Omega 85 (2019) 1–15

Contents lists available at ScienceDirect

Omega

journal homepage: www.elsevier.com/locate/omega

Selection of a sustainable third-party reverse logistics provider based on the robustness analysis of an outranking graph kernel conducted with ELECTRE I and SMAA[☆]

Kannan Govindan[a,*], Miłosz Kadziński[b], Ronja Ehling[a], Grzegorz Miebs[b]

[a] Center for Sustainable Supply Chain Engineering, Department of Technology and Innovation, University of Southern Denmark, Campusvej 55, Odense, DK-5230, Denmark

[b] Institute of Computing Science, Faculty of Computing, Poznan University of Technology, Poznań, Piotrowo 2, 60-965, Poland

ARTICLE INFO

Article history:
Received 20 April 2017
Accepted 14 May 2018
Available online 19 June 2018

Keywords:
Third-party logistics provider
Sustainability
Multiple criteria decision analysis
Robustness analysis
Outranking method
Reinforced preference

ABSTRACT

Pressure from legislation and customers has motivated companies to consider reverse logistics (RL) in their operations. Since it is a complex procedure that requires an adequate system, the recent trend consists in outsourcing RL to third-party reverse logistics providers (3PRLPs). This paper provides the background of sustainable triple bottom line theory with focus on economic, environmental, and social aspects under 3PRL concerns. The relevant sustainability criteria are used in a case study conducted in cooperation with an Indian automotive remanufacturing company. To select the most preferred service provider, we use a hybrid method combining a variant of ELECTRE I accounting for the effect of reinforced preference, the revised Simos procedure, and Stochastic Multi-criteria Acceptability Analysis. The incorporated approach exploits all parameters of an outranking model compatible with the incomplete preference information of the Decision Maker. In particular, it derives the newly defined kernel acceptability and membership indices that can be interpreted as a support given to the selection of either a particular subset of alternatives or a single option. The proposed ELECTRE-based method enriches the spectrum of multiple criteria decision analysis approaches that can be used to effectively approach the problem of the 3PRLP selection. As indicated by the extensive review presented in the paper, this application field was so far dominated by Analytic Hierarchy Process and TOPSIS, whose weaknesses can be overcome by applying the outranking methods.

1. Introduction

Reverse logistics (RL) is defined as "the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal" [96]. Research attention to RL has increased in the past years for several reasons. With the recent focus on sustainability, organizations are mandated to take back end-of-life (EOL) products as part of their environmental service demands [18]. Moreover, the growing popularity of online shopping implies that more and more products need to be returned to their points of origin. Indeed, the return rate of all online purchased items lies between 8 and 12%. The costs of handling them in the reverse supply chain can exceed the costs that were necessary in the forward logistics processes [110].

As noted by Rogers and Tibben-Lembke [97], if the focus of forward logistics is the movement of a material from the point of origin toward the point of consumption, then the focus of reverse logistics should be the movement of a material from the point of consumption toward the point of origin. Thus, the requirements for forward logistics and reverse logistics are clearly different. In this perspective, Decision Makers (DMs) must rethink their strategies when RL issues are adopted, because the methods associated with forward logistics are no longer applicable. Concepts such as RL capacity and RL practices may sound similar to logistics capacity and logistics practices, but the reverse logistics terms have different constraints. For example, logistics capacity generally considers the logistics infrastructure and focuses on collection, delivery, information, and cash flow. Reverse logistics capacity includes more operations such as partial remanufacturing, recycling, and disposal. In addition, the customers' willingness and active engagement play a

☆ This manuscript was processed by AE C. Chen.

* Corresponding author.
E-mail addresses: kgov@iti.sdu.dk (K. Govindan), milosz.kadzinski@cs.put.poznan.pl (M. Kadziński), re@iti.sdu.dk (R. Ehling), grzegorz.miebs@protonmail.ch (G. Miebs).

https://doi.org/10.1016/j.omega.2018.05.007
0305-0483/

vital role in the difference between forward and reverse logistics capacity.

The company can handle its reverse logistics activities in three different ways [94]. Firstly, it can manage the service in-house. Secondly, it could own logistics subsidiaries through setting up or buying a logistics firm [15]. The last option is to outsource the function and buy the service [94]. Indeed, outsourcing the logistics operations is nowadays one of the foremost management strategies [40]. Nevertheless, many companies struggle with the implementation of RL, because they do not have any adequate systems in place to handle the reverse supply chain in-house [53]. Since the implementation of RL is an irreversible decision, manufacturers need to recognize its gravity. It is risky due to involving financial and operational aspects that have a long-term effect on the company [93]. Furthermore, the management of returns is complicated by uncertainties in timing, volume, and condition that may be difficult to predict [110].

If the company chooses to outsource its operations, it has to choose a reliable third-party reverse logistics provider (3PRLP). The provider needs to suit the type of reverse logistics network through an adequate information system, transportation, and material handling equipment, as well as warehousing facilities [42]. Moreover, evaluation of the 3PRLPs is by nature a multiple criteria problem. Formulating a set of relevant attributes for the context of outsourcing the logistics operations is not straightforward. Furthermore, dealing with their multiplicity and conflicting character requires the use of dedicated Multiple Criteria Decision Analysis (MCDA) methods. In this perspective, the contribution of this paper to the literature on the 3PRLP evaluation and selection with MCDA is four-fold.

Firstly, we provide the background of sustainable triple bottom line theory [29,66] with focus on the economic, environmental, and social aspects under 3PRLP concerns. Our in-depth literature review indicates that although all three sustainability dimensions should be considered in the evaluation of 3PRLPs, companies often place more emphasis on some of them (in particular, solely on the economic criteria). Drawing from the literature, we propose a classification that divides the criteria relevant for 3PRLP into the three sustainable concerns. The classification involves fourteen major evaluation categories (e.g., costs and RL capacity in the economic dimension, RL practices and green level within the environmental concerns, and micro- and macro-social impacts among the social aspects), and over seventy elementary viewpoints that can be relevant for a particular problem. Indeed, the importance of defining the appropriate criteria in the context of 3PRLP evaluation has been raised in many studies (see, e.g., [46]). Our classification can be interpreted in terms of critical success factors (CSFs) describing the key areas in business that can ensure competitive performance for a company [95] and can be useful in planning implementations such as outsourcing of the logistics operations. Above all, we detail the significance of sustainability in company's reverse logistics and, in general, supply chain.

Secondly, we provide a comprehensive summary of the journal papers on third-party reverse logistics. We note that their main focus is on prioritizing the importance of relevant criteria, designing reverse logistics networks, and selecting the most preferred provider. In fact, the majority of studies deal with a selection of a suitable RL provider [40,42,79]. In this context, we list the main application fields and note that the reported case studies were conducted in countries with the world's largest economies. Finally, we indicate that when dealing with multiple criteria evaluation of 3PRLPs, the most prevailing methods include different variants of Analytic Hierarchy Process (AHP) [104] and TOPSIS [51], or, in case an efficiency of different solutions had to be examined, Data Envelopment Analysis (DEA) [16]. Conversely, little research has focused on employing outranking methods in the context of sustainable 3PRLP selection although their characteristics have proven useful in other application fields [38].

In this perspective, the third contribution of the paper consists in proposing an ELECTRE-based approach [32] that can be used to support companies to evaluate the third-party logistics providers. When collecting inter-criteria preference information, the method admits incompleteness in the provided statements. On one hand, the preferences of the DM on the importance of particular criteria are collected using the revised Simos procedure [34] (note that it is also called the Simos–Roy–Figueira (SRF) procedure). Precisely, (s)he is expected to rank the criteria from the least to the most important while additionally differentiating the intensity of preference between different pairs of attributes. On the other hand, we tolerate an imprecise range of admissible values for the credibility threshold. As far as intra-criterion preference information is concerned, apart from the comparison thresholds traditionally considered in ELECTRE [102], we account for the effect of reinforced preference [103]. So far, it has not been used in the context of any real-world case study. The effect justifies an additional bonus for the alternative which is very strongly preferred over another alternative.

Since there exist multiple parameter values of an outranking model compatible with thus provided preferences, we tolerate all of them in the exploitation phase and use the results of robustness analysis for the recommendation of the most preferred option [100]. For this purpose, we couple ELECTRE I [98,99] that allows to indicate the most prevailing subset of alternatives with Stochastic Multi-criteria Acceptability Analysis [70,119]. The latter computes some acceptability indices by considering recommendation derived for different feasible sets of parameters.

In ELECTRE I, the most preferred subset of alternatives corresponds to a kernel of an outranking graph. Consequently, our robustness analysis is focused on the stability of a kernel obtained with different compatible instances of the preference model. In particular, we define the kernel acceptability and membership indices that can be interpreted as a support given to the selection of, respectively, a particular subset of alternatives or a single option. Nevertheless, we additionally address the robustness concerns by computing the respective results for pairwise relations and one against all comparisons. A comprehensive analysis of such results allows us to indicate the most preferred provider as well as some optional choices.

The fourth contribution of this paper consists in reporting the results of a case study that was conducted in cooperation with a company in an Indian automotive remanufacturing industry. In this way, we explore the status of 3PRL in the specific context of India, where it is still undeveloped. The study concerned evaluation of five service providers in terms of several economic, environmental, and social criteria. The justification for applying the proposed hybrid approach to support the case company in selecting the most preferred 3PRLP(s) derives from the favourable characteristics of the incorporated elementary approaches. These include:

- An operational simplicity and acceptance of the incomplete preference information on the relative importance of criteria (with the possibility of differentiating the intensity of preference for various pairs of criteria) by the revised Simos procedure [24,34,112];
- accounting for the imperfect knowledge of data and the arbitrariness when building the criteria by ELECTRE [32];
- deriving the recommendation from comparing the alternatives pairwise (without scoring the available options) and indicating the most preferred subset of alternatives by ELECTRE I [99] which is consistent with the type of a problem considered by the company;

- tolerating the incompleteness of preference information and verifying the stability of the choice recommendation by SMAA [119].

The paper is structured in the following way. Section 2 provides relevant literature resources on reverse logistics and third-party reverse logistics. The need for outsourcing logistics operations and the relevant criteria for the evaluation of 3PRLPs are discussed in Section 3. A new hybrid MCDA approach combining Stochastic Multi-criteria Acceptability Analysis with ELECTRE I is presented in Section 4. Section 5 presents a case study where the proposed method is applied to a real-world problem considered by an Indian auto parts remanufacturing company. The concluding section summarizes the managerial implications and draws some avenues for future research.

2. Review of literature on third-party reverse logistics

In this section, we present a literature review concerning third-party reverse logistics. We emphasize that scholarly attention for reverse logistics and 3PRLP has increased in the past years due to the demand of manufacturing companies.

Indeed, more and more firms consider the reverse supply chain as a management strategy that can lead to a competitive advantage [89]. Pokharel and Mutha [88] indicated that research on reverse logistics had been growing since the 1960s. In their review, Agrawal et al. [1] covered more than 240 papers on this topic published within the time frame 1986–2015, whereas Govindan et al. [44] reviewed over 150 works on RL that were published only between 2007 and 2013. The interest in reverse logistics is constantly increasing for legal, environmental, social, and economic reasons. In particular, Steven et al. [113] demonstrated its positive impact on the economic and ecological performance of a company. In the same spirit, Ramirez and Morales [91] analysed how RL could affect costs and organization performance of the companies. [122] dealt with the impact of reverse logistics on supply chain management performance in order to analyse its relations with the order and inventory variance amplification. A focus on the green operations in RL was presented by Kumar and Kumar [68].

