Sustainability in supplier selection and order allocation: Combining integer variables with Markowitz portfolio theory

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A B S T R A C T

This research presents a decision support methodology for the multi-criteria supplier selection and order allocation problem. The proposed approach supports purchasing managers in assembling mid-term supplier portfolios while making them aware of the trade-offs between the supplier sustainability, the purchasing costs, and the overall supply risk. First, we propose a multi-objective optimization model with three objectives: to maximize the supplier sustainability, to select the supplier portfolio with the lowest purchasing costs, and to minimize the supply risk. Our model extends existing mathematical approaches that follow the portfolio theory fathered by H. Markowitz by integrating the aspect 'risk' into the supplier selection problem. Secondly, since we allow for integer variables in our model—in contrast to the classical Markowitz portfolio theory—we use the ε-constraint method to visualize the efficient surface. The possibility of considering the non-dominated set of supplier portfolios is advantageous for purchasing managers as they gain a picture of the different optimal supplier portfolios and are able to analyze the trade-offs between the different purchasing goals before making a decision. Finally, we illustrate the applicability of the proposed methodology in a real-world supplier selection and order allocation case from the automotive industry. In the example case, we identify 1754 optimal supplier portfolios that may be assembled based on the eight available suppliers. Our analyses show that each optimal portfolio consists of two suppliers, with one specific supplier being included in each portfolio. Furthermore, four suppliers are not part of any optimal solution.

1. Introduction

High purchasing costs, a strong trend toward outsourcing in various industry sectors (Vahidi et al., 2018), and the proven effects of supplier selection on a company's business performance are inducing manufacturing firms to select their suppliers very carefully (Boer et al., 2001; Kannan and Tan, 2002; Koufteros et al., 2012; Krause et al., 1998; Spina et al., 2013; Weber and Current, 1993; Wetzstein et al., 2016). The selection of the 'right' suppliers is becoming increasingly crucial because many firms tend to have fewer but at the same time reliable suppliers with whom they have long-term relationships (Ho et al., 2010).

From a methodological point of view, supplier selection presents a multi-criteria decision making problem. Various supplier selection criteria have been used in research and in practice projects (Ho et al., 2010; Kannan and Tan, 2002; Verma and Pullman, 1998). According to Ho et al. (2010), the most popular criteria considered by decision makers for evaluating and selecting suppliers are quality, delivery, and cost. For supplier quality and delivery, the important risk dimension (Torres-Ruiz and Ravindran, 2018) can be referred to as supply risk.

An increasing number of studies are focusing on sustainability considerations (Aktin and Gergin, 2016; Gharaei et al., 2018a; Park et al., 2018; Trapp and Sarkis, 2016; Vahidi et al., 2018). Kannan et al. (2015), Huang et al. (2016), Rezaei et al. (2016), Gupta and Barua (2017), and Yazdani et al. (2017) address supplier selection issues by focusing on environmental aspects. In fact, the combination of awareness about greenhouse gas (GHG) emissions, and environmental and social legislation—such as the Paris Agreement from 2016, the French Grenelle II (Article 225), or the Danish Financial Statements Act of 2008—is forcing companies to manage sustainability aspects. Anthropic GHG emissions are a major contributor to global warming, atmospheric changes, and climate

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disruptions, and logistics activities are major sources of GHG (McKinnon et al., 2015). Thus, by enhancing the level of sustainability standards, especially in supply chains, new legislations such as those mentioned above can be addressed (Bai and Sarkis, 2010a; Govindan et al., 2013; Luthra et al., 2017).

Several organizations have published guidelines on how to quantify GHG emissions (COFRET, 2011) and on how to report on sustainability issues (GRI, 2016). Nevertheless, a globally accepted standard for measuring and reporting the sustainable impact of supply chain activities remains absent. The Global Automotive Sustainability Guiding Principles (GASGP) promoted by the European Automotive Working Group is an internationally-accepted guideline on how to enhance the sustainability performance in supply chains.[1] This guideline aims to achieve excellence, innovation, and performance in a sustainable manner and addresses aspects of business ethics, the environment, working conditions, and human rights in supply chains. As environment-friendly, social, and economic suppliers are crucial for achieving sustainable development and increasing the performance of supply chains (Frostenson and Prenkert, 2015), we present a new integrated framework for supplier selection based on the GASGP.

Various approaches have been suggested for processing the different criteria that are relevant in the supplier selection process to thus solve the supplier selection problem: mathematical programming, data envelopment analysis (DEA), fuzzy set theory, the analytic hierarchy process (AHP), the analytic network process (ANP), case-based reasoning, artificial intelligence/neural networks, and any of their combinations (Chai et al., 2013; Ho et al., 2010; Singh, 2014). Nevertheless, selecting suppliers based on these models often ends with the selection of a single supplier, without, however, determining order shares, i.e., the number of studies investigating the order allocation problem in sustainable supplier selection is rather limited (Gören, 2018). Recent contributions in the field of supplier selection (Gaonkar and Viswanadham, 2007; Hosseininasab and Ahmadi, 2015; Kellner et al., 2019; Lee and Chien, 2014) show that the mathematical framework of the portfolio theory following Harry Markowitz (1952, 1959) supports supplier selection and order allocation decisions effectively—especially when the aspect 'risk' needs to be taken into consideration. Thus, it is possible to assemble supplier portfolios that reduce the long-term risk of failure. In this context, a 'supplier portfolio' reflects the selected suppliers and the proportions of the purchasing company's total demand that are ordered from these sources. In this paper, we combine the sustainable supplier selection with the theoretical concepts of portfolio optimization to compute optimal order shares.

This paper provides a new decision support methodology for the multi-criteria supplier selection and order allocation problem. Our approach supports purchasing managers in assembling mid-term supplier portfolios while making them aware of the trade-offs between the purchasing costs, sustainability, and the overall supply risk. Our contribution is threefold: Firstly, we present a multi-objective optimization model for the supplier selection and order allocation problem. Our model extends existing mathematical models that transferred the portfolio theory fathered by Markowitz (1952, 1959) to the supplier selection case (Gaonkar and Viswanadham, 2007; Hosseininasab and Ahmadi, 2015; Kellner et al., 2019; Lee and Chien, 2014). Secondly, we use the ε-constraint method to visualize the efficient surface for the proposed multi-objective optimization model. The possibility of drawing the efficient surface proves advantageous for purchasing managers as they gain a picture of the available optimal supplier portfolios and are able to analyze the trade-offs between the different purchasing goals before making a decision. Thirdly, we apply our methodology to a real-world supplier selection and order allocation problem from the automotive industry to demonstrate its applicability. What sets this real-world application apart is the fact that the supplier sustainability scores are not 'self-made' sustainability indicators. Instead, we obtained the results of a self-assessment questionnaire that is a standard for rating the sustainability performance of suppliers in the automotive industry.

The paper is organized as follows: Section 2 provides a literature review on the supplier selection problem. Section 3 presents our multi-objective optimization model and the procedure for computing the non-dominated set. Section 4 contains an illustrative real-world application case. Section 5 discusses the decision support methodology, and Section 6 concludes the paper.

2. Literature review

Several researchers view supplier selection as one of the most important processes in the purchasing and supply management function and as a fundamental management responsibility (Amid et al., 2011; Golmohammadi and Mellat-Parast, 2012; Kaufmann et al., 2010; Parthiban et al., 2013; Wetzstein et al., 2016). Thus, it is not surprising that supplier evaluation and selection problems have been studied extensively during the last decades. Boer et al. (2001), Chai et al. (2013), Degraeve et al. (2000), Ho et al. (2010), and Weber et al. (1991) provide comprehensive literature reviews on these topics.

2.1. Supplier selection criteria

Supplier selection decisions involve the evaluation of the performance of potential suppliers against a wide range of often-conflicting criteria (Lee and Chien, 2014). Ho et al. (2010) find that the most popular evaluation criteria are quality, delivery, price/cost, manufacturing capability, service, management, technology, research and development, finance, flexibility, reputation, relationship, risk, and safety and environment. Additionally, quality, delivery, and the net price are among the criteria of 'extreme' or 'considerable importance' for vendor selection criteria and methods (Weber et al., 1991). Kannan and Tan (2002) study the impact of supplier selection and assessment on business performance and report survey results that rank the quality level, the service level, on-time delivery, quick response time in case of emergency, flexibility to respond to unexpected demand changes, the correct quantity delivered, and the price/cost of the product among the most important factors. Lienland et al. (2013) confirm the substantial importance of the aspects 'quality,' 'delivery,' the 'performance history,' and the 'price' in the supplier selection process.

Our paper incorporates these findings as it presents a supplier selection model that processes the above named criteria. The proposed model considers the following aspects: quality, delivery, the performance history of the suppliers, price (cost), and the flexibility to respond to unexpected demand changes, the manufacturing capability, expertise in research and development, and the supply risk. It should be noted that the proposed model can easily be extended with additional criteria.

[1] The European Automotive Working Group on Supply Chain Sustainability is supported by most of the larger automotive manufacturers, i.e., BMW Group, Daimler, Ford, Jaguar, Land Rover, PSA Peugeot Citroën, Scania, Toyota, Volkswagen, and Volvo.

