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Multicriteria sorting method based on global and local search for supplier segmentation

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Abstract

The aim of this research is to develop a robust multicriteria method to classify suppliers into ordered categories and its validation in real contexts. The proposed technique is based on a property of net flows of the PROMETHEE method and uses global and local search concepts, which are common in the optimisation field. The results obtained are compared to those from the most cited sorting algorithm, and an empirical validation and sensitivity analysis is performed using real supplier evaluation data. Furthermore, it does not require additional information from decision-makers as other sorting algorithms do for assigning incomparable or indifferent alternatives to groups. An extension of the silhouette concept from data mining is also contributed to measure the quality of ordered classes. Both contributions are easy to apply and integrate into decision support systems for automated decisions in the supply chain management. Finally, this practical approach is also useful to classify customers and any type of alternatives or actions into ordered categories, which have an increasing number of real applications.

Keywords: supplier segmentation; multicriteria sorting; global search; local search; PROMETHEE; supply chain management

1. Introduction

Supplier management research has grown significantly in recent decades in parallel to its increasing strategic relevance from a managerial standpoint in companies. Different publications have been focused on the analysis of supplier management from different perspectives, including the theory of supply chain agency (Matinheikki et al., 2022), supply chain finance (Phraknoi et al., 2022), efficiency (Ang et al., 2021), disruption risk (Shen and Li, 2017) and supply chain flexibility (Tachizawa and Thomsen, 2007). Nevertheless, some authors highlight that research needs to focus

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more on real-world models and empirical validation to satisfy managers' requirements of having techniques applicable in practice (Wetzstein et al., 2016).

Qualifying and selecting suppliers are the first steps in supply chain management, followed by segmentation and monitoring to support adequate strategies for supplier relationship management (Glock et al., 2017; Segura and Maroto, 2017; Hu et al., 2022). For example, a correct relationship between suppliers and customers can help develop strategies to manage issues, such as sustainable supply chain management and circular economy (Chavez et al. (2022), improve transparency in terms of visibility and to help mitigate the post-COVID-19 (Coronavirus Disease 2019) multi-tier supplier parts supply crisis (Adhi Santharm and Ramanathan, 2022), financial performance through ambidextrous innovations (Wang et al., 2022), reputational risk (Dhingra and Krishnan, 2021), reduce the bullwhip effect in supply networks (Osadchiy et al., 2021) and supply chain disruptions (Durach and Machuca, 2018). The consideration of multiple criteria focused on economics aspects, and social and environmental responsibility are becoming critical supply chain issues that must be balanced in supplier management (Guo et al., 2016), where the evaluation models must adapt to these new sustainability needs (i.e., Hasnain et al., 2021) but not neglecting strategic criteria, such as technological competencies (Kronemeyer et al., 2022).

The review of Shiralkar et al. (2022) concludes that supplier segmentation is a multicriteria problem, where the inclusion of several criteria allows the process to be more inclusive and effective. Multiple criteria decision-making (MCDM) provides a useful approach to address the main issues that arise in supplier management, such as choice, ranking, classification, group decision, elicitation and description problems (Ishizaka and Nemery, 2013; Zamarron-Mieza et al., 2017). This field distinguishes between classification and sorting problems. Alternatives or suppliers are assigned to predefined groups characterised by reference profiles in both cases. Nevertheless, the groups are defined in a nominal way in classification problems, while the ordinal way is used in sorting problems, whose groups, classes or categories are ordered from the most preferred to the least preferred, such as excellent, good and acceptable suppliers (Zopounidis and Doumpos, 2002).

Several reviews have analysed the relevance of MCDM in supplier management and pointed out the increasing interest in sorting problems in the research agenda (Ho et al., 2010; Chai et al., 2013; Chai and Ngai, 2020). According to the literature review of Alvarez et al. (2021), there has been an increasing number of methodological developments related to multicriteria sorting issues. However, providing methods to solve real company problems continues to be a research challenge.

This research aims to develop a sorting method to classify suppliers into ordered categories and its validation in real contexts to check its applicability in supplier management practice and overcome the weaknesses of other techniques in the field, such as the impossibility of classifying all suppliers and the need to define an extra parameter to sort indifferent or incomparable suppliers. The proposed technique is based on knowledge from the outranking methodology. In particular, the algorithm proposed is inspired by the property of net flows of PROMETHEE (Preference Ranking Organization METHods for Enrichment Evaluations) and also uses concepts of global and local search, which are common in the optimisation field. The results obtained are compared to those from the most cited sorting algorithm applied to supplier evaluation (PROMSORT). Both methods are applied and compared to real data on supplier evaluation from a multinational manufacturing company.

The main contributions of this research are as follows. First, the design of a robust algorithm to classify suppliers into ordered categories. It is based on a new property of net flow from

PROMETHEE, and it exploits global and local search processes in a multicriteria context. The global search provides a first classification of the alternatives into categories, which is then modified and improved by two local search processes. First, an intra-category search by applying PROMETHEE to alternatives of each category is generated. Second, an inter-category search by merging alternatives of adjacent categories. Second, the sorting procedure proposed has been validated empirically by real data on supplier evaluation, allows problem-solving with a high number of criteria and suppliers and can be applied by managers using available PROMETHEE software. Furthermore, it does not require new parameters from decision-makers as other sorting algorithms do for assigning incomparable or indifferent alternatives to groups in supplier segmentation. Thus, the new sorting method is a practical approach, which can easily be integrated into decision support systems (DSS) to assist in managerial decisions. Additionally, as it is the MCDM method, it allows decision-makers to classify suppliers according to different criteria such as economic, social and environmental approaches. Third, an extension of the silhouette technique from data mining is also developed to measure the quality of the supplier assignments to ordered classes. This new quality index is based on the net flows from PROMETHEE to calculate the dissimilarities of an alternative with respect to alternatives in its current, upper adjacent and lower adjacent categories. These three dissimilarity measures are integrated into a new formula that indicates the quality of categories generated by the sorting algorithm. Fourth, the proposed sorting method can be directly applied to classify other elements of the supply chain (customers) and any alternatives into ordered categories. This problem appears in an increasing number of real applications (risk assessment, financial management, project evaluation, education, etc.).

The rest of the paper is organised as follows: The second section presents the literature review of supplier sorting, and the methodological base is summarised in the third section. A detailed explanation of the new sorting algorithm and the quality index named silhouette for PROMETHEE sorting is provided in Section 4, followed by their performance results and sensitivity analysis. Finally, discussion and conclusion are presented.

2. Methods for supplier sorting: literature review

The multicriteria decision-making field distinguishes the following types of problems: choice, ranking, classification, group decision, description problem, elimination problem, design problem and cognitive problem (Ishizaka and Nemery, 2013; Zamarron-Mieza et al., 2017). It is important to highlight the distinction between classification and sorting methods. The categories are ordered from the most preferred to the least preferred in sorting, whereas this is not the case in some methods of data mining, which do not consider decision-makers' preferences. Chai and Ngai (2020) indicate that it is not possible to incorporate people's subjective judgements into support vector machines and neural networks. Nevertheless, recent literature provides examples where multicriteria and mining evaluations are integrated into the trace clustering problem, where using non-compensatory similarity measures and a normalised spectral clustering algorithm, they obtain classifications that reflect the preferences of the decision-maker in an initial multicriteria environment (Delias et al., 2023). Other authors have integrated multicriteria methods (local AHP-Analytic Hierarchy Process) and Bayesian clustering to identify homogeneous groups of citizens for group decision-making (Altuzarra et al., 2019, 2022). Han et al. (2020) include decision-makers' preferences by measuring the importance of the criteria with AHP and then using a linguistic fuzzy clustering method.

Several authors pointed out the increasing relevance of sorting methods in solving multicriteria problems in general and supplier management in particular. The significance of sorting problems is shown both in the growing number of articles with new methods and fields of application over the last decade (Alvarez et al., 2021). The need to assign alternatives to classes predefined and preference-ordered appears in scenarios related to supplier selection and supplier management (Araz and Ozkarahan, 2007; Barrera et al., 2022; Segura et al. 2020). In addition, Chai and Ngai (2020) highlighted sorting technique adoption as one of the main trends for future research in supplier selection.

From a methodological perspective, the wide range of sorting methods can be classified as follows: full aggregation approach, goal aspiration or reference-level, non-classical approach and outranking approach (Alvarez et al., 2021). In general, the most appropriate method depends on the nature of the problem to solve, the data availability and the needs of decision-makers.

