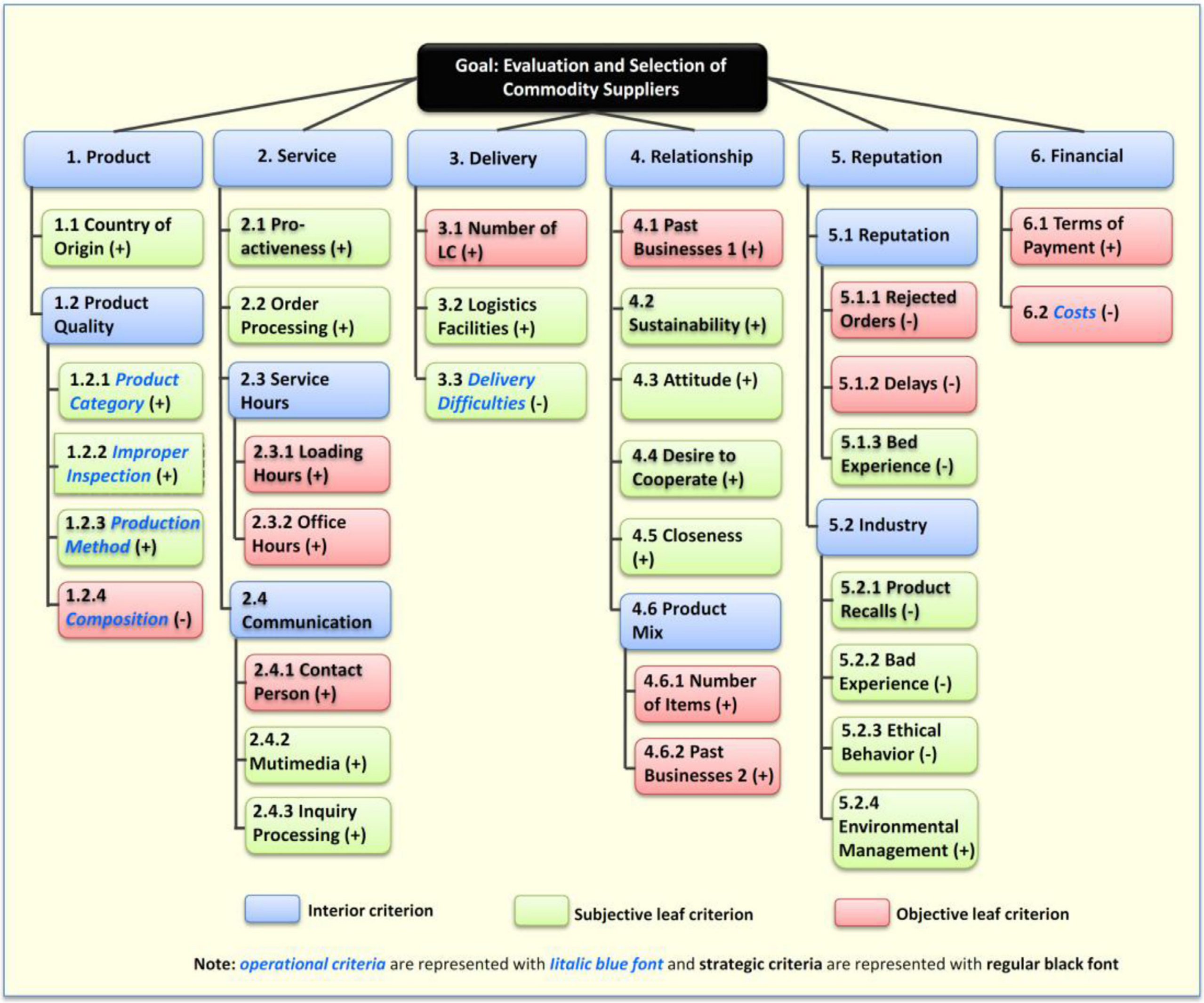

Fig. 3. Structure and classification of decision criteria for crop supplier evaluation.

Table 4
Weights of the top-level decision criteria assigned by the α-level DMs.