Research on reverse logistics has been further developed in connection with the outsourcing of logistics operations to third-party reverse logistics providers. Selecting the appropriate reverse logistics provider is challenging since many criteria influence this decision. These criteria can have environmental, industrial, or operational characteristics [43]. Recent research has been done in the areas of supplier selection and outsourcing decisions, and different solution methodologies for the problem have been presented.

In Table 1, we summarize the journal papers on third party reverse logistics. Their scope varies from prioritizing criteria relevant for 3PRLP through applying various MCDA methods for supplier selection to designing reverse logistics networks. The reported application domains include electronics (e.g., mobile phones or computers) industry, plastic, paper, and carpet recycling, tire, battery, and medical device manufacturing, steel enterprise, and petrol retailing. The majority of studies on selecting the provider for outsourcing forward logistics operations were performed in USA, Brazil, China, Turkey, UK, India, and Iran. The prevailing techniques used to evaluate the service providers include different variants of AHP [104], TOPSIS [51], and Data Envelopment Analysis [16].

The review on 3PRLP proves that little research has included sustainability criteria. Since issues of corporate social responsibility (CSR) and sustainability were introduced to RL, a shift towards sustainable performance models has occurred [85]. Nevertheless, studies that accounted for all three pillars of sustainability (environmental, economic, and social) are rare. For example, Wang and Zhu [125] included the environmental area in their study when they combined the status of domestic third-party reverse logistics and the environmental requirements of a low-carbon economy. Razzaque and Sheng [94] accounted for the social aspect in their work and emphasized the importance of human factors. Social issues were also acknowledged by Boyson et al. [12], who pointed out the importance of human resource policy and labor conditions for their employees. However, according to Kafa et al. [62], there is the need for more research on 3PRLP that includes the triple bottom line of environmental, economic, and social goals. This paper contributes to closing this research gap by providing the background of sustainable triple bottom line theory under 3PRLP concerns. The usefulness of such an approach is demonstrated with a case study in the specific context of India, where the status of third-party logistics is still undeveloped.

3. Framework development

In this section, we discuss the reasons for outsourcing the logistics operations instead of maintaining them in-house. Since this paper emphasizes sustainability, we draw a strong connection with the third-party reverse logistics. We also discuss the critical success factors for the selection of 3PRLP. These had been used as criteria to evaluate the service providers within the case study reported in Section 5.

3.1. Outsourcing of logistics operations

Outsourcing has been defined as “an agreement in which one company contracts out a part of their existing internal activity to another company” [77, p. 68]. There is an ongoing trend in many industries to outsource certain activities, including supply chain management and logistics operations. The primary reasons for this involve globalization of business, rapid growth in global marketplaces [72], cost savings, enhancing revenue potential, and operational benefits.

Since reverse logistics performance generally takes up less than 5% of a company’s performance, it is natural for many companies to delegate this task to third-party reverse logistics providers [12]. According to Bradley [13], company’s logistics costs may be reduced by using a 3PRLP, since the experienced outsourced providers are often more efficient than the company itself. Moreover, production costs can be lowered by specialization effects and the proper utilization of core competencies. Companies can also take advantage of economies of scale by converting RL functions into an activity where profit is created [36]. Outsourcing can have further advantages, such as higher logistics performance, higher quality, optimized asset use, increased flexibility, and reduction in strategic and operational risk management [71]. In choosing the right provider, the DM’s selection can be strategic and can result in the achievement of new technologies, knowledge, and new markets [78].

Furthermore, the providers specialize in managing the reverse flow of the returned products as well as providing services such as remanufacturing, refurbishing, and recycling [96]. Due to the specialization, they can motivate companies to reach environmental sustainability goals, since they offer useful solutions for sustainable supply chains. Moreover, the activity of greening the supply chain may be connected with a better reputation for the company [123]. Consequently, RL providers are considered a key operational element for the development of a sustainable supply chain.

Nevertheless, implementing reverse logistics also carries some risks. These include loss of control over the logistics operations [126], difficulties in implementing environmentally practices due

Table 1
Summary of journal papers on third party reverse logistics published after 2000 (criteria: E = economic, V = environmental, S = social).

No.	Source	Type of study/ Application field / Country	Contribution	Tools	Issues addressed E	V	S
1	[90]	Case study / Electronics industry	Proposed an integrated model based on Fuzzy AHP for evaluation and prioritization of selection criteria and Fuzzy TOPSIS for the selection and development of reverse logistics partners	MCDM – Fuzzy AHP and Fuzzy TOPSIS	X	X	
2	[118]	Case study / Composite pipe manufacturer / USA	Used the Analytic Network Process (ANP) and proposed an analytical framework to systematically model the complex nature of interactions among the selection factors of 3PRLPs	MCDM – ANP	X	X	
3	[81]	Case Study	Proposed a multiple objective additive network DEA model to evaluate and select the most preferred 3PRLPs	Network data envelopment analysis and MONLP	X		
4	[46]	Review / Brazil	Identified the main criteria, the systematic methods that can be used in order to select the most appropriate 3PRLP, and proposed a framework based on a multiple criteria decision aid approach to select 3PRLP		X	X	
5	[109]	Case Study / Plastic recycling / India	Evaluated the most efficient Reverse Logistics Contractor (RLC) through a proposed model, a hybrid method using AHP and the Fuzzy TOPSIS	MCDM – AHP and Fuzzy TOPSIS	X	X	
6	[115]	Numerical example / Copier remanufacturing and paper recycling / Turkey	Presented two hybrid simulation-analytical modelling approaches for the RL network design of the 3PRLP	Stochastic simulation model, Generic method	X		
7	[52]	Case study / Mobile phone company / India	Developed decision support system to assist the top management of the company in selection and evaluation of 3PRLPs by a hybrid approach using AHP and TOPSIS methods	MCDM – TOPIS and AHP	X	X	
8	[7]	Numerical example	Proposed an innovative approach based on a free disposable hull (FDH) to select the most preferred 3PRLP	DEA – FDH	X		
9	[130]	Case study / Supply chain & logistics company / Iran	Investigated the feedback and relationships among attributes, and identified the most important attributes in the evaluation of 3PRLP using ANP	ANP, Intuitionistic fuzzy set (IFS) and Grey Relation Analysis (GRA)	X	X	
10	[75]	Case Study / ELV company / Iran	Defined suitable assumptions given the situation of ELV's management in Iran to model the problem as a 3PRL network	Integer linear programming	X		
11	[41]	Case Study / Tire industry / India	Illustrated the interactions between the attributes for the 3PRLP development using Interpretive Structural Modelling (ISM)	MCDM – ISM	X	X	
12	[128]	Numerical example / Steel enterprise / China	Analysed the closed-form analytic expressions for both united optimization strategies in a centralized closed-loop system and the Stackelberg strategies in a decentralized system	Stochastic modelling	X		
13	[74]		Proposed a model for the logistics business of a large third party service provider; incorporated both forward and reverse product flows for the company, including price, transportation mode, and outsourcing cost		X		
14	[92]	Case study / Computer company / India	Proposed a model to efficiently assist the DMs in determining the most appropriate third-party reverse logistics provider using a combination of AHP and TOPSIS methods	MCDM – AHP and TOPSIS	X	X	
15	[9]	Case studies / Medical device remanufacturing and carpet recycling	Presented a multiple criteria approach for the RL network design	AHP	X		
16	[106]	Numerical example	Proposed a model for dealing with selecting 3PRLPs in the presence of both dual-role factors and imprecise data	DEA	X	X	
17	[5]	Numerical example	Proposed a new chance-constrained data envelopment analysis (CCDEA) approach to support the DMs in determining the most preferred 3PRLPs in the presence of both dual-role factors and stochastic data	DEA	X		
18	[6]	Numerical example	Proposed a new model (output-oriented super slack-based measure (SBM) model in the presence of stochastic data along with non-linear program was derived and further converted to quadratic program) for 3PRLP selection	Output-oriented super SBM model	X		
19	[40]	Case study / Battery company / India	Proposed a structured model for the selection of a 3PRLP under fuzzy environment for the battery industry, which establishes the relative weights for attributes and sub-attributes	Fuzzy extent analysis	X	X	
20	[105]		Proposed a model for selecting 3PRLP in the presence of multiple dual-role factors	DEA	X		
21	[108]	Numerical example	Introduced a heuristic based approach for solving the Vehicle Routing Problem (VRP) of 3PRLs which can be described as the problem of designing optimal routes from one depot to a number of customers subject to constraints	Tabu search, Clarke/Wright algorithm	X		
22	[64]	Case study / Battery recycling industry / India	Developed a multi-criteria group decision making (MCGDM) model in a fuzzy environment to guide the selection process of the most preferred 3PRLP through analysis of the interactions between criteria	MCDM – ISM and TOPSIS	X		

(continued on next page)

Table 1 (*continued*)

No.	Source	Type of study/ Application field / Country	Contribution	Tools	Issues addressed E	V	S
23	[107]	Numerical example	Introduced a methodology (imprecise DEA) to select the most efficient 3PRLP in the conditions for both ordinal and cardinal data	IDEA	X		
24	[50]	Case study / China	Proposed a benchmarking decision making model to assist in the entry of 3PRLPs		X		
25	[63]	Case Study / Battery industry / India	Proposed a structured model for evaluating and selecting the most preferred 3PRLP under a fuzzy environment for the battery industry	MCDM – AHP and Fuzzy AHP	X	X	
26	[65]	Case Study / Tire manufacturing / India	Proposed a structured, MCDM model for evaluating and selecting the most preferred 3PRLP using Fuzzy TOPSIS	MCDM – Fuzzy TOPSIS	X	X	
27	[129]		Proposed a grey comprehension model to evaluate the 3PRLPs	Grey-AHP and Grey Relational Theory	X		
28	[28]	Numerical example	Supported the DMs in determining the most preferred 3PRLP using a two-phase model based on artificial neural networks and fuzzy logic in a holistic manner	Artificial neural networks, MCDM – Delphi and Fuzzy AHP	X		
29	[80]	Numerical example	Proposed a mixed-integer programming model and a genetic algorithm that can solve the reverse logistics problem involving the location and allocation of repair facilities for 3PLs	Genetic algorithm	X		
30	[54]	Numerical example	Selected the logistics service provider	ANP	X		
31	[55]	China	Analysed the interactions among major barriers that hinder or prevent the application of reverse logistics in the Chinese industries	AHP, TOPSIS, Grey Relative Analysis	X		
32	[79]	Numerical example	Evaluated 3PRLPs accounting for the factors such as end-of-life product organization within a decision framework	MCDM – ANP	X		
33	[67]	Review and field study / Third party transportation company / USA	Examined the issues and processes that an organization (reverse logistics provider) has to address to engage in the reverse logistics business		X	X	
34	[11]	Case study – cross case analysis / Petrol retailers / UK	Identified the factors which influence outsourcing decisions and the supply chain implications of outsourcing strategies		X		

to lack of capabilities and resources [35], and the need for maintaining a complex relationship between the company and the provider [124]. The latter needs to account for the trust between the involved parties as well as the exchange of information about materials, waste management, shared profits, and savings [4].

3.2. Critical success factors

The critical success factors (CSF) define key elements that are required to ensure the success of any business and allow company to achieve its goals [95]. If the areas identified as CSFs receive careful attention from the top management, they have the potential to create a competitive advantage for the company. Talib and Hamid [116] summarized the CSFs in various supply chain management fields such as the reverse supply chain, the outsourcing of the logistics operations, and the third-party logistics evaluation. However, they neglected sustainability aspects to a large extent. Instead, Kafa et al. [62] claimed that reverse logistics outsourcing should be environmentally, economically, and socially applied. This is consistent with the findings of Almeida [2] and Govindan et al. [43] who claimed that when selecting the RL provider, the outsourcing contract price is no longer the sole relevant criterion.