UTADIS (UTilités Additives DIScriminantes) is the first full aggregation method for sorting, where alternatives are evaluated with respect to each criterion, followed by an additive or multiplicative aggregation to obtain the global score. These methods are named compensatory, as bad alternative performance in some criteria can be compensated by good ones in others (Zopounidis and Doumpos, 2000; Ishizaka and Nemery, 2013). UTADIS is the most applied method, mainly in education and maintenance management. AHPSort and GAHPSort are other full aggregation methods applied to services and computer technologies, respectively (Ishizaka et al., 2012; López and Ishizaka, 2017). These approaches have provided mostly theoretical contributions, and they require a lot of effort from managers. Thus, they can only consider a small number of alternatives due to the pair comparisons based on value judgements as in AHPSort or utility functions in UTADIS (Ishizaka and Nemery, 2013). Among the non-classical MCDM methods, the decision rule approach is highlighted more for its theoretical contributions than for solving real problems (Alvarez et al., 2021).

The goal, aspiration or reference-level approaches are based on ideal or reference values for each criterion and then evaluate alternatives according to the proximity to these objective values (Ishizaka and Nemery, 2013). The majority of these methods are focused on TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and DEA (Data Envelopment Analysis), such as DEASort (Ishizaka et al., 2018), TOPSIS-SORT (Sabokbar et al., 2016), DEA-based sorting (Karasakal and Aker, 2017) and AHP–TOPSIS-2N (De Souza et al., 2018). DEA only distinguishes between efficient and non-efficient alternatives. The difficulty of defining ideal alternatives and/or their practical usefulness in problems related to supply chain management represents a weakness of TOPSIS, despite the simplicity of the method.

Almost half of the articles published related to multicriteria sorting rely on outranking approaches, mainly based on the ELECTRE (ÉLimination Et Choix Traduisant la REalité) and PROMETHEE methods. Both algorithms and their extensions for sorting, such as ELECTRE Tri and PROMSORT, among others, represent the non-compensatory multicriteria techniques. In this case, the bad score of an alternative with respect to a criterion cannot be compensated by a good score in other criteria and incomparability between alternatives is possible, which allows their partial and complete ordering. The non-compensatory nature of the outranking approach makes it appropriate for solving many different problems. In fact, these multicriteria families provide more applied work than other approaches (38%), although solving real problems still appears as a need in the research agenda according to some authors (Glock et al., 2017; Alvarez et al., 2021).

The ELECTRE family has been developed more for sorting, where ELECTRE TRI (Roy and Bouyssou, 1993) and ELECTRE Tri-C (Almeida-Dias et al., 2010) are representative. Both methods and their extensions have been applied to categorise suppliers in the automotive industry (Galo et al., 2018), for supplier risk assessment (Govindan and Jepsen, 2016) and supplier sorting in the dairy industry (Silva and Sobral, 2017). Other algorithms are GDM (Group Decision-Making) ELECTRE-sort (Bregar et al., 2008), ELECTRE TRI-NC (Almeida-Dias et al., 2012), ELECTRE-SORT (Ishizaka and Nemery, 2014) and MR-Sort (Majority Rule Sorting) (Sobrie et al., 2019).

The most cited PROMETHEE-based algorithm is PROMSORT, which was developed by Araz and Ozkarahan (2007) for supplier evaluation. This method assigns suppliers to predefined categories according to their positive and negative outranking flows from PROMETHEE I and a parameter defined by a decision-maker is required in order to classify indifferent and incomparable suppliers. De Oliveira e Silva et al. (2016) provide a real application of PROMSORT for supplier selection of motor repair services. No further applications or extensions of this method were found in the literature review.

Nemery and Lamboray (2008) proposed FlowSort, which applies PROMETHEE II to the reference profiles set that defines the ordered groups and one alternative at a time. Each alternative is assigned to a category according to its net flow, which has to be between those from limiting profiles. FlowSort has been applied to supplier evaluation in the food sector (Sepulveda and Derpich, 2015; Segura et al., 2020) and the metal-mechanic industry (Sepulveda et al., 2010). FlowSort requires less effort in its application than other outranking approaches, such as ELECTRE Tri, which uses veto thresholds (Ishizaka and Nemery, 2013). Other methods of this outranking family are β-PROMETHEE (Silva and De Almeida-Filho, 2018) and an extension of PROMETHEE for sorting focused on pair comparisons of alternatives and ideal alternatives of each class (Doumpos and Zopounidis, 2004).

Multicriteria sorting applications are mainly concentrated on education, project evaluation, risk assessment and financial management (Alvarez et al., 2021). Proposals from the full aggregation approach (Ishizaka et al., 2012; López and Ishizaka, 2017) and non-classical MCDM approaches (Lima et al., 2013) provide results to distinguish between qualified and not qualified suppliers. However, they do not allow the generation of classes for supplier management. The evaluation of suppliers in recent years has had a growing sustainable approach considering environmental, economic and social issues (Guo et al., 2016; Zhang et al., 2020). Some recent applications of supplier sorting considering sustainable aspects and based on multicriteria methods are the banking sector (Barrera et al., 2022), chemical industry (Rezaei et al., 2022), food industry (Segura et al., 2020), manufacturing industry (Xu et al., 2019) and auto parts industry (Costa et al., 2018). There are also other applications in the supply chain such as customer segmentation in the food industry (Casas-Rosal et al., 2023) and the location of data centres (Covas et al., 2013).

Outranking methods for sorting appear in a higher number of articles applied to supplier evaluation. Nevertheless, when the novel methods are published, they are not validated by real data (i.e., PROMSORT, FlowSort and Interval-FlowSort). In addition, their later applications to real case studies include small numbers of suppliers, seven or less (Sepulveda and Derpich, 2015; Segura et al., 2020). This is another gap found in the literature review, to be covered when the segmentation involves greater numbers of suppliers (i.e., Segura and Maroto, 2017).

The parameter definition required in multicriteria approaches involves considerable cognitive effort. The decision-maker should define the number of groups and the limiting profiles to apply multicriteria sorting method. In addition, PROMETHEE-based methods need the criteria weights and preference functions that require higher cognitive effort than other methods, such as TOPSIS, but lower than ELECTRE and MAUT (Multiple Attribute Utility Theory) (Ishizaka and Nemery, 2013). However, this effort allows obtaining better discriminatory solutions than compensatory methods such as MAUT (Segura and Maroto, 2017; Barrera et al., 2022).

In addition to direct and indirect methods, there is extensive literature on the use of MCDM methods for criterion weighting, such as AHP, ANP (Analytic Network Process) and BWM (Best Worst Method) (Singh and Pant, 2021). In this research, the weights were obtained individually by applying AHP for a group of people in the company's purchasing department and then aggregated by geometric mean. The expert team of the purchasing department defined the most appropriate preference functions and thresholds to be used according to the company's preferences. Good algorithms should generate classifications that are not very sensitive to parameter changes. Thus, previous research carried out sensitivity analysis and method comparison.

In the literature, there are indices to validate the quality of the classifications in clustering. Some classical methods are based on the distances between the centres (Fukuyama and Sugeno, 1989) or on the average dissimilarity of the data that make up the clusters (Rousseeuw, 1987). Other methods, such as Cui et al. (2014), propose an index based on the model 'compactness–separation', and it is not sensitive to the distance between data members and centres of the other. Rosenfeld and De Smet (2020) propose an index for multicriteria clustering based on preference relationships of PROMETHEE. In sorting, the limiting profiles and the number of groups are parameters defined a priori by the decision-maker for which the indices should focus on measuring the quality of the assignments and should not concentrate on evaluating these parameters. However, there is no evidence of the use of multicriteria quality indicators for sorting that focus on the measurement of quality for alternatives assignments.

3. Methodology

3.1. PROMETHEE

The PROMETHEE method builds a preference structure based on pairwise comparisons of the alternatives with respect to their performance in each criterion. Table 1 shows the general evaluation table with suppliers (alternatives) S_i, criteria weights w_j and the reference profiles $(r_1 \ldots r_{k+1})$ that limit the ordered groups for solving the sorting problem with k categories of suppliers.

