An a posteriori decision support methodology for solving the multi-criteria supplier selection problem

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A B S T R A C T

This research presents a novel, state-of-the-art methodology for solving a multi-criteria supplier selection problem considering risk and sustainability. It combines multi-objective optimization with the analytic network process to take into account sustainability requirements of a supplier portfolio configuration. To integrate 'risk' into the supplier selection problem, we develop a multi-objective optimization model based on the investment portfolio theory introduced by Markowitz. The proposed model is a non-standard portfolio selection problem with four objectives: (1) minimizing the purchasing costs, (2) selecting the supplier portfolio with the highest logistics service, (3) minimizing the supply risk, and (4) ordering as much as possible from those suppliers with outstanding sustainability performance. The optimization model, which has three linear and one quadratic objective function, is solved by an algorithm that analytically computes a set of efficient solutions and provides graphical decision support through a visualization of the complete and exactly-computed Pareto front (a posteriori approach). The possibility of computing all Pareto-optimal supplier portfolios is beneficial for decision makers as they can compare all optimal solutions at once, identify the trade-offs between the criteria, and study how the different objectives of supplier portfolio configuration may be balanced to finally choose the composition that satisfies the purchasing company's strategy best. The approach has been applied to a real-world supplier portfolio configuration case to demonstrate its applicability and to analyze how the consideration of sustainability requirements may affect the traditional supplier selection and purchasing goals in a real-life setting.

1. Introduction

High procurement costs induce manufacturing firms to select their suppliers carefully (Krause, Handfield, & Scannell, 1998), particularly because firms tend to have fewer suppliers with whom they have long-term relationships (Ho, Xu, & Dey, 2010). Supplier selection becomes even more complex when following the trends of integrating research and development aspects and the firm's corporate strategy into the supplier selection process (Luo, Kwong, Tang, Deng, & Gong, 2011; Parthiban, Zubar, & Katakar, 2013; Wetzstein, Hartmann, Benton, & Hohenstein, 2016). Besides the common challenges of increased customer requirements, the globalization of procurement markets, the demands and opportunities of e-procurement, shortened product life cycles, and the expansion of just-in-time environments, purchasing firms are confronted with increasing market and legal pressures related to sustainability (Bai & Sarkis, 2010; Gualandris, Klassen, Vachon, & Kalchschmidt, 2015; Linton, Klassen, & Jayaraman, 2007; Micheli, 2008; Parthiban et al., 2013; Spina, Caniato, Luzzini & Ronchi, 2013; Tracey & Leng Tan, 2001; Trent & Monczka, 2003). These challenges make sustainability even more important in the supplier selection process (Amindoust, Ahmed, Saghafinia, & Bahreininejad, 2012; Büyüközkan & Çifçi, 2011; Govindan, Khodaverdi, & Jafarian, 2013; Krause, Vachon, & Klassen, 2009; Wetzstein et al., 2016). Yet, sustainability does not necessarily need to be a burden, but offers several opportunities for purchasing companies. Selecting sustainable suppliers might, for instance, strengthen the competitiveness of the purchasing firm (Humphreys, Wong, & Chan, 2003; Koufteros, Vickery, & Dröge, 2012), increase its corporate reputation (Bai & Sarkis, 2010; Gopalakrishnan, Yusuf, Musa, Abubakar, & Ambursa, 2012), or encourage inter-organizational learning (Baskaran, Nachiappan, & Rahman, 2012). Consequently, sustainability considerations should be part of solving the multi-criteria supplier selection problem. While the traditional selection approaches focus mainly on the suppliers' characteristics of 'quality,' 'price,' and 'delivery' (cf. Ho et al., 2010; Kannan & Tan, 2002; Verma & Pullman, 1998), recent research also takes sustainability aspects into consideration

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(Bai & Sarkis, 2010; Dai & Blackhurst, 2012; Govindan et al., 2013; Neumüller, Lasch, & Kellner, 2016). Thereby, the goal is to balance the economic, environmental, and social impacts of business processes.

Numerous approaches have been developed to study and to solve the multi-criteria supplier selection problem, including the analytic hierarchy process (AHP), data envelopment analysis, neural networks, and mathematical programming (Ho et al., 2010). As we view the supplier selection problem from a portfolio configuration perspective aimed at balancing the traditional goals of supplier selection, i.e., through cost and supply risk minimization and service maximization (cf. Aydın Keskin, İlhan, & Özkan, 2010; Krause et al., 2009), and sustainability objectives, multi-objective optimization is a particularly suitable approach. Recent contributions (Hosseininasab & Ahmadi, 2015; Talluri, Narasimhan, & Chung, 2010) show that the mathematical framework of the investment portfolio theory introduced by Markowitz (1952, 1959) may support supplier selection and development decisions effectively—especially when the factor 'risk' needs to be taken into account. Thus, supplier portfolios that reduce the long-term risk of failure may be assembled. While Markowitz's portfolio model is recognized as a suitable framework for studying the supplier selection problem considering risk and sustainability, the visualization of the entire Pareto front is problematic as there are more than two objectives, with one of them being represented by a quadratic function (Utz, Wimmer, Hirschberger, & Steuer, 2014). Consequently, decision makers are unable to gain an overview of all trade-offs, which is necessary for balancing cost, service, risk, and sustainability aspects.

In this setting, the contribution of our study is threefold: (1) it presents a novel multi-criteria decision support approach for studying the supplier selection problem that considers risk and sustainability. The approach combines multi-objective programming, the Markowitz portfolio theory, and the analytic network process (ANP). This combination of methods allows processing the different aspects of a supplier portfolio configuration with supply risk and sustainability considerations. Multi-objective programming translates the multi-criteria supplier selection problem into a mathematical optimization model with several objective functions and constraints that assure, for instance, that the capacities of the single suppliers are not exceeded, that the total demand of the purchasing company is satisfied, and that a certain minimum level of the logistics service is guaranteed. The mathematical framework of the Markowitz (1952, 1959) portfolio theory allows integrating the aspect 'risk' into the multi-objective optimization model and assembling supplier portfolios that reduce the long-term risk of failure. Finally, the use of the ANP meets the requirements of a supplier portfolio configuration that takes sustainability into consideration. This is due to the fact that ANP allows, for instance, processing quantitative and qualitative sustainability performance measures and the interactions between the criteria. While prior research shows that multi-objective programming, the Markowitz portfolio theory, and the ANP are effective methods for supporting supplier selection decisions, these three methods have not been combined so far. In particular, no attempt has been made to compute and visualize the Pareto front that results from the multi-objective decision making problem. However, as we show in this paper, the visualization and the analysis of the Pareto front provide a better understanding of the decision problem and support more informed decision making as the decision makers gain the full picture of all possible optimal solutions. Thus, they are able to compare and to balance the different trade-offs and goals of the supplier selection problem. Therefore, we (2) extend the existing supplier selection approaches that are based on Markowitz' portfolio model and analyze the supplier portfolio optimization problem that considers risk and sustainability based on the visualization of the complete and non-approximated, i.e., exactly-computed, Pareto front. The computation of the Pareto front is challenging as a quadratic objective function is part of the multi-objective optimization model and there are more than two objectives. Thus, we present an exact algorithm that solves this specific problem. To balance supplier selection objectives, such as cost, quality, risk, and sustainability, we apply the solution procedure developed by Hirschberger, Steuer, Utz, Wimmer, and Qi (2013). (3) Finally, we provide new insights on the effects of considering sustainability in the supplier selection process. To be more precise, we study how sustainability affects the Pareto front and how sustainability goals may be balanced with traditional supplier selection and purchasing goals, i.e., low cost, adequate quality/availability, and low risk (Kraljic, 1983; Krause et al., 2009).

The proposed approach has been applied to the supplier selection problem of a known premium automotive OEM from Germany. As the brand's reputation is of highest importance for the OEM, it is very careful when selecting its suppliers. Previously, suppliers were evaluated on a regular basis with scorecards. Based on this information, the OEM then decided which supplier to select. While the company's current approach for supplier evaluation and selection results in feasible and generally good decisions, it does not allow for a combined analysis that optimizes quality, cost, risk, and sustainability aspects simultaneously. Applying the methodology proposed in this article allows the selection of an optimal supplier portfolio based on the visualization of the complete Pareto front, i.e., all possible trade-offs are shown graphically, and the OEM's own strategy/preferences/priorities (cf. Kraljic, 1983; Krause et al., 2009; Krause, Pagell, & Curkovic, 2001), for example, regarding risk aversion.

The paper is organized as followed: Section 2 provides a literature review on supplier selection, paying particular attention to portfolio models and the integration of sustainability. Section 3 describes the methodology, with a focus on the optimization model, the calculation of the sustainability performance scores for the suppliers, and the procedure used to compute the Pareto front. Section 4 illustrates the numerical example. Section 5 presents a discussion on the proposed decision support methodology and on the case study results. Finally, Section 6 summarizes the main findings and contributions, and provides potential topics for further research.

2. Multi-objective supplier selection

This section is divided into three parts. Section 2.1 analyzes general supplier selection approaches and identifies the 'a posteriori' concept as particularly suitable for solving the multi-objective supplier selection problem. Section 2.2 focuses on portfolio models, which are suitable for integrating risk into the supplier selection, and shows how this research can extend the existing approaches. Finally, Section 2.3 presents current research on the requirements for integrating sustainability into the supplier selection process.

2.1. Supplier evaluation and selection

Researchers have studied supplier evaluation and selection problems extensively. Boer, Labro, and Morlacchi (2001), Degraeve, Labro, and Roodhooft (2000), Ho et al. (2010), and Weber, Current, and Benton (1991) present thorough literature reviews on this topic. They show that contemporary supply chain management evaluates the performance of potential suppliers against a wide range of often-conflicting quantitative and qualitative criteria. According to Ho et al. (2010), the most popular criteria are quality, followed by delivery, price/cost, manufacturing capability, service, management, technology, research and development, finance, flexibility, reputation, relationship, risk, and safety and environment.

Over the years, various approaches have been proposed for solving the supplier selection problem, including data envelopment analysis, mathematical programming, analytic hierarchy process, analytic network process, fuzzy set theory, case-based reasoning, neural networks, or any of their combinations (Ho et al., 2010; Hosseininasab & Ahmadi, 2015). Feng (2012), for instance, presents a decision method for multi-sourcing supplier selection in service outsourcing. The author combines an extended version of the technique for order preference by similarity to ideal solution (TOPSIS) with a bi-objective 0-1 linear programming model and calculates Pareto-optimal solutions for supplier portfolios. Additionally, Qin, Liu, and Pedrycz (2017a) extend the traditional LINMAP (linear programming technique for multi-dimensional analysis of preferences) method (Srinivasan & Shocker, 1973) to solve multi-attribute group decision making problems, in their case, the supplier selection problem, in an interval type-2 fuzzy environment.

Ho et al. (2010) analyze 78 journal articles appearing in the period from 2000 to 2008 that solve the supplier evaluation and selection problem using multi-criteria decision-making approaches. They find that integrated AHP-goal programming is the most popular approach and deem it to be 'beneficial' for the problem at hand. They explain this finding by combining the techniques' individual advantages, which allows the processing of quantitative and qualitative criteria, the use of judgement consistency checks, and the consideration of resource limitations (e.g., budget of buyer or capacities of suppliers). The solution approach presented in this paper is also based on an integrated approach. It combines the ANP with multi-objective programming. The ANP is a generalized form of the AHP that overcomes some of the latter's limitations, namely the sole consideration of one way hierarchical relationships among factors and the failure to consider interactions among the factors (Dou & Sarkis, 2010). Goal programming is a specific method for solving multi-objective optimization problems that is based on a priori articulation of preferences for the criteria in terms of criteria weights. Generally, the methods for solving multi-objective optimization problems may be classified according to the moment in time when the decision maker expresses a preference for the different objectives. There are methods with a priori articulation of preferences, methods with a posteriori articulation of preferences, interactive methods, methods with no articulation of preferences, or variations of all of these (Hwang & Masud, 1979; Marler & Arora, 2004; Mavrotas, 2009).

We suggest investigating the multi-objective supplier selection problem using an a posteriori approach. This means that, first of all, all Pareto-optimal solutions, i.e., all non-dominated supplier portfolios, are computed and visualized graphically. Then, a particular portfolio is selected in accordance with the purchasing company's supply strategy (cf. Kraljic, 1983; Krause et al., 2001; Krause et al., 2009). Based on the visualization of the complete set of Pareto-optimal solutions, the a posteriori approach allows forgoing an ex ante articulation of preferences for the objectives, identifying the trade-offs between the criteria, and studying how the different aspects of supplier portfolio configuration may be balanced.

2.2. Portfolio models for considering risk in supplier selection

Hosseininasab and Ahmadi (2015), Lee and Chien (2014) and Talluri et al. (2010) show that applying the concepts of the investment portfolio theory, which was introduced by Markowitz (1952, 1959) and received significant attention in the finance literature, may effectively be transferred to the supplier selection and development context. Thereby, supplier portfolios that reduce the long-term risk of failure, i.e., the portfolio's instability in supply performance, may be assembled, which promotes long-term relationships. We adopt such a perspective.

Amorim, Curcio, Almada-Lobo, Barbosa-Póvoa, and Grossmann (2016) and Federgruen and Yang (2008), amongst others, introduce stochastic measures for supply risk into the supplier evaluation criteria and select a robust supply portfolio. Such approaches, however, mainly focus on selecting a supply portfolio that guarantees satisfying the buyer's needs in times of fluctuating demand or delivery but do not consider the possibility that the selected suppliers remain the best choice compared to other unselected suppliers. At this point, it should be noted that similar to the research presented by Talluri et al. (2010), our focus is not on the development of a new measure of risk (cf. Jia & Dyer, 1996; Szegö, 2005), but we aim, rather, to study the supplier portfolio configuration problem considering risk and sustainability by applying the concepts of the investment portfolio theory.

We extend the existing supplier selection approaches based on the Markowitz model (cf. Hosseininasab & Ahmadi, 2015; Lee & Chien, 2014; Talluri et al., 2010) as we analyze the supplier portfolio optimization problem under risk conditions based on the visualization of the complete and non-approximated, i.e., exactly-computed, Pareto front. From a mathematical point of view, the exact calculation of the complete Pareto front is challenging as the portfolio model presented below has four objective functions, one of which is quadratic. Thus, in principle, an uncountable number of quadratic programming models need to be solved in order to generate the Pareto front when using the standard approaches, namely the weighted method and the ε-constraint method (Mavrotas, 2009). We show how to overcome this problem by introducing a novel methodology for integrating risk into the supplier portfolio optimization process, independent of the sustainability aspects of supplier selection.