In Table 2, we propose a classification that divides the criteria relevant for 3PRLP into the three sustainable concerns. The environmental, economic, and social aspects include the criteria that fall under each category as well as the examples for these viewpoints seen as sub-criteria. The latter ones were derived from a literature review. The criteria listed in Table 2 lay the groundwork for the selection of the most preferred 3PRLP within the case study, but they can be also adopted for dealing with other problems in the same application area.

4. Multiple criteria decision analysis method for the assessment of the third-party reverse logistics providers

This section describes a multiple criteria decision analysis method that has been used to evaluate the third party logistics providers within the case study, to advance in solving the problem, and to select the most preferred alternative. The incorporated approach employs an outranking model to represent preferences of the DM, and investigates the impact of using different parameter values compatible with the DM's value system on the choice recommendation. In this regard, it combines the ELECTRE I method [99] used to select the most preferred subset of providers for a particular set of parameters of an outranking model, the revised Simos procedure [34] to derive the ranking of criteria, and Stochastic Multi-criteria Acceptability Analysis to conduct robustness analysis while avoiding the arbitrary selection of parameters [120].

The review presented in Section 2 proved that the most prevailing MCDA methods used in the context of 3PRLP evaluation were AHP [104], TOPSIS [51], and Data Envelopment Analysis [16]. The popularity of AHP is mainly due to its intuitiveness, the natural appeal of a semantic scale it employs for expressing relative importance, availability of the user-friendly software, and a hierarchical decomposition of the multiple criteria problems being efficient from both operational and computational viewpoints [10]. Furthermore, TOPSIS is appreciated by the practitioners for a sound logic that represents the rationale of human choice involving the comparisons of each alternative with both the ideal and anti-ideal options, as well as for a simple computation process that can be programmed even in a spreadsheet [111]. Finally, the main advantages of DEA are that it is a non-parametric approach not requiring any functional forms, it can simultaneously handle heterogeneous inputs and outputs, and it provides means for identifying the sources of inefficiency that can be analysed and quantified [20].

Table 2
Sustainability criteria for the evaluation of third-party logistics providers.

Aspect	Criteria	Sub-criteria	References
Economic	Costs	RL costs, cost of relationship, cost of service, cost reduction	[3,62,73,79]
	Quality	Quality of product / service / people, product performance, quality improvement	[37,62]
	RL Capacity	Financial capacity, specialized infrastructures, skilled professionals, capability under uncertainty, RSC performance	[48,62,83,114]
	Technology	Technology capacity, warehouse management, transportation management, inventory management, information technology, demand forecasting, investment in IT	[3,12,37,48,83]
	Relationship	Effective communication, mutual commitment, flexibility, fairness, trust, channel relationship, service quality	[48,117]
	Financial performance	Assets, reputation, primary customer loyalty, understanding business needs, market share, profitability	[3,12,73,82,117]
	Management of risk	Setting standard and monitoring, external and internal communication, supply chain integration, government policy, complaint management, shipping and tracking, order management	[17,19,48,56,83,94]
Environmental	RL practices	Collection, sorting, treatment, redistribution, take back policy, packing, storage, delivery	[17,62,94]
	Organizational role	Reclaim, recycle, remanufacturing, reuse, disposal, treatment	[25,62]
	Green level	Environmental management, pollution, resource consumption	[62,86]
	Low-carbon	Oil consumption, cleaning materials and clean energy use, carbon emissions, average volume of air emission pollutants	[49,86]
	Environmental management system	ISO 14000, environmental policies, environmental objectives, checking of environmental activities	[8,66,69]
Social	Micro-social impact	Employee satisfaction, customer satisfaction, stakeholder satisfaction, overall working relations	[12,62]
	Macro-social impact	Health and safety, local community, human factors	[62,94]

However, each of these approaches has also some major weaknesses. In particular, the completion of the model used by AHP is time consuming because the number of required pair-wise comparisons may become troublesome. Moreover, it applies an arbitrary transformation of the linguistic terms to real numbers [14]. Furthermore, TOPSIS requires an arbitrary normalization of the original evaluations on different criteria scales into a common scale, which affects the ranking of alternatives [131]. Besides, score- and distance-based MCDA methods admit compensation between different criteria. When it comes to Data Envelopment Analysis, it is often criticized for its poor discriminative power (for a discussion on the weaknesses of DEA, see [58]).

ELECTRE methods may be used to overcome the aforementioned problems [32]. In fact, they tolerate qualitative nature of some criteria and heterogeneous criteria scales. Also, they apply non-compensatory aggregation of multiple criteria, additionally offering the possibility to model the effects of strong advantage (i.e., the effect of reinforced preference [103]) or critical weakness (i.e., the veto effect) in the comparison of a pair of alternatives. Moreover, although ELECTRE admits incomparability, it offers a wide spectrum of tools to discriminate between different alternatives. Finally, the proposed method explicitly deals with the incompleteness of the DM's preference information by considering all compatible preference models, which enhances her/his trust in the provided recommendation. Let us use the following notation:

- $A = \{a_1, a_2, \ldots, a_n\}$ is a set of alternatives (third-party logistics suppliers);
- $G = \{g_1, g_2, \ldots, g_m\}$ is a family of evaluation criteria that represent relevant points of view on the quality of assessed alternatives; $J = \{1, 2, \ldots, m\}$;
- $g_j(a)$ is the performance of alternative $a \in A$ with respect to criterion g_j, $j = 1, \ldots, m$ (when presenting the method, without loss of generality, we assume that all criteria are of gain type (i.e., the greater the performance, the better)).

4.1. Preference elicitation

In this section, we discuss the meaning of parameters related to the formulation of an outranking preference model that need to be elicited from the DM. Their use allows to first make the alternatives more comparable and then to identify the most preferred subset of options.

Step P1: Elicit the ranking of criteria g_j, $j = 1, \ldots, m$ using the SRF procedure [34], and determine the constraints on the admissible criteria weights w_j. The SRF procedure assumes the DM would rank the cards with criteria names from the least important to the most important, while admitting that some criteria are deemed indifferent. Then, the DM is asked to quantify the intensity of preferences between successive groups of criteria L_s and L_{s+1} through e_s blank cards inserted between these groups. As a result, each criterion g_j is assigned some importance rank l_j so that the greater the rank, the better. Finally, the DM needs to specify ratio Z between the importances of the most and the least significant criteria denoted by L_v and L_1, respectively [24].

Step P2: Specify the indifference q_j and preference p_j thresholds for each criterion g_j, $j = 1, \ldots, m$. These technical parameters reflect the discriminating character of g_j in face of imperfect knowledge [27]. They indicate, respectively, the maximal performance difference that is negligible on g_j and the minimal performance difference that induces a strict preference of one alternative over another on g_j [102]. Setting $p_j > q_j \geq 0$ allows considering a gradual transition from full concordance (in case $g_j(a) - g_j(b) \geq -q_j$) to no concordance (in case $g_j(a) - g_j(b) \leq -p_j$).

Step P3: Specify the reinforced preference threshold rp_j and the reinforcement factor ω_j for a subset of criteria on which a very strong preference of one alternative over another ($g_j(a) - g_j(b) \geq rp_j > p_j$) should justify an additional bonus ($\omega_j > 1$) when compared with the case where the preference is not that strong [103].

Step P4: Specify the veto threshold v_j for a subset of criteria g_j, $j = 1, \ldots, m$, that should be attributed a sufficient power to impose a strong opposition to outranking of a over b. This threshold represents the minimal performance difference $g_j(b) - g_j(a)$ that would justify not considering a at least as good as b even if it is more advantageous on all remaining criteria.

Step P5: Elicit the minimal λ_* and maximal λ^* value of the credibility threshold λ, i.e., the admissible range of values for the credibility of an outranking relation that would justify the truth of a crisp outranking relation.

4.2. Construction and exploitation of an outranking relation for selecting the most preferred subset of alternatives

In this section, we present a variant of ELECTRE I that has been used in the study to select the most preferred reverse logistics service provider. The method constructs an outranking relation S and represents it with an outranking graph G_S. The latter is exploited to identify the graph kernel that corresponds to the most advantageous subset of options. When recalling the main steps of the method, we assume that a set of precise parameters values ($w_j, q_j, p_j, rp_j, \omega_j, \nu_j$ for $j = 1, \ldots, m$, and λ) related to the formulation of an outranking model is given.

Step O1: For each criterion g_j, $j = 1, \ldots, m$, define the marginal concordance function $c_j(a, b)$ indicating for each pair of alternatives a and b a degree to which a outranks b on g_j. We use $c_j(a, b)$ defined as follows:

$$c_j(a,b) = \begin{cases} \omega_j, & \text{if } g_j(a) - g_j(b) \geq rp_j, \\ 1, & \text{if } rp_j > g_j(a) - g_j(b) \geq -q_j, \\ 0, & \text{if } g_j(a) - g_j(b) < -p_j, \\ \dfrac{g_j(a) - g_j(b) + p_j}{p_j - q_j}, & \text{otherwise.} \end{cases}$$

Thus, if a is very strongly preferred to b on g_j, then $c_j(a,b) = \omega_j > 1$; if a is at least as good as b on g_j, but its superiority is not that strong, then $c_j(a,b) = 1$; if b is weakly preferred to a, then $c_j(a, b) \in (0, 1)$, whereas in case b is strictly preferred to a, there is no concordance with aSb.

Step O2: Compute the comprehensive concordance index $C(a, b)$ indicating the strength of the coalition of criteria supporting the hypothesis about a being at least as good as b:

$$C(a,b) = \frac{\sum_{j=1}^{m} w_j \cdot c_j(a,b)}{\sum_{j \in F^{RP}} w_j \cdot \omega_j + \sum_{j \in J \setminus F^{RP}} w_j} \in [0,1],$$

where $F^{RP}(a,b) = \{j \in J : g_j(a) - g_j(b) \geq rp_j\}$ is a subset of criteria for which a reinforced preference of a over b occurs [103]. In this way, the contribution of a subset of criteria $F^{RP}(a, b)$ in the support of aSb is greater than their contribution in case the effect of reinforced preference was not considered. Clearly, the greater $C(a, b)$, the greater the concordance with the hypothesis that a outranks b.

Step O3: For each criterion g_j for $j = 1, \ldots, m$, define the marginal discordance function $d_j(a, b)$ indicating for each pair of alternatives a and b a degree to which g_j opposes to outranking aSb. We use $d_j(a, b)$ defined as follows:

$$d_j(a,b) = \begin{cases} 1, & \text{if } g_j(b) - g_j(a) \geq \nu_j, \\ 0, & \text{if } g_j(b) - g_j(a) \leq p_j, \\ \dfrac{g_j(b) - g_j(a) - p_j}{\nu_j - p_j}, & \text{otherwise.} \end{cases}$$

Thus, if a is critically worse than b on g_j, then $d_j(a,b) = 1$; if a is not worse than b by more than p_j, there is no discordance, whereas in case b is strictly preferred to a on g_j, but the performance difference is not that critical, then $d_j(a, b) \in (0, 1)$. Also, when ν_j was not specified for g_j, $d_j(a,b) = 0$ for all pairs of alternatives.