The preference of supplier S_1, compared to another S_2, is a function of the difference between their evaluations for each criterion that can be maximised or minimised according to company strategy. This preference function takes absolute values between 0 and 1 and provides the mechanism to eliminate the scale effect among criteria measured in different units (Equations 1 to 3).

$$P_j\left(S_1,\ S_2\right) = F_j\left[d_j\left(S_1,\ S_2\right)\right], \tag{1}$$

$$d_j\left(S_1,\ S_2\right) = g_j\left(S_1\right) - g_j\left(S_2\right), \tag{2}$$

$$0 \le P_j\left(S_1,\ S_2\right) \le 1. \tag{3}$$

Table 1
Evaluation table of suppliers and reference profiles of ordered groups

Suppliers and reference profiles	g_1 w_1	g_2 w_2	…	g_j w_j	…	g_k w_k
S_1	$g_1(S_1)$	$g_2(S_1)$	…	$g_j(S_1)$	…	$g_k(S_1)$
S_2	$g_1(S_2)$	$g_2(S_2)$	…	$g_j(S_2)$	…	$g_k(S_2)$
…	…	…	…	…	…	…
S_i	$g_1(S_\mathrm{i})$	$g_2(S_i)$	…	$g_j(S_i)$	…	$g_k(S_i)$
…	…	…	…	…	…	…
S_n	$g_1(S_n)$	$g_2(S_n)$	…	$g_j(S_n)$	…	$g_k(S_n)$
r_1	$g_1(r_1)$	$g_2(r_1)$	…	$g_j(r_1)$	…	$g_k(r_1)$
…	…	…	…	…	…	…
r_{k+1}	$g_1(r_{k+1})$	$g_2(r_{k+1})$	…	$g_j(r_{k+1})$	…	$g_k(r_{k+1})$

There are several types of preference functions that allow the decision-maker to represent the real preferences of the company. In the usual function, the preference is zero when the deviation is less than or equal to zero and the preference value is one otherwise. The performance of some criteria can be represented by linear function with or without indifferent and preference thresholds. The indifferent threshold q is the value of the largest deviation between two suppliers that the decision-maker considers negligible. The preference threshold p is the smallest value of the deviation to be considered sufficient for a strict preference of one supplier to another in a criterion. The degree to which a supplier S_i is preferred over S_h is calculated by the aggregated preference indices as Equations (4)and (5) indicate:

$$\pi\left(S_i, S_h\right)=\sum_{j=1}^{k} Pj\left(S_i, S_h\right) w_j, \tag{4}$$

$$\pi\left(S_h, S_i\right)=\sum_{j=1}^{k} P_j\left(S_h, S_i\right) w_j. \tag{5}$$

The basic concepts used for supplier selection and ranking are positive outranking flow, negative outranking flow and the net flow, as shown in Equations (6) to (8), respectively, where A represents the set of suppliers. Positive and negative outranking flows allow us to generate partial rankings of suppliers (PROMETHEE I), while net flow generates a complete ranking (PROMETHEE II). These concepts are also the base of procedures to classify suppliers and supporting management strategies as shown in the literature review and in the method proposed in this research. See Brans and De Smet (2016) for further details on PROMETHEE.

$$\varphi^{+}\left(S_i\right)=\frac{1}{n-1}\sum_{x\in A}\pi\left(S_i, x\right), \tag{6}$$

$$\varphi^{-}\left(S_i\right)=\frac{1}{n-1}\sum_{x\in A}\pi\left(x, S_i\right), \tag{7}$$

$$\varphi\left(S_i\right)=\varphi^{+}\left(S_i\right)-\varphi^{-}\left(S_i\right). \tag{8}$$

3.2. PROMSORT

PROMSORT is the algorithm proposed by Araz and Ozkarahan (2007) that uses positive and negative outranking flows from applying PROMETHEE I to suppliers and limiting profiles of categories for an initial assignment of suppliers to ordered groups. An alternative is assigned to category C_h when its flow outranks the flow of profile r_{h+1}, but it does not outrank the flow of profile r_h, where $C_h \succ C_{h+1}$. However, incomparable or indifferent alternatives with a category profile cannot be assigned in the previous step, so they are assigned considering the average distances of net flow with the alternatives that were assigned previously. In this second step, the decision-maker needs to indicate a parameter (b) according to optimistic and pessimistic points of view to assign indifferent and incomparable suppliers. For example, when an alternative i is incomparable with the profile r_h that separates category C_h from C_{h+1}, then the net flow is used to measure the outranking character d_k^+ of i over all alternatives that were previously ranked in the lower category C_{h+1} and the outranked character d_k^- of i by all alternatives assigned to C_h. The result of the average d_k^+ minus average d_k^- is compared with parameter b, which is defined by the decision-maker according to his/her optimistic or pessimistic viewpoint; if this difference is greater than the value of parameter b, then the alternative is classified in the higher category C_h; otherwise, it is assigned to the lower category C_{h+1}. More details can be found in Araz and Ozkarahan (2007).

3.3. Quality index

Rosenfeld and De Smet (2020) proposed a quality index (Equation 9) that measures the quality of clusters generated by different multicriteria clustering approaches. This index considers the homogeneity among alternatives within a class and the heterogeneity among alternatives from different classes, based on the PROMETHEE preference indices. Heterogeneity is the result from the calculation of $|\delta\ (h,\ h+1)$ which is equal to the difference between the preferences of $\pi\ (\bar{y}_h, \bar{y}_{h+1}) - \pi\ (\bar{y}_{h+1}, \bar{y}_h)$ when $h < h+1$ considering that $C_h \succ C_{h+1}$. The values of $\bar{y}_h$ and $\bar{y}_{h+1}$ are the mean values of the alternatives in groups h and $h+1$ for each criterion, respectively. Instead, the homogeneity Δh of a class C_h is calculated by summing the preferences between each pair of alternatives in the class $\sum_{i,\ j\in C_h} \pi\ (i,\ j)$ and dividing the value by the total number of comparisons made in C_h. Thus, the higher the heterogeneity (numerator) and the lower the homogeneity (denominator), the higher the value the quality index will have, which indicates a better quality of the clusters generated by an approach.

$$D = \frac{\sum_{h=1}^{k-1} \delta\ (h, h+1)}{\sum_{h=1}^{k} \Delta \mathrm{h}}. \tag{9}$$

4. New multicriteria sorting method for supplier segmentation

4.1. Sorting algorithm based on global and local search of net flows (GLNF)

The method proposed to solve the multicriteria sorting problem is based on a theoretical property of the net flow of alternatives obtained by PROMETHEE and on combining global and local search

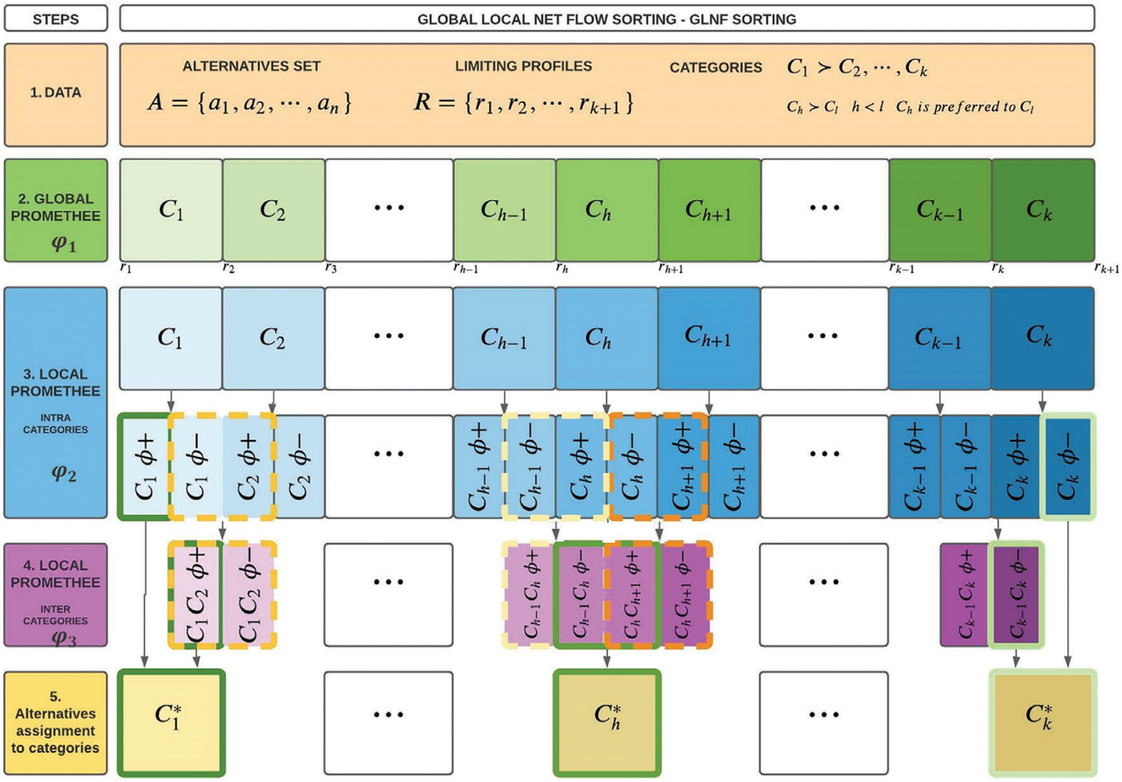

Fig. 1. Multicriteria sorting algorithm based on global and local search of net flows (GLNF).

approaches used to solve optimisation problems. Rosenfeld and De Smet (2020) proved that the set of alternatives with the positive net flow is strongly preferred to the rest. In other words, the set of alternatives with positive net flow maximises the global preference over the others, which have the negative net flow, and minimises the global preference of the latter with respect to the ones with the positive net flow.