2.2. Multi-objective supplier selection

Many approaches have been suggested for solving the multi-criteria supplier selection problem (Lee and Chien, 2014). Chai et al. (2013) and Ho et al. (2010) identify various decision making techniques that have been used for supplier selection so far. These methods include DEA, TOPSIS, DEMATEL, ELECTRE, PROMETHEE, mathematical programming, AHP and ANP, fuzzy set theory, case-based reasoning, neural networks, and genetic algorithms. Besides the 'individual' decision making techniques, numerous 'integrated' approaches have been proposed, such as AHP & DEA, AHP & goal programming, ANP & TOPSIS, DEA & linear programming, and TOPSIS & DEMATEL.

The methodology of our approach belongs to the class of models that formulate the multi-criteria supplier selection problem as a multi-objective decision making model (cf. Chai et al., 2013; Ho et al., 2010). This means that the most important supplier selection criteria are considered as goals that have to be minimized (e.g., cost) or maximized (e.g., sustainability), and that have to be balanced, as the achievement of one goal typically prevents decision makers from achieving the maximum/minimum values in the other goals. Multi-objective decision making approaches for solving the supplier selection problem have previously been presented, for instance, by Gharaei et al. (2018b), Karpak et al. (2001), Kull and Talluri (2008), Narasimhan et al. (2006), Wadhwa and Ravindran (2007), and Yu et al. (2012). Gharaei et al. (2018b) present an optimal integrated lot sizing model in a multi-level supply chain with imperfect quality products. Karpak et al. (2001) construct a goal programming model considering three goals: cost, quality, and delivery reliability. Their approach determines the optimal amount of products ordered, subject to the purchasing company's demand and the suppliers' capacities. Narasimhan et al. (2006) develop a multi-objective programming model to select the optimal suppliers and to determine the optimal order quantity. Their model has five objectives, which may be grouped into three classes: cost minimization and maximization of quality and of delivery-performance. Wadhwa and Ravindran (2007) present a multi-objective programming problem with three objective functions, namely minimization of price, lead time, and the number of rejects. Yu et al. (2012) investigate a multi-objective vendor selection program under lean procurement based on cost and delivery schedule violation minimization and the maximization of the quality level of the purchased quantity. Kull and Talluri (2008) find that firms are increasingly recognizing the importance of including supply risk in the evaluation and selection of suppliers for strategic partnerships. Therefore, they propose a goal programming approach for supplier selection in the presence of supply risk measures.

Techniques for solving multi-objective optimization models can be categorized according to the moment in time when the decision makers (e.g., purchasing managers) express their preference for the different objectives (Hwang and Masud, 1979; Marler and Arora, 2004; Mavrotas, 2009): (1) techniques with a priori articulation of preferences, (2) techniques with a posteriori articulation of preferences, (3) interactive techniques, (4) techniques with no articulation of preferences, and (5) variations of these. We implement an a posteriori approach because this allows the user to forgo an ex ante articulation of preferences, identify the trade-offs between the objectives, and study how the different aspects of supplier portfolio configuration may be balanced. From the decision maker's point of view, this means that firstly, all Pareto efficient solutions are computed and visualized graphically. Then, a specific portfolio can be chosen in accordance with the purchasing company's supply strategy.

2.3. Multi-objective portfolio models for supplier selection

Recent research shows that the multi-objective optimization framework of the Markowitz (1952, 1959) portfolio theory can be applied effectively for the supplier selection case. This allows decision makers to assemble supplier portfolios that reduce the mid- to long-term risk of failure because the suppliers selected are those that compensate each other with respect to the service delivered, i.e., when a certain supplier performs poorly, the others perform well.

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. Hosseininasab and Ahmadi (2015) develop 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. Unlike Hosseininasab and Ahmadi (2015), we do not use a composite indicator expressing the 'global value' of a supplier because the traditional purchasing goals of cost, quality, delivery, flexibility, and supply risk (Kraljic, 1983; Krause et al., 2009) cannot be analyzed separately and the trade-offs cannot be studied. Therefore, we suggest an a posteriori approach to support decision making, which goes beyond the model of Hosseininasab and Ahmadi (2015). Kellner et al. (2019) present an optimization model with four objectives: to minimize the purchasing costs, to select the supplier portfolio with the highest logistics service, to minimize the supply risk, and to order as much as possible from those suppliers with outstanding sustainability performance. As their model is a non-standard portfolio selection problem with three linear and one quadratic objective function, they employ a novel algorithm that analytically computes a set of non-dominated solutions and provides graphical decision support through a visualization of the complete and exactly-computed Pareto front. While this algorithm allows the processing of linear and quadratic objective functions, it can only be used in optimization models with continuous decision variables. Finally, 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 and delivery risk. 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.

Summing up, studies effectively integrating the mathematical framework of the portfolio theory into supplier selection exist; however, they are few in number. Kellner et al. (2019) is the only contribution in line with our intention of proposing an approach for a posteriori decision making. However, the algorithm used by Kellner et al. (2019) does not support decision problems that limit the number of suppliers to a certain range, contain minimum ordering quantities, or describe the characteristics of the suppliers with binary or integer variables (Hoseini Shekarabi et al., 2018; Kilic, 2013). Therefore, we apply the ε-constraint method to draw the efficient surface for processing integer variables and generalizing the a posteriori application of the portfolio theory for the

Table 1
Overview of research proposals for integrating sustainability into supplier selection.

Methodological approach	Example
AHP & quality function deployment; AHP & multi-objective linear programming	Dai and Blackhurst (2012)
ANP	Dou and Sarkis (2010)
Fuzzy logic, fuzzy numbers, fuzzy inference systems, and/or fuzzy TOPSIS	Govindan et al. (2013)
ANP-VIKOR	Liu et al. (2018)
Multi-objective optimization	Govindan and Sivakumar (2016)
Multi-agent systems approach	Ghadimi et al. (2018)
Grey approach; grey system and rough set theory	Bai and Sarkis (2010b)

supplier selection case.

2.4. *Integrating sustainability into supplier selection*

Sustainability considerations are receiving increased attention in the supplier evaluation and selection process, both in practice and in research. Strategies on how to measure the effectiveness of organizational strategies are provided by Sobhanallahi et al. (2016a) and Sobhanallahi et al. (2016b). Examples of companies that are rating the sustainability performance of their suppliers include Apple, BMW, and Walmart (for more information, see the company websites). In addition, researchers propose diverse approaches that support the supplier evaluation and selection process (Table 1). These concepts comprise single- and multi-echelon supply chains. Gharaei et al. (2017), Gharaei and Pasandideh (2017a), Gharaei and Pasandideh (2017b), and Gharaei and Pasandideh (2016) provide a comprehensive overview on the latest developments.

We present an approach for multi-objective supplier selection and order allocation that also takes sustainability into account. However, unlike the aforementioned proposals, the sustainability performances of single suppliers are not indicated by self-made sustainability scores but rather the sustainability ratings are based on a self-assessment questionnaire that is standard in the automotive industry. The details are explained in Section 4.

3. Methodology

At the heart of the proposed decision support methodology is a multi-objective optimization model that is based on the investment portfolio theory fathered by H. Markowitz. This model transfers the traditional risk-expected return trade-off to the supplier selection and order allocation context and extends the classical model through the addition of objective functions and constraints with integer variables (Section 3.1). To solve the multi-objective optimization problem, i.e., for the computation of the non-dominated set, we suggest using the ε-constraint method (Section 3.2). As will be shown in the numerical example in Section 4, different analyses may be carried out for the non-dominated set. These analyses provide deeper insights into the decision-making problem at hand (Section 4.3). Finally, we show how the identification of the most preferred supplier portfolio may be facilitated by means of an interactive dashboard (Section 4.4).

3.1. *Multi-objective supplier selection and order allocation model*

The proposed optimization model has three objectives: to minimize the overall purchasing costs, to source as much as possible from those suppliers with an outstanding sustainability performance, and to reduce the supply risk.