2.3. Integrating sustainability into supplier selection

During the last decade, sustainability considerations have attracted increasing attention in the supplier evaluation and selection process, both in practice and in research. Some examples of companies that are actively rating the sustainability performance of their suppliers are Adidas, Apple, and Walmart (see the websites of these firms; cf. Klassen & Vereecke, 2012). Moreover, researchers developed different approaches that support the supplier evaluation and selection process. Some of these approaches are based on the combination of the AHP with quality function deployment or multi-objective linear programming (Dai & Blackhurst, 2012; Shaw, Shankar, Yadav, & Thakur, 2013). Another way of tackling the supplier evaluation and selection problem considering sustainability is the use of the ANP (Büyüközkan & Çifçi, 2011; Dou & Sarkis, 2010). Some researchers suggest applying fuzzy logic, fuzzy numbers, fuzzy inference systems, and/or fuzzy TOPSIS to handle the subjectivity of decision makers' assessments for sustainability criteria and performance (Amindoust et al., 2012; Govindan et al., 2013; Öztürk & Özçelik, 2014). Liu, Liu, and Qin (2018) propose a combined approach in order to handle uncertain information in the sustainable supplier selection process: the integrated ANP-VIKOR methodology with interval type-2 fuzzy sets. Govindan and Sivakumar (2016) and Hamdan and Cheaitou (2017) focus on the environmental dimension of sustainability. They provide decision support methodologies for the green supplier selection problem based on multi-objective optimization. Qin, Liu, and Pedrycz (2017b), also focusing on green supplier selection, extend the TODIM (an acronym in Portuguese of interactive and multi-criteria decision making; cf. Gomes & Lima, 1992) technique to solve multi-criteria group decision making problems in the context of interval type-2 fuzzy sets. Ghadimi, Ghassemi Toosi, and Heavey (2018) propose a multi-agent systems approach for sustainable supplier selection. Finally, Bai and Sarkis (2010) and Baskaran et al. (2012) suggest the grey approach to handle the subjectivity of the criteria or the grey system and rough set theory.

Neumüller et al. (2016) critically review the existing approaches for supplier selection under sustainability considerations based on a literature review on the foundations of corporate sustainability and strategic supplier selection. They identify eight requirements that should be met by a comprehensive decision support methodology for sustainable strategic supplier portfolio configuration. These are the consideration of (1) three-dimension sustainability, (2) quantitative and qualitative criteria, (3) interrelationships between the sustainability criteria, (4) group decision making, (5) the time horizon, (6) the strategic orientation of the company, (7) dual sourcing, and (8) portfolio configuration. Furthermore, Neumüller et al. (2016) develop a combined ANP-goal programming model that meets all eight requirements.

Our research is based on these eight requirements; however, unlike Neumüller et al. (2016), we suggest the use of an a posteriori approach for solving the multi-objective decision problem as the trade-offs between sustainability and the classical cost-performance goals may be better represented through the visualization of the Pareto front. In addition, uncertainty/risk in the performance of the potential suppliers is taken into account, unlike in the model proposed by Neumüller et al. (2016).

3. Methodology

3.1. Framework: overview of the multi-criteria decision support approach

In this section, we present a novel decision support framework for studying and solving the supplier selection problem. In summary, we approach the supplier selection problem from a multi-objective portfolio optimization perspective. The selected suppliers and the proportions of the purchasing company's total demand that are ordered from these sources are conceptualized as 'supplier portfolio.' The goal is to identify the portfolio that is better than any other according to a set of objectives (criteria) and with respect to the preferences of a certain decision maker.

The proposed approach combines the Markowitz portfolio theory (Section 3.2), the ANP (Section 3.3), and multi-objective programming (Section 3.4). Multi-objective programming translates the multi-criteria supplier selection problem into a mathematical optimization model. The different constrains make sure that the capacities of the single suppliers and the budget of the purchasing company are not exceeded, that the purchasing company's total demand is satisfied, and that a predefined minimum level of the logistics service is guaranteed. The fact that our proposed multi-objective programming model is based on the mathematical framework of the Markowitz portfolio theory allows integrating the aspect 'risk' into the optimization model and assembling supplier portfolios that reduce the long-term risk of failure. One objective of the optimization model is the maximization of the share of orders that is sourced from those suppliers that are outstanding with regard to sustainability. In this paper, we propose the use of the ANP to calculate indicators for the sustainability performances of the single suppliers. Besides that, the a posteriori decision making approach is a fundamental aspect of this research because we suggest to analyze the supplier portfolio optimization problem based on the visualization of the complete and exactly-computed Pareto front. Thus, the presentation of an algorithm that exactly computes the Pareto front is part of our methodology.

3.2. Multi-objective supplier portfolio optimization model

In the proposed supplier portfolio optimization model, there are four objectives: to minimize the purchasing costs, to select the supplier portfolio with the highest logistics service, to select the portfolio that minimizes the supply risk, and to order as much as possible from those suppliers with an outstanding sustainability performance.

Indices

i, j	$1, \ldots, N$	Suppliers
t	$1, \ldots, T$	Time periods

Decision variables

$\boldsymbol{x} = (x_1, \ldots, x_N)$	$\in [0, 1]^N$	Vector of the proportions of the total demand ordered from the single suppliers

Parameters

$\boldsymbol{c} = (c_1, \ldots, c_N)$	$\in \mathbb{R}^N$	Vector of the per unit selling price of the single suppliers
$\boldsymbol{l} = (l_1, \ldots, l_N)$	$\in [0, 1]^N$	Vector of indicators of the logistics performances of the single suppliers
$\boldsymbol{Q} = (\sigma_{ij})_{i,j=1,\ldots,N}$	$\in \mathbb{R}^{N \times N}$	Covariance of the logistics performance in suppliers i and j
$\boldsymbol{s} = (s_1, \ldots, s_N)$	$\in [0, 1]^N$	Vector of the sustainability performance (sustainability score) of the single suppliers
$\boldsymbol{G} = (C_1, \ldots, C_N)$	$\in [0, 1]^N$	Vector of the capacities of the single suppliers
B	$\in \mathbb{R}$	Budget (maximum average variable purchasing cost)
L	$\in [0, 1]$	Minimum logistics service offered by the supplier portfolio

Objectives

Costs
$$min \sum_i c_i * x_i \tag{1}$$

Logistics service
$$max \sum_i l_i * x_i = \sum_i \left(\frac{\sum_t t * l_{it}}{\sum_t t} \right) * x_i \tag{2}$$

Supply risk
$$min \sum_{ij} \sigma_{ij} * x_i * x_j \tag{3}$$

Sustainability
$$max \sum_i s_i * x_i \tag{4}$$

Constraints

Demand satisfaction
$$\sum_i x_i = 1 \tag{5}$$

Supplier capacity
$$0 \le x_i \le C_i \qquad \forall i \tag{6}$$

Budget
$$\sum_i c_i * x_i \le B \tag{7}$$

Overall service
$$\sum_i l_i * x_i \ge L \tag{8}$$

Objective function (1) minimizes the purchasing costs. Objective function (2) selects the supplier portfolio that maximizes the mean/expected logistics service. The logistics service l_i offered by a supplier i is expressed as the percentage share of the deliveries that meets five of the 'six R's of logistics,' i.e., 'the Right product, in the Right quantity, in the Right condition/quality, at the Right time, at the Right place.' The sixth 'R' ('for the Right costs') is represented by Eq. (1). As we do not assume the logistics service of the suppliers to be constant throughout time, the logistics performance l_i is calculated as the weighted average over the last T periods to put more emphasis on the most recent performance scores. Objective function (3) minimizes the supply risk. Supply risk occurs when there is uncertainty concerning the logistics service, i.e., the share of the deliveries meeting the ‘five R’s of logistics’ may vary more or less strongly throughout time, depending on the suppliers. In accordance with Markowitz’s portfolio theory, uncertainty is measured with the variance of the logistics service $\boldsymbol{l}$. The supply risk of the supplier portfolio as a whole is minimized by minimizing the covariance of the logistics service between the suppliers (see below). Finally, objective function (4) maximizes the proportion of orders placed with those suppliers that are achieving a high sustainable performance. The sustainability performance of the single suppliers is indicated by the sustainability scores s. These are determined by taking into account current research specifying the requirements for integrating sustainability into supplier portfolio selection. The details are explained in Section 3.3.

Constraint (5) guarantees that the total demand of the purchasing company is satisfied. Constraint (6) assures that the amount sourced from the suppliers is not greater than their capacities. Constraint (7) is the budget constraint that guarantees that the purchasing cost does not exceed B. Note that B is the average variable purchasing cost that can be spent for any given demand. And constraint (8) ensures that the expected overall logistics service is at minimum L. This means that suppliers with a lower average logistics performance than L may be part of the portfolio; however, the overall expected logistics service is at minimum L.

The multi-objective portfolio model resembles the classical risk-expected return trade-off that is at the heart of the portfolio theory fathered by Markowitz (1952, 1959). Removing all equations except (3), (4), and (5) results in the standard portfolio selection formulation. The objective functions (1), (2), and (4) are synonymous with the maximization of the portfolio’s expected return. The objective function (3), which minimizes the supply risk by minimizing the covariance $\Sigma_{ij}\sigma_{ij}$ of the logistics service between the suppliers, is synonymous with the minimization of the variance of the portfolio’s return. This means that, in accordance with Markowitz’s portfolio theory, supply risk is measured with the variance of the logistics service of the supplier portfolio as a whole. The goal is not to make the single suppliers less risky but to minimize (‘to pool’) the overall supply risk by minimizing the covariance of the logistics service between the suppliers. The covariance, in turn, measures the ‘interaction’ between two suppliers, i.e., the fact that when a certain supplier fails the other one is likely to fail as well. There is great interaction when the supply of i breaks down, e.g., due to a natural disaster, and the supply of j is likely to break down too, e.g. due to close geographical proximity. Interactions between suppliers may also occur when the suppliers are supplied by the same sub-supplier(s) or when the suppliers use the same means of transport to supply the purchasing company. This means that the reasons for non-/interactions between the suppliers do not need to be known for applying the model presented above; the interactions only have to be derived from historical observations. Thus, according to Eq. (3), the overall supply risk may be minimized by assembling those suppliers that compensate each other at best, i.e., when one supplier performs poorly, the other(s) perform(s) well, and vice versa. This is in line with Hosseininasab and Ahmadi (2015), who find that assessing the correlations of the suppliers’ performances is effective for long-term relationships as it reduces the risk of failure, i.e., the instability in the logistics service of the portfolio. Some suppliers are similarly affected by certain disruptions and assembling a portfolio of similar suppliers may be crucial for when such disruptions occur. At this point, it should be noted that, as reported by Talluri et al. (2010), Markowitz’s portfolio model is only applicable for the case of elliptic distribution such as normal or t-distribution with finite variance (Szegö, 2005). As we assume that the distribution of the logistics service of the suppliers is normal, the adoption of variance as the measure of risk is appropriate (Jia & Dyer, 1996; Szegö, 2005; Talluri et al., 2010).

When comparing our proposed model with research that transferred the investment portfolio framework to the supplier selection case, several differences can be identified: Gaonkar and Viswanadham (2007) study supplier non-performance in terms of the complete failure of a supplier to deliver components or the inability to deliver components at the promised price. They present a model with two objectives: minimizing the expected cost of operating the supply chain and, at the same time, minimizing the risk of variations in the total supply chain cost. We extend their model by adding additional criteria. Lee and Chien (2014) present a supplier portfolio model with three objectives: maximizing the performance of the selected vendors, diversifying the portfolio risk, and minimizing the total cost. According to Lee and Chien (2014), there are two types of risks in the supplier selection problem: vendor’s performance risk (performance variation) and delivery risk (ratio of on-time deliveries). The researchers suggest minimizing the covariance of the performance in a portfolio to address performance risk and using stochastic programming to handle uncertain deliveries. To solve the supplier selection problem, a probabilistic and a robust optimization model are developed. Our approach extends the one presented by Lee and Chien (2014) because we take sustainability considerations into account. In addition, Lee and Chien (2014) address the trade-offs among the objectives of their model by means of a single value function, which is based on a normalization of the three objective functions. This is not the case in our research because we suggest studying and solving the supplier selection problem based on an a posteriori approach. This allows visualizing and analyzing all the trade-offs of the decision problem at hand. This is not possible with the proposal of Lee and Chien (2014). Hosseininasab and Ahmadi (2015) developed a two-phase supplier selection procedure. In the first phase, the potential sources are assigned a comparable value based on a set of criteria. In the second phase, this value is fed into a multi-objective portfolio optimization model. The model determines a supplier portfolio by maximizing the expected value and the development of the suppliers, and by minimizing the correlated risk. In comparison to the proposal of Hosseininasab and Ahmadi (2015), we do not suggest using a composite indicator expressing the ‘global value’ of a supplier because the traditional purchasing goals of cost, quality, delivery, and supply risk (cf. Kraljic, 1983; Krause et al., 2009) cannot be analyzed separately and the trade-offs cannot be studied. For instance, it is not possible to analyze the consequences for the costs and the logistics service of choosing a specific portfolio. Furthermore, our paper presents an a posteriori approach to support decision making, which is not the case in the research of Hosseininasab and Ahmadi (2015).