	Weights assigned by the α-level DMs			
	Top managerM_1	Purchasing managerM_2	Customer 1 C_1	Customer 2 C_2
Product	0.13	0.11	0.35	0.38
Service	0.08	0.05	0.00	0.00
Delivery	0.16	0.11	0.25	0.18
Relationship	0.12	0.05	0.03	0.08
Reputation	0.15	0.20	0.22	0.21
Financial	0.36	0.48	0.15	0.15
Total	1.00	1.00	1.00	1.00

Step 7: Sub-procedure 7.1

Table 5 also provides the performance evaluations of the three individual crop suppliers based on three objective non-synergistic criteria, i.e. “Composition”, “Past businesses 1” and “Terms of Payment”, as well as their estimates according to three subjective non-synergistic criteria, i.e. “Sustainability”, “Country of Origin” and “Product recalls”.

Table 6 presents the performance evaluations of all the supplier combinations on the synergistic criterion “Costs”. The prices offered by the crop suppliers in Euro per ton were:

$$p(S_1, c*^{Obj,\bar{\sigma}}{}_{PricePerTon}) = 95, \quad p(S_2, c*^{Obj,\bar{\sigma}}{}_{PricePerTon}) = 94,$$

$$p(S_3, c*^{Obj,\bar{\sigma}}{}_{PricePerTon}) = 97.$$

Crop costs for an order is the sum of suppliers’ offering prices per ton multiplied by the order quantities. That is, for every $j = 1, \dots, J$,

$$CP(G_j) = \sum_{d=1}^{D_j} p(S_d, c*^{Obj,\bar{\sigma}}{}_{PricePerTon}) \cdot x_{G_j}^{S_d}. \tag{29}$$

The problem of optimal route planning and estimation of the associated freight costs can be solved by one of the shortest path algorithms (Fu, Sun, & Rilett, 2006). In general, the transportation cost, $CD(G_j)$, associated with the jth supplier set is a function of

Table 5
Suppliers' data on some non-synergistic criteria in the case study.

Supplier S_d	β-level DMs $\langle m, n, a\rangle$	DMs' voting power $w^{\beta}(mna, c_i, S_d)$/DMs' estimates $p^{mna}(S_d, c_i)$	Subjective not-synergistic criteria, $c*_i^{Sbj,\bar{\sigma}}$			Objective not-synergistic criteria, $c*_i^{Obj,\bar{\sigma}}$		
			Sustainability $c*_{42}$	Country of origin$c*_{11}$	Product recalls$c*_{521}$	Composition $c*_{124}$	Past businesses 1$c*_{41}$	Terms of pay-ment$c*_{61}$
S_1	M_1	$w^{\beta}(M_1, c_i, S_1)$	0.7	0.25	0.3	20	850,002.77	14
		$p^{M_1}(S_1, c_i)$	10	0.4	2			
	M_2	$w^{\beta}(M_2, c_i, S_1)$	0.3	0.25	0.7			
		$p^{M_2}(S_1, c_i)$	6	0.38	2			
	C_1	$w^{\beta}(C_1, c_i, S_1)$	0	0.3	0			
		$p^{C_1}(S_1, c_i)$	0	0.5	0			
	C_2	$w^{\beta}(C_2, c_i, S_1)$	0	0.2	0			
		$p^{C_2}(S_1, c_i)$	0	0.34	0			
S_2	M_1	$w^{\beta}(M_1, c_i, S_2)$	0.4	0.25	0	30	1,521,561.15	21
		$p^{M_1}(S_2, c_i)$	6	0.25	0			
	M_2	$w^{\beta}(M_2, c_i, S_2)$	0.6	0.25	1			
		$p^{M_2}(S_2, c_i)$	5	0.32	1			
	C_1	$w^{\beta}(C_1, c_i, S_2)$	0	0.3	0			
		$p^{C_1}(S_2, c_i)$	0	0.2	0			
	C_2	$w^{\beta}(C_2, c_i, S_2)$	0	0.2	0			
		$p^{C_2}(S_2, c_i)$	0	0.33	0			
S_3	M_1	$w^{\beta}(M_1, c_i, S_3)$	0.7	0.25	0.8	17	7,645,000.95	14
		$p^{M_1}(S_3, c_i)$	8	0.35	3			
	M_2	$w^{\beta}(M_2, c_i, S_3)$	0.3	0.25	0.2			
		$p^{M_2}(S_3, c_i)$	7	0.3	1			
	C_1	$w^{\beta}(C_1, c_i, S_3)$	0	0.3	0			
		$p^{C_1}(S_3, c_i)$	0	0.3	0			
	C_2	$w^{\beta}(C_2, c_i, S_3)$	0	0.2	0			
		$p^{C_2}(S_3, c_i)$	0	0.33	0			

Table 6
Suppliers' data on the "cost" criterion in the case study.