Indices		
i,j	$1\ldots N$	Suppliers
t	$1\ldots T$	Time periods
Decision variables		
x_i	$\in[0,1]$	Proportion of the total demand ordered from supplier i
y_i	$\in\{0;1\}$	Takes the value 1 if supplier i is part of the portfolio, 0 otherwise
Parameters		
cv_i	$\in R$	Per unit selling price of supplier i (variable cost)
cf_i	$\in R$	Fixed costs of sourcing from supplier i
log_i	$\in[0,1]$	Indicator of supplier i's logistics performance
log_{it}	$\in[0,1]$	Indicator of supplier i's logistics performance during period t
srs_i	$\in[0,1]$	Supplier i's sustainability performance (sustainability rating score)
σ_{ij}	$\in R$	Covariance of the logistics performance in suppliers i and j
CAP_i	$\in[0,1]$	Capacity of supplier i (share of the total demand that can be sourced from i)
MOQ_i	$\in[0,1]$	Minimum order quantity of supplier i (in percent of the total demand)
$strat_i$	$\in\{0;1\}$	Takes the value 1 if supplier i is a 'strategic' supplier, 0 otherwise
reg_i	$\in\{0;1\}$	Takes the value 1 if supplier i is a regional supplier, 0 otherwise
D	$\in R$	Demand of the purchasing company
B	$\in R$	Budget of the purchasing company
L	$\in[0,1]$	Minimum logistics service desired
N_{max}	$\in Z$	Maximum number of suppliers in the portfolio
N_{str}	$\in Z$	Number of strategic suppliers in the portfolio
N_{reg}	$\in Z$	Number of regional suppliers in the portfolio

Objectives

Costs $$min\sum_i (cv_i \cdot x_i \cdot D + cf_i \cdot y_i) \tag{1}$$

Sustainability $$max\sum_i srs_i \cdot x_i \tag{2}$$

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

Constraints

Demand satisfaction $$\sum_i x_i = 1 \tag{4}$$

Supplier capacity $$x_i \le CAP_i \cdot y_i \;\; \forall i \tag{5}$$

Minimum order quantity $$MOQ_i \cdot y_i \le x_i \;\; \forall i \tag{6}$$

$$\text{Budget} \quad \sum_i (cv_i \cdot x_i \cdot D + cf_i \cdot y_i) \leq B \tag{7}$$

$$\text{Logistics service} \quad L \leq \sum_i log_i \cdot x_i = \sum_i \left(\frac{\sum_t t \cdot log_{it}}{\sum_t t} \right) \cdot x_i \tag{8}$$

$$\text{Dual sourcing} \quad 2 \leq \sum_i y_i \tag{9}$$

$$\text{Maximum number of suppliers} \quad \sum_i y_i \leq N_{max} \tag{10}$$

$$\text{Nb. of strategic suppliers} \quad N_{str} \leq \sum_i y_i \cdot strat_i \tag{11}$$

$$\text{Nb. of regional suppliers} \quad N_{reg} \leq \sum_i y_i \cdot reg_i \tag{12}$$

Equation (1) minimizes the overall purchasing costs, which consist of variable and fixed costs. Variable costs are calculated as a function of the per unit selling prices cv_i. Fixed costs cf_i are costs for building up and maintaining the relationship to the supplier during the period under consideration.

Equation (2) maximizes the share of orders placed with those suppliers that are achieving a high sustainable performance. The sustainability performance of the suppliers is indicated by the sustainability rating scores *srs* ranging between 0 and 1.

Equation (3) minimizes the supply risk of the supplier portfolio. Supply risk occurs as the logistics service log_{it} of the single suppliers may vary more or less strongly over the time. The logistics service log_{it} offered by a certain supplier i indicates the percentage share of the deliveries that meets the '5 Rs in Logistics' (the Right product, in the Right quantity, in the Right quality, at the Right place, at the Right time) within a certain period of time t, for instance, one month. Thus, supply risk represents the fact that even if some suppliers offer quite a good service on average, their performance can fluctuate to a more or less significant degree. In accordance with Markowitz's portfolio theory, the variation in the logistics performance of the single suppliers is indicated by the standard deviation, and the overall supply risk is measured with the variance of the logistics service of the supplier portfolio as a whole. Equation (3) minimizes the supply risk of the supplier portfolio by assembling those suppliers that compensate each other the best, i.e., when one supplier performs poorly, the other(s) perform(s) well—and vice versa (Kellner et al., 2019). Thus, the desirable situation is when the performances of the suppliers are negatively correlated, i.e., when log_{it} is low, log_{jt} becomes high. As stated by Hosseininasab and Ahmadi (2015), some suppliers are similarly affected by certain disruptions, and assembling a portfolio of similar suppliers may be crucial for when such disruptions occur. There are different reasons for why two or more suppliers may break down simultaneously: (1) a natural disaster occurs and the suppliers are geographically located close to each other; (2) several suppliers are supplied by the same sub-supplier; and (3) suppliers use the same means of transport (railway, maritime, or air transport), which breaks down or is delayed. Following the idea of portfolio theory, these interactions in the logistics performance between two suppliers i and j are measured with the covariance σ_{ij}.

Equation (4) assures that the total demand of the purchasing company is satisfied. Equation (5) guarantees that no more orders are placed at the single suppliers than the sources can deliver. Equation (6) ensures that the minimum order quantities of the suppliers are respected. Equation (7) limits the financial resources spent to the maximum budget available. Equation (8) guarantees that the minimum overall logistics service desired by the purchasing company is achieved. To place more emphasis on the most recent performance values log_{it}, the overall logistics performance of a certain supplier (log_i) is calculated as the weighted average over the last T periods. Thus, the performance histories of the suppliers are taken into account. According to Equation (8), it is possible that suppliers with a logistics performance (log_i) below L may be part of the portfolio. However, the overall performance of the portfolio is at least L. This approach allows the selection of 'low-performance' suppliers who are, however, very desirable from a cost, supply risk, or sustainability point of view. Equation (9) ensures that the portfolio consists of at least two suppliers. This reduces the risk of short-term supply disruptions because if one suppliers breaks down, there is still another one who can supply the purchasing company. Furthermore, this facilitates competition among the vendors (Lee and Chien, 2014). Equation (10) limits the number of suppliers in the portfolio to a predefined value. This allows decision makers to limit the number of relationships that have to be maintained. Equations (11) and (12) ensure that the numbers of the strategic and regional suppliers in the portfolio are at least N_{str} and N_{reg}, respectively. The term 'strategic' means that a supplier is particularly important for the purchasing company for at least one reason, e.g., because it has particular expertise in the field of research and development, is very flexible in responding to unexpected demand changes, or has a certain manufacturing capability. Clearly, Equation (11) may be 'split,' so that there is one equation for each strategic property of the suppliers. Equation (12) is an illustrative example of this because it makes sure that there is at least one regional supplier.

3.2. Using the ε-constraint method for solving the supplier selection model

The optimization problem presented above is a non-standard portfolio selection model because it is a combination of the classical risk-expected return trade-off (Markowitz, 1952, 1959)—which could be associated with the mean/expected sustainability performance and the supply risk—and an additional third objective. Computing the efficient surface in multi-objective programming is generally a broadly discussed challenge (Ehrgott et al., 2012; Steuer et al., 2005). Due to computational restrictions, it is difficult to determine the efficient surface in the majority of the optimization models. Indeed, a posteriori decision making, as intended in our study, necessitates the calculation of the non-dominated set. Until Hirschberger et al. (2013), who present an a posteriori method for computing the efficient frontier of investment portfolios, it had not been possible to compute a tri-criterion non-dominated surface. However, this algorithm cannot be applied for the optimization model presented above because it does not allow the processing of integer variables. Thus, this research suggests solving the proposed optimization model by the means of the ε-constraint method (Haimes et al., 1971). The idea is to optimize one of the objectives while using the other objective functions as constraints with varying binding values.

We suggest minimizing the quadratic objective function, which refers to 'Supply risk,' and binding the linear functions representing the overall costs and the sustainability performance to predefined values, namely ε_{Cost} and $\varepsilon_{Sustainability}$. This results in the following optimization problem:

Objective

$$\text{Supply risk} \quad min\sum_{ij}\sigma_{ij}\cdot x_i\cdot x_j \tag{13}$$

Constraints

$$\text{Costs} \quad \sum_i (cv_i\cdot x_i\cdot D + cf_i\cdot y_i) \le \varepsilon_{Cost} \tag{14}$$

$$\text{Sustainability performance} \quad \sum_i srs_i\cdot x_i \ge \varepsilon_{Sustainability} \tag{15}$$

Equations (4)–(12) see above

For applying the ε-constraint method, it is necessary to first determine the ranges of the objective functions that are used as constraints. While the best values are easily attainable as the optima of the individual optimizations, the worst values (the nadir values) are not (Bechikh et al., 2010; Deb and Miettinen, 2010; Mavrotas, 2009). As, however, the knowledge of the exact nadir values is not required for calculating the efficient surface, we suggest the use of the optima of the 'negative' individual optimizations to approximate the nadir values. This means that the nadir value for the costs is obtained by maximizing Equation (1) subject to Equations (4)–(12), and the nadir value for the sustainability performance is obtained by minimizing Equation (2) subject to Equations (4)–(12). Another possibility for calculating the ranges of the objective functions is to fall back on the payoff table, i.e., the table with the results from the individual optimization of the objective functions. The nadir values can then be approximated with the minimum of the corresponding column (Mavrotas, 2009).

Once the ranges of the two linear objective functions have been determined, these ranges are sub-divided into m intervals with $(m+1)$ equidistant grid points. For the calculation of the non-dominated set, the $(m+1)$ grid points of the cost function and the $(m+1)$ grid points of the sustainability function are used as the binding values ε_{Cost} and $\varepsilon_{Sustainability}$. We then solve the optimization model $(m+1)*(m+1)$ times. Thus, the non-dominated set is composed of, at the most, $(m+1)^2$ grid points, and the objective value of Equation (13) is projected in the third dimension. Obviously, the number of m determines the density of the efficient surface. The higher the number of grid points, the denser the representation of the efficient surface and the higher the cost of computation time (Mavrotas, 2009). Fig. 1 summarizes the procedure for solving the multi-objective supplier selection model.