To solve the problem statement (1)–(8), we follow Hirschberger et al. (2013) and transfer our multi-objective model into the equivalent multi-parametric optimization model

$$\begin{aligned} \max\ & \left\{-\boldsymbol{x}'\boldsymbol{Q}\boldsymbol{x} + (-\lambda_c \boldsymbol{c} + \lambda_l \boldsymbol{l} + \lambda_s \boldsymbol{s})'\boldsymbol{x}\right\}, \\ \text{s.t.}\ & \boldsymbol{D}\boldsymbol{x} = \boldsymbol{d} \\ & \boldsymbol{A}\boldsymbol{x} \le \boldsymbol{a} \\ & \boldsymbol{x} \le \boldsymbol{G} \\ & \boldsymbol{x} \ge 0 \end{aligned} \tag{P_λ}$$

with $\boldsymbol{Q}$ being the covariance matrix of the logistics service, $\boldsymbol{c}$ being the vector of the per unit selling prices, $\boldsymbol{l}$ being the vector of the logistics performances, and $\boldsymbol{s}$ being the vector of the sustainability scores of each possible supplier. $\boldsymbol{D}$ represents the equality conditions with a right hand side $\boldsymbol{d}$, $\boldsymbol{A}$ represents the inequality conditions with a right hand side $\boldsymbol{a}$, and $\boldsymbol{G}$ indicates the vector of the maximum supplier capacities. In this multi-parametric representation of the multi-objective optimization model, the preference parameters λ_c, λ_l, and λ_s display the preferences of a decision maker among the four objectives. For instance, a value of $\lambda_l = 1$ indicates that the decision maker accepts an increase in service risk by 1% if the service level also increases by 1% (ceteris paribus) to gain equal utility from the respective supplier portfolio. As discussed earlier, the main advantage of the following approach is the fact that the three preference parameters have not to be set to certain values a priori to solve the multi-objective supplier selection model. Yet, we compute a set of Pareto-optimal decision vectors $\boldsymbol{x}$ as a function of the three preference parameters λ_c, λ_l, and λ_s. Therefore, we apply the Karush-Kuhn-Tucker conditions to (P_λ) and obtain the linear system:

$$\begin{aligned}
&2\boldsymbol{Qx} + \boldsymbol{D}'\boldsymbol{v} + \boldsymbol{A}'\boldsymbol{u^y} - \boldsymbol{I_N u^x} + \boldsymbol{I_N u^G} = -\lambda_c \boldsymbol{c} + \lambda_l \boldsymbol{l} + \lambda_s \boldsymbol{s}\\
&\boldsymbol{Dx} = \boldsymbol{d}\\
&\boldsymbol{Ax} + \boldsymbol{I_M y} = \boldsymbol{a}\\
&\boldsymbol{G} - \boldsymbol{x} \geq 0,\ \boldsymbol{x} \geq 0,\ \boldsymbol{u^y} \geq 0,\ \boldsymbol{u^x} \geq 0,\ \boldsymbol{u^C} \geq 0,\ \boldsymbol{y} \geq 0,\\
&\boldsymbol{v} \quad \text{unrestricted},\\
&\boldsymbol{x}'\boldsymbol{u^x} = 0,\ \boldsymbol{y}'\boldsymbol{u^y} = 0,\ (\boldsymbol{G} - \boldsymbol{x})'\boldsymbol{u^G} = 0,
\end{aligned} \tag{CC}$$

where $\boldsymbol{I_N} \in \mathbb{R}^{\boldsymbol{N}\times\boldsymbol{N}}$ is the identity matrix, M is the number of inequalities in constraints of the optimization model, and (CC) constitutes the complementarity conditions. For computational reasons, this system of (in)equalities can be reduced (see Eaves, 1971; Hirschberger et al., 2013). In general, the only unknowns in the upper systems are the decision vector $\boldsymbol{x}$ and the preference parameters λ_c, λ_l, and λ_s. The way to solve this system is based on the idea to find combinations of λ_c, λ_l, and λ_s for which the system has a solution. In particular, there exist combinations of λ_c, λ_l, and λ_s (so-called stability sets) in the $\lambda_c - \lambda_l - \lambda_s$-space, which correspond to one certain basis representation solving the problem, i.e., a certain subset of suppliers. In order to identify all Pareto-optimal supplier portfolios, we determine all stability sets and their vertices for the given supplier selection optimization problem. Knowing all vertices of one stability set, all possible combinations of exact supplier portfolio weights can be easily calculated by convex combinations of the weights of the vertices of the respective stability set.

3.3. Supplier sustainability performance scores

We follow the approach of Neumüller et al. (2016) and use the ANP (Saaty, 2004) to establish a score for each supplier to indicate its sustainability performance. The sustainability performance s_i of supplier i is the weighted sum of the scores attributed to supplier i with respect to K sustainability criteria (sc), i.e.,

$$s_i = \sum_k \left(\frac{w_k}{\sum_k w_k} \right) * sc_{ik} \ \forall i \tag{9}$$

where sc_{ik} indicates supplier i's performance with respect to criterion k. It is within a [0,1]-interval, with '0' representing a very poor performance and '1' representing a very good performance. For all suppliers i, $(w_k/\Sigma_k w_k)$ is the relative weight of criterion k, which is also within a [0,1]-interval. To meet the above-named requirements for sustainable supplier portfolio configuration, the ANP is used to determine the criteria weights $\boldsymbol{w}$.

The ANP is a systematic process with well-established calculations. Detailed information on ANP concepts and methodologies is presented by Saaty (2001). The first step of the analytic network process consists of selecting the decision criteria (the K sustainability criteria), grouping the decision criteria into clusters, and creating the decision network. For a comprehensive consideration of the manifold sustainability aspects of supplier selection, this step as well as the subsequent rating of the interrelationships between the criteria should be carried out in a group decision-making environment, with the relevant stakeholders shedding light on the different facets and consequences of supplier selection. The systematic and comprehensive lists of supplier evaluation criteria that are provided by Dou and Sarkis (2010), Ho et al. (2010), and Lienland, Baumgartner, and Knubben (2013) may support the identification of important aspects.

The decision network for determining the criteria weights $\boldsymbol{w}$ is shown in Fig. 1. The boxes represent the ANP clusters. The items inside the clusters are the ANP nodes. The arrows indicate interdependencies: if a cluster has a line with an arrow pointing to another cluster, this means that at least one element inside that cluster influences at least one element inside the other cluster. The complete set of interactions can also be found in the ANP supermatrix.

The ANP determines the importance of the different sustainability criteria with respect to the overall 'Sustainability Performance,' which is inside the 'Objective' cluster. Thereby, it is taken into account that a good/bad performance in certain aspects influences the performance in other aspects, at least in the long run. For instance, a supplier's 'Reputation' depends, among other things, on its capabilities in 'Know-how & Innovations' and its 'Contribution to the Economic development' of the community. Furthermore, a supplier's 'Profitability' is influenced, among other things, by its capabilities in the fields of 'Resource consumption,' 'Know-how & Innovations,' and 'Training & development programs' for its employees. This means that the weight of a criterion will be higher (a) when it is contributing relatively more to the overall sustainability performance than other criteria and (b) when it is promoting the performance of other criteria that are, for their part, contributing considerably to the overall sustainability performance score. The ANP allows all sorts of direct and indirect interactions between the criteria to be captured, where the direct and indirect impacts are processed both uni- and multi-directionally.

The dynamic nature of the sustainability supplier selection problem is represented by interactions between criteria, for example, if a supplier is good at 'Know-how & Innovations,' this will promote its performance in other fields. Furthermore, the 'Time horizon' cluster asks whether a short- or a long-term sustainability performance is preferable. The 'Time horizon' cluster can also be used to analyze which criteria particularly determine the sustainability performance in the short and the long run, and whether the single criteria are more important in the short or the long run.

The clusters 'Resource consumption' and 'Emissions,' 'Tangible capital' and 'Intangible capital,' and 'Employees & Suppliers' and 'Society & Community' reflect the triple bottom line approach of sustainability. They contain the K sustainability criteria for which the importance coefficients (vector w) are to be calculated. These clusters have been established in accordance with the views expressed by Carter and Rogers (2008), Dou and Sarkis (2010), Dyllick and Hockerts (2002), and Krause et al. (2009) on how to translate the concepts of sustainability into business processes, i.e., economically sustainable companies maintain and develop the tangible capital and the intangible capital. Furthermore, environmental sustainability requires that natural resources are not consumed faster than they can regenerate and that the emissions produced do not exceed the absorbance capacity of the environment. The social performance is seen in the company's impacts on its stakeholders. In addition to employees and other contractual stakeholders, the interests of the society and communities have to be taken into account.

The second step in the ANP consists of conducting pairwise comparisons to indicate which one of two nodes inside an ANP cluster is affecting a given node more. The ratings are expressed on Saaty's 9-point rating scale. The same is done on the cluster level to indicate which one of two aspects (clusters) is more important for the elements inside another cluster; one of several questions to be answered, for example, is whether the progress in a company's 'Tangible capital' depends on progress in 'Resource consumption' or on progress in its 'Intangible capital.'

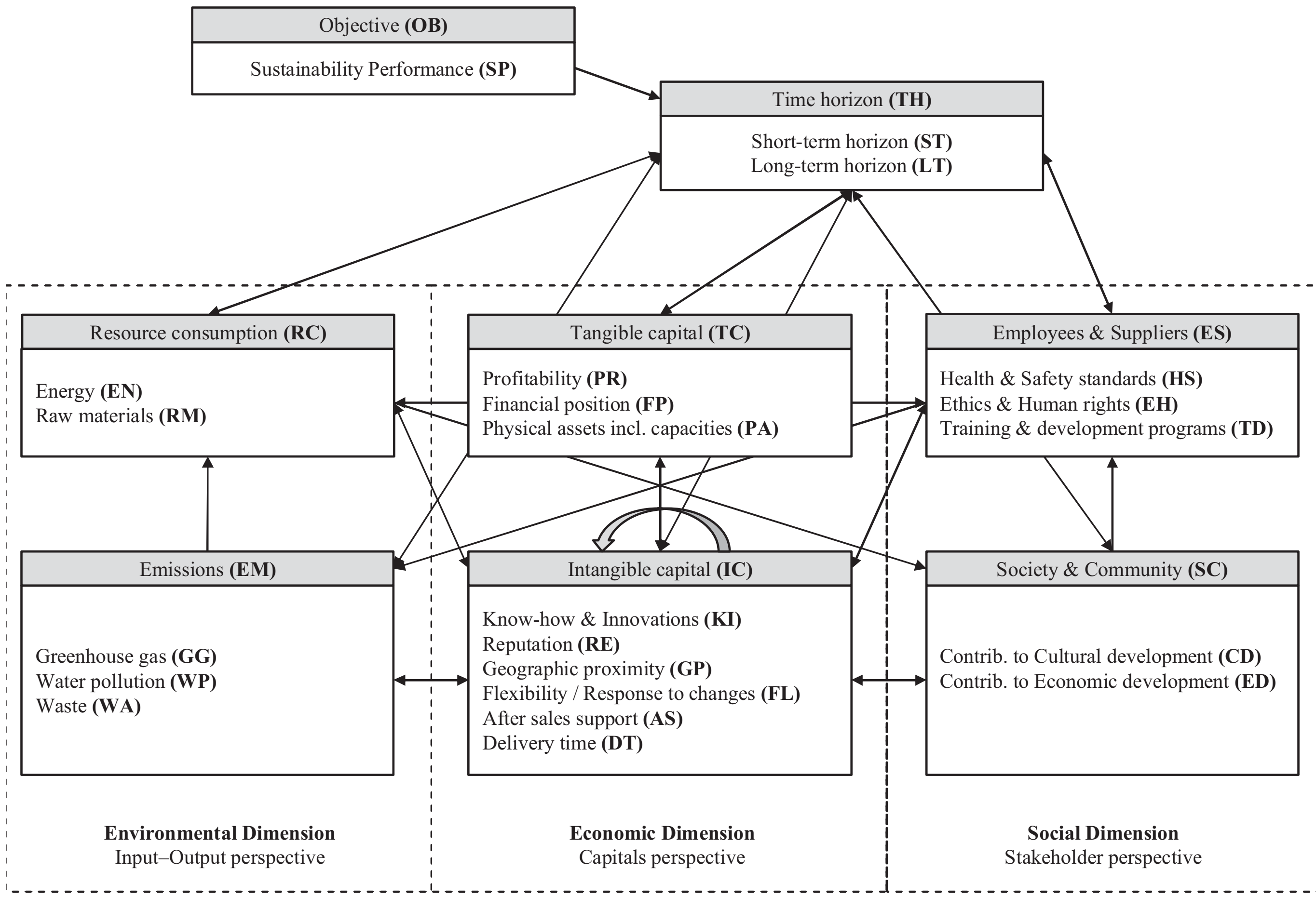


Fig. 1. ANP network for calculating the weights of the sustainability criteria.

Third, on the basis of all ratings, the local priority vectors are derived and the unweighted supermatrix, the cluster matrix, the weighted supermatrix, and the limit matrix are calculated consecutively. The latter contains the vector of the global priorities, i.e., the criteria weights $\boldsymbol{w}$, which takes into account all direct and indirect interactions between the ANP nodes.

Note that the approach used to determine the sustainability performance scores of the suppliers is independent from the supplier portfolio model presented in Section 3.2. Furthermore, from a technical point of view, it does not interrupt the calculation of the non-dominated surface, as long as the sustainability scores attributed to the single suppliers do not change as a function of the available and finally-selected suppliers. Therefore, the ANP can be seen as a module that could be replaced by other multi-criteria processing techniques, such as simple scoring models (e.g., the cost-utility analysis). However, decision-making benefits that arise with the use of the ANP, such as the consideration of interactions between the criteria or the use of consistency checks, will not be achieved. The use of techniques that explicitly determine the alternatives' ratings as a function of the available alternatives, such as TOPSIS, is possible, but not recommended.

3.4. Computing the Pareto front

In Markowitz's model, a portfolio is referred to as 'non-dominated' or 'efficient' if it has the best possible expected level of return for a given level of risk, which is represented by the variance of the portfolio's return. The risk–expected return relationship of efficient portfolios is graphically represented by the efficient frontier, which was first computed by Markowitz (1956). One approach to determine the efficient frontier is to vary the risk tolerance and to optimize the expected return of the portfolio.

While the proposed supplier selection model is based on the concepts of portfolio theory, it is a non-standard four-objective portfolio selection problem in which the cost–service–risk–sustainability non-dominated surface needs to be visualized. The computation of the Pareto front in multi-objective mathematical programming is a broadly discussed challenge in multi-criteria decision making (see, among others, Ehrgott, Löhne, & Shao, 2012; Sayin, 2003; Steuer, 1986; Steuer, Qi, & Hirschberger, 2005). Due to computational restrictions, an exact determination of the Pareto front is difficult to achieve in the majority of the optimization models. Until Hirschberger et al. (2013), who present an a posteriori method for computing the non-dominated set of investment portfolios in a multi-criteria decision making problem, it had not been possible to compute a tri-criterion non-dominated surface. We transfer the solution procedure from Hirschberger et al. (2013) to solve the four-objective supplier selection problem considering risk and sustainability in which there are three linear and one quadratic objective.