Combinations G_j	G_1	G_2	G_3	G_4	G_5	G_6	G_7
Suppliers S_d	S_1	S_2	S_3	$\{S_1, S_2\}$	$\{S_1, S_3\}$	$\{S_2, S_3\}$	$\{S_1, S_2, S_3\}$
Crop price, $CP(G_j)$	$95 \cdot x_{G_1}^{S_1}$	$94 \cdot x_{G2}^{S_2}$	$97 \cdot x_{G_3}^{S_3}$	$95 \cdot x_{G_4}^{S_1} + 94 \cdot x_{G_4}^{S_2}$	$95 \cdot x_{G_5}^{S_1} + 97 \cdot x_{G_5}^{S_3}$	$94 \cdot x_{G6}^{S_2} + 97 \cdot x_{G_6}^{S_3}$	$95 \cdot x_{G_7}^{S_1} + 94 \cdot x_{G_7}^{S_2} + 97 \cdot x_{G_7}^{S_3}$
Cost of delivery, $CD(G_j)$	820	1050	970	1150	1100	1200	1250

the quantities to order $x_{G_j}^{S_d}$, where $d = 1, \ldots, D_j$. That is, $CD(G_j) = f(x_{G_j}^{S_1}, \ldots, x_{G_j}^{S_{D_j}})$.

In the case study, the overall costs associated with the jth supplier set were given by the sum of the crop costs and the delivery costs:

$$p(G_j, c*^{Obj,\sigma}_{Costs}) = CP(G_j) + CD(G_j). \tag{30}$$

The total quantity to order from the suppliers was fixed at $Y = 700$. Freight costs are listed in Table 6.

Step 7: Sub-procedure 7.2

DMs' estimates of the single crop suppliers were calculated using Eq. (19). For example, the collective assessment of the first supplier on the side of all β-level DMs for the criterion "Country of origin" was the following:

$$p(S_1, c*_{11}) = 0.25 \cdot 0.4 + 0.25 \cdot 0.38 + 0.3 \cdot 0.5 + 0.2 \cdot 0.34 = 0.413.$$

The collective estimates obtained for the other suppliers were:

$$p(S_1, c*_{42}) = 8.8; \quad p(S_1, c*_{521}) = 2; \quad p(S_2, c*_{42}) = 5.4;$$
$$p(S_2, c*_{11}) = 0.269; \quad p(S_2, c*_{521}) = 1; \quad p(S_3, c*_{42}) = 7.7;$$
$$p(S_3, c*_{11}) = 0.319; \quad p(S_3, c*_{521}) = 2.6.$$

Step 7: Sub-procedure 7.3

Table 7 shows the normalized performance values of the suppliers relative to the criteria of Table 5. The rest of the performance data was also normalized. The global leaf criteria weights were calculated using Eq. (14).

On the other hand, normalized costs depend on the quantities to order. For instance, the total normalized costs associated with the fourth alternative G_4 are:

$$p'(G_4, c*_{62}) = \frac{95 \cdot x_{G_4}^{S_1} + 94 \cdot x_{G_4}^{S_2} + 1150}{\sum_{j=1}^{7}(CP(G_j) + CD(G_j))},$$

where $\sum_{j=1}^{7} CD(G_j) = 820 + 1050 + 970 + 1150 + 1100 + 1200 + 1250 = 7540$ and $\sum_{j=1}^{7} CP(G_j) = 95 \cdot (x_{G_1}^{S_1} + x_{G_4}^{S_1} + x_{G_5}^{S_1} + x_{G_7}^{S_1}) + 94 \cdot (x_{G_2}^{S_2} + x_{G_4}^{S_2} + x_{G_6}^{S_2} + x_{G_7}^{S_2}) + 97 \cdot (x_{G_3}^{S_3} + x_{G_5}^{S_3} + x_{G_6}^{S_3} + x_{G_7}^{S_3})$.