4. Application: a real-world case study

This section demonstrates the applicability of the proposed approach using an illustrative real-world case from the automotive industry. The example is concerned with the supplier selection and order allocation problem for embedded navigation systems at a leading premium automotive OEM in Germany.

Step 1: Determine the ranges for the objectives 'Costs' and 'Sustainability'

1.1) The approximated nadir value for the cost function v_{Cost}^{Nad} is obtained by solving…

| Objective | max Equation (1) |
| Constraints | Equations (4)–(12) |

1.2) The optimal value for the cost function v_{Cost}^{Opt} is obtained by solving…

| Objective | min Equation (1) |
| Constraints | Equations (4)–(12) |

1.3) The approximated nadir value for the sustainability function v_{Sust}^{Nad} is obtained by solving…

| Objective | min Equation (2) |
| Constraints | Equations (4)–(12) |

1.4) The optimal value for the sustainability function v_{Sust}^{Opt} is obtained by solving…

| Objective | max Equation (2) |
| Constraints | Equations (4)–(12) |

Step 2: Compute the non-dominated set

For a = 0 to m

For b = 0 to m

2.1) Set: $\varepsilon_{Cost} = v_{Cost}^{Nad} - \frac{a}{m} * (v_{Cost}^{Nad} - v_{Cost}^{Opt})$

2.2) Set: $\varepsilon_{Sustainability} = v_{Sust}^{Opt} + \frac{b}{m} * (v_{Sust}^{Opt} - v_{Sust}^{Nad})$

2.3) Solve:

| Objective | min Equation (13) |
| Constraints | Equations (4)–(12), (14)–(15) |

2.4) Record: Objective value of Equation (13), ε_{Cost}, $\varepsilon_{Sustainability}$

b = b + 1

a = a + 1

Step 3: Draw the efficient surface using the values recorded in step 2.4.

Fig. 1. Procedure for solving the multi-objective supplier selection model.

4.1. Setting and data

The example case represents a situation with a purchasing manager who is responsible for the procurement of embedded navigation systems and has to make decisions about the sourcing concept for the next 24 months. This includes the selection of the suppliers and the allocation of the order shares to the single sources. The company that supported our research provided real-world data—with the exception of the costs. The cost data comprises standardized values that correspond to the proportions of the real-world cost data. As the purchasing company has already worked together with the eight pre-selected suppliers, it is possible to fall back on the suppliers' performance histories for the last 36 months; this means that historical values for log_{it} are available. Using these 36 log_{it} values for each of the eight suppliers allows us to calculate the logistics service covariance matrix. Furthermore, the supplier specific data concerning the per unit selling prices cv_i, the fixed costs cf_i, the capacities CAP_i, the minimum order quantities MOQ_i, and the values for $strat_i$ (strategic supplier) and reg_i (regional supplier) are given. Table 2 summarizes the information about the eight suppliers. According to the case company, the deviations from 100% in the logistics service *log* are, in general, not associated with product quality problems but with tardy deliveries, where a tardy delivery is defined as a delivery that does not arrive on the day specified in the delivery notice.

Besides the supplier specific data, the general conditions of the purchasing situation are as follows: there is a demand D of 100,000 units, the maximum budget available B is 14,000,000, and the minimum logistics service desired (L) is 90%. Furthermore, the maximum number of suppliers (N_{max}) is 4, and the number of the strategic suppliers N_{str} and of the regional suppliers N_{reg} has to be at least 2 and 1, respectively.

Row 4 in Table 2 shows the sustainability rating scores of the eight suppliers. What sets this study apart is the fact that it is not based on self-made sustainability performance indicators, but rather the sustainability scores *srs* are determined by means of a self-assessment questionnaire based on the Global Automotive Sustainability Guiding Principles (GASGP). The GASGP have been formulated by the initiative 'Drive Sustainability' (drivesustainability.org), which is a partnership between ten leading automotive OEMs (BMW Group, Daimler AG, Ford, Honda, Jaguar Land Rover, Scania CV AB, Toyota Motor Europe, Volkswagen Group, Volvo Cars, and Volvo Group). This partnership aims to drive sustainability throughout the automotive supply chain by promoting a common approach within the industry and by integrating sustainability in the overall procurement process. The self-assessment questionnaire upon which the sustainability performance scores of the eight investigated suppliers are based was developed in 2014 and represents at present the common standard for the sustainability rating of suppliers in the automotive industry. Even if the approach of determining the sustainability performance of the single suppliers by means of a self-assessment questionnaire is, at first glance, not as sophisticated as other approaches that have been suggested in literature, such as TOPSIS, PROMETHEE, DEA, the AHP, or ANP, it has several advantages:

- The assessment of the sustainability performance of third parties (as in the case of a purchasing company rating the sustainability performance of its potential suppliers) is challenging because good knowledge of the suppliers' performance in the different domains of sustainability is necessary. We argue that it is easier for a company to concentrate on its own sustainability performance (self-assessment) and communicate the results in a standardized way.
- The GASGP offer a standardized approach for the assessment of the sustainability performance of suppliers in the automotive industry. Based on a questionnaire consisting of more than 50 items, suppliers are asked to provide information about their practices in different sustainability domains. The responses are then summarized, and a sustainability rating score ranging between 0 and 1 is calculated. The fact that the sustainability performance is measured consistently (same questions, same rating) across the whole industry allows for a better comparability of the potential suppliers.
- While more sophisticated approaches enjoy some methodology-inherent advantages (e.g., consistency checks in the case of AHP and ANP), they suffer from the fact that they are not commonly accepted and that a certain expertise is required to carry out the corresponding calculations and analyses. We argue that this hinders an industry-wide application of these methods. In addition, each one of the 'more sophisticated' methods enjoys its own comparative advantages over the other methods. There is no single method that describes a company's sustainability performance best, that is commonly accepted, or that is practical enough to guarantee an industry-wide application.

Therefore, we view the information about the sustainability performance of the eight suppliers based on the standardized self-assessment questionnaire as very useful.

Table 2
Summary of the supplier characteristics.

	S1	S2	S3	S4	S5	S6	S7	S8
Variable costs *cv*	115	100	108	107	113	110	109	101
Fixed costs *cf*	2.00E+06	9.00E+05	1.00E+06	1.10E+06	1.50E+06	1.10E+06	1.15E+06	9.50E+05
Logistics service *log*	0.992	0.753	0.859	0.878	0.979	0.906	0.858	0.799
Sustainability score *srs*	0.82	0.32	0.72	0.48	0.53	0.69	0.79	0.41
Min. order qty *MOQ*	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Capacity *CAP*	1.0	0.7	1.0	1.0	1.0	0.6	1.0	1.0
Strategic sup. *strat*	1	0	0	1	1	1	1	0
Regional sup. *reg*	1	0	1	0	1	1	0	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

Table 3
Effect of the parameter m on the non-dominated set and on the computation time.

m	Max./theoretical number of portfolios = $(m+1)\bullet(m+1)$	Number of feasible solutions	Number of feasible unique solutions	Computation time[a] (hh:mm:ss)
25	676	386	55	00:00:14
50	2601	1498	119	00:00:43
100	10,201	5815	248	00:02:42
250	63,001	35,912	693	00:16:30
500	251,001	142,783	1559	01:07:10
1000	1,002,001	570,305	3574	04:24:00

[a] Win7 64bit, Intel i7-3520 2.9 GHz, 8 GB RAM.

4.2. *Visualizing the efficient surface*

To determine the non-dominated set, we execute the procedure shown in Fig. 1. All optimizations are carried out with CPLEX 12.6.1; for the visualization of the efficient surface and for the portfolio selection process an interactive web application has been built based on R Shiny.

First, the optimal and the nadir values of the objectives ‘Costs’ and ‘Sustainability’ are determined by solving the corresponding optimization models. The nadir values for the costs and for the overall sustainability performance are 14,000,000 and 0.49, respectively. The optimal values are 13,430,954 and 0.70. Next, the ranges of the objectives ‘Costs’ and ‘Sustainability’ are sub-divided into m intervals. For the parameter m, we use six different values to observe the effect on the non-dominated set and on the computation time. The results are summarized in Table 3.

The second column in Table 3 presents the number of optimization runs started and, simultaneously, the number of portfolios that the non-dominated set can be theoretically composed of. For each value of m, the $(m+1)^2$ optimization runs are started while the parameters a and b (cf. Fig. 1) are increased permanently, and the results of each optimization run are recorded. The time for carrying out all optimization runs is shown in the far right column of Table 3. As can be seen from the third and the fourth column of Table 3, not all optimization runs resulted in feasible solutions. More interestingly, the number of the feasible unique solutions is relatively small when compared to the total number of optimization runs. The number of the feasible unique solutions can be reduced further by rounding off the three objective values, the logistics service, and the shares ordered from the selected suppliers to a reasonable number of decimals. When rounding off the supply risk, the logistics service, the sustainability score, and the shares ordered to 4 decimals and the costs to zero decimals, 1754 unique solutions in the case of $m = 1000$ remain. The further analyses rely on the latter setting where the non-dominated set is composed of 1754 unique portfolios.

