

Managing risks in supplier selection and order allocation

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Abstract

Purpose – Supplier Selection (SS) and Order Allocation (OA) are strategic procurement processes crucial for mitigating supply chain uncertainties and potentially becoming a competitive advantage for companies in the mitigation strategies. Most of the previous studies dealing with SS and OA focused on straight rebuy situations, while there is a limited number of studies focusing on modified rebuy and new task situations, where uncertainty is higher, and comparison between historical and new suppliers is needed in a world, where the demand for new, technologically advanced products and services keeps increasing, pushing companies to continuously search for new suppliers.

Design/methodology/approach – Considering this gap, this paper aims to propose a Multiple-Criteria Decision-Making (MCDM) model to compare new and historical suppliers, with limited knowledge about the new suppliers, using measurable and forecastable decision criteria through a scenario planning approach that considers decision-makers' different risk attitudes in evaluating suppliers' performance. The proposed model adopts the Best-Worst Method and a two-stage Linear Programming model. The effectiveness of the model has been tested in a real industrial setting.

Findings – This model would support companies in their decision-making process to anticipate and address potential risks inherent in SS and OA decisions, thus enhancing supply chain resilience and agility in dynamic market environments.

Originality/value – The proposed model, requiring minimal computational resources, is accessible to a broad range of companies. It fills a literature gap by enabling comparison between new and historical suppliers in modified rebuy and new task situations, where uncertainty is higher, thereby enhancing supply chain decision-making.

Keywords Supply chain management, Supplier selection, Order allocation, Purchasing, Risk mitigation, Best-worst method

Paper type Research paper

1. Introduction

The recent disruptions in global supply chains have highlighted the importance of managing and controlling the risk within a supply chain. Supply Chain Risk Management (SCRM) is thus playing an increasingly strategic role within the Supply Chain Management (SCM) related activities.

Suppliers represent a major source of risk for supply chains, and a properly managed procurement process should mitigate these risks as much as possible (Jain *et al.*, 2013). Given the complexity of the procurement process, several authors analysed proposed frameworks for its optimization (see, e.g. De Boer, 1998), distinguishing the different activities that contribute

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to the procurement process, such as Supplier Selection (SS) and Order Allocation (OA) (Singh, 2014). While SS aims at selecting the best supplier based on criteria such as time, cost, quality and risk, OA aims at allocating the orders among the selected suppliers, based on several objectives, which include risk minimization (Jolai *et al.*, 2011).

The complexity of SS and OA varies based on the nature of the buying situation. Robinson *et al.* (1967) distinguish three different buying situations, characterized by increasing levels of complexity: a straight rebuy, a modified rebuy and a new task situation. In straight rebuy, the buyer regularly buys routine items or strategic bottleneck items from historical suppliers. These situations are generally considered “safe” and characterized by low complexity, with little need for supplier reevaluation unless there are problems with performance (Leonidou, 2005). The criteria and historical data are well-established, which frequently results in minimal supplier interaction and simple decisions based on past performance. In contrast, modified rebuy and new task situations are characterized by increasing uncertainty in the purchasing process. The higher complexity of the modified rebuy and the new task situation depends on the fact that Decision-Makers (DMs) can rely on a limited amount of historical data for the assessment of supplier performance and supplier-related risk. In a new task buying situation, the purchasing organization purchases a product or service for the first time, without prior data or predefined criteria. DMs must choose and assess new criteria, often leading to extensive interaction and the use of multi-criteria models to evaluate a small pool of potential suppliers (De Boer *et al.*, 2001). In modified rebuy situations, where a company adjusts its supplier base, the decisions are moderately complex, with the availability of historical data, involving a large initial pool of suppliers that gets refined based on ranking and sorting also in terms of allocation volumes (De Boer *et al.*, 2001; Leonidou, 2005).

Despite this higher complexity, there is a limited number of studies focusing on modified rebuy and new task situations and most of the previous studies deal with SS and OA in straight rebuy situations, using historical data on the performance of suppliers in the decision-making process. There are very few examples of studies that adequately consider the uncertainty in SS and OA problems in new task situations when a comparison between historical and new suppliers is needed (Acar Alagoz *et al.*, 2022; Stewart *et al.*, 2013). Because of the lack of information that usually characterizes the knowledge of buyers about new suppliers, DMs are frequently prone to select a historical supplier rather than a new one (Aditi *et al.*, 2023). Uncertainty is a characterizing feature of modified rebuy and new task situations; indeed, DMs might differently behave in the same uncertain situations; for this reason, the risk attitude of a single DM plays a critical role. However, previous approaches supporting SS and OA do not consider that different DMs might have different risk attitudes. Considering the different risk attitudes of the DMs is essential for a robust risk mitigation strategy.