Step O4: Combine the comprehensive concordance index and the marginal discordance indices into a credibility $\sigma(a, b)$ of an outranking relation aSb in the following way [84]:

$$\sigma(a,b) = C(a,b) \cdot [1 - \max_{j \in J} d_j(a,b)].$$

Thus, in case there is no discordance on any criterion, then $\sigma(a,b) = C(a,b)$, whereas in case $d_j(a, b) > 0$ for some $j = 1, \ldots, m$, then the credibility is decreased with respect to $C(a, b)$. In particular, if some criterion strongly opposes to aSb ($d_j(a,b) = 1$), then $\sigma(a,b) = 0$.

Step O5: For each pair of alternatives a and b, compare $\sigma(a, b)$ with the credibility threshold λ to verify the truth of a crisp outranking relation aSb in the following way:

$$\sigma(a,b) \geq \lambda \Rightarrow aSb.$$

If $\sigma(a, b) < \lambda$, a does not outrank b (aS^Cb). Knowing if aSb and bSa hold, one can verify the truth of preference $\succ$, indifference $\sim$, and incomparability R relations in the following way:

$$aSb \wedge bS^Ca \Rightarrow a \succ b,$$
$$aSb \wedge bSa \Rightarrow a \sim b,$$
$$aS^Cb \wedge bS^Ca \Rightarrow aRb.$$

Note that while constructing an outranking relation S, we have replaced the original concordance and discordance tests considered in ELECTRE I by their more recent implementations. This allowed us to better represent the preferences of the DM involved in the case study. Firstly, when conducting the concordance test, we considered the effect of reinforced preference, because at the stage of problem structuring we identified some criteria on which a very strong preference of one alternative over another should justify some bonus with respect to the case where the preference is not that strong. Secondly, we employed a fuzzified marginal discordance so that to account for the criteria weakly opposing to an outranking relation ($0 < d_j(a, b) < 1$). The binary marginal discordance with $d_j(a, b)$ defined solely with respect to the veto threshold ν_j was found too restrictive for the considered study. It would simply occur too rarely to imply that the arguments against the outranking have an actual impact on the obtained results. Such an impact was found appealing by the involved experts. Thirdly, when computing the comprehensive discordance, we accounted for the greatest observed marginal discordance rather than all marginal discordances. Let us note that our study involved 14 criteria, but only 5 of them were attributed a power to veto against the outranking. In this perspective, a maximal marginal discordance was found as an adequate measure quantifying a power of such a limited subset of criteria potentially opposing to an outranking. Note that under such a setting, in case there were multiple criteria weakly opposing to an outranking, their impact on the outranking credibility would be reduced as only the strongest opposition against the outranking would be taken into account. Nonetheless, when there was at least one criterion strongly opposing to an outranking, the credibility would be nullified. Fourthly, the implemented outranking credibility clearly distinguishes the ways concordance and discordance are implemented as the criteria that negatively intervene in the credibility are not restricted to those for which the discordance is greater than the comprehensive concordance as, e.g., in the ELECTRE TRI method [32].

Step O6: Represent the outranking relation S with an outranking graph G_S whose nodes correspond to the alternatives and arcs reflect the truth of S. Select the most preferred subset of alternatives in A by identifying the kernel K of graph G_S [98]. K is defined as a subset of alternatives (nodes) which are incomparable in terms of S, and the alternatives not contained in K are outranked by at least one alternative belonging to K [101,127]. If G_S is acyclic, there exists a unique kernel. Otherwise, the cycle(s) need to be reduced before K is identified. For this purpose, we aggregate all elementary nodes in a cycle into a singleton (an artificial node) inheriting all in- and out-arcs from its component nodes (for an example, see Fig. 1(a)). Consequently, all alternatives which form a cycle are considered indifferent.

Note that the interpretation of an outranking graph kernel as the most preferred subset of alternatives derives from its definition. On one hand, a condition of an internal stability implies that the alternatives contained in the kernel do not outrank each other. This means that they are incomparable in terms of S, and hence there are no sufficiently strong reasons to judge one alternative from the kernel as more advantageous than another. On the other

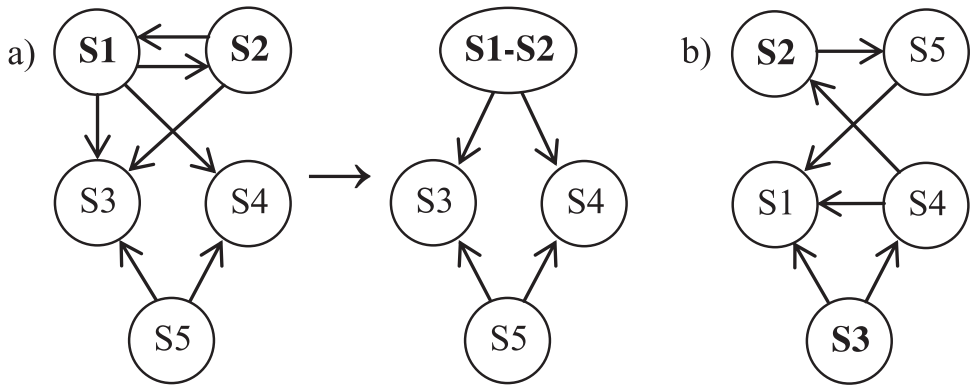

Fig. 1. Example outranking graphs: a) elimination of a cycle involving $S1$ and $S2$, b) identification of the kernel {$S2$, $S3$}.

hand, a condition of an external stability implies that the alternatives not contained in the kernel are outranked by at least one alternative from the kernel. In this perspective, the alternatives contained in the kernel jointly offer sufficiently strong arguments to neglect the remaining alternatives. However, as noted by Figueira et al. [33], in practical decision aiding, the computation of an outranking graph kernel can be treated as a pre-processing step. Then, the kernel is not treated as the most preferred subset of alternatives, but rather as a limited subset of options, from which the best compromise solution could be subsequently selected. In our study, we refer to both above interpretations. That is, when discussing the results obtained for a particular set of parameters, we treat the kernel as the most preferred subset of alternatives. However, since we consider multiple sets of parameters compatible with the DM's preferences, the analysis of all respective graph kernels is used to identify the most preferred alternative.

In what follows, we present the steps of an algorithm for identifying a kernel in an acyclic graph:

I. Construct a table with three columns (denoted as status, key and value) and n rows, where n is the number of nodes (alternatives). For each row, the status is initially empty, the key corresponds to the identifier of some node and the respective value is composed of all predecessors of this node.
II. Repeat until the status of each row is marked with either Y or N:
   a) Mark with Y all rows with the empty values (i.e., nodes with no predecessors that would be in the kernel; note that each value, which contains solely the crossed out identifiers, is also treated as empty).
   b) Mark with N all rows whose values contain at least one key of a row marked with Y (i.e., nodes which have some predecessor in the kernel).
   c) Cross out the keys of rows marked with N from all values of the rows which have not been yet marked with Y or N.
III. The graph kernel contains all keys of rows marked with Y.

In Table 3, we report the elementary steps of the above algorithm applied to the graph illustrated in Fig. 1(b). The kernel is composed of nodes $S2$ and $S3$.

4.3. Robustness analysis with stochastic multi-criteria acceptability analysis applied to ELECTRE I

In this section, we discuss the results that can be derived from the robustness analysis incorporating all parameter values related to the formulation of an outranking model that are compatible with the preference information provided by the DM. In this regard, let us remind that the plurality of different sets of weights compatible with the preference of the DM expressed within the SRF procedure can be handled in different ways. In particular, [112] proposed different robust rules for selection of the precise weights consistent with the DMs' rankings of criteria. Moreover, [39] computed the variety of results that can be obtained for the whole set of compatible weight vectors by means of Linear Programming techniques. Finally, [22] exploited this set using Stochastic Multi-criteria Acceptability Analysis [70,120], while additionally extending the SRF procedure to handling a hierarchical structure of criteria as well as an imprecision in the number of blank cards inserted between successive subsets of criteria and in the ratio between the most and the least important criteria. We follow the last approach by incorporating the Monte Carlo simulation [121] to estimate the values of acceptability indices measuring the variety of different preferences that confirm a particular choice recommendation.

Step R1: Define the space $(w, \lambda)^{DM}$ of weights and credibility thresholds compatible with preferences of the DM by considering the following constraint set $E(w, \lambda)$:

$$\left.\begin{array}{l}
[C1]\ w_i > w_j,\ \text{for all } g_i \in L_t, g_j \in L_s \text{ and } t > s,\\
[C2]\ w_i = w_j,\ \text{for all } g_i, g_j \in L_s,\\
[C3]\ w_{j+1} - w_j > w_{p+1} - w_p,\ \text{if } e_j > e_p,\\
[C4]\ w_i = Z \cdot w_j,\ \text{for all } g_i \in L_v, g_j \in L_1,\\
[C5]\ \sum_{j=1}^{m} w_j = 1,\\
[C6]\ w_j > 0,\ j = 1, \ldots, m,\\
[C7]\ \lambda_* \leq \lambda \leq \lambda^*,
\end{array}\right\} E(w, \lambda)$$

where constraints [$C1$], [$C2$], [$C3$] and [$C4$] reproduce the ranking of criteria provided by the DM while accounting for the preference intensities (see [$C3$]) as well as the ratio between the weights of the most and the least significant criteria (see [$C4$]), [$C5$] normalizes the sum of weights, [$C6$] guarantees that all weights are positive, and [$C7$] sets the bounds for the credibility threshold.

Note that constraint [$C3$] interprets the number of blank cards inserted between successive subsets of criteria in terms of preference intensities. For example, a difference between the weights of all pairs of criteria separated by two blank cards should be greater than a difference between the weights of all pairs of criteria separated by a single blank card. This interpretation is consistent with both an intuitive understanding of the SRF procedure by the experts involved in our case study and a discussion provided by [112]. However, it implies that values assigned to blank cards inserted between various groups of criteria may differ. Note that even though [22] postulated that these values should be equal, they also admitted that the differences between weights of criteria separated by the same number of blank cards could be different.

Let us remark that assigning exactly the same value to each blank card by means of equalities rather than inequalities would imply that – in case there is no imprecision in the number of blank

Table 3
Elementary steps of the algorithm for identifying a kernel in an example acyclic graph.

Step I			Step IIa			Step IIb		
Status	Key	Value	Status	Key	Value	Status	Key	Value
	S1	S3, S4, S5		S1	S3, S4, S5	N	S1	**S3**, S4, S5
	S2	S4		S2	S4		S2	S4
	S3	–	Y	S3	–	Y	S3	–
	S4	S3		S4	S3	N	S4	**S3**
	S5	S2		S5	S2		S5	S2
Step IIc			Step IIa			Step IIb		
Status	Key	Value	Status	Key	Value	Status	Key	Value
N	S1	S3, S4, S5	N	S1	S3, S4, S5	N	S1	**S3**, S4, S5
	S2	~~S4~~	Y	S2	~~S4~~	Y	S2	~~S4~~
Y	S3	–	Y	S3	–	Y	S3	–
N	S4	S3	N	S4	S3	N	S4	S3
	S5	S2		S5	S2	N	S5	**S2**

cards between successive subsets of criteria and/or in the ratio between the most and the least important criteria – there exists just a single compatible weight vector. This, in turn, would prevent the need for conducting robustness analysis.

Step R2: For each $(w, \lambda) \in (w, \lambda)^{DM}$, construct an outranking relation $S^{(w,\lambda)}$ and exploit it to derive a respective graph kernel $K^{(w,\lambda)}$.