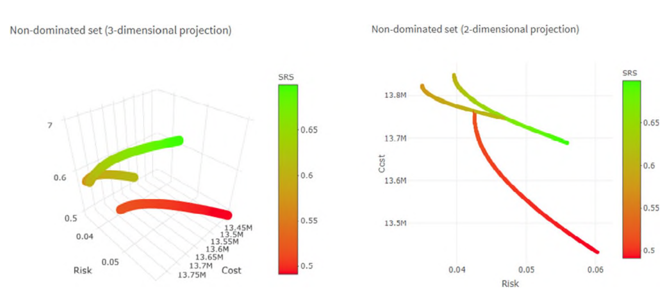

Fig. 2. Efficient Surface for the Example Case (3- and 2-Dimensional Projection). These graphs illustrate the non-dominated order share solutions in criterion space. Color indicates the level of sustainability.

Fig. 2 shows two views of the efficient surface: a 3- and 2-dimensional projection. Obviously, the efficient surface consists of three parabolas. The color scale (red-green) indicates the value of the overall sustainability rating scores (*srs*), i.e., the sustainability performances of the supplier portfolios. We measure risk with the standard deviation of the logistics service of the supplier portfolios. The 2-dimensional projection of the non-dominated portfolios in criterion space shows that the portfolios with the lowest costs have low sustainability (red curve from southeast to northwest). This curve illustrates that costs rise with decreasing risk and a slight increase in sustainability. The interpretation of both of the other curves is similar and shows the trade-off between the three objectives.

4.3. *Analyzing the decision making problem*

An advantage of the a posteriori decision making approach is that it allows the analysis of the non-dominated set and, thus, provides deeper insights into the decision making problem. Table 4 presents summary statistics for the 1754 optimal supplier portfolios, and Table 5 reports statistics for the eight potential suppliers.

Table 4 shows that the costs of the optimal supplier portfolios range between 13,430,954 and 13,849,388. However, more than 50% of the portfolios have costs in an interval ranging from 13,700,000 to 13,800,000. Furthermore, there is a significant gap between the minimal and the maximal achievable sustainability performance *srs*. The average and the median values, however, indicate that the average realization of overall sustainability performance is close to 0.6. Concerning the supply risk (Table 4, column ‘Supply risk’), the standard deviation of the logistics performance of the portfolio with the highest supply risk is almost two times greater than the standard deviation of the portfolio with

Table 4
Summary statistics for the three objective values of the non-dominated set in the example case.

	Total costs	Sustainability (*srs*)	Supply risk	Logistics service	Number of suppliers
Minimum	13,430,954	0.4909	0.0350	0.9000	2
Mean	13,713,550	0.5906	0.0455	0.9298	2
Median	13,746,205	0.6018	0.0445	0.9305	2
Maximum	13,849,388	0.6991	0.0603	0.9600	2
Standard deviation	105,223	0.0674	0.0059	0.0169	0

Table 5
Summary statistics for the eight suppliers over the 1754 optimal portfolios.

	S1	S2	S3	S4	S5	S6	S7	S8
Minimal order share	0.00	0.00	0.00	0.00	0.2183	0.00	0.00	0.00
Average order share	0.00	0.00	0.00	0.1671	0.5389	0.0745	0.2195	0.00
Maximal order share	0.00	0.00	0.00	0.7817	0.7720	0.5146	0.6503	0.00
Frequency (in %) of being included in an opt. portfolio	0.0%	0.0%	0.0%	32.7%	100%	19.4%	47.9%	0.0%

the lowest supply risk (0.0603 versus 0.0350).

Each of the 1754 optimal supplier portfolios consists of two suppliers. S5 receives particular attention as this supplier is included in each optimal portfolio and has an average order share of 53.9%. This means that, depending on the purchasing company's preferences for the three objectives, S5 will be combined with one other supplier. This can also be seen in Fig. 2, which shows that the efficient surface consists of three parabolas: for each parabola, the suppliers are the same—only the order shares change when moving along the curves. Thus, one parabola consists of the suppliers S4 and S5, another of S5 and S6, and the third of S5 and S7. Furthermore, Table 5 shows there are four suppliers that are not part of any optimal supplier portfolio (S1, S2, S3, and S8). These suppliers may be excluded from further considerations.

4.4. Identifying the most preferred solution

The a posteriori approach has the advantage that the decision maker can instantly access the full picture of all optimal options and trade-offs that are associated with the supplier selection problem. At the same time, it does provide one challenge, namely the selection of a specific point from the non-dominated set. 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 often used in practice. Nevertheless, a good solution can only be found if the decision maker is aware of alternative solutions and then selects the most appropriate one.

To facilitate the decision-making process for the purchasing manager, we developed and implemented an interactive web application. This web application provides different views of the non-dominated set and allows us to set filters that exclude the disliked options. Fig. 3 shows the interactive dashboard.

The first row of the dashboard contains three filters that allow the preferred ranges for the three objective values to be set. The second row shows three views of the efficient surface, a 3- and a 2-dimenisional projection as well as a ternary plot. The third row presents the histograms for the three objective values over the non-dominated set plus summary statistics. Finally, the fourth row lists the single portfolios, including the total costs, the supply risk, the logistics performance, the *srs*, the supplier shares, the number of suppliers, and the information about whether a certain portfolio is the minimum-risk, minimum-cost, or maximum-sustainability portfolio.

The identification of the purchasing manager's most preferred solution is carried out in a step-wise process. In each step, the least preferred portfolios are eliminated from the non-dominated set. In the example case, this was carried out as follows: First, the purchasing manager focused on the leftmost line of the ternary plot (Fig. 3). This line represents supplier portfolios that are far away from the maximum *srs* value achievable. Next, the manager concentrated on the three histograms in Fig. 3 and noticed a significant gap in the rightmost histogram representing the *srs* values of the 1754 supplier portfolios. As a consequence, the manager moved the *srs* lower bound filter to the right side, thereby deselecting all supplier portfolios with *srs* values below 0.6. The result is shown in Fig. 4.

In the next step, the purchasing manager decided to limit the overall supply risk by moving the corresponding upper bound filter to the middle of the scale range. She then moved the upper bound filter for the total cost to the left, thereby excluding the high-cost

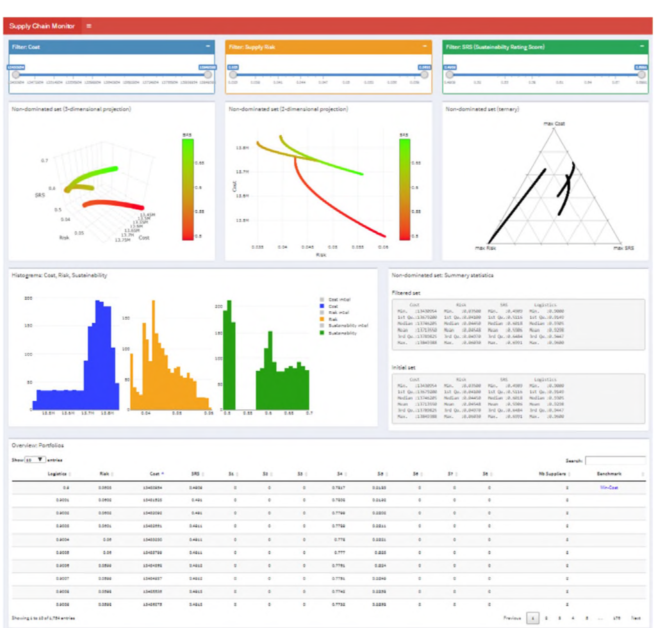

Fig. 3. Interactive Dashboard to Support the Decision Making Process. In the upper part of the dashboard, we show the projections of the three criteria in criterion space. The middle section of the dashboard shows the range of the values for each objective as well as some descriptive statistics on the right hand side. The lower section of the dashboard contains a list of the efficient portfolios with the objective values and the portfolio weights.

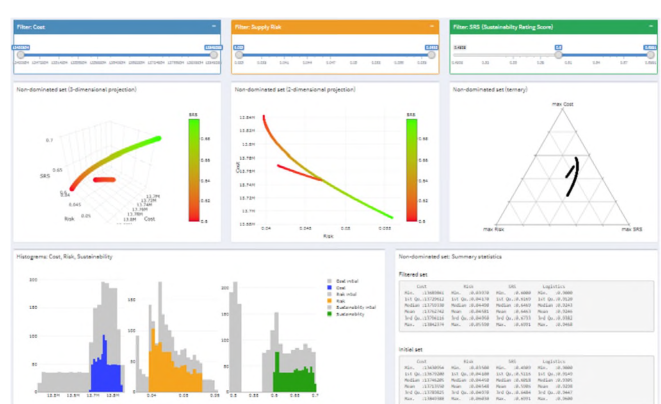

Fig. 4. Interactive Supplier Portfolio Selection: Step 1. We deselect all portfolios with low levels of sustainability with the upper right filter. The upper graphs show how the non-dominated set changes. The lower graphs indicate how the ranges of the objectives are affected by excluding low-sustainability portfolios. The gray shadows show the initial ranges without filters, while the colored ranges are the ones that are still achievable after increasing the minimum sustainability level of the portfolios.

portfolios (Fig. 5).