Considering these gaps and the relevance of embedding risk and uncertainty in SS and OA problems, this paper proposes a Multiple-Criteria Decision-Making (MCDM) model enabling a comparison between new and historical suppliers, with limited knowledge of the new suppliers. The proposed MCDM model adopts the Best-Worst Method (BWM) (Rezaei, 2015, 2016), a pairwise comparisons-based method and a two-stage Linear Programming (LP) model for the OA problem. The model includes two crucial novelties to enhance supplier evaluation under uncertainty. First, it enables a structured comparison between new and historical suppliers by distinguishing between measurable and forecastable decision criteria. This structured distinction ensures a more accurate and reliable SS process integrating both qualitative and quantitative factors. While measurable criteria (e.g. cost, delivery time) can be directly assessed from supplier bids, forecastable criteria (e.g. quality, business integration and punctuality) require different evaluation approaches. Past performance data serve as a reference for historical suppliers, whereas for new suppliers, the absence of historical data requires an assessment based on DMs’ expertise through a scenario planning approach. Second, indeed, this approach accounts for the varying risk attitudes of DMs when evaluating forecastable criteria. Given the inherent uncertainty in assessing new suppliers, five distinct scenarios (optimistic, medium-optimistic, expected, medium-pessimistic and pessimistic) are introduced, with DMs assigning probabilities

of occurrence based on historical supplier performance. This feature strengthens the centrality of DMs and reduces evaluation biases linked to the DMs' varying risk attitudes and perceptions.

The remainder of this paper is organized as follows. [Section 2](#) provides an overview of the literature on MCDM for SS and OA, posing the research gaps in the end. [Section 3](#) explains the proposed model. [Section 4](#) shows the results of a real-world industrial application. [Section 5](#) summarizes the conclusions, highlighting theoretical and managerial contributions and proposing avenues for future research.

2. Literature review

The field of SCRM ([Mentzer et al., 2001](#)) has seen the proposition of several models assisting DMs in the identification and assessment of risk, as well as in the definition of risk mitigation measures ([Micheli and Vitrano, 2024](#); [Micheli et al., 2014](#); [Wu et al., 2006](#)). The procurement process plays a pivotal role in an SCRM strategy ([Micheli et al., 2008](#)), and several studies have analysed the possibility of mitigating risk through procurement-related activities ([Lee, 2017](#)), such as SS and OA. Indeed, the selection of the right supplier enables mitigating the risks related to regulatory and quality standards, customer demand, as well as firm reputation ([Hruška et al., 2014](#)). Similarly, the OA procedure can allocate supplies among the selected suppliers in such a way that the corresponding risks are minimized.

The first stage of the purchasing process is to formally choose suppliers by screening them via an assessment process that incorporates both qualitative and quantitative metrics ([Luo et al., 2009](#)). The second stage is OA, which determines the order quantity, for each supplier ([Govindan et al., 2015](#)). Even though there are many works on SS and OA in the literature, very few companies consider these approaches perhaps because the manual implementation of these models is time-intensive, complicated and frequently necessitates the use of a model expert ([Bruno et al., 2012](#)). Furthermore, the decision process's objectives and accompanying restrictions are prone to alter over time. As a result, connected databases should be used to assist the models. All these characteristics should be integrated into a Decision Support System (DSS) that delivers a dynamic, rapid and flexible decision-making environment ([Lee et al., 2001](#); [Ordoobadi, 2009](#); [Yang and Chen, 2006](#)).

This paper proposes an MCDM model enabling a comparison between new and historical suppliers in the SS and OA. Accordingly, this section will introduce the model by providing an overview of the literature on SS ([2.1](#)) and OA ([2.2](#)) focusing on the related MCDM models used in the context of risk mitigation.

2.1 Supplier selection (SS)

Thanks to its leading role in structuring and managing a supply chain, SS has received extensive attention over the years. Many authors have proposed categorizations of the SS process itself, in addition to the mentioned classification given by [Robinson et al. \(1967\)](#), [De Boer et al. \(2001\)](#) integrated this classification with Kraljic's portfolio matrix, where items are classified according to two factors: supply risk and profit impact ([Kraljic, 1983](#)). Considering both the buying situation and the position of the purchased product/service in the Kraljic matrix, a structured framework was created where each specific buying circumstance finds its place. Suppliers are considered the most valuable intangible assets of any industrial organization ([Hruška et al., 2014](#)), for this reason, it is not surprising that the issues related to the SS process have been widely examined by academics. Based on [Chai et al. \(2013\)](#) work, it is possible to classify the proposed methods for solving the SS problem into three main groups: (1) Mathematical Programming (MP), (2) Multiple-Criteria Decision-Making (MCDM) and (3) Artificial Intelligence (AI) methods. The first two, relevant to the purpose of this study, are below detailed.