Figure 1 shows the steps of the new algorithm. The algorithm is based on the PROMETHEE method, specifically on the properties of the net flows obtained from the initial global search (φ_1), as well as the net flows from the following two local searches, in particular, the net flows from the intra-category search (φ_2) and the inter-category search (φ_3). First, the evaluation table, which includes the set of alternatives (suppliers) and limiting profiles to identify categories, provides the initial data. The categories are ordered from C_1 as the most preferred to C_k, the least preferred. Second, PROMETHEE is applied to all alternatives and limiting profiles. This step provides an initial classification of suppliers according to net flow (φ_1) obtained from the global search, and Fig. 1 shows it in green. Alternatives assigned to the C_h category are those with scores between the values of net flows of profile r_h and r_{h+1}. If a category does not have any alternatives, it is not considered in the following steps. The algorithm does not necessarily require the maximum (r_1) and minimum (r_{k+1}) profiles.

The third step consists of applying local PROMETHEE to alternatives within each category, including their limiting profiles. This step represents a local calculation of net flows of alternatives at the intra-categories level (φ_2), which Fig. 1 shows in blue. Then, according to the results obtained (φ_2), alternatives are divided into two groups, one with the positive net flow and another with the negative net flow.

By applying the property of net flows, the fourth step of the sorting algorithm carries out the second local search by PROMETHEE in the new sets generated by partially merging alternatives from two adjacent groups with different signs of net flow obtained in step three as illustrated in Fig. 1 (inter-category search). For example, alternatives with the negative net flow from the most preferred category (C_{h-1}) and alternatives with the positive net flow from the adjacent least preferred (C_h). The values of net flows obtained from this second search (inter-category search) are named φ_3 that are divided into two new groups according to the positive and negative net flow, represented in violet in Fig. 1.

The final assignment of alternatives (suppliers) to categories is shown in Fig. 1. In general, category C_h^* is obtained after applying local PROMETHEE to two adjacent categories by merging the worst alternatives of the preferred group with the best of the following category. That is, according to negative and positive φ_3 values. That is, C_{h-1} and C_h as well as C_h and C_{h+1}. The alternatives in C_h^* come from those with a negative net flow of the merging set C_{h-1} and C_h and those with a positive net flow of the merging set of C_h and C_{h+1} as calculated in the fourth step of the sorting algorithm (φ_3). Finally, the most preferred category C_1^* includes the alternatives with positive net flow of C_1 based on the first local search (φ_2) and those with positive net flow resulting from merging C_1 and C_2 in the second local search (φ_3). Similarly, the worst category C_k^* is generated by merging the alternatives with negative net flow (φ_2) of the least preferred category C_k in the first local search with the negative net flow from the second local search (φ_3), as Fig. 1 shows.

The global search allows ranking all alternatives into categories defined by limiting profiles of the decision problem. Thus, the algorithm clearly distinguishes the most preferred alternatives from the least preferred ones. However, in real decision-making problems such as supplier segmentation, there are alternatives with net flows very close to the net flow of limiting profiles between two adjacent categories. In this case, these alternatives may be assigned to the most preferred or the least preferred group. This situation represents a very important problem for managers. For example, some suppliers can be considered excellent and be candidates to be partners of the company, or they can be considered good/acceptable for purchasing only if necessary, the supplier is accepted or rejected and so forth.

Local intra- and inter-category searches provide relevant information by comparing only alternatives with similar overall performance, which is essential in the practice of supplier management, as well as for the algorithm to be included in DSS for managers. The underlying idea is to compare the alternatives to those with similar performance locally in order to improve the quality of supplier assignments.

4.2. Quality index based on an extension of silhouette for PROMETHEE sorting

The clustering problem differs from the multicriteria classification problem in which clusters are unknown a priori, whereas classes or groups are predefined in nominal or ordinal ways (sorting problem). Using data mining terminology, cluster analysis is an unsupervised method, which does not consider preferences, and distances between objects are represented by symmetric matrices. On the contrary, multicriteria classification of a set of alternatives relies on a supervised method and preferences between alternatives provide non-symmetric matrices. Nevertheless, some concepts from data mining can be extended to be applied in sorting procedures.

Rousseeuw (1987) introduced a graphical method based on the silhouette concept to analyse and interpret the quality of clusters generated by any method from data mining. First, it computes $a(i)$, which is the average dissimilarity for each object i to all other objects of the same cluster C_h. Second, it computes the average dissimilarity for each object i to all other objects of the cluster $C_m (C_m \neq C_h)$ for all clusters. Then, it defines $b(i)$ as the minimum of all these latter dissimilarities, which is called the neighbour of cluster C_h. Finally, Rousseeuw (1987) defines the silhouette (SIL) of an object i as follows:

$$SIL(i) = \frac{b(i) - a(i)}{\max\left(a(i),\ b(i)\right)}\ , \tag{10}$$

where

$$a(i) = \frac{1}{|C_h| - 1} \sum_{\mathrm{j} \in C_h, i \neq j} d\,(i, j)\,; \tag{11}$$

$$b(i) = \min_{\mathrm{m} \neq \mathrm{h}} \frac{1}{|C_m|} \sum_{\mathrm{j} \in C_m} d\,(i, j)\,. \tag{12}$$

From Equation (10), the silhouette value of an object i is between -1 and 1.

$$-1 \leq SIL(i) \leq 1. \tag{13}$$

If $SIL(i)$ is close to 1, it is because $b(i)$ is much higher than $a(i)$. In this case, the object i is assigned to an appropriate cluster. In contrast, if the silhouette is close to -1, it indicates dissimilarity of $b(i)$ is much smaller than $a(i)$, which shows object i would be better classified in the neighbour cluster. If $SIL(i)$ is about 0, it means the object i is an intermediate case and the cluster to be assigned is unclear. The silhouette is set to 0 in clusters with one object as Equation (10) indicates (Rousseeuw, 1987).

In this section, a new quality index for sorting is proposed based on net flows of the alternatives, inspired by the silhouette developed for cluster analysis. This silhouette for sorting (SILS) allows measuring the quality of ordered groups from PROMETHEE sorting methods.

The net flows of alternatives (suppliers) are obtained by applying PROMETHEE. Therefore, the values to measure their performance are between -1 and 1. Then, $u(i)$, which measures the dissimilarity of alternative i with respect to others within the same category, is computed. In sorting problems, it only requires the calculation of dissimilarity of alternative i concerning two adjacent categories: the higher $h(i)$ and the lower $l(i)$.

The distances to compute $u(i)$ are based on net flows of the alternatives and measured in absolute terms, as differences between net flows of alternatives of the same category can be positive or negative. Calculations also include the distance from i to the category centroid to evaluate the dissimilarity in classes with one alternative. Since $u(i)$, $h(i)$ and $l(i)$ represent average dissimilarities, centroids provide an important reference in classes without alternatives or few of them as appear in real contexts. The centroid E_h of category C_h is defined in Equation (14).

$$E_h = \frac{\varphi r_h + \varphi r_{h+1}}{2}, \tag{14}$$

where φr_h is the net flow of the higher limiting profile of the category C_h and φr_{h+1} the lower limiting profile of the category C_h. When the highest r_1 and the lowest r_{k+1}limiting profiles are not defined, maximum and minimum values of net flows, one and minus one, respectively, are used in calculations. The equations to compute dissimilarities are as follows:

$$u(i) = \frac{\left(\sum_{j \in C_h} |\varphi(i) - \varphi(j)|\right) + |\varphi(i) - \varphi(E_h)|}{n_h}, \tag{15}$$

$$h(i) = \frac{\left(\sum_{j \in C_{h-1}} (\varphi(j) - \varphi(i))\right) + (\varphi(E_{h-1}) - \varphi(i))}{n_{h-1} + 1}, \tag{16}$$

$$l(i) = \frac{\left(\sum_{j \in C_{h+1}} (\varphi(i) - \varphi(j))\right) + (\varphi(i) - \varphi(E_{h+1}))}{n_{h+1} + 1}. \tag{17}$$

After defining the average dissimilarities, silhouettes are computed with reference to the lower $SIL_l(i)$ and higher $SIL_h(i)$ categories. The silhouette value indicates if an alternative is well-classified in its current class or whether it would be better to assign it to a neighbour category.