The input parameters to compute the Pareto front are the vector of the per unit selling prices of each supplier $\boldsymbol{c}$, the vector of the expected logistics service of each supplier $\boldsymbol{l}$, the vector of the sustainability scores of each supplier $\boldsymbol{s}$, and the covariance matrix representing the supply risk $\boldsymbol{Q}$ as described in Section 3.2. The generality of the algorithm allows linear constraints such as the supplier capacity, an upper bound for the budget constraint, or a lower bound for the least required service level to be added. Preferences between the four objectives are superfluous in this stage.

Using these input parameters, the algorithm computes a set of turning portfolios, which enables us to compute the entire Pareto front. Turning portfolios (see, for example, Niedermayer & Niedermayer, 2010) are portfolios that define certain stability sets corresponding to a respective area on the Pareto front. Within these stability sets, the selected supplier base is fixed but the weights (order shares) may change. Moving from one stability set to another, a change takes place in the selected supplier base, i.e., a new supplier is added or an existing supplier is excluded from the portfolios. Linear changes in the order shares within one stability set cause linear changes in the three objectives (1), (2), and (4), which are linear functions in the order shares, and a quadratic change in the supply risk objective (3) since it is a quadratic function in the order shares. Thus, it is possible to compute each portfolio on a stability area of the Pareto front and the values of the objectives by building a convex combination of the turning portfolios that limit the respective stability set. This also allows two- and three-dimensional representations of the Pareto front to be drawn exactly. For instance, it is possible to draw three dimensions, the quadratic objective, and two linear objectives. A linear change in the supplier order shares then causes a linear change in two dimensions and a quadratic change in the third dimension. This shape defines a paraboloid in three dimensions. Thus, the entire Pareto front can be composed of a set of parabolic platelets (Hirschberger et al., 2013).

4. Numerical example

This section describes the application of the approach presented above to a real-world supplier portfolio configuration case. The goal is to demonstrate the applicability of the methodology and to investigate the trade-offs between cost, service, risk, and sustainability for the example case. Thereby, it is shown how the consideration of sustainability affects the achievement of the traditional goals, i.e., cost and risk minimization, and service maximization. Note that the results presented in the remainder of this section are based on a single case.

4.1. Data

The approach presented is applied to the supplier selection for embedded navigation systems at a worldwide leading premium automotive OEM from Germany. The OEM provided the authors with general data and supplier specific data. The general data is based on the OEM's requirements and includes information on demand, budget, and the overall required logistics service L. The overall maximum normalized average cost per unit (B) is 110 USD, which means that the OEM is not paying more than 110 USD per piece on average across all selected suppliers. The overall minimum logistics service L is 85%. The OEM has not established a specific product quality indicator as the suppliers are asked to only deliver high-quality products. Suppliers with product quality deviations are delisted in the medium term and are therefore not included in further supplier selections. The deviations from 100% in l_i are primarily associated with tardy deliveries, where a tardy delivery is defined as a delivery that does not arrive on the day specified in the delivery notice.

The supplier-specific data covers the suppliers' maximum production capacities C, the per unit selling prices c, the suppliers' logistics service levels $\boldsymbol{l}$ during the last 36 months, and the ratings on the suppliers performance with respect to the sustainability criteria shown in the ANP network in Fig. 1. To ensure a high logistics service standard, the OEM provided supplier data for eight preselected suppliers that had previously met the OEM's minimum product quality and logistics service requirements. These suppliers are located both in high-cost (Western Europe) and low-cost regions (Asia). Suppliers from high-cost regions typically have higher per unit selling prices of up to 15% compared to the suppliers from the low-cost regions. In return, the low-cost region suppliers are often confronted with uncertain lead times, particularly due to sea transportation.

4.2. Calculating sustainability scores

Supplier sustainability scores are calculated using the ANP network shown in Fig. 1. The network (clusters, nodes, interactions) was validated by a logistics manager from the focal company. The pairwise comparisons on the node and on the cluster levels were conducted together with the logistics manager. The AHP/ANP consistency ratios are used to check the consistency of the evaluations. In total, 57 ratings were made on the cluster level and 112 ratings on the node level. Then, the principal eigenvectors of the comparison matrices were calculated. The results are summarized in Table 1 (unweighted supermatrix containing the local priorities) and Table 2 (cluster matrix).

The local priorities in Table 1 indicate the importance of the single sustainability criteria with respect to a certain node of the ANP network. For the long-term horizon ('LT;' Column 3 in Table 1), for instance, the value for the local priority of 0.67 for profitability ('PR;' Row 4 in Table 1) indicates that the decision maker assigns profitability a greater importance in the long run compared to the financial position ('FP;' value of 0.11 in Row 5) and physical assets ('PA;' value of 0.22 in Row 6). In the short run (Column 2 in Table 1), however, the importance of the financial position increases. The cluster matrix (Table 2) shows that according to the decision makers' ratings concerning the importance for the intangible capital ('IC;' Column 4 in Table 2), it is important that a supplier is outstanding with respect to its (combined short- and long-term) sustainability performance ('TH;' value of 0.35 in Row 2), as well as in the domains of the tangible capital ('TC;' value of 0.19 in Row 3), the intangible capital ('IC;' value of 0.18 in Row 4), and employees & suppliers ('ES;' value of 0.12 in Row 7).

Next, the weighted supermatrix is calculated by multiplying all the elements in a component of the unweighted supermatrix (Table 1) by the corresponding cluster weight. To obtain the overall priorities of the sustainability criteria (vector $\boldsymbol{w}$), taking into account all direct and indirect interdependencies, the weighted supermatrix is raised to powers. The columns of the resulting limit matrix contain the weights of the sustainability criteria. All calculations have been carried out using the software SuperDecisions. Table 3 shows the vector $\boldsymbol{w}$ that is derived from the ANP (Column 6). Column 7 (Relative weight) contains the normalized importance of the single sustainability criteria and Column 4 shows the aggregated values for the relative importance of the six sustainability aspects. Finally, the ratings of the three sustainability dimensions are given in Column 2. Note that the values in Columns 2 and 4 are included for illustrating purposes while we use the values in Column 6 for the calculation of the supplier sustainability scores.

After the relative weights of the sustainability criteria have been determined, the performance of the eight suppliers are rated with respect to the single sustainability criteria on a 5-point scale: 'Very good' 100%; 'Good' 75%; 'Fair' 50%; 'Poor' 25%; 'Very poor' 0%. In order to evaluate the sustainability performance of the eight suppliers, we prepared a questionnaire and asked the logistics manager to rate the suppliers using the 5-point scale. Table A.1 in the Appendix presents the results. The sustainability scores result from summing up the performance scores of the suppliers with respect to the single sustainability criteria multiplied with the respective criteria weights. Table 4 summarizes the characteristics of the eight suppliers. The logistics performance is the weighted av-

Table 1
Unweighted supermatrix of the criteria.

	SP	ST	LT	PR	FP	PA	KI	RE	GP	FL	AS	DT	EN	RM	GG	WP	WA	HS	EH	TD	CD	ED
SP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ST	0.25	0.00	0.00	0.20	0.86	0.11	0.13	0.14	0.75	0.83	0.89	0.50	0.50	0.50	0.17	0.25	0.50	0.50	0.17	0.13	0.10	0.20
LT	0.75	0.00	0.00	0.80	0.14	0.89	0.88	0.86	0.25	0.17	0.11	0.50	0.50	0.50	0.83	0.75	0.50	0.50	0.83	0.88	0.90	0.80
PR	0.00	0.27	0.67	0.00	0.00	0.00	0.00	0.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FP	0.00	0.66	0.11	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PA	0.00	0.07	0.22	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
KI	0.00	0.07	0.38	0.80	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.00	0.50	0.00	0.50	0.00	0.00	0.00	0.00	0.86	0.00	0.83
RE	0.00	0.03	0.12	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.17
GP	0.00	0.09	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.50	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FL	0.00	0.35	0.20	0.00	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AS	0.00	0.12	0.03	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DT	0.00	0.33	0.19	0.00	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EN	0.00	0.50	0.50	0.25	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RM	0.00	0.50	0.50	0.75	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00
GG	0.00	0.33	0.33	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.33	0.33
WP	0.00	0.33	0.33	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.33	0.33
WA	0.00	0.33	0.33	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.33	0.33
HS	0.00	0.71	0.43	0.25	0.00	0.00	0.00	0.64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.14
EH	0.00	0.14	0.43	0.00	0.00	0.00	0.20	0.26	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00
TD	0.00	0.14	0.14	0.75	0.00	0.00	0.80	0.10	0.00	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.86
CD	0.00	0.33	0.33	0.00	0.00	0.00	0.25	0.50	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ED	0.00	0.67	0.67	0.00	0.00	0.00	0.75	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 2
Cluster matrix.

	OB	TH	TC	IC	RC	EM	ES	SC
OB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TH	1.00	0.00	0.53	0.35	0.56	0.60	0.50	0.50
TC	0.00	0.17	0.00	0.19	0.00	0.00	0.00	0.00
IC	0.00	0.17	0.29	0.18	0.32	0.20	0.25	0.17
RC	0.00	0.17	0.09	0.04	0.00	0.20	0.00	0.00
EM	0.00	0.17	0.00	0.04	0.00	0.00	0.25	0.17
ES	0.00	0.17	0.09	0.12	0.00	0.00	0.00	0.17
SC	0.00	0.17	0.00	0.07	0.12	0.00	0.00	0.00

erage over the last 36 months (cf. Eq. (2)). C_i is the share of the total demand that can be sourced from the single suppliers. These characteristics, in combination with the covariance matrix of the logistics service, are used to calculate the Pareto front.

4.3. Visualization of the Pareto front

In the standard bi-criterion portfolio problem of Markowitz (1952, 1956), the Pareto front is a line in two dimensions. The Pareto front in a tri-criterion optimization problem (see Hirschberger et al., 2013; Utz et al., 2014; Utz, Wimmer, & Steuer, 2015) can be displayed in three dimensions. The illustration of four dimensions in one graph, as required for the supplier optimization model presented above, is, however, problematic. It would be possible to use three dimensions for three objectives and color for the fourth objective, but it would take a certain amount of time and effort to work with four dimensions in one figure. Therefore, in the following, the level of sustainability is fixed to certain values and the projections of Pareto fronts are shown for the objectives supply risk, average purchasing costs, and overall logistics service.

Fig. 2 shows the Pareto front for a decision situation in which sustainability is unimportant, i.e., we set the minimum required sustainability threshold of the supplier portfolio to 0. The supply risk, i.e., the variance in the logistics service of a given portfolio,

Table 3
Weights $\boldsymbol{w}$ of the sustainability criteria.

Dimension		Aspect (Cluster)		Criterion (Node)	w	Relative weight
Economic dimension	35%	Tangible capital	13%	Profitability (PR)	0.038093	7%
				Financial position (FP)	0.021938	4%
				Physical assets incl. capacities (PA)	0.012046	2%
		Intangible capital	22%	Know-how & Innovations (KI)	0.055282	10%
				Reputation (RE)	0.011341	2%
				Geographic proximity (GP)	0.020852	4%
				Flexibility / Response to changes (FL)	0.019589	3%
				After sales support (AS)	0.004576	1%
				Delivery time (DT)	0.017287	3%
Environmental dimension	31%	Resource consumption	14%	Energy (EN)	0.041443	7%
				Raw materials (RM)	0.039197	7%
		Emissions	17%	Greenhouse gas (GG)	0.033525	6%
				Water pollution (WP)	0.033525	6%
				Waste (WA)	0.033525	6%
Social dimension	34%	Employees & Suppliers	19%	Health & Safety standards (HS)	0.041676	7%
				Ethics & Human rights (EH)	0.032057	6%
				Training & development programs (TD)	0.034283	6%
		Society & Community	15%	Contrib. to Cultural development (CD)	0.037682	6%
				Contrib. to Economic development (ED)	0.052665	9%

Table 4
Supplier characteristics.

	S1	S2	S3	S4	S5	S6	S7	S8
Selling price c_i	115	100	108	107	113	110	109	101
Logistics l_i	0.992	0.753	0.859	0.878	0.979	0.906	0.858	0.799
Sustainability s_i	0.798	0.311	0.640	0.508	0.546	0.626	0.680	0.505
Capacity C_i	1.0	0.7	1.0	1.0	1.0	0.6	1.0	1.0
Covariance S1	2.3E-04	−3.2E-05	5.8E-05	1.6E-04	3.0E-04	−1.3E-04	−3.3E-04	2.3E-04
Covariance S2	−3.2E-05	1.4E-02	−2.3E-03	−4.2E-04	−4.3E-04	−5.1E-05	7.3E-04	−2.4E-04
Covariance S3	5.8E-05	−2.3E-03	3.6E-03	3.0E-05	2.3E-04	7.2E-04	−1.1E-04	−6.4E-04
Covariance S4	1.6E-04	−4.2E-04	3.0E-05	5.4E-03	6.2E-04	−1.9E-03	1.5E-03	−2.2E-03
Covariance S5	3.0E-04	−4.3E-04	2.3E-04	6.2E-04	2.2E-03	−1.6E-03	−2.7E-04	1.4E-03
Covariance S6	−1.3E-04	−5.1E-05	7.2E-04	−1.9E-03	−1.6E-03	9.5E-03	−1.9E-03	−1.8E-03
Covariance S7	−3.3E-04	7.3E-04	−1.1E-04	1.5E-03	−2.7E-04	−1.9E-03	7.1E-03	−3.1E-04
Covariance S8	2.3E-04	−2.4E-04	−6.4E-04	−2.2E-03	1.4E-03	−1.8E-03	−3.1E-04	1.4E-02