Step 7: Sub-procedure 7.4

The TVP of all the seven supplier combinations was calculated using Eq. (28). For example, the TVP for the fourth alternative was:

$$TVP(G_4) = p^{Pro,\bar{\sigma}}(G_4) - p^{Con,\bar{\sigma}}(G_4) - p^{Con,\sigma}(G_4),$$

where $p^{Pro,\bar{\sigma}}(G_4) = 0.112 \cdot x_{G_4}^{S_1} + 0.088 \cdot x_{G_4}^{S_2}$, $p^{Con,\bar{\sigma}}(G_4) = 0.130 \cdot x_{G_4}^{S_1} + 0.128 \cdot x_{G_4}^{S_2}$ and $p^{Con,\sigma}(G_4) = 0.312 \cdot \frac{95 \cdot x_{G_4}^{S_1} + 94 \cdot x_{G_4}^{S_2} + 1150}{\sum_{j=1}^{7}(CP(G_j) + CD(G_j))}$.

Similarly, the TVPs for the remaining six alternatives G_j, with $j \neq 4$, were derived.

Finding the optimal solution to the SSOA problem

Recall that Problem (1) can be rewritten as Problem (3). Thus, to identify feasible and sub-optimal solutions, we can use the constraints as they are defined in Problem (3). The credit limits

Table 7
Normalized suppliers' data on some criteria in the case study.

Supplier S_d	Subjective non-synergistic criteria $c{*_i}^{Sbj,\bar{\sigma}}$			Objective non-synergistic criteria $c{*_i}^{Obj,\bar{\sigma}}$		
	Sustainability $c*_{42}$ $w_G(c*_{42})$	Country of origin$c*_{11}$ $w_G(c*_{11})$	Product recalls$c*_{521}$ $w_G(c*_{521})$	Composition $c*_{124}$ $w_G(c*_{124})$	Past businesses 1, $c*_{41}$ $w_G(c*_{41})$	Terms of payment$c*_{61}$ $w_G(c*_{61})$
	0.040	0.017	0.026	0.019	0.019	0.028
S_1	0.402	0.413	0.357	0.299	0.085	0.286
S_2	0.247	0.269	0.179	0.448	0.152	0.429
S_3	0.352	0.319	0.464	0.254	0.763	0.286

Table 8
Feasibility of decision alternatives in the case study.

Combinations G_j	Suppliers S_d	$MaxQ\ (G_j)$	$MinQ\ (G_j)$	Feasible (F)/Not feasible (NF)
G_1	S_1	331.58	200	NF
G_2	S_2	353.72	0	NF
G_3	S_3	412.37	250	NF
G_4	$\{S_1, S_2\}$	681.58	200	NF
G_5	$\{S_1, S_3\}$	752.63	450	F
G_6	$\{S_2, S_3\}$	779.26	250	F
G_7	$\{S_1, S_2, S_3\}$	1102.63	450	F

Table 9
Feasible sub-optimal alternatives in the case study.

Feasible G_j	Supplier S_d	Total value of purchasing $TVP\,(G_j)$	Financial costs of purchasing $p\,(G_j, c_{Costs})$	Order quantities $x_{G_j}^{S_d}$	Maximum offered quantities $MaxQ(S_d)$	Credit limits expressed in tons of crop $MaxQ_{CL}(S_d)$	Minimum offered quantities $MinQ\ (S_d)$
G_5	S_1	0.3467	71,738.00	331.00	550	331.58	200
	S_3			369.00	500	412.37	250
G_6	S_2	0.2950	69,841.00	353.00	450	353.72	0
	S_3			347.00	500	412.37	250
G_7	S_1	0.3484	71,881.00	331.00	550	331.58	200
	S_2			119.00	450	353.72	0
	S_3			250.00	500	412.37	250

defined by each supplier under consideration were:

$$CL(S_1) = 31500.00\,\text{Euro}, \quad CL(S_2) = 33250.00\,\text{Euro},$$
$$CL(S_3) = 40000.00\,\text{Euro}.$$