Having carried out these adaptations, the manager realized that while the remaining ranges for the total costs and the supply risk were relatively narrow, a new gap appeared for the *srs*. As a consequence, the manager deselected the low-sustainability portfolios (Fig. 6).

The manager then gradually moved the filters representing the upper bounds for the costs and for the supply risk to the left until only a few portfolios remained (Fig. 7).

This process was continued until one portfolio was left. In the case of the most preferred portfolio, 49.2% of the total demand is sourced from supplier S5, and 50.8% is sourced from S7. This portfolio has the following characteristics: total purchasing costs = 13,746,875; *srs* = 0.66; supply risk = 0.047; logistics service = 91.7%.

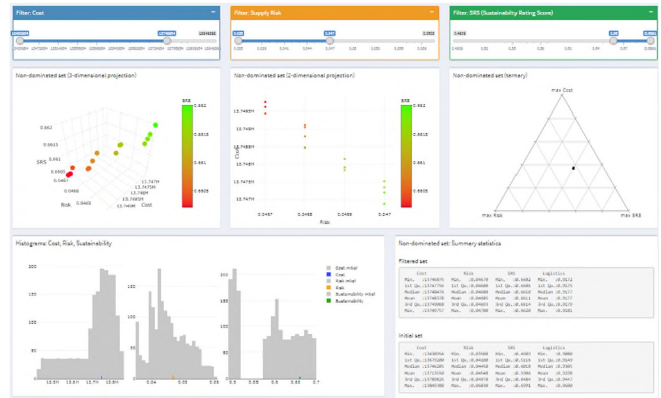

Fig. 7. Interactive Supplier Portfolio Selection: Step 5. We further reduce the non-dominated set.

5. Discussion

5.1. *Closing a gap in research*

The presented approach for supplier selection is based on multi-objective optimization and the mathematical framework of the investment portfolio theory. Up to now, only few studies used this framework for the supplier selection case. Moreover, only one study (Kellner et al., 2019) combining the classical risk-expected return trade-off with a posteriori decision making exists. This is surprising because the example case showed that the combination of the investment portfolio theory with a posteriori decision making is a promising approach for solving the supplier selection problem. As the algorithm used by Kellner et al. (2019) cannot process objective functions and constraints with integer variables, the applicability of their approach is limited. This paper closes a gap in research by showing how to overcome this shortcoming.

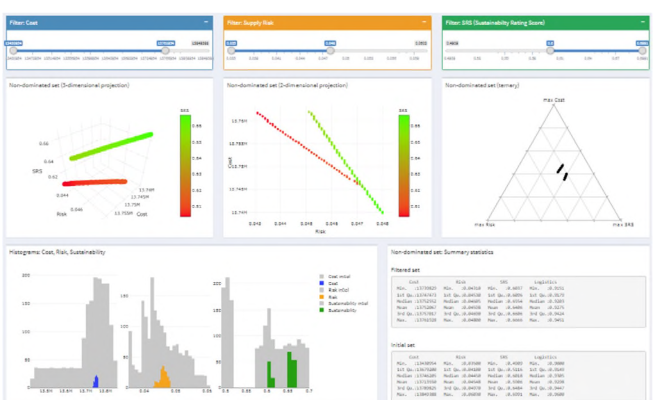

Fig. 5. Interactive Supplier Portfolio Selection: Steps 2 and 3. We remove the high-risk and high-cost portfolios (we include filters for cost and risk by decreasing their maximum accepted levels).

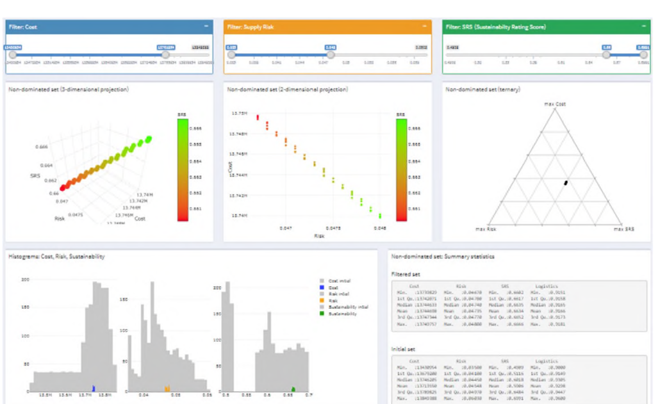

Fig. 6. Interactive Supplier Portfolio Selection: Step 4. We remove the low-sustainability portfolios.

5.2. *The representation of risk in the optimization model*

As stated by Hosseininasab and Ahmadi (2015), a particularity of adopting the investment portfolio theory for the supplier selection case is the representation of supply risk: supply risk is measured with the variation of the performance of the supplier portfolio as a whole, and the goal is to minimize the supply risk by minimizing the covariance of the logistics service between the suppliers. This is achieved by grouping together those suppliers that perform well when others perform poorly, i.e., the desirable situation is when the performances of the suppliers are negatively correlated.

When adopting this approach, it is not important to know the exact reasons for why there are interactions in the logistics performances of the suppliers (e.g., geographical proximity, same sub-suppliers, same means of transport). The interactions only have to be derived from past observations. Moreover, the method used to manage supply risk in the supply chain can be described as ‘preventive’ (Gaonkar and Viswanadham, 2007). Despite the possibility of installing mechanisms that reduce the chance of supplier breakdowns or mechanisms that mitigate the consequences when supply chain disruptions occur, the risk of a simultaneous breakdown across all suppliers is minimized. Finally, the proposed approach is conceived for supplier selection situations with a mid- to long-term planning horizon because the method does not reduce the risk of short-term supply disruptions. Instead, it gathers together those suppliers that compensate each other with respect to variations in their performance in the mid- to long-term. To mitigate the risk of short-term supply disruptions, the dual sourcing constraint is part of the optimization model.

5.3. *The integration of sustainability into the supplier selection process*

The real-world case shows that the visualization and the analysis of the non-dominated set allow the immediate identification among all optimal supplier portfolios of those that perform well or badly from a sustainability point of view. Thus, it is possible, for instance, to quickly exclude portfolios achieving extremely low sustainability scores from further considerations. Generally, the visualization of the efficient surface is beneficial because it gives an overview of all trade-offs between sustainability and the other purchasing goals. It should be noted that it would have been possible to analyze more statistics and carry out statistical tests on the non-dominated set; however, this is beyond the scope of this paper. The interactive portfolio selection process presented in Section 4.4 further shows that it is possible to immediately recognize the consequences when increasing the desired level of sustainability. This promotes transparency and allows for a better understanding of the decision making process.

Concerning the rating of the sustainability performance of the suppliers, what sets our paper apart is the fact that the supplier sustainability scores are not 'self-made' sustainability indicators. Instead, we have the chance to obtain the results of a self-assessment questionnaire that is a standard in the automotive industry for rating the sustainability performance of suppliers. We argue that the literature provides numerous approaches for creating sustainability indicators for supplier evaluation and selection—and each approach will lead to different results. While the different approaches certainly have numerous methodological strengths, they suffer from the fact that they do not represent a standard for determining the sustainability performance of suppliers. This makes the comparison of the different studies difficult.

5.4. The 'a posteriori' decision making approach: managerial implications and insights

Another important element of the proposed methodology, particularly with regard to the managerial implications and insights, is the 'a posteriori' decision making approach.

The real-world case confirms that the 'a posteriori' decision making approach is beneficial to purchasing managers for several reasons. Firstly, the decision makers get the full picture of all optimal options, and they have an overview of all trade-offs that are associated with the supplier selection problem. This allows for a better understanding of the decision problem and facilitates the communication between the parties involved in the supplier selection process. Furthermore, the presented approach allows users to carry out different numerical analyses that identify, amongst other things, the ranges of the objective values, the optimal numbers of the suppliers, and those suppliers that will in any case (not) be part of the selected portfolio. In the eyes of the purchasing manager interviewed, the knowledge about the characteristics of the non-dominated set is beneficial because the fact that none of the potential solutions remains unrevealed strengthens the confidence in the final decision. Generally, the (de-)selection of a certain portfolio may be better justified when all optimal solutions have been compared. Another advantage of the 'a posteriori' approach is the fact that it is not necessary to predefine the weights of the different objectives, as would be the case in an a priori setting.

However, it should also be noted that the great challenge that comes with the 'a posteriori' decision making approach is the selection of a certain point on the efficient surface. One way of handling this challenge is the approach used in the case study, i.e., the step-wise procedure of iteratively excluding the most disliked portfolios. In the example case, this procedure in combination with an interactive dashboard turned out to be efficient.