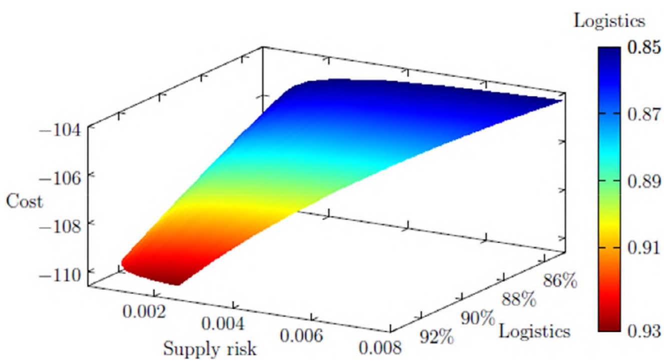
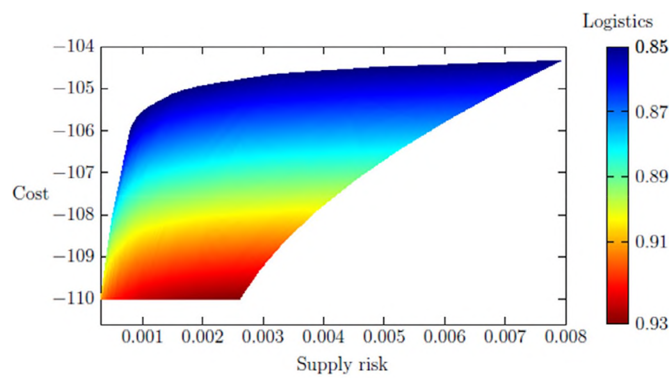
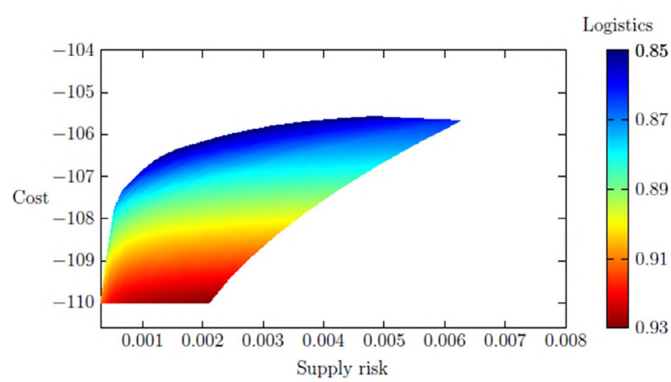


Fig. 2. Three-dimensional Pareto front for supplier portfolios.



a. Pareto front for supplier portfolios with no sustainability considerations



b. Pareto front for supplier portfolios with high sustainability considerations (the sustainability of a portfolio has to be at least 0.60)

Fig. 3. Effects of high sustainability requirements on the Pareto front.

is reported on the *x*-axis, the average per unit purchasing cost on the *y*-axis, and the overall expected logistics service is displayed on the *z*-axis and in color. The Pareto-efficient portfolios range in costs from 104 to 110 USD, in the logistics service from 0.85 to 0.935, and in supply risk from 0.00031 to 0.00791. As there is a maximum cost restriction of 110 USD, a line limits the area in the cost dimension. Furthermore, due to the overall logistics service constraint, there is no supplier portfolio with an overall logistics service below 0.85. The graph shows the entire Pareto front. The latter is drawn using the turning portfolios (cf. Section 3.4), which define small areas on the entire Pareto front. The composition of all these small areas results in the entire front.

Each point on the area displayed represents one candidate for a Pareto-efficient combination of objectives matching one certain portfolio. Each portfolio is optimal for a corresponding set of preferences between the four objectives. To draw a final decision about the supplier portfolio, decision makers can choose the specific candidate from the entire set that fits best to their preferences.

When the logistics manager from the case company was confronted with the Pareto front, it took a moment for him to understand the idea of the representation. It then took another moment for him to make his decision. Finally, he selected a portfolio with the following objective function values: supply risk 0.002, cost 107, and logistics 0.9. According to the manager, he intuitively focused first on the supply risk dimension, which is the criterion that is present in most of the purchasing situations in which he is involved, and it is an extremely important aspect. Thus, his eyes moved first to the region of the Pareto front with a low level of supply risk. Next, he focused on the cost dimension and selected a region between the extremes 104 and 110. Finally, for the pre-selected risk-cost combination, the manager selected the maximum achievable logistics service.

4.4. Insights into the effects of sustainability considerations on optimal supplier portfolios

4.4.1. Effects of high sustainability requirements on the Pareto front

Since the three-dimensional graph is hard to interpret, the two-dimensional projection of Fig. 2 (with no sustainability requirements) is provided in Fig. 3a. Applying higher sustainability requirements—the sustainability of a portfolio has to be at least 0.60—reduces the area that covers the set of non-dominated portfolios (see Fig. 3b). The value of 0.60 has been chosen because this value reflects, in the numerical example, relatively high sustainability requirements (the minimum sustainability achievable by a supplier portfolio is 0.412, and the maximum sustainability achievable is 0.699). When applying higher sustainability requirements,

Table 5
Summary statistics for the objectives of the turning portfolios on the Pareto front with no sustainability requirements (Panel A), high sustainability turning portfolios (Panel B), and the difference (Panel C).

	Supply risk (Variance)	Cost	Logistics service	Sustainability
Panel A: Portfolio without sustainable requirements				
Average	0.00229	−1.07312	0.88614	0.55479
Standard deviation	0.00187	0.02227	0.03016	0.04644
Minimum	0.00031	−1.10000	0.85000	0.50175
Maximum	0.00626	−1.04500	0.92983	0.65707
Panel B: High sustainability portfolio				
Average	0.00229	−1.07814	0.88612	0.60225
Standard deviation	0.00187	0.01744	0.03021	0.00947
Minimum	0.00031	−1.10000	0.85000	0.60000
Maximum	0.00626	−1.06000	0.93000	0.65707
Panel C: Difference of high sustainability portfolio minus no sustainability portfolio				
Average	−8.4225E-08	−0.00414	−3.6858E-06	0.04747
Standard deviation	1.7116E-07	0.00459	4.1590E-05	0.04303
Minimum	−8.8100E-07	−0.01275	−0.00047	0.00000
Maximum	4.9900E-18	−6.0200E-09	2.2200E-16	0.09825
Change	0.0037%	0.3857%	0.0004%	8.556%
t-stat		10.0136		12.4146
p-value		< 1e-17		<1e-24

the minimum per unit purchasing costs increase to 106 USD, the maximum supply risk decreases to 0.00626, and the maximum expected overall logistics service decreases to 0.93. This results in a smaller area of candidates for optimality. In order to illustrate this effect, the same scale is applied for Fig. 3a and 3b.

To gain a picture of the characteristics of the portfolios on both Pareto fronts (Fig. 3), the characteristics of the turning portfolios are analyzed. Table 5 summarizes the descriptive statistics of the four objectives for the turning portfolios of the Pareto front for no sustainability requirements (Panel A) and for the high sustainability turning portfolios (Panel B). Panel A presents the average values, the standard deviation, the minimum, and the maximum of the supply risk (measured by variance), of the costs, of the logistics service, and of the sustainability of 129 turning portfolios with no sustainability requirements. Panel B shows the same statistics for the 129 non-dominated portfolios with similar logistics and supply risk, and an overall sustainability performance of 0.60. Panel C reports on descriptive and test statistics of the differences in the objectives (high sustainability portfolios minus portfolios with no sustainability requirements). Moreover, the average change in the objectives switching from portfolios with no sustainability requirements to high sustainability portfolios is shown. The last two rows in Table 5 present the Student's t test statistics and the corresponding p-values. The results indicate that an on average 8.556% increase in supplier sustainability is associated with an on average 0.3857% increase in cost keeping supply risk and the logistics performance at a fixed level. Both increases are statistically significant at any arbitrary significance level.

4.4.2. Effects of high sustainability requirements on the supplier order shares

Table 6 shows summary statistics for the supplier characteristics and the order shares of the Pareto-efficient turning portfolios without sustainability requirements and for the turning portfolios with high sustainability requirements. Panel A presents the frequency for each supplier of being included in the efficient portfolio, as well as the average order shares, the standard deviation, the minimum, and the maximum order shares of the portfolios without sustainability requirements. Panel B shows the same statistics for the turning portfolios with high sustainability requirements.

Panel A shows that Suppliers 5 and 8 are in every portfolio and have high average order shares. For the high sustainability portfolios (Panel B), Supplier 1 enjoys greater attention. Suppliers 1 and 8 are contained in every portfolio, and on average, these two suppliers cover 54.95% of the supplier portfolios. The last row in Table 6 presents the difference in the relative frequencies of whether a supplier is contained in a turning portfolio or not. The differences show that Suppliers 1, 3, and 7 experience a significant increase in the frequency of being in a turning portfolio when sustainability plays a prominent role in the decision process. In contrast, Supplier 5 loses about 60% turning portfolio membership mainly due to a weak sustainability.

4.4.3. Effects of high sustainability requirements on the number of suppliers

Since the number of suppliers may play a prominent role for the supplier portfolio decision, this section addresses this topic with respect to the Pareto-efficient portfolios. Table 7 presents evidence of the relation between supply risk, number of suppliers in portfolios, and sustainability. Therefore, the turning portfolios have been clustered on each Pareto front (with respect to an increase in sustainability) into supply risk quartiles, and then ANOVA tests have been applied. The benchmark Pareto front has a portfolio sustainability of 0.45. The portfolio sustainability is increased step-wise by 5% of the initial sustainability, i.e., to 0.4725, 0.4950, and so forth (Table 7). Columns 5 and 6 contain F-statistics and p-values for ANOVA testing of whether the number of suppliers in different supply risk quantiles is equal on each Pareto front.

The results clearly show a negative significant relation between the number of suppliers in a portfolio and the risk of this portfolio (see variation within each row). This finding indicates that increasing the number of suppliers may be an effective measure for reducing the supply risk. On the other hand, other objectives, such as cost minimization or logistics performance maximization, typically prescribe the placing of orders with only a few suppliers, namely with those who are outstanding in the respective domains (cf. Section 4.4.4.). This is why, amongst other reasons, many firms do not aim to maximize the number of supplier relationships. For the relationship between sustainability and the number of suppliers, the results suggest quite a constant number of suppliers for increasing sustainability requirements.

Table 6
Summary statistics for the order shares of the non-dominated turning portfolios.

	S1	S2	S3	S4	S5	S6	S7	S8
Costs	115	100	108	107	113	110	109	101
Logistics service	0.99	0.75	0.86	0.88	0.98	0.91	0.86	0.8
Sustainability	0.8	0.31	0.64	0.51	0.55	0.63	0.68	0.5
Panel A: Portfolio without sustainable requirements								
Frequency [%] of being included in the eff. portfolio	23.5	64.7	29.4	88.2	100	60	9.4	100
Average	0.0599	0.0594	0.0649	0.2331	0.22514	0.0855	0.0108	0.2352
Std Dev	0.1324	0.0577	0.0981	0.1322	0.2313	0.0659	0.0233	0.1689
Min	0	0	0	0	0.0166	0	0	0.0772
Max	0.4240	0.1490	0.2640	0.4610	0.7500	0.1740	0.0651	0.7220
Panel B: High sustainability portfolio								
Frequency [%] of being included in the eff. portfolio	100	37.2	48.1	71.3	39.5	62.8	30.2	100
Average	0.2406	0.0300	0.1206	0.1264	0.0764	0.0593	0.0378	0.3089
Std Dev	0.0794	0.0402	0.1315	0.1076	0.1319	0.0550	0.0638	0.1788
Min	0.0664	0	0	0	0	0	0	0.0772
Max	0.4240	0.1130	0.3870	0.3290	0.4480	0.1350	0.2470	0.6670
Difference in the frequency [%] of being included in the eff. portfolio	76.5	−27.5	18.7	−16.9	−60.5	2.8	20.8	0

Table 7
Relation of supply risk and the number of suppliers in a portfolio on different Pareto fronts.

	Q1	Q2	Q3	Q4	F-Statistics	p-values
Benchmark	6.7059	4.9412	3.2143	3.1429	67.179	7.31E-19
5%	6.6667	5.6471	3.3889	3.1429	68.3	8.89E-20
10%	6.6471	5.6471	3.2941	3.0769	66.611	4.42E-19
15%	6.5882	5.6842	4.4286	3.2759	49.458	1.02E-20
20%	6.875	6.2424	4.3333	3.5	91.874	1.75E-29
25%	6.7727	5.8667	4.4615	3.4762	70.843	1.85E-22
30%	6.6071	5.375	4.6129	3.5152	54.147	1.43E-20
35%	7.0417	5.2222	4.2258	3.2917	111.59	3.29E-29
40%	6.9583	5	3.9048	3.1364	103.01	7.03E-27
45%	7.1176	4.96	4	2.9474	95.457	2.36E-26
50%	7	5.5	3.913	2.5714	89.993	1.39E-20

4.4.4. Effects of high sustainability requirements on specific/benchmark portfolios

While the average values over all turning portfolios, as presented above, may indicate an overall conclusion for the Pareto front, decision makers could be interested in certain portfolios. In finance literature, for instance, the minimum variance portfolio and the maximum return portfolio are two portfolios of major importance. When transferring them into the supplier selection setup, consideration is given to the minimum supply risk portfolio, the minimum cost portfolio, and the maximum logistics service portfolio. Decision makers may ask about the influence of an increase in sustainability on these three portfolios. Therefore, they are computed for the same levels of sustainability as in Table 7. Table 8 presents the results. The first set of 11 rows contains the results for the minimum supply risk portfolio, the second set of 11 rows contains the results for the minimum cost portfolio, and the last set of 11 rows contains the results for the maximum logistics service portfolio. Supply risk is measured as the square root of the variance of supply quality.

The results show that the constraint for costs is binding in the example case since the portfolios experience constant values in the objective cost for the minimum supply risk portfolio and the maximum logistics service portfolio. In addition, the logistics service is constant for the majority of the cases in the minimum supply risk portfolio and the minimum cost portfolio.

The minimum supply risk portfolio has, coincidently, a very high portfolio sustainability and therefore does not change before the sustainability requirement reaches 0.675. Then, however, the supply risk increases by 12.5% (=(0.0198 − 0.0176)/0.0176) and the logistics service decreases by 0.4%. The number of suppliers decreases by one supplier.

An increase in sustainability influences the minimum cost portfolio, especially through an increase in costs. A plus of 50% in sustainability (compared to the 0.45 sustainability requirement) causes a 4.3% increase in cost. The increase in cost (and sustainability) is also associated with a tiny increase in logistics performance and a small decrease in supply risk. The number of suppliers is almost stable at two or three suppliers.

Finally, the impact of an increase in the level of sustainability on the objective values of the maximum logistics service portfolio is a 1.2% decrease in logistics for a 50% increase of sustainability. Supply risk, however, also decreases and the number of suppliers in the portfolios ranges from two to three again.

Summarizing, the results indicate that an increase in sustainability to a certain level (in this case 45%) appears to have no negative consequences for supply risk for either the minimum supply risk portfolio or the minimum cost and the maximum logistics service portfolio. However, the results indicate a trade-off between sustainability and cost for the minimum cost portfolio.