Step R3: Compute a set of stochastic acceptability indices by exploiting the consequences of applying all compatible sets of parameters of an outranking model $(w, \lambda)^{DM}$ on the set of alternatives A:

- *Acceptability indices derived from the pairwise comparisons*
  Let us define a *relation acceptability index RelAI*(a, b, *Rel*) for $Rel \in \{S, S^C, \succ, \prec, \sim, R\}$ as the share of compatible weights and credibility threshold $(w, \lambda) \in (w, \lambda)^{DM}$ for which *Rel* holds for the comparison of a and b. Formally, the index is computed as an integral over the space $(w, \lambda)^{DM}$ of uniformly distributed parameters of an outranking model:

  $$RelAI(a, b, Rel) = \int_{(w,\lambda)\in(w,\lambda)^{DM}} m((w, \lambda), a, b, Rel)\, d(w, \lambda),$$

  where $m((w, \lambda), a, b, Rel)$ is the confirmation function of a specific relation $Rel \in \{S, S^C, \succ, \prec, \sim, R\}$:

  $$m((w, \lambda), a, b, Rel) = \begin{cases} 1, & \text{if } aRel^{(w,\lambda)}b, \\ 0, & \text{otherwise.} \end{cases}$$

  The definition of *RelAI*(a, b, *Rel*) can be adapted to the case of S, S^C, $\succ$, $\prec$, $\sim$, or R. Let us call the respective indices as *outranking* (*OAI*), *non-outranking* (*NOAI*), *preference* (*PAI*), *inverse preference* (*IPAI*), *indifference* (*IAI*), and *incomparability* (*IRAI*) *acceptability indices*. For example:

  $$OAI(a, b) = \int_{(w,\lambda)\in(w,\lambda)^{DM}} m((w, \lambda), a, b, S)\, d(w, \lambda),$$

  where $m((w, \lambda), a, b, S) = 1,$ if $aS^{(w,\lambda)}b$, and 0, otherwise. Further:

  $$IRAI(a, b) = \int_{(w,\lambda)\in(w,\lambda)^{DM}} m((w, \lambda), a, b, R)\, d(w, \lambda),$$

  where $m((w, \lambda), a, b, R) = 1,$ if $aS^{C,(w,\lambda)}b$ and $bS^{C,(w,\lambda)}a$, and 0, otherwise. Note that for each $(a, b) \in A \times A$: $OAI(a, b) + NOAI(a, b) = 1$ and $PAI(a, b) + IPAI(a, b) + IAI(a, b) + IRAI(a, b) = 1$.
- *Acceptability indices derived from the comparison of one alternative against all remaining ones:*
  - *Comprehensive outranking index COI*(a) is the share of $(w, \lambda)^{DM}$ for which a outranks all remaining alternatives $b \in A\backslash\{a\}$ jointly, i.e.:

    $$COI(a, A, S) = \int_{(w,\lambda)\in(w,\lambda)^{DM}} m((w, \lambda), a, A, S)\, d(w, \lambda),$$

    where $m((w, \lambda), a, A, S) = 1,$ if $aS^{(w,\lambda)}b$ for all $b \in A \setminus \{a\}$, and 0, otherwise.
  - *Comprehensive non-outranked index CNOI*(a) is the share of $(w, \lambda)^{DM}$ for which a is not outranked by any other alternative $b \in A\backslash\{a\}$, i.e.:

    $$CNOI(a, A, S^C) = \int_{(w,\lambda)\in(w,\lambda)^{DM}} m((w, \lambda), a, A, S^C)\, d(w, \lambda),$$

    where $m((w, \lambda), a, A, S^C) = 1$ if $bS^{C(w,\lambda)}a$ for all $b \in A \setminus \{a\}$, and 0, otherwise.

  Thus defined *COI*(a, A, S) and *CNOI*(a, A, S^C) indicate the joint superiority of a over all remaining alternatives while taking into account, respectively, the positive (S) or negative (S^C) arguments.
- *Acceptability indices related to the stability of a graph kernel*
  The *kernel acceptability index KAI*(A') for each subset of alternatives $A' \subseteq A$ is the share of $(w, \lambda)^{DM}$ that indicate A' as the graph kernel $K^{(w,\lambda)}$, i.e.:

  $$KAI(A') = \int_{(w,\lambda)\in(w,\lambda)^{DM}} m((w, \lambda), K, A')\, d(w, \lambda),$$

  where $m((w, \lambda), K, A')$ is the kernel membership function:

  $$m((w, \lambda), K, A') = \begin{cases} 1, & \text{if } K^{(w,\lambda)} = A', \\ 0, & \text{otherwise.} \end{cases}$$

  Further, we compute the share of $(w, \lambda) \in (w, \lambda)^{DM}$ for which $a \in A$ is in the graph kernel $K^{w,\lambda}$, i.e., the share of parameters of an outranking model confirming that a is contained in the most preferred subset of options. Let us define such a *kernel membership index KMI*(a) as:

  $$KMI(a) = \sum_{a\in A'\subseteq A} KAI(A').$$

  Overall, *KAI*(A') and *KMI*(a) can be interpreted as a support given to the selection of, respectively, A' or a.

5. Case study

Remanufacturing auto parts is one of the most successful businesses in the Indian scenario. We made a web-based review along with the references of Indian industrial (official) data books to identify the focal firms that practice auto parts remanufacturing. Our research revealed that many auto parts remanufacturing units

Table 4
The evaluation of 5 service providers in terms of 14 criteria provided by the DM (↑ and ↓ denote, respectively, the maximizing and minimizing criteria).

	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9	g_{10}	g_{11}	g_{12}	g_{13}	g_{14}
	↓	↑	↑	↑	↑	↑	↑	↑	↑	↑	↓	↑	↑	↑
S1	3	8	7	6	6	7	8	7	6	6	4	8	6	8
S2	5	8	6	7	7	6	6	8	7	6	4	8	9	8
S3	2	8	8	8	9	8	7	6	5	5	4	7	7	3
S4	4	7	8	7	6	7	8	6	7	6	3	8	6	6
S5	4	8	8	8	8	7	8	9	8	8	2	9	8	6

Table 5
The order of cards with criteria names and blank cards provided by the DM within the SRF procedure (the higher $l(j)$, the more important criterion g_j).

$l(j)$	1	2		3	4	5		6	7	8		9	10
g_j	g_1, g_4	g_6		g_5	g_{13}, g_{14}	g_3, g_8		g_9	g_{10}, g_{11}	g_{12}		g_2	g_7
e_s			1				1				1		

were active in India, but only eleven companies followed the formal remanufacturing process and, in addition, had foreign customers. The latter increased the chances of third-party reverse logistics. The research proposal was sent via mail to the selected companies along with the preliminary conceptualization of the study. Five companies replied to the inquiry. In this section, we report the results of a case study that was conducted in cooperation with one of these companies.

The case company was run in 1973 in Spain as a manufacturer of replacement auto parts by offering a wide range of products, including steering gears, pumps, air conditioning compressors, and electronic control units. Due to the influence of globalization development, the firm extended its branches in various countries including France, Germany, and India. Within the study, we dealt with a subsidiary started in Chennai (India) in 2013. This plant was limited to the production of steering gears and pumps. Nevertheless, they were aware of the complexity of third-party reverse logistics processes in their parent company. Due to the versatile cultural developments in the Indian context, they were less aware about the selection of third-party logistics service providers. However, we confirmed the company's interest in concentrating on their logistics systems, mainly because their customers were reputed ones in the automotive field, including companies such as Tata, Suzuki, Hyundai, Honda, Toyota, and Ford.

The study focused on three different dimensions of sustainability in the third-party reverse logistics service provider selection, which would be likely to improve the effectiveness of the company's logistics processes. Five potential third-party reverse logistics providers $SUP = \{S1, S2, S3, S4, S5\}$ were identified. These were rated in terms of the following criteria: g_1 (costs, min), g_2 (quality, max), g_3 (RL capacity, max), g_4 (technology, max), g_5 (relationship, max), g_6 (financial performance, max), g_7 (management of risk, max), g_8 (RL practices, max), g_9 (organizational role, max), g_{10} (green level, max), g_{11} (low-carbon, min), g_{12} (environmental management, max), g_{13} (micro-social, max), and g_{14} (macro-social, max). Note that "max" and "min" denote, respectively, gain- and cost-type criteria. Thus, the family of constructed criteria involved economic, environmental, and social aspects. The performances of 5 service providers in terms of 14 criteria are provided in Table 4.

5.1. Preference information

The results of the elicitation process that was conducted with the revised Simos procedure for the case study are presented in Table 5. The DM divided 14 criteria into 10 groups, thus, judging some pairs of criteria as equally important. For example, g_1 and g_4 were grouped together as the least significant criteria. The DM differentiated the intensity of preference between different groups by introducing 0 or 1 blank card between them. Although the most important criteria g_2 (quality) and g_7 (management of risk) represented economic viewpoints, the environmental aspects were of great importance for the case company as confirmed by the high ranks of g_8, g_9, g_{10}, g_{11}, and g_{12}. The ratio between the weights of the most and the least significant was set to $Z = 7$.

The indifference, preference, reinforced preference, and veto thresholds, and reinforcement factors elicited from the DM are provided in Table 6. When it comes to q_j and p_j, these differ from one criterion to another. They have been elicited so that to relate the difference in performance levels on a given criterion with the desired outranking degree. For example, with $q_j = 0$ and $p_j = 0$, the concordance index $c_j(a, b)$ fully agrees that provider a outranks provider b when the performance of a is at least as good as the performance of b and does not agree with the hypothesis about outranking if the performance of a is worse than that of b. On the other hand, in case $q_j = 0.5$ and $p_j = 1.5$, $c_j(a, b)$ partially agrees with the concordance if the performance of a is one level below the performance of b.

When it comes to the effect of reinforced preference, it was admitted only for the five most important criteria (g_7, g_8, g_{10}, g_{11}, g_{12}) for which the variation of performances between the providers was great enough so that a considerable performance difference could imply a very strong preference of one provider over another. The elicited reinforcement factors ranged between 1.2 and 1.5. In this way, a very large performance difference on these criteria was judged meaningful for considering them as more important in the coalition supporting the outranking relation by increasing their weights.

Analogously, the veto thresholds were not specified for the criteria that were judged the least important by the DM nor for the attributes with low differentiation of performances. Consequently, the discordance effect was considered in the context of five criteria (g_9, g_{10}, g_{11}, g_{12}, g_{14}) and elicited by asking the DM to provide the number of levels that would be sufficient for assessing one supplier critically worse than another supplier irrespective of their performances on all remaining criteria. For all discordance criteria, v_j was significantly greater than p_j. Finally, the credibility threshold was allowed to vary in the range [0.5, 0.9]. In this way, the weighted majority of criteria was always required to validate the truth of a crisp outranking relation ($\lambda_* \geq 0.5$), but the support of all criteria was required in none of the considered scenarios ($\lambda^* < 1$).

5.2. Results

The robustness analysis involved a set of criteria weights and credibility thresholds compatible with the preferences of the DM. The stochastic indices were derived from 10,000 uniformly dis-

Table 6
Indifference, preference, reinforced preference, and veto thresholds along with the reinforcement factors elicited from the DM for 14 criteria ("-" means that the respective parameter was not specified).

	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9	g_{10}	g_{11}	g_{12}	g_{13}	g_{14}
q_j	0	0	0.5	1	0.5	0	0.5	1	0.5	1	0.5	1	0	0
p_j	1	1	1.5	2	2.5	1	1.5	2	2	2	1.5	1	1	1
rp_j	–	–	–	–	–	–	2	3	–	3	3	2	–	–
ω	–	–	–	–	–	–	1.5	1.2	–	1.3	1.3	1.5	–	–
v_j	–	–	–	–	–	–	–	–	4	6	3.5	5	–	6

Table 7
Outranking, preference, indifference, and incomparability acceptability indices for all pairs of service providers.