6. Conclusion

6.1. Summary of the findings

In this paper, we present an 'a posteriori' decision making approach for the supplier selection and order allocation problem that takes three purchasing objectives into consideration: cost minimization, sustainability maximization, and supply risk minimization. We propose a multi-objective optimization model based on the investment portfolio theory, and the ε-constraint method is used to solve the optimization problem. The analysis of the non-dominated set of the example case results in some interesting findings. First, among the uncountable number of possible supplier portfolios that may be assembled based on the eight available suppliers, we identify 1754 optimal solutions. Further analyses show that each optimal portfolio consists of exactly two suppliers, with one specific supplier being included in each portfolio. Furthermore, there are four suppliers that are not part of any optimal solution. In addition, we are able to indicate the ranges of the three objective values of the non-dominated set. Finally, the most preferred portfolio can be identified by means of an interactive web application.

Prior research proved that the mathematical framework of the investment portfolio theory may effectively be used to support mid- and long-term supplier selection problems. In addition, Kellner et al. (2019) showed that the combination of portfolio theory with a posteriori decision making provides even deeper insights into the decision making problem and, thus, supports better decision making. As the algorithm used by Kellner et al. (2019) does not allow the processing of integer and binary variables, we show how the ε-constraint method may be applied to overcome this shortcoming. Thus, it is possible to model and solve more complex mid-term supplier selection and order allocation problems that are based on the Markowitz framework.

6.2. Research limitations

Our research has some limitations. First, for the computation of the non-dominated set, a certain amount of information has to be collected over a certain amount of time in order to measure the performance interactions between the single suppliers, which could hinder decision makers who do not have long-term data observations at their disposal. Second, our optimization model is based on the mathematical framework of the Markowitz portfolio theory and, therefore, uses the variance as the measure of risk. Although variance is widely accepted as a risk measure in the literature (e.g., Deng et al., 2005; Hirschberger et al., 2007; Leung et al., 2001; Liu et al., 2003), there is much discussion on the question of what the correct measure for risk is. One of the limitations of variance as a risk measure lies in the fact that it measures symmetric deviations from the mean value, i.e., it increases with downward as well as upward deviations. If the decision maker's target is to consider only downward deviations as risk, other risk measures such as semi-variance could be included into the decision model (Choobineh and Branting, 1986; Grootveld and Hallerbach, 1999; Kaplan and Alldredge, 1997; Markowitz, 1959). Finally, in light of the generalizability of the case study results, it should be noted that the goal of the numerical example was to demonstrate the applicability of the decision making approach.

6.3. Further research

Future research could survey a representative sample of cases to find out if the proposed decision making approach fits the requirements of different purchasing situations. Furthermore, future research could examine the transfer of additional mathematical frameworks from the finance literature to decision making problems from the supply chain and operations sector. In particular, rewards-driven systems and maintenance concepts (Duan et al., 2018; Gharaei et al., 2015) could be promising to integrate sustainability into the supplier selection process.

References

Aktin, T., Gergin, Z., 2016. Mathematical modelling of sustainable procurement strategies: three case studies. J. Clean. Prod. 113, 767–780.
Amid, A., Ghodsypour, S.H., O'Brien, C., 2011. A weighted max–min model for fuzzy multi-objective supplier selection in a supply chain. Int. J. Prod. Econ. 131 (1), 139–145.
Bai, C., Sarkis, J., 2010a. Green supplier development: analytical evaluation using rough set theory. J. Clean. Prod. 18 (12), 1200–1210.
Bai, C., Sarkis, J., 2010b. Integrating sustainability into supplier selection with grey system and rough set methodologies. Int. J. Prod. Econ. 124 (1), 252–264.
Bechikh, S., Ben Said, L., Ghedira, K., 2010. Estimating nadir point in multi-objective optimization using mobile reference points. In: 2010 IEEE Congress on Evolutionary Computation (CEC). Barcelona, Spain, pp. 1–9.
Boer, L. de, Labro, E., Morlacchi, P., 2001. A review of methods supporting supplier selection. Eur. J. Purch. Supply Manag. 7 (2), 75–89.
Chai, J., Liu, J.N.K., Ngai, E.W.T., 2013. Application of decision-making techniques in supplier selection. Expert Syst. Appl. 40 (10), 3872–3885.
Choobineh, F., Branting, D., 1986. A simple approximation for semivariance. Eur. J. Oper. Res. 27 (3), 364–370.
COFRET (Carbon Footprint of Freight Transport), 2011. Existing Methods and Tools for Calculation of Carbon Footprint of Transport and Logistics. http://www.cofret-project.eu/downloads/pdf/COFRET_Deliverable_2.1_final.pdf. (Accessed 5 April 2016).
Dai, J., Blackhurst, J., 2012. A four-phase AHP–QFD approach for supplier assessment: a sustainability perspective. Int. J. Prod. Res. 50 (19), 5474–5490.
Deb, K., Miettinen, K., 2010. Nadir point estimation using evolutionary approaches: better accuracy and computational speed through focused search. In: Ehrgott, M., Naujoks, B., Stewart, T.J., Wallenius, J. (Eds.), Multiple Criteria Decision Making for Sustainable Energy and Transportation Systems. Springer, Berlin, pp. 339–354.
Degraeve, Z., Labro, E., Roodhooft, F., 2000. An evaluation of vendor selection models from a total cost of ownership perspective. Eur. J. Oper. Res. 125 (1), 34–58.
Deng, X.-T., Li, Z.-F., Wang, S.-Y., 2005. A minimax portfolio selection strategy with equilibrium. Eur. J. Oper. Res. 166 (1), 278–292.
Dou, Y., Sarkis, J., 2010. A joint location and outsourcing sustainability analysis for a strategic offshoring decision. Int. J. Prod. Res. 48 (2), 567–592.
Duan, C., Deng, C., Gharaei, A., Wu, J., Wang, B., 2018. Selective maintenance scheduling under stochastic maintenance quality with multiple maintenance actions. Int. J. Prod. Res. 59 (2), 1–19.
Ehrgott, M., Löhne, A., Shao, L., 2012. A dual variant of Benson's "outer approximation algorithm" for multiple objective linear programming. J. Global Optim. 52 (4), 757–778.
Frostenson, M., Prenkert, F., 2015. Sustainable supply chain management when focal firms are complex: a network perspective. J. Clean. Prod. 107, 85–94.
Gaonkar, R.S., Viswanadham, N., 2007. Analytical framework for the management of risk in supply chains. IEEE Trans. Autom. Sci. Eng. 4 (2), 265–273.
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. Eur. J. Oper. Res. 269 (1), 286–301.
Gharaei, A., Karimi, M., Shekarabi, S.A.H., 2018a. An integrated multi-product multi-buyer supply chain under the penalty, green, and VMI-CS policies: OA/ER/AP algorithm. Appl. Math. Model. (forthcoming).
Gharaei, A., Naderi, B., Mohammadi, M., 2015. Optimization of rewards in single machine scheduling in the rewards-driven systems. Management Science Letters 5 (6), 629–638.
Gharaei, A., Pasandideh, S.h.r., 2016. Modeling and optimization the four-level integrated supply chain: sequential quadratic programming. Int. J. Comput. Sci. Inf. Secur. 14 (7), 650–669.
Gharaei, A., Pasandideh, S.h.r., 2017a. Four-echelon integrated supply chain model with stochastic constraints under shortage condition: sequential quadratic programming. Industrial Engineering & Management Systems 16 (3), 316–329.
Gharaei, A., Pasandideh, S.h.r., 2017b. Modeling and optimization of four-level integrated supply chain with the aim of determining the optimum stockpile and period length: sequential quadratic programming. Journal of Industrial and Production Engineering 34 (7), 529–541.
Gharaei, A., Pasandideh, S.h.r., Akhavan Niaki, S.T., 2018b. An optimal integrated lot sizing policy of inventory in a bi-objective multi-level supply chain with stochastic constraints and imperfect products. Journal of Industrial and Production Engineering 35 (1), 6–20.
Gharaei, A., Pasandideh, S.h.r., Arshadi Khamseh, A., 2017. Inventory model in a four-echelon integrated supply chain: modeling and optimization. J. Model. Manag. 12 (4), 739–762.
Golmohammadi, D., Mellat-Parast, M., 2012. Developing a grey-based decision-making model for supplier selection. Int. J. Prod. Econ. 137 (2), 191–200.
Gören, H.G., 2018. A decision framework for sustainable supplier selection and order allocation with lost sales. J. Clean. Prod. 183, 1156–1169.
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. J. Clean. Prod. 47, 345–354.
Govindan, K., Sivakumar, R., 2016. Green supplier selection and order allocation in a low-carbon paper industry. Ann. Oper. Res. 238 (1), 243–276.
GRI (Global Reporting Initiative), 2016. Consolidated Set of GRI Sustainability Reporting Standards 2016. https://www.globalreporting.org/standards/gri-standards-download-center/. (Accessed 17 May 2018).
Grootveld, H., Hallerbach, W., 1999. Variance vs downside risk: is there really that much difference? Eur. J. Oper. Res. 114 (2), 304–319.
Gupta, H., Barua, M.K., 2017. Supplier selection among SMEs on the basis of their green innovation ability using BWM and fuzzy TOPSIS. J. Clean. Prod. 152, 242–258.
Haimes, Y.Y., Lasdon, L.S., Wismer, D.A., 1971. On a bicriterion formulation of the problems of integrated system identification and system optimization. IEEE Trans Syst Man Cybern 1 (3), 296–297.
Hirschberger, M., Qi, Y., Steuer, R.E., 2007. Randomly generating portfolio-selection covariance matrices with specified distributional characteristics. Eur. J. Oper. Res. 177 (3), 1610–1625.
Hirschberger, M., Steuer, R.E., Utz, S., Wimmer, M., Qi, Y., 2013. Computing the nondominated surface in tri-criterion portfolio selection. Oper. Res. 61 (1), 169–183.
Ho, W., Xu, X., Dey, P.K., 2010. Multi-criteria decision making approaches for supplier evaluation and selection. Eur. J. Oper. Res. 202 (1), 16–24.
Hoseini Shekarabi, S.A., Gharaei, A., Karimi, M., 2018. Modelling and optimal lot-sizing of integrated multi-level multi-wholesaler supply chains under the shortage and limited warehouse space: generalised outer approximation. Int. J. Syst. Sci.: Operations & Logistics 14 (7), 1–21.
Hosseininasab, A., Ahmadi, A., 2015. Selecting a supplier portfolio with value, development, and risk consideration. Eur. J. Oper. Res. 245 (1), 146–156.
Huang, Y., Wang, K., Zhang, T., Pang, C., 2016. Green supply chain coordination with greenhouse gases emissions management: a game-theoretic approach. J. Clean. Prod. 112, 2004–2014.
Hwang, C.L., Masud, A.S.M., 1979. Multiple Objective Decision Making, Methods and Applications. A State-of-the-art Survey. Springer-Verlag, Berlin.
Kannan, D., Govindan, K., Rajendran, S., 2015. Fuzzy Axiomatic Design approach based green supplier selection: a case study from Singapore. J. Clean. Prod. 96, 194–208.
Kannan, V.R., Tan, K.C., 2002. Supplier selection and assessment. J. Supply Chain Manag. 38 (4), 11–21.
Kaplan, P.D., Alldredge, R.H., 1997. Semivariance in risk-based index construction. JOI (J. Oral Implantol.) 6 (2), 82–87.
Karpak, B., Kumcu, E., Kasuganti, R.R., 2001. Purchasing materials in the supply chain. Eur. J. Purch. Supply Manag. 7 (3), 209–216.
Kaufmann, L., Carter, C.R., Buhrmann, C., 2010. Debiasing the supplier selection decision. Int Jnl Phys Dist & Log Manage 40 (10), 792–821.
Kellner, F., Lienland, B., Utz, S., 2019. An a posteriori decision support methodology for solving the multi-criteria supplier selection problem. Eur. J. Oper. Res. 272 (2), 505–522.
Kilic, H.S., 2013. An integrated approach for supplier selection in multi-item/multi-supplier environment. Appl. Math. Model. 37 (14–15), 7752–7763.
Koufteros, X., Vickery, S.K., Dröge, C., 2012. The effects of strategic supplier selection on buyer competitive performance in matched domains. J. Supply Chain Manag. 48 (2), 93–115.
Kraljic, P., 1983. Purchasing must become supply management. Harv. Bus. Rev. 61 (5), 109–117.
Krause, D.R., Handfield, R.B., Scannell, T.V., 1998. An empirical investigation of supplier development. J. Oper. Manag. 17 (1), 39–58.
Krause, D.R., Vachon, S., Klassen, R.D., 2009. Special topic forum on sustainably supply chain management. J. Supply Chain Manag. 45 (4), 18–25.
Kull, T.J., Talluri, S., 2008. A supply risk reduction model using integrated multi-criteria decision making. IEEE Trans. Eng. Manag. 55 (3), 409–419.
Lee, C.-Y., Chien, C.-F., 2014. Stochastic programming for vendor portfolio selection and order allocation under delivery uncertainty. Spectrum 36 (3), 761–797.
Leung, M.T., Daouk, H., Chen, A.-S., 2001. Using investment portfolio return to combine forecasts: a multiobjective approach. Eur. J. Oper. Res. 134 (1), 84–102.
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. J. Purch. Supply Manag. 19 (2), 84–97.
Liu, K., Liu, Y., Qin, J., 2018. An integrated ANP-VIKOR methodology for sustainable supplier selection with interval type-2 fuzzy sets. Granular Computing 3 (3), 193–208.
Liu, S., Wang, S.Y., Qiu, W., 2003. Mean-variance-skewness model for portfolio selection with transaction costs. Int. J. Syst. Sci. 34 (4), 255–262.
Luthra, S., Govindan, K., Kannan, D., Mangla, S.K., Garg, C.P., 2017. An integrated framework for sustainable supplier selection and evaluation in supply chains. J. Clean. Prod. 140, 1686–1698.
Markowitz, H., 1952. Portfolio selection. J. Finance 7 (1), 77–91.
Markowitz, H., 1959. Portfolio Selection. Efficient Diversification of Investments. Yale University Press, New Haven.
Marler, R.T., Arora, J.S., 2004. Survey of multi-objective optimization methods for engineering. Struct. Multidiscip. Optim. 26 (6), 369–395.
Mavrotas, G., 2009. Effective implementation of the ε-constraint method in multi-objective mathematical programming problems. Appl. Math. Comput. 213 (2), 455–465.
McKinnon, A., Browne, M., Whiteing, A., Piecyk, M., 2015. Green Logistics. Improving the Environmental Sustainability of Logistics. Kogan Page, London.
Narasimhan, R., Talluri, S., Mahapatra, S.K., 2006. Multiproduct, multicriteria model for supplier selection with product life-cycle considerations. Decis. Sci. J. 37 (4), 577–603.