Both silhouettes $SIL_l(i)$ and $SIL_h(i)$ can be equal to 1 when $u(i) = 0$ (alternative i is assigned perfectly to the current group). Nevertheless, it is not possible that both $SIL_l(i)$ and $SIL_h(i)$ have value -1 because $l(i)$ and $h(i)$ should be equal to 0. Equations for both silhouettes are as follows:

$$SIL_l(i) = \frac{l(i) - u(i)}{\max(l(i), u(i))}, \tag{18}$$

$$SIL_h(i) = \frac{h(i) - u(i)}{\max(h(i), u(i))}. \tag{19}$$

Silhouette for Sorting $SILS(i)$ is defined as the difference between silhouettes with reference to the lower $SIL_l(i)$ and higher $SIL_h(i)$ categories.

$$SILS(i) = SIL_l(i) - SIL_h(i), \tag{20}$$

$$SILS(i) = \frac{l(i) - u(i)}{\max(l(i), u(i))} - \frac{h(i) - u(i)}{\max(h(i), u(i))}. \tag{21}$$

Fig. 2. Graphical scale of the silhouette for sorting (SILS).

It can be written as

$$SILS(i) = \begin{cases} \left(\frac{l(i)}{u(i)} + \frac{u(i)}{h(i)}\right) - 2, & \text{if } u(i) > l(i)\Lambda u(i) < h(i) \\ 0, & \text{if } u(i) = 0 \\ 2 - \left(\frac{u(i)}{l(i)} + \frac{h(i)}{u(i)}\right), & \text{if } u(i)\,\langle l(i)\Lambda u(i)\rangle\, h(i). \end{cases}$$

Therefore,

$$-2 < SILS(i) < 2. \tag{22}$$

If $SILS(i)$ has a value close to -2 or 2, alternative i would be better assigned to one of the neighbour categories. For example, if $SILS(i)$ is close to -2, $SIL_l(i)$ is near -1 and $SIL_h(i)$ is near 1. This satisfies $l(i) \ll u(i) \ll h(i)$ and indicates that alternative i would be better assigned to the lower class because its dissimilarity is smaller than from the current category. It is also smaller than the dissimilarity of the higher class as in sorting problem the groups are ordered.

In case $SILS(i)$ is close to 0, alternative i is well-classified in its current group, satisfying $l(i) \gg u(i) \ll h(i)$.

When $l(i) \gg u(i) \gg h(i)$, then $SIL_l(i)$ is near 1, $SIL_h(i)$ is near -1 and $SILS(i)$ is close to 2. This shows a better assignment of i to a higher category than the current one.

Figure 2 shows a graphical scale of SILS, which facilitates the interpretation of this quality indicator for categories generated by a sorting PROMETHEE-based. In short, when the absolute value of $SILS(i)$ is equal or close to 1, the alternative is next to a profile. Nevertheless, when it is higher than 1, the alternative i should be reassigned to a neighbour category according to the scale of Fig. 2.

A variation in the dissimilarity formulas $l(i)$ and $h(i)$ has been considered in the SILS calculation of the extreme groups. For example, if alternative i is in the highest category, C_h can only be compared to alternatives within the same group and to alternatives of the lower group C_{h+1} ($C_h \succ C_{h+1}$). In this case, a very large value is assigned to $h(i)$, for example, 100, due to its dissimilarity should not be preferable as it would represent a class that does not exist.

Similarly, if alternative i is within the lowest category C_k, $l(i)$ value has to represent a large dissimilarity. For example, there are three ordered groups ($C_1 \succ C_2 \succ C_3$) with alternative i assigned to C_3. Then, it is required calculations of $h(i)$ with reference to C_2 and $u(i)$ concerning C_3, while 100 is the value of $l(i)$ because there is no C_4 in order to avoid negative values for silhouette $SILS(i)$.

Finally, the SILS average of each category of suppliers and the average of $|SILS(i)|$ for all alternatives provide relevant information. The average values close to 0 are preferable, as they indicate homogeneous classification, while values far from 0 reveal that perhaps some alternatives may be misclassified.

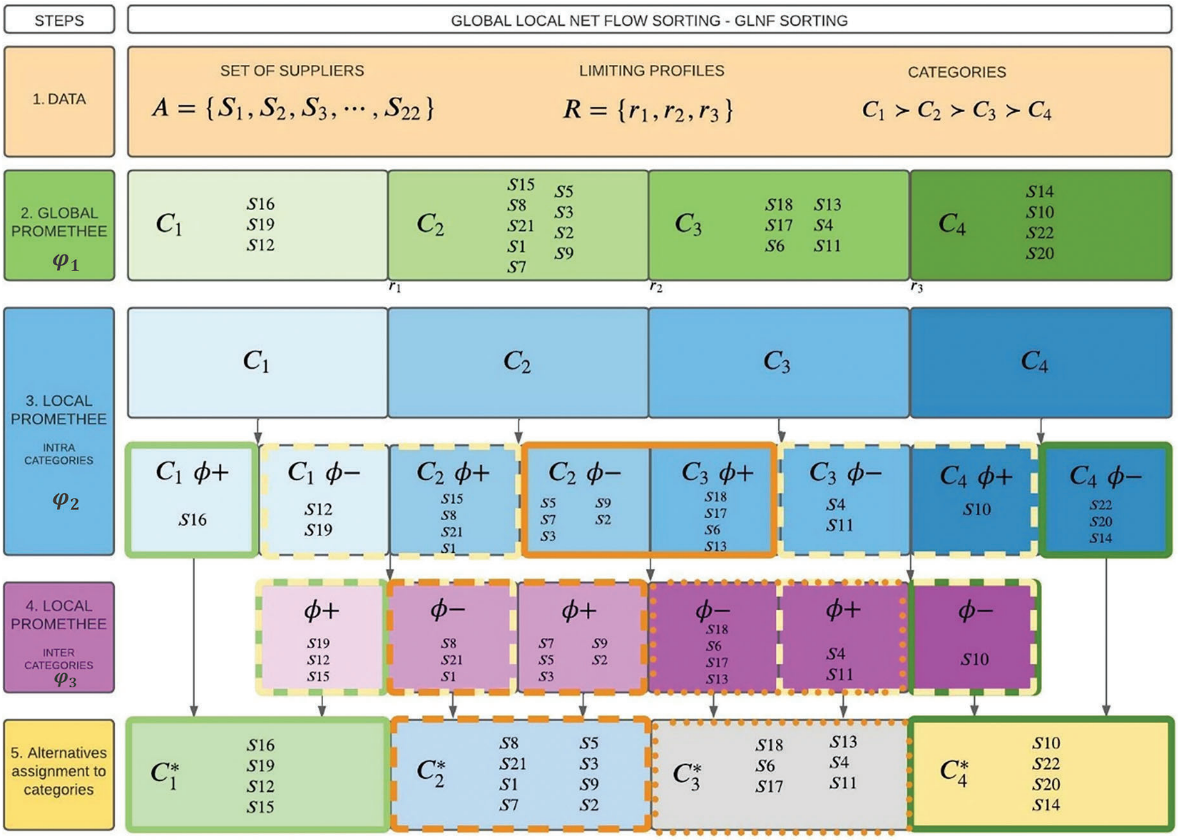

Fig. 3. Results of the GLNF algorithm steps applied to the supplier evaluation example from Araz and Ozkarahan (2007).

5. Results

This section presents the results of comparing the new algorithm GLNF with PROMSORT. First, both techniques are applied to the hypothetical example of sorting suppliers of PROMSORT authors (Araz and Ozkarahan, 2007). Second, PROMSORT and GLNF algorithms are also compared by real data from supplier evaluation in an industry context.