5. Discussion

5.1. Methodology: Benefits, drawbacks, challenges, and limitations

This section discusses the approach in general and two of its core elements, namely the representation of supply risk in the optimization model and the calculation of the supplier sustainability performance scores.

5.1.1. A posteriori decision making in the supplier selection and order allocation process

The novelty of the presented approach is, partly, based on the concept of an a posteriori selection of a supplier portfolio from the efficient frontier. The possibility of drawing the entire Pareto front exactly is a key feature for decision makers because they can make decisions with the knowledge of all other Pareto-efficient portfolios.

Table 8
Objective values and number of suppliers of three certain portfolios (minimum supply risk portfolio, minimum cost portfolio, and maximum logistics service portfolio) for different levels of sustainability.

	Supply risk	Cost	Logistics service	Nb. of suppliers
Minimum supply risk portfolio				
Benchmark	0.0176	110	0.9101	8
5%	0.0176	110	0.9101	8
10%	0.0176	110	0.9101	8
15%	0.0176	110	0.9101	8
20%	0.0176	110	0.9101	8
25%	0.0176	110	0.9101	8
30%	0.0176	110	0.9101	8
35%	0.0176	110	0.9101	8
40%	0.0176	110	0.9101	8
45%	0.0176	110	0.9101	8
50%	0.0198	110	0.9065	7
Minimum cost portfolio				
Benchmark	0.0890	104.33	0.85	2
5%	0.0890	104.33	0.85	2
10%	0.0890	104.33	0.85	2
15%	0.0888	104.35	0.85	3
20%	0.0881	104.47	0.85	3
25%	0.0875	104.6	0.85	3
30%	0.0814	104.94	0.85	3
35%	0.0652	105.88	0.85	3
40%	0.0622	106.83	0.85	3
45%	0.0729	107.78	0.8508	2
50%	0.0817	108.78	0.8583	2
Maximum logistics portfolio				
Benchmark	0.0510	110	0.9350	2
5%	0.0510	110	0.9350	2
10%	0.0510	110	0.9350	2
15%	0.0510	110	0.9350	2
20%	0.0508	110	0.9348	3
25%	0.0486	110	0.9329	3
30%	0.0468	110	0.9311	3
35%	0.0454	110	0.9292	3
40%	0.0445	110	0.9273	3
45%	0.0440	110	0.9255	3
50%	0.0439	110	0.9236	3

The numerical example proves that this decision making approach offers several benefits in the supplier selection and order allocation process: (1) The purchasing manager gets the full picture of all optimal supplier portfolios and an immediate overview of all reasonable trade-offs between the relevant criteria. There is no need for an a priori articulation of preferences because decision makers can relate all possible solutions to each other, compare them at once, and then choose the composition among all optimal possibilities that satisfies their needs to the highest extent. For instance, a decision maker may pick a certain Pareto-efficient portfolio with a certain combination of the objectives from the Pareto front. It is then easily possible to relate this particular combination to other Pareto-efficient combinations of costs, logistics performance, supply risk, and sustainability, i.e., a decision maker is made aware of other candidates for optimal solutions, for instance, by a small modification in the expected level of sustainability and the corresponding changes in the other three objectives. (2) The visualization of the Pareto front allows for a better understanding of the decision problem as all dependencies between the objectives are displayed in a single graph. According to the logistics manager, this might also facilitate the communication between the parties involved in the supplier selection process (internal and external managers and business units). (3) The analyses in Section 4.4 show that the Pareto front may also be used as an object of analysis to study sensitivities of supplier portfolios and to gain deeper insights into the trade-offs between the traditional purchasing goals and sustainability.

It should be noted that the a posteriori decision making approach implicates one great challenge, namely, the selection of a specific point on the Pareto front. In fact, such a choice may constitute a complex task and a cognitive challenge for decision makers, which is a comprehensible reason for why a priori approaches are applied in other decision problems. The fact that it took a moment for the logistics manager to understand the idea of the Pareto front and another moment to then make a decision indicates that it requires a certain amount of practice to make a decision, especially when the Pareto front reflects the trade-offs between several objectives.

A limitation of the method's applicability may be seen in the fact that the approach assumes a rich knowledge of suppliers' performance, including their past logistics performance and the ability to evaluate the performance of the suppliers with respect to several sustainability criteria, at least roughly. However, the presented methodology can also be applied when the amount of information is limited. If, for instance, there is no historical data available, the required information for the objectives has to be acquired from other sources, such as opinions of experts and analysts. In summary, the more information is available, the more reliable the decision support will be.

5.1.2. Representation of supply risk in the optimization model

A peculiarity of the proposed approach is the representation of supply risk in the optimization model. In accordance with Markowitz's portfolio theory, supply risk is measured with the variance of the logistics service of the supplier portfolio as a whole. The goal is to minimize the overall supply risk by minimizing the covariance of the logistics service between the suppliers.

In that respect, the proposed approach may be designated as a decision support methodology for situations with a mid- to long-term planning horizon because the method does not mitigate the risk of short-term supply disruptions, i.e., the risk that a supplier will fail 'tomorrow.' Instead, it assembles those suppliers that compensate each other with respect to variations in their logistics performance in the mid- to long-term. One possibility to mitigate the risk of short-term supply disruptions would be to implement a dual sourcing strategy. This would mean selecting one of the many portfolios on the Pareto front with at least two suppliers. Note that the mid-/long-term perspective in assembling supplier portfolios is also incorporated in the representation of the other objectives of the optimization model: the average, expected logistics service shall be maximized across the whole supplier portfolio in the long and not in the short run. Furthermore, the ANP takes interrelationships between the criteria into account to reflect the fact that a good/bad performance in one domain of sustainability may, in the mid to long run, affect a supplier's performance in another domain of sustainability.

According to the results presented above, a lower level of supply risk may be achieved when the number of suppliers included in a portfolio is increased. This finding is a typical consequence when adopting Markowitz's theory to measure risk. To implement a multi-sourcing strategy, however, it is important that the goods sourced from the suppliers are identical, substitutable, or quite similar. This is often the case for so-called B- and C-goods (from ABC analysis). These goods, especially the C-goods, are typically not complex from a technical point of view, and they can be sourced from many suppliers (e.g., screws). In contrast, A-goods are often very complex. They can typically only be delivered by a few, specialized suppliers. Concerning the navigation systems in the numerical example, the logistics manager interviewed classifies these products as 'B-goods,' because they are indeed technically complex. However, they are not so functionally-complex that they can only be sourced from one or two suppliers.

Summing up, the proposed approach for supplier selection is particularly suitable (1) for decision problems with a mid- to long-term planning horizon, (2) when there is a good knowledge of the suppliers' performance, and (3) when the goods/service sourced from the suppliers are identical or quite similar.

5.1.3. Calculation of the supplier sustainability performance scores

In the proposed approach, the ANP is used to calculate the supplier sustainability scores. Two main arguments justify the choice of this method: (1) Existing literature (Chen, Lee, & Wu, 2008; Demirtas and Üstün, 2008; Dou & Sarkis, 2010; Sarkis & Talluri, 2002) indicates that the ANP is particularly suitable for the configuration of supplier portfolios when interactions between the criteria have to be taken into account. This fits perfectly into the decision problem addressed in this research, i.e., a dynamic decision situation with a mid- to long-term planning horizon, because in the mid- to long-term, the sustainability criteria are influencing each other (Dyllick & Hockerts, 2002; Neumüller et al., 2016). For instance, a supplier with a good performance in the field of 'Know-how & Innovations' is likely to build up a good performance in the field of 'Reputation,' at least in the mid- to long-term, and employees may benefit from a good performance in the domain of 'Know-how & Innovations' through training programs. (2) Furthermore, the ANP is generally a suitable method in the context of decision-making with sustainability considerations (Dou & Sarkis, 2010; Neumüller et al., 2016; Neumüller, Kellner, Gupta, & Lasch, 2014). This is the case for supplier portfolio configuration under sustainability considerations (Dou & Sarkis, 2010; Neumüller et al., 2016) because the economic, environmental, and social dimensions of sustainability are interrelated (Dyllick & Hockerts, 2002; Munda, 2005; Porter & Van der Linde, 1995). Tan, Ahmed, and Sundaram (2009), for example, show that lower job satisfaction leads to lower motivation and productivity among employees. Furthermore, the reduction of environmental impacts often requires investments that lead to a decrease in the financial capital (Byrne, Heavey, Ryan, & Liston, 2010). Therefore, the decision support method should allow the capturing of the interdependencies between the sustainability criteria (Dou & Sarkis, 2010; Neumüller et al., 2016). Generic benefits of using the ANP, independent of the supplier selection context, stem from the method's inherent principles that support rational decision making, including problem structuring through decision networks, judgements based on pairwise comparisons and relative scales, and consistency checks for the ratings (Saaty, 1990). Calculating the supplier sustainability scores by means of the ANP allows the consideration of the following requirements to be met: (1) three-dimension sustainability, (2) quantitative and qualitative criteria, (3) interrelationships between the sustainability criteria, (4) group decision making, and (5) the time horizon. For the aspect 'quantitative and qualitative criteria,' the ANP is used to calculate the weights $\boldsymbol{w}$ for the sustainability criteria. The performance of the suppliers with respect to the single criteria *sc*, which can be quantitative (e.g., profitability, delivery time) or qualitative (e.g., reputation, ethics and human rights), is expressed with ordinal criterion scores, as suggested by Munda (2005). This allows the processing of both quantitative and qualitative sustainability criteria and their aggregation to a sustainability index. The consideration of (6) the strategic orientation of the company, (7) dual sourcing, and (8) portfolio configuration is supported through the selection of a certain point on the non-dominated surface in the decision space.

Munda (2005) determined a set of desirable properties for choosing a multi-criteria methodology for decision problems with sustainability considerations. Based on these characteristics, applying the ANP, as presented in this paper, may be viewed as a suitable approach for the following reasons: (1) Both qualitative and quantitative information on the sustainability criteria are processed in the form of ordinal criterion scores. (2) The use of weights with ordinal criterion scores implies a non-compensatory aggregation of the sustainability criteria. This means that the weights can be interpreted as importance coefficients and not as trade-offs. This, in turn, is important because in decision problems with a strong focus on sustainability, the different aspects of sustainability are deemed critical and not readily substitutable, i.e., a complete compensability between the criteria is not desirable (cf. Munda, 2005). (3) The method is simple as it uses only a few ad hoc parameters. (4) The approach allows for a complete ranking of the alternatives. (5) Dominated alternatives are also considered. Furthermore, earlier research (Dou & Sarkis, 2010; Neumüller et al., 2016) shows that the ANP is a useful method for calculating supplier sustainability scores.

Even if the ANP is generally a suitable method for calculating the sustainability scores for the suppliers, some aspects need to be discussed. Firstly, a problem may be seen in the fact that the ANP is a 'subjective' method, i.e., its outcome depends on the subjective judgments of the decision maker. This might affect the shape of the efficient frontier. In fact, the ANP depends on subjective judgments. The subjectivity starts with the problem structuring process and the selection of the evaluation criteria. However, in the sustainability decision making problem, this subjectivity is unavoidable, independent of the selected method (Munda, 2005). Concerning the ANP, there are many features integrated in the method that prevent arbitrary decision making, e.g., problem structuring through decision networks, judgements based on pairwise comparisons and relative scales, and consistency checks for the ratings. Thus, even if the application of the ANP may result in different weighting vectors for the sustainability criteria depending on the decision maker, the differences are expected to be minor in most cases. In addition, the ANP is 'only' used to calculate indicators for the sustainability performance of the suppliers. Once these indicators have been calculated, there is no need for any further judgement of the decision makers until they finally select a point on the efficient frontier. Alternatively, it would be possible to use other indicators for the sustainability performance of the suppliers, e.g., CO_2 emissions. On the other hand, prior research (Dou & Sarkis, 2010; Neumüller et al., 2014; Neumüller et al., 2016) shows that the ANP is a useful technique for integrating sustainability aspects into operations decisions, such as facility location or supplier selection. Finally, we discuss the application of Saaty's 9-point rating scale for conducting the pairwise comparisons on the criteria. Harker and Vargas (1987) and Saaty (2005) point out that the 9-point scale is not appropriate for all sorts of applications. For instance, the ability to make accurate comparisons of widely disparate objects is limited when using the 1–9 scale. Furthermore, arguments have been raised that the 1–9 scale causes inconsistencies in judgment to occur because of having to remain in this interval. However, as there is no a priori reason for choosing a scale other than the one suggested by Saaty (2005), i.e., the one for the 'general applications,' we follow the recommendations of Harker and Vargas (1987) and Saaty (2005) and adopt this scale.

In order to check whether the application of the ANP generates robust outcomes in the decision problem, we apply a sensitivity analysis. The goal is to see whether the vector $\boldsymbol{w}$, which represents the weights of the sustainability criteria, reacts sensitively to varying judgements of the decision maker or not. The implementation of this analysis follows the approaches presented by Dou and Sarkis (2010), May, Shang, Tjader, and Vargas (2013), and Neumüller et al. (2014), and is based on three scenarios. The impact of alternative judgements is studied by modifying the local priorities of the sustainability criteria in the unweighted supermatrix (Table 1) and in the cluster matrix (Table 2). From the unweighted supermatrix, which is composed of 176 local priority vectors, 15 vectors are randomly selected while for the cluster matrix, which is composed of 8 local priority vectors, 3 of them are randomly selected. From the selected vectors, an arbitrary number of the local priorities are increased by 50% and the other priorities are adapted accordingly to ensure that each local priority vector sums up to 1. Then, the perturbed columns are introduced into the unweighted supermatrix and the cluster matrix, respectively, and the final priorities are computed (Dou & Sarkis, 2010; May et al., 2013; Neumüller et al., 2014). The results are presented in Table A.2 in the Appendix. They indicate that in the case studied, the ANP generates relatively stable priorities. Obviously, there will be greater changes in the percentage values when the modifications of the judgements are sufficiently important. Yet, as long as the ratings are within a reasonable range, the priorities remain stable.