The minimum and maximum offered quantities were:

$$MinQ_{offered}(S_1) = 200\,\text{Tons}, \quad MinQ_{offered}(S_2) = 0\,\text{Tons},$$
$$MinQ_{offered}(S_3) = 250\,\text{Tons}, \quad MaxQ_{offered}(S_1) = 550\,\text{Tons},$$
$$MaxQ_{offered}(S_2) = 450\,\text{Tons}, \quad MaxQ_{offered}(S_3) = 500\,\text{Tons}.$$

Finally, the maximum available shared resource quantities in Tons were:

$$MaxQ_{shared}(G_4) = 800, \quad MaxQ_{shared}(G_5) = 1000,$$
$$MaxQ_{shared}(G_6) = 950, \quad MaxQ_{shared}(G_7) = 1300.$$

The demand was $Y = 700$.

Stage 1: Table 8 shows the feasible and not feasible alternatives based on the feasibility constraints as formulated in Problem (3).

Stage 2: Table 9 also shows the optimal values of the decision variables and the corresponding TVPs obtained for all the feasible supplier combinations.

Stage 3: From Table 9, it follows that $G* = G_7$. Thus, the optimal solution was to distribute the order of 700 Tons among the three suppliers S_1, S_2 and S_3 composing G_7, placing an order of 331, 119 and 250 Tons, respectively.

6. Conclusions and future research directions

The size and complexity of real-life problems together with their ill-defined nature call for an integration of human capabilities with the power of computational techniques. This is done for the purpose of analyzing, envisioning, reasoning, and deliberating on complex real-life problems (Andrienko et al., 2007). The framework proposed in this study is designed to guide and assist DMs in the process of international supplier evaluation and selection in ACT companies within complex supply chains in multi-objective collaborative environments. Both single- and multiple-sourcing strategies are considered as potential solutions. The selection of an appropriate sourcing strategy is situational and depends on the data set and the TVP goals. The method proposed in this study is flexible enough to allow for applications to specific problems and situations, including different criteria and restrictions. The synergy effects that are encountered in multiple-sourcing problems can be incorporated systematically into the evaluation process proposed here. The number of DMs and the depth of the criteria hierarchy are flexible. The approach relies on rigorous mathematical methods that utilize objective data and expert judgments. The abstract framework introduced to describe our method is proved to have concrete applications by the parallel analysis of a case study: the multi-criteria problem is customized and formulated as a SSOA problem in the ACT industry. Thus, the novel approach proposed here can directly assist purchasing managers in their day-to-day SSOA decisions.

In spite of its promising features, the method proposed in this study presents several limitations when it comes to solve real-life SSOA problems. These limitations are described below and can open the way for further research.

1. In the case study, only one synergistic parameter (freight costs) is considered, whereas real problems may face multivariate positive and negative synergism of alternatives. The proposed

formal model facilitates performance synergies of alternatives on multiple criteria simultaneously.

2. The model proposed in this study is designed to use precise values. However, it could be further extended by representing vague measures using fuzzy numbers (Chou et al., 2008; Fu, 2008; Tavana, Sodenkamp, & Suhl, 2010), neutrosophic values (Arora & Biswas, 2010), fuzzy AHP (Buckley, 1985; van Laarhoven & Pedrycz, 1983), or estimating correlation of vague group estimates (Aldian & Taylor, 2005; Tavana & Sodenkamp, 2009; Tavana, Sodenkamp, & Bourgeois, 2009).
3. The method proposed here does not consider incomplete or unknown data which may influence the reliability of the outcome. For future research, we suggest the study and development of synergistic SSOA under uncertainty.
4. The integer programming problem (1) must be modified if conditions entailing non-linearity of suppliers' individual performances, such as suppliers' volume discounts (Kokangul & Susuz, 2009; Ghodsypour & O'Brien, 2001) are to be taken into consideration.
5. The decision criteria used in this study are based on the analysis of the scholarly and business literature, as well as the interviews with the representatives of the German ACT company who participated in this research. These criteria can be extended or reduced and the structure of criteria interconnections can be modified and adjusted to address the organizational requirements.

Future research can extend the meta-model proposed here by taking into account the above listed shortcomings. Additionally, sensitivity analysis could be performed in order to validate the robustness of the outcome.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2016.04.015.

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