5.1. Evaluation of the GLNF algorithm by synthetic data

Figure 3 shows the results of the GLNF algorithm steps applied to hypothetical data of the supplier evaluation from the PROMSORT article, which includes 22 suppliers $A = \{S1, S2, \ldots, S22\}$. The first step is to establish the number of categories and their limiting profiles. In this case, Araz and Ozkarahan (2007) considered four categories $C_1 \succ C_2 \succ C_3 \succ C_4$ separated by three limiting profiles. $R = \{r_1, r_2, r_3\}$. As in Fig. 1, in Fig. 3, the five steps of the algorithm are identified with a

Table 2
Supplier assignments obtained by global and local search of net flows (GLNF) sorting and PROMSORT algorithms applied to the example from Araz and Ozkarahan (2007)

Categories	GLNF sorting	PROMSORT Optimistic ($b = 0$)	PROMSORT Pessimistic ($b = 1$)
C_1	{S12, S15, S16, S19}	{S12, S15, S16, S19}	{S12, S16, S19}
C_2	{S1, S2, S3, S5, S7, S8, S9, S21}	{S1, S2, S3, S5, S7, S8, S21}	{S1, S5, S7, S8, S15, S21}
C_3	{S4, S6, S11, S13, S17, S18}	{S4, S6, S9, S11, S13, S17, S18}	{S2, S3, S4, S6, S9, S11, S13, S17, S18}
C_4	{S10, S14, S20, S22}	{S10, S14, S20, S22}	{S10, S14, S20, S22}

different colour and the arrows represent the movement of suppliers in the categories for each step. The C^* represent the final sorting for the categories.

The second step consists of applying PROMETHEE to the supplier set A that is referred to as global PROMETHEE. The results allow the classification of all suppliers to one of the four categories, according to the supplier and limiting profiles net flow value (φ_1). For example, the best class C_1 is made up of S16, S19 and S12, and these suppliers have a higher net flow than r_1. In the following step, PROMETHEE is only applied to suppliers from each category and their limiting profiles, so it can be considered a local search in order to evaluate the supplier performance inside their class. This intra-category application of PROMETHEE divides C_1 into two groups of alternatives, those with positive net flow φ_2 (S16) and those with negative net flow φ_2 (S19 and S12).

S16 is definitively assigned to category C_1^*, and suppliers S19 and S12 go to a second local search that includes the suppliers with negative net flow from C_1 and the best ones from C_2, which are those with the positive net flow. For example, in this case, suppliers S19, S12 and S15 have positive net flow (φ_3) in this second local search, so they are assigned to C_1^*, while S8, S21 and S1, with negative net flow (φ_3) are assigned to C_2^*. Figure 3 shows the results of this second local search combining two consecutive categories, as well as the final allocation of suppliers to the four classes considered.

Table 2 indicates the classification obtained with the GLNF sorting, optimistic PROMSORT ($b = 0$) and pessimistic PROMSORT ($b = 1$) methods. The PROMSORT results belong to those published by Araz and Ozkarahan (2007), taking into account that in this work, the order of the categories is as follows: $C_1 \succ C_2 \succ C_3 \succ C_4$, while these authors considered C_4 as the best group.

According to the results of Araz and Ozkarahan (2007), the unstable suppliers for having incomparable or indifferent outranking relations with some limit profile are: S2, S3, S9 and S15. When the results of the classifications generated with GLNF and optimistic PROMSORT were compared, they showed that the only difference is S9, which GLNF classifies into C_2 instead of C_3. On the other hand, there are several differences between the GLNF classification and the pessimistic PROMSORT. While GLNF classifies S2, S3 and S9 in C_2 and S15 into C_1, with pessimistic PROMSORT, the assignments are to C_3 and C_2 respectively.

The results of the SILS index calculation for the classification obtained with the GLNF and PROMSORT method are in Table A1 in Appendix A. Figure 4 is a bar chart of the SILS index for the classification obtained with GLNF. The class assignment is identified by colours, where the abscissa is the SILS values indicated on the scale in Fig. 2. The results show a $|SILS| < 1$ for all providers. Therefore, it is evident that all suppliers are well classified. At the category level, it is observed that suppliers classified in C_1 and C_4 present more homogeneous silhouettes with

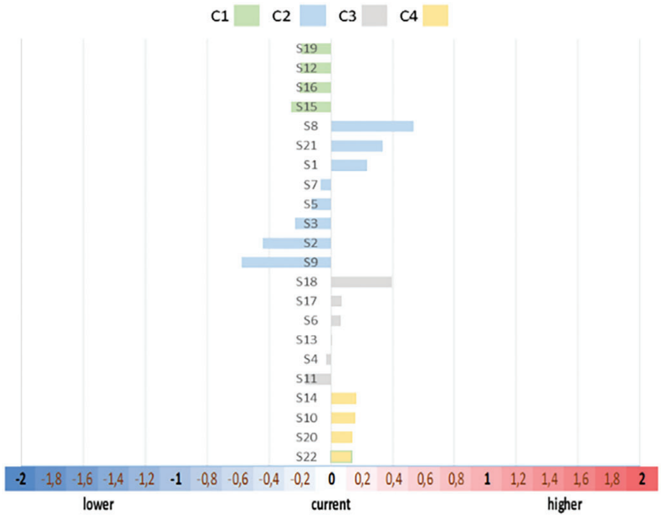

Fig. 4. SILS applied to assignments by GLNF sorting for set of suppliers of Araz and Ozkarahan (2007).

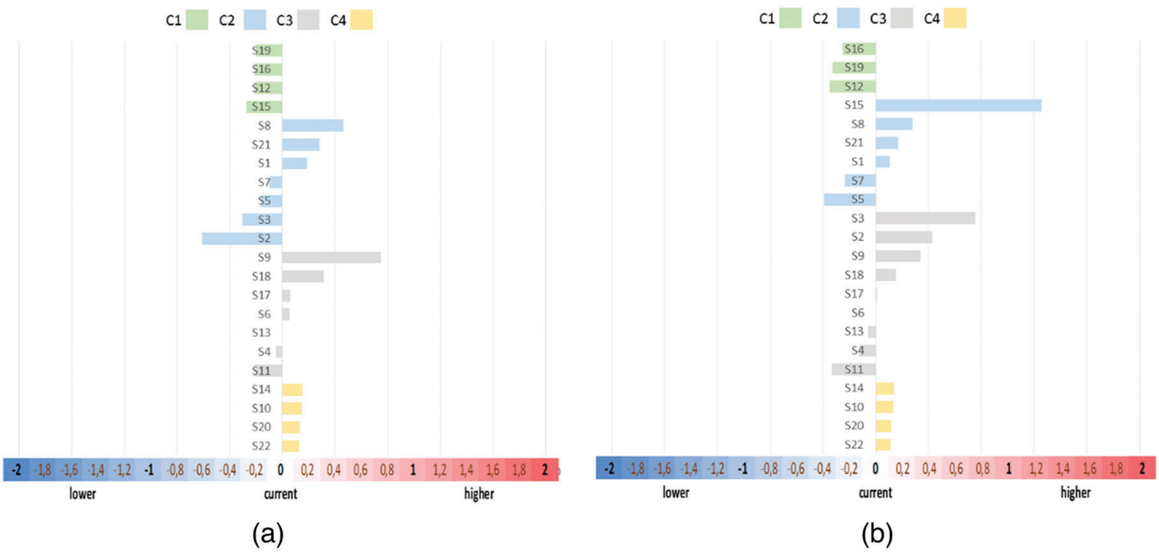

Fig. 5. SILS applied PROMSORT. (a) PROMSORT optimistic ($b = 0$) and (b) PROMSORT pessimistic ($b = 1$).

values close to zero. On the other hand, in C_2 there is a greater dispersion of silhouettes where S9 has the lowest index (-0.577) and S8 has the highest (0.536), which indicates that they may share some preferences with suppliers in the lower and higher categories, respectively. Finally, the average absolute SILS value for this classification is 0.215. Although the SILS values are not zero, these values are close and within acceptable ranges.

Figure 5 shows the graphical results of applying SILS to the optimistic ($b = 0$) and pessimistic ($b = 1$) classifications obtained with PROMSORT. Figure 5a highlights that by applying optimistic

Table 3
Rosenfeld and De Smet's (2020) quality index applied to the classification obtained in Table 2

	Class	GLNF sorting	PROMSORT ($b = 0$)	PROMSORT ($b = 1$)
Homogeneity	C_1	0.09	0.09	0.10
	C_2	0.31	0.29	0.27
	C_3	0.36	0.35	0.34
	C_4	0.31	0.31	0.31
	Total	1.08	1.05	1.01
	Average	0.27	0.26	0.25
Heterogeneity		5.04	4.85	4.92
Quality Index		4.68	4.63	4.85

PROMSORT, the suppliers have an $|SILS| < 1$, so the classifications generated are acceptable. The supplier with the lowest SILS index is S2 (−0.610) and the highest is S9 (0.749). The average absolute SILS value is 0.228 for optimistic PROMSORT. The pessimistic PROMSORT results are in Fig. 5b, and they show a lower-quality assignment. The SILS obtained for S15 is 1.260, a positive value far enough away from zero to suggest a reclassification to the higher class C_1. In contrast, there are no relevant negative values, and S5 is the lowest with an SILS of −0.390. The average absolute SILS value for this method is 0.276.