	Outranking acceptability index					*Preference acceptability index*				
a	*S*1	*S*2	*S*3	*S*4	*S*5	*S*1	*S*2	*S*3	*S*4	*S*5
*S*1	1.000	1.000	0.787	0.974	0.000	0.000	0.303	0.787	0.653	0.000
*S*2	0.697	1.000	0.726	0.494	0.000	0.000	0.000	0.726	0.317	0.000
*S*3	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
*S*4	0.321	0.177	0.587	1.000	0.124	0.000	0.000	0.587	0.000	0.000
*S*5	0.592	0.546	1.000	1.000	1.000	0.592	0.546	1.000	0.876	0.000
Indifference acceptability index						*Incomparability acceptability index*				
a	*S*1	*S*2	*S*3	*S*4	*S*5	*S*1	*S*2	*S*3	*S*4	*S*5
*S*1	1.000	0.697	0.000	0.321	0.000	0.000	0.000	0.213	0.026	0.408
*S*2	0.697	1.000	0.000	0.177	0.000	0.000	0.000	0.274	0.506	0.454
*S*3	0.000	0.000	1.000	0.000	0.000	0.213	0.274	0.000	0.413	0.000
*S*4	0.321	0.177	0.000	1.000	0.124	0.026	0.506	0.413	0.000	0.000
*S*5	0.000	0.000	0.000	0.124	1.000	0.408	0.454	0.000	0.000	0.000

Table 8
Kernel acceptability indices for different subsets of third-party reverse logistics providers.

A'	{*S*5}	{*S*1, *S*5}	{*S*1, *S*2, *S*5}	{*S*1, *S*2, *S*4, *S*5}	All other subsets
KAI	0.468	0.303	0.124	0.105	0.0

Table 9
Kernel membership, comprehensive outranking and non-outranked indices for all service providers.

a	*S*1	*S*2	*S*3	*S*4	*S*5
KMI	0.532	0.229	0.0	0.124	1.0
COI	0.0	0.0	0.0	0.124	0.546
CNOI	0.303	0.0	0.0	0.0	0.876

tributed values of the admissible parameters of an outranking model. In Table 7, we report the respective relation acceptability indices for all pairs of service providers. Let us discuss the most representative results when referring to a pairwise relation perspective.

For three pairs of service providers (*S*1, *S*2), (*S*5, *S*3), and (*S*5, *S*4), the outranking acceptability index is equal to one. Thus, these relations need to be treated with certainty, and three providers *S*2, *S*3, and *S*4 can be deemed as less advantageous as there is some other alternative, which necessarily outranks them. In this same spirit, *S*3 never outranks any other supplier ($OAI(S3, \cdot) = 0$), while *S*1, *S*2, and *S*3 do not outrank *S*5 for any compatible set of parameters.

When analysing *RelAI*s for different pairs of service providers, one can indicate the relations observed for the vast majority of feasible parameters (e.g., $PAI(S5, S4) = 0.876$ or $IAI(S1, S2) = 0.697$ and these which are extremely unlikely, being confirmed by few feasible weights (e.g., $IRAI(S1, S4) = 0.026$). Such direct pairwise comparisons of the providers offer means to suggest benchmarks for guiding the less advantageous suppliers to improve their performance by attaining the levels derived from the better rated 3PRLPs. For other pairs of suppliers, the observed relation varies depending on the admissible parameters used for the comparison (e.g., $PAI(S2, S4) = 0.317$, $IAI(S2, S4) = 0.177$, and $IRAI(S2, S4) = 0.506$).

For all feasible parameters, we ran the ELECTRE I method and identified a respective graph kernel. Note that a kernel can be interpreted as the most advantageous subset of 3PRLPs. In Table 8, we present the kernel acceptability indices. There are only four subsets of service providers for which this index is greater than zero: {*S*5}, {*S*1, *S*5}, {*S*1, *S*2, *S*5}, and {*S*1, *S*2, *S*4, *S*5}. For the greatest number of considered scenarios (46.8%), *S*5 is the unique supplier contained in the kernel and for other 30% of feasible parameter values it is accompanied only by *S*1. In Fig. 2, we present four outranking graphs with different kernels that were obtained for at least one feasible set of parameters. These graphs support comprehension of the conditions under which each subset of suppliers was selected.

In Table 9, we present the kernel membership indices along with the comprehensive outranking and non-outranked indices for all 3PRLPs. The robust conclusions that can be derived from their analysis are as follows:

- *S*5 was included in all kernels ($KMI(S5) = 1$); in fact, for the majority of considered scenarios *S*5 was not outranked by any other service provider ($CNOI(S5, A, S^C) = 0.876$) and it was outranking all remaining suppliers jointly ($COI(S5, A, S) = 0.546$);
- *S*3 was not contained in any kernel ($KMI(S3) = 0$); what is more, *S*3 was never deemed at least as good as any other service provider ($OAI(S3, \cdot) = 0$);
- *S*1 was found in the majority of kernels ($KMI(S3) = 0.532$); in most cases, this followed a scenario in which *S*1 was incomparable with *S*5; moreover, for over 30% of considered parameter values, *S*1 was not outranked by any other supplier ($CNOI(S1, A, S^C) = 0.303$), while proving its superiority over other alternatives;
- for *S*2 and *S*4 the kernel membership indices are positive though significantly lower than for *S*5 and *S*1; on one hand, *S*2 was contained in the kernel only when it became indiffer-

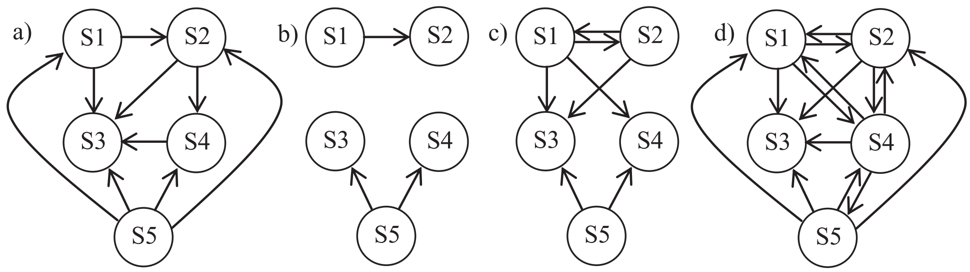

Fig. 2. Outranking graphs with four different kernels: a) {*S*5}, b) {*S*1, *S*5}, c) {*S*1, *S*2, *S*5} (after eliminating a cycle involving *S*1 and *S*2), and d) {*S*1, *S*2, *S*4, *S*5} (after eliminating a cycle involving *S*1, *S*2, *S*4, and *S*5).

ent with *S*1; on the other, for 12.4% of considered settings, *S*4 was assessed to be at least as good as all remaining service providers (being in this way indifferent with *S*5 and, thus, contained in the kernel); in both cases, it was sufficient to increase the credibility threshold to eliminate *S*2 and *S*4 from the respective kernels.

5.3. Recommendation

The robust conclusions led to the following recommendations that were submitted to the case company:

- If a single 3PRLP needed to be selected, *S*5 should be retained to take over the reverse logistics activities;
- in case two suppliers were acceptable (which was considered as the upper limit by the company), *S*1 could be considered jointly with *S*5;
- *S*3 should be eliminated with certainty, whereas *S*2 and *S*4 could be neglected being always outranked by, respectively, *S*1 and *S*5.

The recommendation was followed by the company with selecting *S*5 as the third-party logistics provider, and considering *S*1 as an optional/supplementary choice.

6. Conclusions

A supply chain is only as strong as its weakest part [30]. It is even more true in case products are returned into the supply chain. In order to have a more sustainable supply chain, to fulfil legislation requirements, and to increase customer satisfaction, companies need to investigate reverse logistics. Since most companies do not have the adequate systems or space to meet the requirements for reverse logistics activities, the specialized service providers offer exactly these opportunities. Many firms have learned not to see this option as a threat to their profits, but rather as a marketplace advantage against their competitors based on resources that the 3PRLP can offer. This paper highlighted the increase in attention of this topic by the literature review and discussed the opportunities of outsourcing the logistics activities to 3PRLP.

When companies begin to consider outsourcing their reverse logistics activities, they should be supported by information on a suitable decision making model [43]. This includes details on the viewpoints that are relevant for the evaluation of 3PRLPs and multiple criteria analysis methods for selecting the appropriate service provide while taking into account the preferences of the involved stakeholders.

As far as the criteria relevant for the context of 3PRL are concerned, we provided the background of sustainable triple bottom line theory with focus on economic, environmental, and social aspects. If companies seek to outsource their reverse logistics activities under the consideration of sustainability criteria, there is a potential for gaining a competitive advantage. Based on the literature review, we pointed out that the economic and environmental viewpoints are often included in the sustainable models, but the social aspect is commonly left out and should attract more attention. In this perspective, the classification of criteria proposed in this paper may help the company's management involved in the strategic decisions to implement a framework for evaluating 3PRLPs. In particular, the constructed family of criteria involving three sustainability pillars can be adopted in other case studies. The prioritization of criteria within the study reported in this paper confirmed that there has been a shift towards more acceptance of sustainable criteria in reverse logistics activities. Companies do not only see reverse logistics opportunities to gain a financial advantage, but also include environmental and social aspects in their decision making.

When it comes to the MCDA methods, our extensive literature review showed that different variants of AHP, TOPSIS, and DEA have been so far most widely used in the context of 3PRLPs evaluation and selection. However, these approaches require great cognitive effort from the DMs, need some arbitrary transformation of the performances scales, or offer poor discriminative power. For these reasons, we have proposed a new outranking-based approach that was used to support the 3PRLP selection problem for the Indian manufacturing company.

The introduced method combines a variant of ELECTRE I accounting for the effect of reinforced preference, the revised Simos procedure, and Stochastic Multi-criteria Acceptability Analysis. It indicates the most preferred option by analysing the stability of alternatives' membership in the kernel of an outranking graph obtained for different parameters of an outranking model compatible with the incomplete preference information of the Decision Maker. Let us note that it was the first time both ELECTRE and SMAA were used in the context of 3PRLP, even though the specific areas of past applications of these MCDA methods in logistics and supply chain management already included facility layout and location, supplier selection, inventory decisions, vehicle fleet planning, transportation modes, and supply chain design [38]. Obviously, the approach presented in this paper can be rigorously followed to deal with multiple criteria choice problems also in other application areas such as policy analysis [87], environmental management [61], or energy planning [76].

From the application point of view, the research results in our study could be further validated by collecting data related to the evaluation of 3PRLPs from more respondents. One can also emphasize the role of social criteria such as micro- and macro-social impacts, since they have been comprehensively judged less relevant by the DM than the economic and environmental factors. Moreover, a comparison with other MCDA methods can be established to demonstrate further benefits of using ELECTRE and SMAA in relation to AHP, TOPSIS, and DEA.

From the methodological viewpoint, the proposed approach can be extended to a group decision making framework [47,59]. The compromise between different DMs may be searched at the input (preference) or at the output (recommendation) levels [26]. Furthermore, the method can be extended to dealing with a hierarchical structure of criteria [23], interactions between criteria [31] as well as to tolerating imprecision in the specification of comparison thresholds [45] or in the judgements provided in the revised Simos procedure [22]. Additionally, the analysis of stochastic acceptability indices can be enriched with selection of a representative robust set of parameters of an outranking model [57] and with consideration of the necessary and possible results [45,61] derived with linear programming. These results indicate the parts of recommendation confirmed by, respectively, all or at least one feasible set of parameters. Finally, if all alternatives need to be ordered from the best to the worst, one can use the net flow rules to compute a unique score based on the relation acceptability indices (see, e.g., [21,22,60]).