2.1.1 Mathematical programming (MP). MP is a very well-known term in decision-making research. It has different SS techniques out of which six techniques were adopted from [Chai et al. \(2013\)](#). They include Data Envelopment Analysis (DEA), Linear Programming (LP),

Nonlinear Programming (NLP), Multi-Objective Programming (MOP), Goal Programming (GP) and Stochastic Programming (SP).

DEA is a nonparametric MP approach for comparing the relative efficiency of comparable entities about decision-making units (DMUs). A simple DEA model is a performance assessor that may be used to assess DMU efficiency based on numerous outputs and inputs. DEA is very important in terms of complementing the different models of SS selections (Adler *et al.*, 2002). Different types of LP have been developed for SS such as the fuzzy LP (Amin *et al.*, 2011), the simple LP employment (Chen *et al.*, 2011), the mixed-integer LP (Amin and Zhang, 2012) and the multi-objective LP (Ozkok and Tiryaki, 2011). NLP enables some nonlinear restrictions or objective functions. NLP is mostly used in two ways, first is the usage of NLP as a decision tool and second is the usage of NLP as a problem solver for the mixed-integer formulations of NLP (Hsu *et al.*, 2010; Rezaei and Davoodi, 2012; Yeh and Chuang, 2011). MOP is used to solve decision problems with multiple, conflicting objective functions that can be optimized across a collection of viable solutions. From 2008 to 2012, fuzzy Multi-Objective Linear Programming (MOLP) was the most popular research topic for SS (Haleh and Hamidi, 2011). GP may be considered as an extension of MOLP that can be used to deal with various conflicting objective measurements. Each of these metrics has a target value that must be met. There are seven GP models which are used for SS: directly employed GP as a decision tool (Kull and Talluri, 2008), fuzzy GP approach (Tsai and Hung, 2009), GP and ANP hybrid decision modelling (Demirtas and Ustun, 2009), integrated multiple MP techniques using GP (Chen *et al.*, 2011), Genetic Algorithm (GA) based GP models (Sadeghieh *et al.*, 2012), multi-choice GP (Liao and Kao, 2011). The last MP technique is SP. Despite the presence of numerous unknown factors, SP is a framework for modelling uncertainty optimization issues in which the probability distributions controlling the data are known or may be approximated. This method is a useful mathematical tool for handling a variety of real-world SS issues (Kara, 2011).

2.1.2 Multiple-Criteria Decision-Making (MCDM). In the SS background, MCDM represents the approach that has received the greatest attention over the years. Several reasons support the choice to select MCDM methods: (1) MCDM models are intuitive for real-world decision-makers, (2) they allow to consider not only quantitative criteria but also qualitative ones, (3) they can effectively integrate the opinions of individual DMs in the selection process, (4) they enable integration of risk and uncertainty in estimating the suppliers' performances, (5) while MP and AI methods are completely automated techniques, MCDM approaches guarantee a high level of interaction between the DM(s) and the decision process. DMs, the players of the decision process, criteria, representing the features considered in the evaluation process and the ranking process, are the milestones of MCDM methods. Because they constitute fundamental elements for applying an MCDM method, great effort has been spent by authors so far for their analysis.

2.1.2.1 Decision-makers. In real-life work environments, the way decisions are taken has significantly changed over the last decades, indeed it has evolved from single-criterion-single-decision maker to multi-criteria-multi-decision makers (Büyükožkan and Göçer, 2017). The different contributions provided by each DM lead to more robust choices. Therefore, new MCDM methods have been introduced, such as Group Decision-Making (GDM), as the most collaborative way to make decisions. In this context, Chan and Chan (2004) exploited the geometric average to integrate the opinions of single DMs, Rezaei (2016) gave the same weight to all the experts composing the decision group, and Zhang *et al.* (2009) defined the weights of single DMs employing Vague Set Theory (VST). Furthermore, since DMs have different attitudes towards gains and losses (Sun *et al.*, 2024), they need a gradual process to understand the situation of suppliers and both past and present information should be considered when selecting suppliers (Li *et al.*, 2022).

2.1.2.2 Criteria. The set of criteria considered in the literature is very wide and includes both quantitative and qualitative criteria (Luo *et al.*, 2009). Price, quality and delivery are the most frequently adopted criteria, but their relative importance has changed over time, indeed if once price was dominant, nowadays quality and delivery have gained a primary role (Ho *et al.*,

2010). Kumar Kar and Pani (2014) offered one of the most recent investigations about SS criteria, pointing out over 60 generic criteria that have been used in the SS context. Moreover, moved by the growing concern about environmental issues and sustainable processes that have characterized recent years, many authors have tried to integrate the so-called green criteria with traditional ones (e.g. Genovese *et al.*, 2013).