Even though both classifications obtained with GLNF and optimistic PROMSORT are acceptable, it is noted that the divergence between these methods originates from the assignment of S9. This is due to the closeness of S9 to the edge separating C_2 and C_3. However, GLNF yields a lower absolute SILS value than that obtained with optimistic PROMSORT. Therefore, it can be stated that S9 is slightly better classified in C_3. An example of how the assignment of one alternative negatively affects others can be seen in the SILS of S9 and S2 with optimistic PROMSORT, where the SILS of S2 decreases and that of S9 increases, as they are not in the same class, in contrast to what happens with GLNF.

When comparing the SILS values obtained with the pessimistic PROMSORT and GLNF classifications, a disadvantage for PROMSORT is observed for supplier S15. By classifying S15 in C_2, there is a decrease in the SILS of the providers that were classified into C_1 and an increase in S15, whereas if this provider is in C_1 all the SILS of this class, such as GLNF, decrease. On the other hand, although S2 is classified differently in both methods, the absolute value of SILS does not differ much because S2 seems to be close to the edge separating C_2 from C_3.

Table 3 shows the values of the quality index proposed by Rosenfeld and De Smet (2020). Category C_1 is the most homogeneous in all methods, followed by C_2, C_4 and C_3. In general, there is no relevant difference between the heterogeneity and homogeneity of the classifications made with GLNF and PROMSORT.

5.2. Evaluation of the GLNF algorithm by real data from a manufacturing company

The proposed method has also been evaluated with real data from a multinational manufacturing company that makes products for the pharmaceutical and food sectors, among others. These data

Table 4
GLNF sorting and PROMSORT assignments applied to real data from a manufacturing industry

Class	GLNF sorting	PROMSORT Optimistic ($b = 0$)	PROMSORT Pessimistic ($b = 1$)
C_1	{S7, S11, S17, S18, S20}		
C_2	{S1, S3, S8, S12, S13, S14}	{S1, S3, S4, S12, S13, S14, S16, S20}	{S1, S3, S4, S12, S13, S14, S16, S20}
C_3	{S4, S5, S6, S10, S16,}	{S5, S6, S8, S10, S15}	{S5, S6, S8, S10, S15}
C_4	{S2, S9, S15, S19}	{S2, S9, S19}	{S2, S9, S19}
Unclassified		{S7, S11, S17, S18}	{S7, S11, S17, S18}

were previously used in a hybrid multicriteria model proposed in Segura and Maroto (2017) to segment 67 suppliers into four groups according to their critical and/or strategic nature. The evaluation explained in this section has applied a stratified sample of 20 suppliers randomly selected for each of the four groups obtained in Segura and Maroto (2017). They are classified into four groups, where $C_n \succ C_{n+1}$, divided by five profiles ($r_1, \ldots, r_5$). The criteria weights were obtained individually by applying AHP for a group of people in the company's purchasing department and then aggregated by geometric mean. Similarly, the preference functions were defined according to the assessment of the procurement experts. Details on the criteria weights and preference functions can be found in Appendix B, Table B1.

Table 4 includes the results of the classifications generated by the GLNF sorting and PROMSORT algorithms. The classifications obtained as a result of applying optimistic ($b = 0$) and pessimistic ($b = 1$) PROMSORT are equal. The PROMSORT results indicate that the unstable providers for having incomparable or indifferent outranking relations with some limit profile are: S2, S7, S8, S9, S11, S17 and S18. Of the above, it is not possible to classify providers S7, S11, S17 and S18, as there are no alternatives assigned to category C_1 with which the outranked character distance (d_k^-) can be measured.

Figure 6 shows that the SILS calculated with GLNF sorting are acceptable with the exception of provider S15, which has a value of 1.789. Therefore, this provider could be better allocated in the upper group C_3. Additionally, the SILS value of -1.090 for provider S8 suggests that it is almost at the edge of the profile bounding C_2 and C_3, which is an unstable provider. The graphical representation of SILS for PROMSORT is not included, as not having four sorted suppliers the values of this index would not be comparable with those of GLNF sorting, which classifies all suppliers. However, the quality index SILS values for both methods can be found in Table A2 in Appendix A.

Table 5 reveals that the quality index proposed by Rosenfeld and De Smet (2020) is higher when applying GLNF (3.22) than PROMSORT (2.37). With GLNF sorting, the suppliers that make up classes C_2 and C_3 are more homogeneous than with PROMSORT. The sum of homogeneity is lower in PROMSORT, but it has to be considered that PROMSORT does not have suppliers classified in C_1. However, the average homogeneity is lower in GLNF. Finally, applying GLNF the heterogeneity of the classes is higher, which indicates that the method has higher quality.

The GLNF sorting method applies global and local searches based on PROMETHEE. Therefore, a sensitivity analysis is necessary to assess the influence of the variation of the preference function parameters on the supplier classifications generated. The more stable the

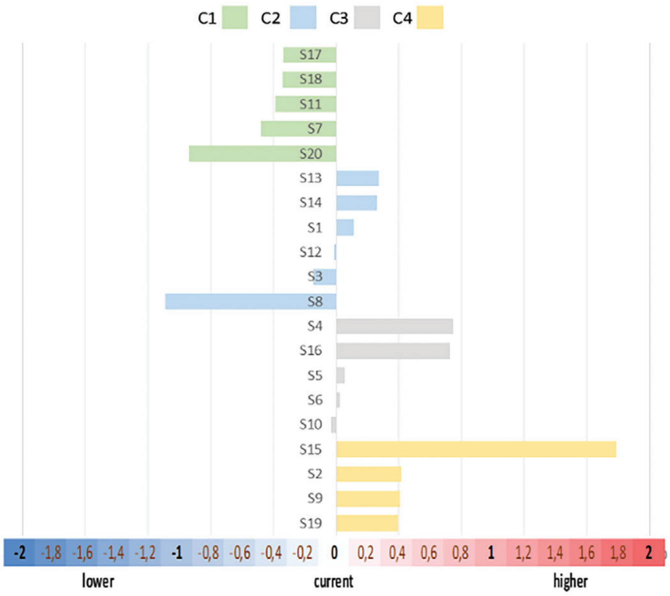

Fig. 6. SILS applied to assignments by GLNF sorting for real data of supplier evaluation.

Table 5
Rosenfeld and De Smet's (2020) quality index applied to the classification obtained in Table 4

	Class	GLNF sorting	PROMSORT ($b = 0$; $b = 1$)
Homogeneity	C_1	0.09	No classifications
	C_2	0.16	0.23
	C_3	0.26	0.31
	C_4	0.24	0.15
	Total	0.76	0.69
	Average	0.19	0.23
Heterogeneity		2.44	1.64
Quality Index		3.22	2.37

classifications obtained with multicriteria methods in real contexts, the more robust the methods will be.

Table 6 shows the results of varying the parameters defined in the preference functions. The values of these parameters have been increased and decreased by 50%, 30% and 10%, compared to those used in the initial solution. Table 6 indicates the variations and supplier movements for GLNF sorting and PROMSORT. The GLNF method is not very sensitive to parameter variation, as only a 50% increase in parameters generates a movement of S15 towards C_3. The other providers remain in the same ordered groups as in the initial solution. On the contrary, PROMSORT is sensitive to parameter values, as all negative variations generate group changes in the suppliers, the most remarkable is the impossibility of classifying 18 suppliers when the parameter value decreases by 50%.

Table 6
Sensitivity analysis

Parameter variation	GLNF sorting	PROMSORT optimistic ($b = 0$)	PROMSORT pessimistic ($b = 1$)
−50%	No changes	Unclassified→S1, S2, S3, S4, S5, S6, S7, S8, S9, S11, S12, S13, S14, S16, S17, S18, S19, S20	Unclassified→S1, S2, S3, S4, S5, S6, S7, S8, S9, S11, S12, S13, S14, S16, S17, S18, S19, S20
−30%	No changes	Unclassified→S13, S14, S20	Unclassified→S13, S14, S20; C3→S12, S16
−10%	No changes	C3→S4, S16	C3→S4, S16
+10%	No changes	No changes	No changes
+30%	No changes	No changes	No changes
+50%	C3→S15	No changes	No changes

6. Discussion

The method proposed based on the GLNF sorting algorithm provides several strengths and advantages when it is compared to PROMSORT. First, GLNF sorting discriminates more between groups of suppliers, as it involves global and local inter- and intra-category comparisons based on PROMETHEE II. This greater discriminating power is founded on a theoretical property of the net flow proved by Rosenfeld and De Smet (2020), which allows an easy interpretation of results and therefore its application in practice by managers. The PROMSORT algorithm, based on PROMETHEE I, requires an additional parameter to be defined by the decision-maker in order to assign all incomparable and indifferent alternatives with the limiting profiles of the groups of suppliers. Thus, an additional step to define optimistic and pessimistic values is needed in order to know how this parameter affects supplier assignments.