Acknowledgements

The authors thank the three anonymous referees for many insightful comments, which helped us to significantly improve the paper. The work of Miłosz Kadziński and Grzegorz Miebs was supported by the Polish Ministry of Science and Higher Education under the Iuventus Plus program in 2016–2019 grant number IP2015 029674 - 0296/IP2/2016/74.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.omega.2018.05.007.

References

[1] Agrawal S, Singh RK, Murtaza Q. A literature review and perspectives in reverse logistics. Resour Conserv Recycl 2015;97:76–92.
[2] Almeida AT. Multicriteria decision model for outsourcing contracts selection based on utility function and ELECTRE method. Comput Oper Res 2007;34(12):3569–74.
[3] Andersson D, Norrman A. Procurement of logistics services – a minutes work or a multi-year project. Eur J Purchasing Supply Manag 2002;8(1):3–14.
[4] Anttonen M, Halme M, Houtbeckers E, Nurkka J. The other side of sustainable innovation: is there a demand for innovative services? J Clean Prod 2013;45:89–103.
[5] Azadi M, Saen RF. A new chance-constrained data envelopment analysis for selecting third-party reverse logistics providers in the existence of dual-role factors. Expert Syst Appl 2011;38(10):12231–6.
[6] Azadi M, Saen RF. Developing an output-oriented super slacks-based measure model with an application to third-party reverse logistics providers. J Multi--Criteria Decis Anal 2011;18(5–6):267–77.
[7] Azadi M, Saen RF. Developing a chance-constrained free disposable hull model for selecting third-party reverse logistics providers. Int J Oper Res Inf Syst 2013;4(4):96–113.
[8] Bai C, Sarkis J. Flexibility in reverse logistics: a framework and evaluation approach. J Clean Prod 2013;47:306–18.
[9] Barker TJ, Zabinsky ZB. A multi-criteria decision making model for reverse logistics using analytical hierarchy process. Omega 2011;39(5):558–73.
[10] Belton V, Stewart T. Multiple criteria decision analysis. An integrated approach. New York: Springer; 2002.
[11] Bolumole YA. The supply chain role of third–party logistics providers. Int J Logist Manag 2001;12(2):87–102.
[12] Boyson S, Corsi T, Dresner M, Rabinovich E. Managing effective third party logistics relationships: what does it take? J Bus Logist 1999;20(1):73–100.
[13] Bradley P.. Contract logistics: it's all about costs. 1994. Purchasing, pp. 56, A3–A14.
[14] Brunelli M. Introduction to the analytic hierarchy process. SpringerBriefs in operations research. Cham: Springer; 2015.
[15] Candler J. You make it, they distribute it. Nations Bus 1994;82(3):46–8.
[16] Charnes A, Cooper W, Rhodes E. Measuring the efficiency of decision making units. Eur J Oper Res 1978;2(6):429–44.
[17] Cochran J, Ramanujan B. Carrier-mode logistics optimization of inbound supply chains for electronics manufacturing. Int J Prod Econ 2006;103(2):826–40.
[18] Colicchia C, Marchet G, Melacini M, Perotti S. Building environmental sustainability: empirical evidence from logistics service providers. J Clean Prod 2013;59:197–209.
[19] Conlon DE, Murray NM. Customer perceptions of corporate responses to product complaints: the role of explanations. Acad Manag J 1996;39(4):1040–56.
[20] Cook WD, Tone K, Zhu J. Data envelopment analysis: prior to choosing a model. Omega 2014;44:1–4.
[21] Corrente S, Figueira J, Greco S. The SMAA-PROMETHEE method. Eur J Oper Res 2014;239(2):514–22.
[22] Corrente S, Figueira J, Greco S, Słowiński R. A robust ranking method extending ELECTRE III to hierarchy of interacting criteria, imprecise weights and stochastic analysis. Omega 2017;71:1–17.
[23] Corrente S, Greco S, Słowiński R. Multiple criteria hierarchy process with ELECTRE and PROMETHEE. Omega 2013;41(5):820–46.
[24] Corrente S, Greco S, Słowiński R. Multiple criteria hierarchy process for ELECTRE TRI. Eur J Oper Res 2016;252(1):191–203.
[25] Demir I, Orhan M. Reuse of waste bricks in the production line. Build Environ 2003;38:1451–5.
[26] Dias LC, Climaco JN. ELECTRE tri for groups with imprecise information on parameter values. Group Decis Negotiation 2000;9(5):355–77.
[27] Dias LC, Antunes CH, Dantas G, de Castro N, Zamboni L. A multi-criteria approach to sort and rank policies based on delphi qualitative assessments and ELECTRE TRI: the case of smart grids in brazil. Omega 2018;76:100–11.
[28] Efendigil T, Semih O, Elif K. A holistic approach for selecting a third-party reverse logistics provider in the presence of vagueness. Comput Ind Eng 2008;54(2):269–87.
[29] Elkington J. Towards the sustainable corporation: win-win-win business strategies for sustainable development. Calif Manage Rev 1994;36(2):90–100.
[30] Ertay T, Kahveci A, Tabanli RM. An integrated multi-criteria group decision–making approach to efficient supplier selection and clustering using fuzzy preference relations. Int J Computer Integr Manuf 2011;24(12):1152–67.
[31] Figueira J, Greco S, Roy B. ELECTRE Methods with interaction between criteria: an extension of the concordance index. Eur J Oper Res 2009;199(2):478–95.
[32] Figueira J, Greco S, Roy B, Słowiński R. An overview of ELECTRE methods and their recent extensions. J Multi-Criteria Decis Anal 2013;20:61–85.
[33] Figueira J, Mousseau V, Roy B. ELECTRE methods. In: Figueira JR, Greco S, Ehrgott M, editors. Multiple criteria decision analysis: state of the art surveys. New York: Springer; 2016. p. 155–85.
[34] Figueira J, Roy B. Determining the weights of criteria in the ELECTRE type methods with a revised simos' procedure. Eur J Oper Res 2002;139(2):317–26.
[35] Gonzalez-Torre P, Alvarez M, Sarkis J, Adenso-Diaz B. Barriers to the implementation of environmentally oriented reverse logistics: evidence from the automotive industry sector british. J Manag 2010;21(4):889–904.
[36] Govindan K. Fuzzy approach for the selection of third party reverse logistics provider. Asia Pacific J Market Logist 2009;21(3):397–416.
[37] Govindan K, Haq A. Analysis of interactions of criteria and sub-criteria for the selection of supplier in the built-in-order supply chain environment. Int J Prod Res 2007;45(11):3831–52.
[38] Govindan K, Jepsen M. ELECTRE: A comprehensive literature review on methodologies and applications. Eur J Oper Res 2016;250(1):1–29.
[39] Govindan K, Kadziński M, Sivakumar R. Application of a novel PROMETHEE-based method for construction of a group compromise ranking to prioritization of green suppliers in food supply chain. Omega 2017;71:129–45.
[40] Govindan K, Murugesan P. Selection of third-party reverse logistics provider using fuzzy extent analysis. Benchmarking Int J 2011;18(1):149–67.
[41] Govindan K, Palaniappan M, Zhu Q, Kannan D. Analysis of third party reverse logistics provider using interpretive structural modeling. Int J Prod Econ 2012;140(1):204–11.
[42] Govindan K, Pokharel S, Kumar P. A hybrid approach using ISM and fuzzy TOPSIS for the selection of reverse logistics provider. Resour Conserv Recycl 2009;54(1):28–36.
[43] Govindan K, Roohollah K, Ahmad J. A fuzzy multi-criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. J Clean Prod 2013;47:345–54.
[44] Govindan K, Soleimani H, Kannan D. Reverse logistics and closed loop - supply chain: a comprehensive review to explore the future. Eur J Oper Res 2015;240(3):603–26.
[45] Greco S, Kadziński M, Mousseau V, Słowiński R. ELECTRE^{GKMS}: Robust ordinal regression for outranking methods. Eur J Oper Res 2011;214(1):118–35.
[46] Guarnieri P, Sobreiro VA, Nagano MS, Serrano ALM. The challenge of selecting and evaluating third-party reverse logistics providers in a multicriteria perspective: a brazilian case. J Clean Prod 2015;96:209–19.
[47] Hatami-Marbini A, Tavana M. An extension of the electre i method for group decision-making under a fuzzy environment. Omega 2011;39:373–86.
[48] Hong J, Chin A, Liu B. Logistics outsourcing by manufacturers in china: a survey of the industry. Transp J 2004;43(1):17–25.
[49] Hu Z, Rao C, Zheng Y, Huang D. Optimization decision of supplier selection in green procurement under the mode of low carbon economy. Int J Comput Intell Syst 2015;8(3):407–21.
[50] Hung Lau K, Wang Y. Reverse logistics in the electronic industry of china: a case study. Supply Chain Manag 2009;14(6):447–65.
[51] Hwang CL, Yoon K. Multiple attribute decision making. Methods and applications. New York: Springer; 1981.
[52] Jayant A, Gupta P, Garg SK, Khan M. TOPSIS-AHP Based approach for selection of reverse logistics service provider: a case study of mobile phone industry. Procedia Eng 2014;97:2147–56.
[53] Jayaraman V, Guide VDR, Srivastava R. A closed-loop logistics model for remanufacturing. J Oper Res Soc 1999;50(5):497–508.