Finally, it should be noted that the ANP has two peculiarities in our context: (1) The network presented in Fig. 1 does not include the alternatives (suppliers), which means that the vector $\boldsymbol{w}$ is established independent of the available suppliers' characteristics. This approach is convenient and promotes transparency as once $\boldsymbol{w}$ has been determined, it remains constant and may be applied to rate any supplier i. Furthermore, the vector $\boldsymbol{w}$ is a pure, alternative-independent expression of the expectations and goals of the purchasing company (strategic orientation), i.e., it reflects, in terms of the portfolio theory, the desired 'rate of return.' Moreover, determining $\boldsymbol{w}$ independently from the alternatives guarantees a constant sustainability performance score for each supplier, independent of which suppliers are available and which are finally selected. This is a necessary technical precondition for establishing the non-dominated surface. (2) The ANP is used for the calculation of the weights of the sustainability criteria but not for the determination of the suppliers' overall sustainability scores. The reason for this is the fact that the ANP calculates relative priorities that depend on the available alternatives (Saaty, 2005). If the ANP were to be used for the determination of the overall sustainability scores, i.e., if the suppliers were to be included in the ANP network, the sustainability scores would vary depending on which suppliers are compared. This is undesirable because the purchasing company cannot specify the desired (minimal) level of sustainability of the portfolio that is independent from the characteristics of the alternatives. In the case of the cost and the logistics service, for instance, the purchasing manager can indicate the maximum budget available and the minimum logistics service desired. Specifying these values is only meaningful when the coefficients do not alter depending on which suppliers are available. In addition, if the criteria weights are determined without taking into account the characteristics of the suppliers, the weights can then be interpreted as importance weights and not as trade-off weights. If the available suppliers and their characteristics were to have an impact on the criteria weights and the overall sustainability scores, then the criteria weights could be interpreted as trade-off weights and result in a compensatory preference relation between the criteria. This, however, is undesirable in decision problems with sustainability considerations, because it implies the possibility of offsetting a disadvantage on some criteria by a sufficiently large advantage on another criterion. In decision problems with a strong focus on sustainability, however, the different aspects of sustainability are deemed critical and not readily substitutable (Munda, 2005). Therefore, it is necessary that the weights are interpreted in the sense of importance weights.

5.2. Case study results

Even if the results from the case study represent the situation of only one purchasing situation, they provide some interesting insights. First, high sustainability considerations limit the decision space; the minimum purchasing costs increase and the maximum supply risk and logistics service decrease. This observation is intuitive and may be explained by the fact that the number of portfolios that assure a certain level of sustainability is lower than the number of portfolios that are independent from sustainability considerations. Another analysis shows that, in the example case, an on average 8.556% increase in supplier sustainability is associated with an on average 0.3857% increase in cost. This indicates that there are many supplier portfolios that are (very) good from a sustainability point of view; however, in a situation where sustainability is not taken into account, these portfolios are not identified as optimal solutions because they are (slightly) outperformed by low-sustainability portfolios in the cost domain. If, however, a certain level of sustainability needs to be achieved, the high-sustainability portfolios become part of the optimal solutions. In the example case, this leads to a situation in which the increase in sustainability is, in percentage values, much greater than the increase in costs. This analysis shows the usefulness of conducting sensitivity analyses in order to check whether a higher level in sustainability may be achieved with a justifiable increase in costs. In addition, analyzing the Pareto front allows identifying those suppliers that should be included in the purchasing company's supplier portfolio in any case, independent of whether sustainability is important or not. Finally, the results support us in identifying the 'critical' suppliers, i.e., suppliers that are only part of the set of optimal solutions depending on whether sustainability is important or not.

Concerning the generalizability of these findings, it should be noted that the goal of the numerical example was to demonstrate the applicability of the decision support method and to gain insights into the trade-offs between cost, service, risk, and sustainability in the supplier selection process. As the results are based on a single case, they have to be regarded with suspicion and their generalizability requires confirmation through the analysis of more cases because the numerical example is certainly not representative for each purchasing situation. Future studies could apply the proposed methodology to survey a representative sample of cases in order to confirm the external validity.

6. Conclusion

This article presents a state-of-the-art a posteriori solution approach based on the visualization of the complete and non-approximated Pareto front for a multi-objective supplier selection problem taking into account price, service, risk, and sustainability. We extend prior work that mostly focuses on a priori approaches or on computing incomplete Pareto fronts. The possibility of considering the entire Pareto front is advantageous for purchasing managers for at least one major reason: they instantly gain the full picture of all possible optimal supplier portfolios and are able to compare the different trade-offs of the decision problem immediately—at least for three criteria/dimensions and the fourth being fixed to a certain value, as shown in this article. They are then in a beneficial position when selecting the supplier configuration that best reflects the supply strategy of the purchasing company. This is in contrast to the decision situation with an a priori algorithm in which the decision maker has to determine the preferences early in the optimization procedure and obtains one final solution. The major drawback in the a priori context is the fact that this stand-alone optimal solution does not allow a comparison between different solutions without applying the whole optimization again with other preference parameters. By using the a posteriori algorithm in the version presented by Hirschberger et al. (2013) for four criteria, all candidates for optimality are computed at once.

In addition, the results of the approach's application, i.e., the derived implications regarding the balancing of sustainability, might support decision makers reflecting on sustainable suppliers' pricing strategies. To be precise, the results of the method's real-life application show that besides reducing the decision space of optimal supplier portfolios, sustainability may also affect the optimal number of suppliers and generally changes the portfolio regarding the sourced suppliers and the respective order shares. Our research is not only relevant for purchasing managers, but also for other departments. Sales representatives, for example, might use the outcomes in price negotiations with the customer to justify sales prices because additional costs may be incurred if suppliers that have better sustainability performance charge higher unit prices as a result of their own higher costs (Krause et al., 2009).

The proposed procedure consists of the combination of single 'modules.' The modular setup allows decision makers in different environments to replace single modules with different methods that fit their specific requirements better. Consequently, future research could focus, among other things, on remodeling sustainability in a different way or substituting the ANP with another approach. Additional modules are also possible, such as filtering the Pareto front by, for example, only displaying solutions fulfilling a pre-defined set of criteria. Thereby, the decision maker could exclusively select portfolios with, for example, at least one local supplier included. Furthermore, to mitigate the risk of short-term supply disruptions, a dual sourcing strategy may be implemented, which would mean selecting one of the many portfolios on the Pareto front with at least two suppliers. Besides customizing the proposed procedure to individual requirements, future research could also focus on applying the procedure to different application areas and deriving company or industry specific conclusions, such as the specific cost of sustainability. Furthermore, to confirm the external validity, future studies could survey a representative sample of cases at a subsequent stage. The methodology presented in this research may aid considerably in designing such an effort.

Appendix A

Table A1
Sustainability assessment of the eight suppliers.

	S1	S2	S3	S4	S5	S6	S7	S8
Sustainability criterion *sc*	Rating/Score	Rating/Score	Rating/Score	Rating/Score	Rating/Score	Rating/Score	Rating/Score	Rating/Score
Profitability	● 100%	◔ 25%	● 100%	◑ 50%	● 100%	◑ 50%	◕ 75%	◑ 50%
Financial position	● 100%	◔ 25%	◕ 75%	◔ 25%	◕ 75%	◑ 50%	◕ 75%	◑ 50%
Physical assets incl. capacities	◑ 50%	◑ 50%	◕ 75%	◑ 50%	◔ 25%	◕ 75%	◕ 75%	◔ 25%
Know-how & Innovations	● 100%	○ 0%	◕ 75%	◑ 50%	● 100%	◑ 50%	● 100%	◑ 50%
Reputation	● 100%	◔ 25%	◕ 75%	◕ 75%	● 100%	◑ 50%	◕ 75%	● 100%
Geographic proximity	◑ 50%	◕ 75%	◔ 25%	◔ 25%	◑ 50%	◕ 75%	◔ 25%	◑ 50%
Flexibility / Response to changes	◕ 75%	○ 0%	◕ 75%	◕ 75%	◕ 75%	◑ 50%	◕ 75%	◕ 75%
After sales support	◕ 75%	◑ 50%	◕ 75%	◑ 50%	● 100%	◕ 75%	◕ 75%	◑ 50%
Delivery time	● 100%	◑ 50%	◑ 50%	◑ 50%	◕ 75%	● 100%	◑ 50%	◕ 75%
Energy	◕ 75%	○ 0%	◕ 75%	◕ 75%	◑ 50%	◕ 75%	◕ 75%	◕ 75%
Raw materials	◕ 75%	◔ 25%	◑ 50%	◑ 50%	◑ 50%	◑ 50%	◑ 50%	◕ 75%
Greenhouse gas	◕ 75%	◑ 50%	◕ 75%	◕ 75%	◔ 25%	◕ 75%	◕ 75%	◕ 75%
Water pollution	◕ 75%	◑ 50%	◕ 75%	◑ 50%	◔ 25%	◕ 75%	◑ 50%	● 100%
Waste	◕ 75%	◔ 25%	◑ 50%	◑ 50%	◔ 25%	◑ 50%	◕ 75%	◑ 50%
Health & Safety standards	◕ 75%	◕ 75%	◑ 50%	◕ 75%	◑ 50%	◕ 75%	◕ 75%	◔ 25%
Ethics & Human rights	◕ 75%	◑ 50%	◑ 50%	◑ 50%	◑ 50%	◕ 75%	◕ 75%	◔ 25%
Training & development programs	◕ 75%	◔ 25%	◑ 50%	◔ 25%	◔ 25%	◑ 50%	◑ 50%	○ 0%
Contrib. to Cultural development	◕ 75%	◔ 25%	◕ 75%	◑ 50%	○ 0%	◕ 75%	◕ 75%	○ 0%
Contrib. to Economic development	◕ 75%	◔ 25%	◑ 50%	◔ 25%	◕ 75%	◑ 50%	◑ 50%	◑ 50%

Table A2
Sensitivity analysis for the ANP.

Criterion	Original (Table 3)	Scenario 1	Scenario 2	Scenario 3
Profitability	7%	5%	6%	9%
Financial position	4%	3%	4%	6%
Physical assets incl. capacities	2%	2%	2%	3%
Know-how & Innovations	10%	9%	10%	8%
Reputation	2%	2%	2%	2%
Geographic proximity	4%	3%	4%	5%
Flexibility / Response to changes	3%	2%	3%	3%
After sales support	1%	1%	1%	1%
Delivery time	3%	2%	3%	2%
Energy	7%	5%	7%	12%
Raw materials	7%	5%	7%	7%
Greenhouse gas	6%	6%	6%	4%
Water pollution	6%	7%	6%	4%
Waste	6%	6%	6%	4%
Health & Safety standards	7%	10%	6%	6%
Ethics & Human rights	6%	8%	6%	4%
Training & development programs	6%	6%	7%	5%
Contrib. to Cultural development	6%	8%	6%	8%
Contrib. to Economic development	9%	11%	9%	6%

References

Amindoust, A., Ahmed, S., Saghafinia, A., & Bahreininejad, A. (2012). Sustainable supplier selection: A ranking model based on fuzzy inference system. *Applied Soft Computing, 12*(6), 1668–1677. doi:10.1016/j.asoc.2012.01.023.

Amorim, P., Curcio, E., Almada-Lobo, B., Barbosa-Póvoa, A. P. F. D., & Grossmann, I. E. (2016). Supplier selection in the processed food industry under uncertainty. *European Journal of Operational Research, 252*(3), 801–814. doi:10.1016/j.ejor.2016.02.005.

Aydın Keskin, G., İlhan, S., & Özkan, C. (2010). The fuzzy ART algorithm: A categorization method for supplier evaluation and selection. *Expert Systems with Applications, 37*(2), 1235–1240. doi:10.1016/j.eswa.2009.06.004.

Bai, C., & Sarkis, J. (2010). Integrating sustainability into supplier selection with grey system and rough set methodologies. *International Journal of Production Economics, 124*(1), 252–264. doi:10.1016/j.ijpe.2009.11.023.

Baskaran, V., Nachiappan, S., & Rahman, S. (2012). Indian textile suppliers' sustainability evaluation using the grey approach. *International Journal of Production Economics, 135*(2), 647–658. doi:10.1016/j.ijpe.2011.06.012.

Boer, L. de, Labro, E., & Morlacchi, P. (2001). A review of methods supporting supplier selection. *European Journal of Purchasing & Supply Management, 7*(2), 75–89. doi:10.1016/S0969-7012(00)00028-9.

Büyüközkan, G., & Çifçi, G. (2011). A novel fuzzy multi-criteria decision framework for sustainable supplier selection with incomplete information. *Computers in Industry, 62*(2), 164–174. doi:10.1016/j.compind.2010.10.009.

Byrne, P. J., Heavey, C., Ryan, P., & Liston, P. (2010). Sustainable supply chain design: Capturing dynamic input factors. *Journal of Simulation, 4*(4), 213–221. doi:10.1057/jos.2010.18.

Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: Moving toward new theory. *International Journal of Physical Distribution & Logistics Management, 38*(5), 360–387. doi:10.1108/09600030810882816.

Chen, S.-H., Lee, H.-T., & Wu, Y.-F. (2008). Applying ANP approach to partner selection for strategic alliance. *Management Decision, 46*(3), 449–465. doi:10.1108/00251740810863889.

Dai, J., & Blackhurst, J. (2012). A four-phase AHP–QFD approach for supplier assessment: A sustainability perspective. *International Journal of Production Research, 50*(19), 5474–5490. doi:10.1080/00207543.2011.639396.

Degraeve, Z., Labro, E., & Roodhooft, F. (2000). An evaluation of vendor selection models from a total cost of ownership perspective. *European Journal of Operational Research, 125*(1), 34–58. doi:10.1016/S0377-2217(99)00199-X.

Demirtas, E. A., & Üstün, Ö. (2008). An integrated multiobjective decision making process for supplier selection and order allocation. *Omega, 36*(1), 76–90. doi:10.1016/j.omega.2005.11.003.

Dou, Y., & Sarkis, J. (2010). A joint location and outsourcing sustainability analysis for a strategic offshoring decision. *International Journal of Production Research, 48*(2), 567–592. doi:10.1080/00207540903175145.

Dyllick, T., & Hockerts, K. (2002). Beyond the business case for corporate sustainability. *Business Strategy and the Environment, 11*(2), 130–141. doi:10.1002/bse.323.

Eaves, B. C. (1971). On quadratic programming. *Management Science, 17*(11), 698–711. doi:10.1287/mnsc.17.11.698.

Ehrgott, M., Löhne, A., & Shao, L. (2012). A dual variant of Benson's "outer approximation algorithm" for multiple objective linear programming. *Journal of Global Optimization, 52*(4), 757–778. doi:10.1007/s10898-011-9709-y.