Second, GLNF sorting ensures that all alternatives are classified, while PROMSORT may leave some of them without assignment to any class and thus being unclassified. When two categories C_{h-1} and C_h are limited by a profile r_h, which is incomparable or indifferent to some alternatives, PROMSORT requires that both groups have at least one alternative assigned. Otherwise, it is not possible to measure the distance of the unassigned alternatives with respect to categories C_{h-1} and C_h. Likewise, the quality of supplier assignments can be affected negatively. This represents an important weakness of PROMSORT when there are many incomparable alternatives with the limiting profiles as in real problems of supplier evaluation illustrated in this research.

Third, the performance of GLNF sorting also presents an advantage according to the quality of the groups of alternatives generated. The quality has been evaluated by an index from multicriteria clustering literature, as well as by a new indicator for silhouette sorting SILS. When comparing both quality indicators, the advantages of SILS focus on its scale and graphical representation. On the one hand, SILS facilitates result interpretation and enables decision-makers to identify those suppliers that should be reclassified or analysed in detail. On the other hand, it allows a group interpretation by averaging the absolute SILS values of the alternatives, with values close to zero being an indicator of compactness for the group.

The quality index of Rosenfeld and De Smet (2020) has advantages related to homogeneity and heterogeneity, as it measures these characteristics specifically to be aggregated into a single index to measure the classification quality. However, this index does not allow the identification of alternatives assigned wrongly and lacks scale for an appropriate interpretation of their values. Therefore, in order to know how good or bad a quality index is, a comparison with other quality indices from other clustering scenarios is required.

According to both quality indicators, the GLNF sorting method can achieve equal or better supplier assignments than those obtained with PROMSORT. For the hypothetical data of Araz and Ozkarahan (2007), GLNF provides a classification with better values of SILS and a similar quality index to that of the one generated by PROMSORT. For this case study, differences between both algorithms are related to unstable suppliers. In the real case study of the manufacturing company, the GLNF sorting method overcomes PROMSORT because it has a better quality index and allows the classification of all suppliers.

Fourth, the sensitivity analysis carried out using real data on supplier evaluation shows that GLNF sorting is a robust algorithm, as modifications in the parameters of preference functions do not affect the results obtained significantly. The robustness of the proposed sorting method is a relevant contribution to multicriteria research, as well as to supplier segmentation for supply chain management (Alvarez et al., 2021). The reason for obtaining more stable classifications lies in global and local searches, which require sign changes in the net flow of suppliers in local comparisons. The PROMSORT performance is more unstable, which can be an important problem when the exact values of parameters are unknown. In addition, the parameter modifications can increase the number of incomparable and indifferent alternatives, making it impossible to assign them to any group, as is the case in Table 6 for the -50% variation.

On the one hand, GLNF could present a disadvantage when some alternatives are too optimistic or too pessimistic to be assigned to the best and worst classes of $C_1$and C_k, respectively. This situation may arise because in the local search, the alternatives of these categories are only compared with another category (C_1 with C_2 and C_k with C_{k-1}). On the other hand, this is not a management problem in practice, as the decision-maker's objective is to discriminate between suppliers from adjacent categories. Moreover, the SILS index helps improve decisions with respect to those alternatives.

Another disadvantage is that the proposed method does not consider the calculation of the weights of the criteria, therefore the decision-maker should previously use another method to obtain these values. However, in the literature, there is a wide range of objective, subjective and hybrid methods.

7. Conclusion

This research provides a robust multicriteria sorting method for supplier segmentation into ordered categories and also proposes an indicator to measure the classification quality, both contributions being very useful to the supply chain management in practice. The multicriteria sorting algorithm is referred to as GLNF sorting, as it is based on global and local searches of the net flow, the main concept of the PROMETHEE II method. GLNF sorting exploits the discriminant power of PROMETHEE II to classify suppliers into ordered classes by an initial global search, followed by intra- and inter-category local searches. The algorithm is easy to apply, and the decision-maker only needs to specify the PROMETHEE parameters (weights of criteria and preference functions), as well as the limiting profiles of categories or groups of suppliers according to company needs and objectives.

The SILS quality index is an extension of the silhouette concept, used in data mining, to measure the quality of the alternatives' assignments into ordered classes. SILS considers the asymmetric multicriteria relations due to differences between net flows of alternatives. Its scale and graphical representation allow users to identify if a supplier is appropriately assigned to a category or whether it should be reassigned to an adjacent category.

The analysis of the performance of the GLNF sorting algorithm using hypothetical data and real data from a multinational company has shown the strengths of the method, which are founded on the algorithm design, based on theoretical multicriteria properties and strategies from the optimisation field. In short, GLNF is a robust method for multicriteria sorting, classifies all suppliers and requires less information from the decision-maker than PROMSORT. The greater stability of the generated classifications by GLNF makes it a powerful tool for decision-making in real contexts where there is frequent incomparability between suppliers and limiting profiles, as well as inaccurate parameters. Thus, this new algorithm can easily be integrated into DSS to evaluate suppliers for segmentation in order to select and monitor the supplier portfolio and establish the appropriate relationships in supply chain management. In particular, the GLNF sorting method allows automatically classifying suppliers and decision-maker to evaluate wrongly assigned suppliers when SILS shows unacceptable values. This possibility would broaden its application in management practice.

Both contributions, the GLNF sorting method and the SILS quality index can be applied to classify alternatives into ordered groups in other multicriteria problems related to supply chain management. Although the GLNF sorting algorithm and SILS quality index can be applied to classify alternatives in other contexts, such as education, risk management and so forth, and implemented with other multicriteria techniques, these aspects should be validated with data from real problems. Future research will also focus on validating the performance of the algorithm and the quality index in problems with a large number of alternatives and exploring hybridisation with techniques from data mining.

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Appendix A

Table A1
SILS applied to assignments by GLNF sorting and PROMSORT for set of suppliers of Araz and Ozkarahan (2007)

Suppliers	GLNF sorting	PROMSORT optimistic	PROMSORT pessimistic
S1	0.233	0.189	0.109
S2	−0.444	−0.610	0.428
S3	−0.230	−0.305	0.755

Continued

Table A1
(Continued)

Suppliers	GLNF sorting	PROMSORT optimistic	PROMSORT pessimistic
S4	−0.029	−0.050	−0.125
S5	−0.127	−0.166	−0.390
S6	0.064	0.055	0.003
S7	−0.068	−0.095	−0.235
S8	0.536	0.464	0.280
S9	−0.577	0.749	0.342
S10	0.159	0.148	0,133
S11	−0.164	−0.213	−0.335
S12	−0.198	−0.211	−0.351
S13	0.009	−0.002	−0.061
S14	0.165	0.154	0.137
S15	−0.259	−0.276	1.260
S16	−0.200	−0.211	−0.253
S17	0.068	0.059	0.006
S18	0.397	0.310	0.153
S19	−0.191	−0.203	−0.327
S20	0.140	0.131	0.118
S21	0.337	0.282	0.167
S22	0.134	0.126	0.113

Table A2
SILS applied to assignments by GLNF sorting for real data of supplier evaluation

Suppliers	GLNF sorting
S1	0.111
S2	0.415
S3	−0.145
S4	0.744
S5	0.053
S6	0.022
S7	−0.481
S8	−1.090
S9	0.404
S10	−0.033
S11	−0.386
S12	−0.013
S13	0.271
S14	0.263
S15	1.789
S16	0.726
S17	−0.335
S18	−0.340
S19	0.393
S20	−0.942

Appendix B

Table B1
PROMETHEE: criteria, weights and parameters

	Criteria						
Parameters	Critical performance of products	Delays	Commercial risk	Risk supplier country	Risk supplier billing	Strategic performance of products	Purchase volume
Weights (%)	24.55	11.30	5.55	3.25	5.35	42.50	7.50
Type function	linear	linear	usual	usual	linear	linear	linear
Indifference Threshold	0.0	0.0	N/A	N/A	2.0	0.0	2.3
Preference Threshold	10.0	50.0	N/A	N/A	15.0	10.0	20.0
Maximise / Minimise	Max.	Min.	Max.	Min.	Min.	Max.	Min.