[54] Jharkharia S, Shankar R. Selection of logistics service provider: an analytic network process (ANP) approach. Omega 2007;35(3):274–89.
[55] Ji G. Market-motivated value systems, reverse logistics and the evaluation model for the third party reverse logistics providers. Int Logist Trade 2006;4(1):53–92.
[56] Jing AL, Wu Y, Kin KL, Liu K. Optimal ordering policy in a distribution system. Int J Prod Econ 2006;103:527–34.
[57] Kadziński M, Greco S, Słowiński R. Selection of a representative set of parameters for robust ordinal regression outranking methods. Comput Oper Res 2012;39(11):2500–19.
[58] Kadziński M, Labijak A, Napieraj M. Integrated framework for robustness analysis using ratio-based efficiency model with application to evaluation of polish airports. Omega 2017;67:1–18.
[59] Kadziński M, Rocchi L, Miebs G, Grohmann D, Menconi M, Paolotti L. Multiple criteria assessment of insulating materials with a group decision framework incorporating outranking preference model and characteristic class profiles. Group Decis Negotiation 2018;27(1):33–59.
[60] Kadziński M, Słowiński R, Greco S. Multiple criteria ranking and choice with all compatible minimal cover sets of decision rules. Knowl Based Syst 2015;89:569–83.
[61] Kadziński M, Tervonen T, Figueira J. Robust multi-criteria sorting with the outranking preference model and characteristic profiles. Omega 2015;55:126–40.
[62] Kafa N, Hani Y, Mhamedi AE, B Grabot B, Vallespir S, Gomes A, Bouras, Kiritsis D. A fuzzy multi criteria approach for evaluating sustainability performance of thirdǣ party reverse logistics providers. in: advances in production management systems. In: Innovative and knowledge-based production management in a global-local world.. Heidelberg: Springer Berlin; 2014. p. 270–7.
[63] Kannan G. Fuzzy approach for the selection of third party reverse logistics provider. Asia Pacific J Market Logist 2009;21(3):397–416.
[64] Kannan G, Murugesan P, Senthil P, Haq AN. Multicriteria group decision making for the third party reverse logistics service provider in the supply chain model using fuzzy TOPSIS for transportation services. Int J Serv Technol Manag 2009;11(2):162–81.
[65] Kannan G, Pokharel S, Kumar PS. A hybrid approach using ISM and fuzzy TOPSIS for the selection of reverse logistics provider. Resour Conserv Recycl 2009;54(1):28–36.
[66] Kannan D. Role of multiple stakeholders and the critical success factor theory for the sustainable supplier selection process. Int J Prod Econ 2018;195:391–418.
[67] Krumwiede DW, Sheu C. A model for reverse logistics entry by third-party providers. Omega 2002;30(5):325–33.
[68] Kumar NR, Kumar RMS. Closed loop supply chain management and reverse logistics – a literature review. Int J Eng Res Technol 2013;6(4):455–68.
[69] Kuo RJ, Wang YC, Tien FC. Integration of artificial neural network and MADA methods for green supplier selection. J Clean Prod 2010;18(12):1161–70.
[70] Lahdelma R, Salminen P. SMAA-2: Stochastic multicriteria acceptability analysis for group decision making. Oper Res 2001;49(3):444–54.
[71] Lalonde BJ, Maltz AD. Some proposition about outsourcing the logistics function. Int J Logist Manag 1992;3(1):1–11.
[72] Lambert S, Riopel D, Abdul-Kader W. A reverse logistics decisions conceptual framework. Comput Ind Eng 2011;61(3):561–81.
[73] Lao SI, Choy KL, Ho GTS, Tsim YC, Chung NSH. Determination of the success factors in supply chain networks: a Hong Kong-based manufacturer's perspective. Meas Bus Excellence 2011;15(1):34–48.
[74] Lee YJ, Baker T, Jayaraman V. Redesigning an integrated forward reverse logistics system for a third party service provider: an empirical study. Int J Prod Res 2012;50(19):5615–34.
[75] Mahmoudzadeh M, Mansour S, Karimi B. To develop a third-party reverse logistics network for end-of-life vehicles in iran. Resour Conserv Recycl 2013;78:1–14.
[76] Marinakis V, Doukas H, Xidonas P, Zopounidis C. Multicriteria decision support in local energy planning: an evaluation of alternative scenarios for the sustainable energy action plan. Omega 2017;69:1–16.
[77] McCarthy I, Anagnostou A. The impact of outsourcing on the transaction costs and boundaries of manufacturing. Int J Prod Econ 2004;88(1):61–71.
[78] McCarthy I, Silvestre BS, Kietzmann JH. Understanding outsourcing contexts through information asymmetry and capability fit. Prod Plan Contr 2013;24(4–5):277–83.
[79] Meade L, Sarkis J. A conceptual model for selecting and evaluating third-party reverse logistics providers. Supply Chain Manag 2002;7(5):283–95.
[80] Min H, Ko HJ. The dynamic design of a reverse logistics network from the perspectives of third party logistics service providers. Int J Prod Econ 2008;113(1):176–92.
[81] Momeni E, Azadi M, Saen RF. Measuring the efficiency of third party reverse logistics provider in supply chain by multi objective additive network DEA model. Int J Shipping Transp Logist 2015;7(1):21–41.
[82] Monczka RM, Ternt RJ, Callahn TJ. Supply based strategies to maximize supplier performance. Int J Phys Distrib Logist 1994;23(4):42–54.
[83] Mothilal S, Gunasekaran A, Nachiappan SP, Jayaram J. Key success factors and their performance implications in the Indian third-party logistics (3PL) industry. Int J Prod Res 2012;50:2407–22.
[84] Mousseau V, Dias L. Valued outranking relations in ELECTRE providing manageable disaggregation procedures. Eur J Oper Res 2004;156:467–82.
[85] Nikolaou I, Evangelinos K, Allan S. A reverse logistics social responsibility evaluation framework based on the triple bottom line approach. J Clean Prod 2013;56:173–84.
[86] Noci G. Designing green vendor rating systems for the assessment of a supplier's environmental performance. Eur J Purchasing Supply Manag 1997;3(2):103–14.
[87] Pinto FS, Costa AS, Figueira J, Marques RC. The quality of service: an overall performance assessment for water utilities. Omega 2017;69:115–25.
[88] Pokharel S, Mutha A. Perspectives in reverse logistics: a review. Resour Conserv Recycl 2009;53(4):175–82.
[89] Prahinski C, Kocabasoglu C. Empirical research opportunities in reverse supply chains. Omega 2006;34(6):519–32.
[90] Prakash C, Barua MK. An analysis of integrated robust hybrid model for third–party reverse logistics partner selection under fuzzy environment. Resour Conserv Recycl 2016;108:63–81.
[91] Ramirez AM, Morales VJG. Improving organisational performance through reverse logistics. J Oper Res Soc 2014;65(6):954–62.
[92] Ravi V. Selection of third-party reverse logistics providers for end-of-life computers using TOPSIS-AHP based approach. Int J Logist Syst Manag 2011;11(1):24–37.
[93] Ravi V, Shankar R. Analysis of interactions among the barriers of reverse logistics. Technol Forecast Soc Change 2005;72(8):1011–29.
[94] Razzaque MA, Sheng CC. Outsourcing of logistics functions: a literature survey. Int J Phys Distrib Logist Manag 1998;28(2):89–107.
[95] Rockart JF. Chief executives define their own data needs. Harv Bus Rev 1979;57(2):81–93.
[96] Rogers DS, Tibben-Lembke RS. Going backwards: reverse logistics trends and practices. Centre for logistics management, University of Nevada, Reno, Reverse logistics executive council 1998.
[97] Rogers DS, Tibben-Lembke RS. An examination of reverse logistics practices. J Bus Logist 2001;22(2):129–48.
[98] Roy B. Classement et choix en presence de points de vue multiples (la methode ELECTRE). La Revue d'Informatique et de Recherche Operationelle (RAIRO) 1968;8:57–75.
[99] Roy B. The outranking approach and the foundations of ELECTRE methods. In: Bana e Costa C, editor. Readings in multiple criteria decision aid. Berlin: Springer-Verlag; 1990. p. 155–83.
[100] Roy B. Robustness in operational research and decision aiding: a multi–faceted issue. Eur J Oper Res 2010;200(3):629–38.
[101] Roy B, Bouyssou D. Aide multicritere a la decision: methodes et cas. Paris: Economica; 1993.
[102] Roy B, Figueira J, Almeida-Dias J. Discriminating thresholds as a tool to cope with imperfect knowledge in multiple criteria decision aiding: theoretical results and practical issues. Omega 2014;43:9–20.
[103] Roy B, Słowiński R. Handling effects of reinforced preference and counter-veto in credibility of outranking. Eur J Oper Res 2008;188:185–90.
[104] Saaty T. The analytic hierarchy process. New York: McGraw-Hill; 1980.
[105] Saen RF. A new model for selecting third-party reverse logistics providers in the presence of multiple dual-role factors. Int J Adv Manuf Technol 2010;46(1–4):405–10.
[106] Saen RF. A decision model for selection third-party reverse logistics providers in the presence of both dual-role factors and imprecise data. Asia-Pacific J Oper Res 2011;28(2):239–54.
[107] Saen RF. A mathematical model for selecting third-party reverse logistics providers. Int J Procurement Manag 2009;2(2):180–90.
[108] Sasikumar P, Kannan G, Haq AN. A heuristic based approach to vehicle routing model for third party reverse logistics provider. Int J Serv Technol Manag 2009;12(1):106–25.
[109] Senthil S, Srirangacharyulu B, Ramesh A. A robust hybrid multi-criteria decision making methodology for contractor evaluation and selection in third–party reverse logistics. Expert Syst Appl 2014;41(1):50–8.
[110] Serrato MA, Gaytan J, Ryan SM. A Markov decision model to evaluate outsourcing in reverse logistics. Int J Prod Res 2007;45(18–19):4289–315.
[111] Shih HS, Shyur HJ, Lee ES. An extension of TOPSIS for group decision making. Math Comput Model 2007;45(78):801–13.
[112] Siskos E, Tsotsolas N. Elicitation of criteria importance weights through the simos method: a robustness concern. Eur J Oper Res 2015;246(2):543–53.
[113] Steven M, Dyckhoff H, Lackes R, Reese J. Networks in reverse logistics. In: Supply chain management and reverse logistics. Berlin Heidelberg: Springer; 2004. p. 163–80.
[114] Stock GN, Greis NP, Kasarda JD. Logistics, strategy and structure: a conceptual framework. Int J Phys Distrib Logist Manag 1999;29:224–39.
[115] Suyabatmaz AC, Altekin FT, Sahin G. Hybrid simulation-analytical modeling approaches for the reverse logistics network design of a third-party logistics provider. Comput Ind Eng 2014;70:74–89.
[116] Talib MSA, Hamid ABA. Application of critical success factors in supply chain management. Supply Chain Manag 2014;3(1):21–33.
[117] Tate K. The elements of a successful logistics partnership. Int J Phys Distrib Logist Manag 1996;26(3):7–13.
[118] Tavana M, Zareinejad M, Santos-Arteaga FJ, Kaviani MA. A conceptual analytic network model for evaluating and selecting third-party reverse logistics providers. Int J Adv Manuf Technol 2016;86(5–8):1705–21.
[119] Tervonen T, Figueira J. A survey on stochastic multicriteria acceptability analysis methods. J Multi-Criteria Decis Anal 2008;15(1–2):1–14.
[120] Tervonen T, Lahdelma R. Implementing stochastic multicriteria acceptability analysis. Eur J Oper Res 2007;178(2):500–13.

[121] Tervonen T, van Valkenhoef G, Basturk N, Postmus D. Hit-and-run enables efficient weight generation for simulation-based multiple criteria decision analysis. Eur J Oper Res 2013;224(3):552–9.
[122] Turrisi M, Bruccoleri M, Cannelle S. Impact of reverse logistics on supply chain performance. Int J Phys Distrib Logist Manag 2013;43(7):564–85.
[123] Vachon S, Klassen RD. Green project partnership in the supply chain: the case of the package printing industry. J Clean Prod 2006;14(67):661–71.
[124] Wallenburg C.M.. Kundenbindung in der logistik-eine empirische untersuchung zu ihren einflussfaktoren. 2004. Bern, Stuttgart, Wien.
[125] Wang J, Zhu Y. Research on third-party reverse logistics provider selection based on fuzzy clustering in perspective of low-carbon economy. Commun Inf Sci Manag Eng 2012;2(2):63–6.
[126] Wentworth F. Outsourcing services: the case against. Logist Transp Focus 2003;5(2):57–9.
[127] Vincke P. Robust solutions and methods in decision-aid. J Multi-Criteria Decis Anal 1999;8(3):181–7.
[128] Yan NN, Sun BW. Optimal Stackelberg strategies for closed-loop supply chain with third-party reverse logistics. Asia-Pacific J Oper Res 2012;29(05):125–6.
[129] Yin ZH, Lu Q. The grey comprehensive evaluation model of a third-party reverse logistics provider selection. In: ieee international joint conference on artificial intelligence 2009 (JCAI'09); 2009. p. 497–500.
[130] Zareinejad M, Javanmard H. Evaluation and selection of a third-party reverse logistics provider using ANP and IFG-MCDM methodology. Life Sci J 2013;10(6):350–5.
[131] Zielniewicz P. A ranking method based on the aggregate distance measure function in the value space. Int J Inf Technol Decision Making 2017;16(3):685–710.