Federgruen, A., & Yang, N. (2008). Selecting a portfolio of suppliers under demand and supply risks. *Operations Research, 56*(4), 916–936. doi:10.1287/opre.1080.0551.

Feng, B. (2012). Multisourcing suppliers selection in service outsourcing. *Journal of the Operational Research Society, 63*(5), 582–596. doi:10.1057/jors.2011.61.

Gaonkar, R. S., & Viswanadham, N. (2007). Analytical framework for the management of risk in supply chains. *IEEE Transactions on Automation Science and Engineering, 4*(2), 265–273. doi:10.1109/TASE.2006.880540.

Ghadimi, P., Ghassemi Toosi, F., & Heavey, C. (2018). A multi-agent systems approach for sustainable supplier selection and order allocation in a partnership supply chain. *European Journal of Operational Research, 269*(1), 286–301. doi:10.1016/j.ejor.2017.07.014.

Gomes, L., & Lima, M. (1992). TODIM: Basics and application to multicriteria ranking of projects with environmental impacts. *Foundations of Computing and Decision Sciences, 16*(4), 113–127.

Gopalakrishnan, K., Yusuf, Y. Y., Musa, A., Abubakar, T., & Ambursa, H. M. (2012). Sustainable supply chain management: A case study of British Aerospace (BAe) Systems. *International Journal of Production Economics, 140*(1), 193–203. doi:10.1016/j.ijpe.2012.01.003.

Govindan, K., Khodaverdi, R., & Jafarian, A. (2013). A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. *Journal of Cleaner Production, 47*, 345–354. doi:10.1016/j.jclepro.2012.04.014.

Govindan, K., & Sivakumar, R. (2016). Green supplier selection and order allocation in a low-carbon paper industry: Integrated multi-criteria heterogeneous decision-making and multi-objective linear programming approaches. *Annals of Operations Research, 238*(1), 243–276. doi:10.1007/s10479-015-2004-4.

Gualandris, J., Klassen, R. D., Vachon, S., & Kalchschmidt, M. (2015). Sustainable evaluation and verification in supply chains: Aligning and leveraging accountability to stakeholders. *Journal of Operations Management, 38*, 1–13. doi:10.1016/j.jom.2015.06.002.

Hamdan, S., & Cheaitou, A. (2017). Supplier selection and order allocation with green criteria: An MCDM and multi-objective optimization approach. *Computers & Operations Research, 81*, 282–304. doi:10.1016/j.cor.2016.11.005.

Harker, P. T., & Vargas, L. G. (1987). The theory of ratio scale estimation: Saaty's analytic hierarchy process. *Management Science, 33*(11), 1383–1403. doi:10.1287/mnsc.33.11.1383.

Hirschberger, M., Steuer, R. E., Utz, S., Wimmer, M., & Qi, Y. (2013). Computing the nondominated surface in tri-criterion portfolio selection. *Operations Research, 61*(1), 169–183. doi:10.1287/opre.1120.1140.

Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research, 202*(1), 16–24. doi:10.1016/j.ejor.2009.05.009.

Hosseininasab, A., & Ahmadi, A. (2015). Selecting a supplier portfolio with value, development, and risk consideration. *European Journal of Operational Research, 245*(1), 146–156. doi:10.1016/j.ejor.2015.02.041.

Humphreys, P. K., Wong, Y. K., & Chan, F. T. S. (2003). Integrating environmental criteria into the supplier selection process. *Journal of Materials Processing Technology, 138*(1-3), 349–356. doi:10.1016/S0924-0136(03)00097-9.

Hwang, C. L., & Masud, A. S. M. (1979). *Multiple objective decision making, methods and applications: A state-of-the-art survey*. Berlin: Springer-Verlag.

Jia, J., & Dyer, J. S. (1996). A standard measure of risk and risk-value models. *Management Science, 42*(12), 1691–1705. doi:10.1287/mnsc.42.12.1691.

Kannan, V. R., & Tan, K. C. (2002). Supplier selection and assessment: their impact on business performance. *Journal of Supply Chain Management, 38*(4), 11–21. doi:10.1111/j.1745-493X.2002.tb00139.x.

Klassen, R. D., & Vereecke, A. (2012). Social issues in supply chains: Capabilities link responsibility, risk (opportunity), and performance. *International Journal of Production Economics, 140*(1), 103–115. doi:10.1016/j.ijpe.2012.01.021.

Koufteros, X., Vickery, S. K., & Dröge, C. (2012). the effects of strategic supplier selection on buyer competitive performance in matched domains: does supplier integration mediate the relationships? *Journal of Supply Chain Management, 48*(2), 93–115. doi:10.1111/j.1745-493X.2012.03263.x.

Kraljic, P. (1983). Purchasing must become supply management. *Harvard Business Review, 61*(5), 109–117.

Krause, D. R., Handfield, R. B., & Scannell, T. V. (1998). An empirical investigation of supplier development: Reactive and strategic processes. *Journal of Operations Management, 17*(1), 39–58. doi:10.1016/S0272-6963(98)00030-8.

Krause, D. R., Pagell, M., & Curkovic, S. (2001). Toward a measure of competitive priorities for purchasing. *Journal of Operations Management, 19*(4), 497–512. doi:10.1016/S0272-6963(01)00047-X.

Krause, D. R., Vachon, S., & Klassen, R. D. (2009). Special topic forum on sustainably supply chain management: Introduction and reflections on the role of purchasing management. *Journal of Supply Chain Management, 45*(4), 18–25. doi:10.1111/j.1745-493X.2009.03173.x.

Lee, C.-Y., & Chien, C.-F. (2014). Stochastic programming for vendor portfolio selection and order allocation under delivery uncertainty. *OR Spectrum, 36*(3), 761–797. doi:10.1007/s00291-013-0342-7.

Lienland, B., Baumgartner, A., & Knubben, E. (2013). The undervaluation of corporate reputation as a supplier selection factor: An analysis of ingredient branding of complex products in the manufacturing industry. *Journal of Purchasing and Supply Management, 19*(2), 84–97. doi:10.1016/j.pursup.2013.04.001.

Linton, J., Klassen, R. D., & Jayaraman, V. (2007). Sustainable supply chains: An introduction. *Journal of Operations Management, 25*(6), 1075–1082. doi:10.1016/j.jom.2007.01.012.

Liu, K., Liu, Y., & Qin, J. (2018). An integrated ANP-VIKOR methodology for sustainable supplier selection with interval type-2 fuzzy sets. *Granular Computing*. doi:10.1007/s41066-017-0071-4.

Luo, X. G., Kwong, C. K., Tang, J. F., Deng, S. F., & Gong, J. (2011). Integrating supplier selection in optimal product family design. *International Journal of Production Research, 49*(14), 4195–4222. doi:10.1080/00207543.2010.544337.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance, 7*(1), 77–91. doi:10.2307/2975974.

Markowitz, H. (1956). The optimization of a quadratic function subject to linear constraints. *Naval Research Logistics Quarterly, 3*(1-2), 111–133. doi:10.1002/nav.3800030110.

Markowitz, H. (1959). *Portfolio selection: Efficient diversification of investments*. New Haven: Yale University Press.

Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. *Structural and Multidisciplinary Optimization, 26*(6), 369–395. doi:10.1007/s00158-003-0368-6.

Mavrotas, G. (2009). Effective implementation of the ε-constraint method in multi-objective mathematical programming problems. *Applied Mathematics and Computation, 213*(2), 455–465. doi:10.1016/j.amc.2009.03.037.

May, J. H., Shang, J., Tjader, Y. C., & Vargas, L. G. (2013). A new methodology for sensitivity and stability analysis of analytic network models. *European Journal of Operational Research, 224*(1), 180–188. doi:10.1016/j.ejor.2012.07.035.

Micheli, G. J. L. (2008). A decision-maker-centred supplier selection approach for critical supplies. *Management Decision, 46*(6), 918–932. doi:10.1108/00251740810882671.

Munda, G. (2005). Multiple Criteria Decision Analysis and Sustainable Development. In J. Figueira, S. Greco, & M. Ehrgott (Eds.), *Multiple criteria decision analysis: State of the art surveys* (pp. 953–986). New York, N.Y.: Springer.

Neumüller, C., Kellner, F., Gupta, J. N. D., & Lasch, R. (2014). Integrating three-dimensional sustainability in distribution centre selection: The process analysis method-based analytic network process. *International Journal of Production Research, 53*(2), 409–434. doi:10.1080/00207543.2014.939241.

Neumüller, C., Lasch, R., & Kellner, F. (2016). Integrating sustainability into strategic supplier portfolio selection. *Management Decision, 54*(1), 194–221. doi:10.1108/MD-05-2015-0191.

Niedermayer, A., & Niedermayer, D. (2010). Applying Markowitz's critical line algorithm. In J. B. . Guerard (Ed.), *Handbook of portfolio construction* (pp. 383–400). Boston, MA: Springer US.

Öztürk, B. A., & Özçelik, F. (2014). Sustainable supplier selection with a fuzzy multi-criteria decision making method based on triple bottom line. *Business & Economics Research Journal, 5*(3), 129–147.

Parthiban, P., Zubar, H. A., & Katakar, P. (2013). Vendor selection problem: A multi-criteria approach based on strategic decisions. *International Journal of Production Research, 51*(5), 1535–1548. doi:10.1080/00207543.2012.709644.

Porter, M. E., & Van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives, 9*(4), 97–118. doi:10.1257/jep.9.4.97.

Qin, J., Liu, X., & Pedrycz, W. (2017a). A multiple attribute interval type-2 fuzzy group decision making and its application to supplier selection with extended LINMAP method. *Soft Computing, 21*(12), 3207–3226. doi:10.1007/s00500-015-2004-y.

Qin, J., Liu, X., & Pedrycz, W. (2017b). An extended TODIM multi-criteria group decision making method for green supplier selection in interval type-2 fuzzy environment. *European Journal of Operational Research, 258*(2), 626–638. doi:10.1016/j.ejor.2016.09.059.

Saaty, T. L. (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research, 48*(1), 9–26. doi:10.1016/0377-2217(90)90057-I.

Saaty, T. L. (2001). *The analytic network process: Decision making with dependence and feedback*. Pittsburgh: PA, RWS Publications.

Saaty, T. L. (2004). Fundamentals of the analytic network process — Dependence and feedback in decision-making with a single network. *Journal of Systems Science and Systems Engineering, 13*(2), 129–157. doi:10.1007/s11518-006-0158-y.

Saaty, T. L. (2005). The analytic hierarchy and analytic network processes for the measurement of intangible criteria and for decision-making. In J. Figueira, S. Greco, & M. Ehrgott (Eds.), *Multiple criteria decision analysis: State of the art surveys* (pp. 345–405). New York, N.Y.: Springer.

Sarkis, J., & Talluri, S. (2002). A model for strategic supplier selection. *Journal of Supply Chain Management, 38*(4), 18–28. doi:10.1111/j.1745-493X.2002.tb00117.x.

Sayin, S. (2003). A procedure to find discrete representations of the efficient set with specified coverage errors. *Operations Research, 51*(3), 427–436. doi:10.1287/opre.51.3.427.14951.

Shaw, K., Shankar, R., Yadav, S. S., & Thakur, L. S. (2013). Global supplier selection considering sustainability and carbon footprint issue: AHP multi-objective fuzzy linear programming approach. *International Journal of Operational Research, 17*(2), 215. doi:10.1504/IJOR.2013.053624.

Spina, G., Caniato, F., Luzzini, D., & Ronchi, S. (2013). Past, present and future trends of purchasing and supply management: An extensive literature review. *Industrial Marketing Management, 42*(8), 1202–1212. doi:10.1016/j.indmarman.2013.04.001.

Srinivasan, V., & Shocker, A. D. (1973). Linear programming techniques for multidimensional analysis of preferences. *Psychometrika, 38*(3), 337–369. doi:10.1007/BF02291658.

Steuer, R. E. (1986). *Multiple criteria optimization: Theory, computation, and application*. New York: Wiley.

Steuer, R. E., Qi, Y., & Hirschberger, M. (2005). Multiple objectives in portfolio selection. *Journal of Financial Decision Making, 1*(1), 5–20.

Szegö, G. (2005). Measures of risk. *European Journal of Operational Research, 163*(1), 5–19. doi:10.1016/j.ejor.2003.12.016.

Talluri, S., Narasimhan, R., & Chung, W. (2010). Manufacturer cooperation in supplier development under risk. *European Journal of Operational Research, 207*(1), 165–173. doi:10.1016/j.ejor.2010.03.041.

Tan, K.-S., Ahmed, M. D., & Sundaram, D. (2009). Sustainable warehouse management. In *Proceedings of the international workshop on enterprises & organizational modeling and simulation (EOMAS)* (pp. 1–15). New York, USA.

Tracey, M., & Leng Tan, C. (2001). Empirical analysis of supplier selection and involvement, customer satisfaction, and firm performance. *Supply Chain Management: An International Journal, 6*(4), 174–188. doi:10.1108/EUM0000000005709.

Trent, R. J., & Monczka, R. M. (2003). Understanding integrated global sourcing. *International Journal of Physical Distribution & Logistics Management, 33*(7), 607–629. doi:10.1108/09600030310499286.

Utz, S., Wimmer, M., Hirschberger, M., & Steuer, R. E. (2014). Tri-criterion inverse portfolio optimization with application to socially responsible mutual funds. *European Journal of Operational Research, 234*(2), 491–498. doi:10.1016/j.ejor.2013.07.024.

Utz, S., Wimmer, M., & Steuer, R. E. (2015). Tri-criterion modeling for constructing more-sustainable mutual funds. *European Journal of Operational Research, 246*(1), 331–338. doi:10.1016/j.ejor.2015.04.035.

Verma, R., & Pullman, M. E. (1998). An analysis of the supplier selection process. *Omega, 26*(6), 739–750. doi:10.1016/S0305-0483(98)00023-1.

Weber, C. A., Current, J. R., & Benton, W. C. (1991). Vendor selection criteria and methods. *European Journal of Operational Research, 50*(1), 2–18. doi:10.1016/0377-2217(91)90033-R.

Wetzstein, A., Hartmann, E., Benton, W. C., jr., & Hohenstein, N.-O. (2016). A systematic assessment of supplier selection literature – State-of-the-art and future scope. *International Journal of Production Economics, 182*, 304–323. doi:10.1016/j.ijpe.2016.06.022.