Park, K., Okudan Kremer, G.E., Ma, J., 2018. A regional information-based multi-attribute and multi-objective decision-making approach for sustainable supplier selection and order allocation. J. Clean. Prod. 187, 590–604.

Parthiban, P., Zubar, H.A., Katakar, P., 2013. Vendor selection problem. Int. J. Prod. Res. 51 (5), 1535–1548.

Rezaei, J., Nispeling, T., Sarkis, J., Tavasszy, L., 2016. A supplier selection life cycle approach integrating traditional and environmental criteria using the best worst method. J. Clean. Prod. 135, 577–588.

Singh, A., 2014. Supplier evaluation and demand allocation among suppliers in a supply chain. J. Purch. Supply Manag. 20 (3), 167–176.

Sobhanallahi, M.A., Gharaei, A., Pilbala, M., 2016a. Provide a new method to determine effectiveness or performance rate of organization strategies based on Freeman model and using improved dimensional analysis method. In: 12th International Conference on Industrial Engineering (ICIE). 2016, Tehran, Iran, pp. 125–133.

Sobhanallahi, M.A., Gharaei, A., Pilbala, M., 2016b. Provide a practical approach for measuring the performance rate of organizational strategies. In: 12th International Conference on Industrial Engineering (ICIE). 2016, Tehran, Iran, pp. 115–124.

Spina, G., Caniato, F., Luzzini, D., Ronchi, S., 2013. Past, present and future trends of purchasing and supply management. Ind. Market. Manag. 42 (8), 1202–1212.

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

Torres-Ruiz, A., Ravindran, A.R., 2018. Multiple criteria framework for the sustainability risk assessment of a supplier portfolio. J. Clean. Prod. 172, 4478–4493.

Trapp, A.C., Sarkis, J., 2016. Identifying Robust portfolios of suppliers: a sustainability selection and development perspective. J. Clean. Prod. 112, 2088–2100.

Vahidi, F., Torabi, S.A., Ramezankhani, M.J., 2018. Sustainable supplier selection and order allocation under operational and disruption risks. J. Clean. Prod. 174, 1351–1365.

Verma, R., Pullman, M.E., 1998. An analysis of the supplier selection process. Omega 26 (6), 739–750.

Wadhwa, V., Ravindran, A.R., 2007. Vendor selection in outsourcing. Comput. Oper. Res. 34 (12), 3725–3737.

Weber, C.A., Current, J.R., 1993. A multiobjective approach to vendor selection. Eur. J. Oper. Res. 68 (2), 173–184.

Weber, C.A., Current, J.R., Benton, W.C., 1991. Vendor selection criteria and methods. Eur. J. Oper. Res. 50 (1), 2–18.

Wetzstein, A., Hartmann, E., Benton jr., W.C., Hohenstein, N.-O., 2016. A systematic assessment of supplier selection literature – state-of-the-art and future scope. Int. J. Prod. Econ. 182, 304–323.

Yazdani, M., Chatterjee, P., Zavadskas, E.K., Hashemkhani Zolfani, S., 2017. Integrated QFD-MCDM framework for green supplier selection. J. Clean. Prod. 142, 3728–3740.

Yu, M.-C., Goh, M., Lin, H.-C., 2012. Fuzzy multi-objective vendor selection under lean procurement. Eur. J. Oper. Res. 219 (2), 305–311.