The wide-ranging literature not only regards the considered criteria but also the methods applied to calculate the associated weights. Criteria weights determine the importance covered by criteria in the decision process, thus, the higher the weight the more influential the criterion in the evaluation. Eight methods for criteria evaluation have been identified by the literature review with the majority of them belonging to pairwise comparison-based methods: Analytic Hierarchy Process (AHP); Analytic Network Process (ANP); Best-Worst Method (BWM); Pivot Pairwise Relative Criteria Importance Assessment (PIPRECIA); Measuring Attractiveness through a Categorical-Based Evaluation Technique (MACBETH); Stepwise Weight Assessment Ratio Analysis (SWARA); Rank Order Centroid (ROC); Criteria Importance Through Intercriteria Correlation (CRITIC).

The AHP is a popular method that structures the decision problem into a hierarchy of criteria, enabling pairwise comparisons to determine their relative importance. Many cases in the literature, such as those presented by Hazza *et al.* (2022), Koc *et al.* (2023) and Menon and Ravi (2022), illustrate the application of AHP in SS processes. Additionally, fuzzy logic is frequently integrated with AHP to address uncertainties and enhance decision-making, such as in Erdebilli *et al.* (2023), Jafari-Raddani *et al.* (2024), Yalcin *et al.* (2023), Zeydan *et al.* (2011) and Zhou and Chen (2023). A more advanced version, the ANP, considers interdependencies between criteria, addressing more complex supply chain scenarios where criteria influence one another (Sarkis and Talluri, 2002). This is the case in Bakeshlou *et al.* (2017) and Büyükoçkan and Ifi (2012), where ANP is employed to tackle the complex multi-criteria evaluation of green suppliers based on both quantitative and qualitative factors. Another pairwise comparison-based method is BWM, recently developed, which compares the most and least important criteria against others, providing consistent weight allocation. This method reduces comparison workload, making it particularly suitable for SS. Since its introduction in 2015, numerous applications in the SS process have been proposed (Aditi *et al.*, 2023; Afrasiabi *et al.*, 2022; Asadabadi *et al.*, 2023; Gupta and Barua, 2018; Nemati, 2024; Rezaei *et al.*, 2015, 2016; Rezaei and Fallah Lajimi, 2019; Shaw *et al.*, 2023; Shidpour *et al.*, 2023; Song *et al.*, 2024), with some studies introducing modifications, such as fuzzy BWM in Masoomi *et al.* (2022) and stratified BWM in Zhang *et al.* (2024). PIPRECIA, another pairwise comparison-based method, introduces a stepwise approach with sequential pairwise comparisons of criteria where weights are assigned incrementally, allowing for gradual refinement of criteria importance; it is especially desirable for dynamic decision environments such as in Mishra *et al.* (2023). Similarly, still using pairwise comparisons but differently compared to traditional methods like AHP or BWM, the MACBETH method evaluates criteria based on categorical attractiveness ratings, converting subjective preferences into numerical weights. For example, Pamucar *et al.* (2023) employed this method to address the complex SS problem faced by healthcare centres during the COVID-19 pandemic.

Other methods do not involve pairwise comparisons and some of them assign weights based on ratios, direct assessments or specialized procedures. ROC, such as in Esangbedo *et al.* (2024) and Sureeyatanapas *et al.* (2018), assigns weights to criteria based on their rank order and may lack precision for more complex problems due to its oversimplification of weight assignment. Similarly, but with a stepwise evaluation, SWARA ranks criteria and adjusts their importance ratios based on relative significance, as applied in Debnath *et al.* (2023) for the sustainable SS process in healthcare facilities.

CRITIC is another method that differs from the others because it minimizes subjectivity in the weighting process and requires quantitative data to quantify criteria importance by analysing the standard deviation and the correlation between criteria, as seen in Mishra *et al.* (2023) and Xu *et al.* (2023). To address the interdependence among criteria, the Decision-

Making Trial and Evaluation Laboratory (DEMATEL) method is particularly useful, as it analyses the cause-effect relationships between criteria. However, since DEMATEL itself does not assess alternatives directly, it is frequently combined with other methods to evaluate alternatives, as evidenced by [Mohammed et al. \(2019\)](#).

2.1.2.3 Ranking process. The literature on SS using MCDM models is rich with methods, each with its own set of theoretical foundations and applications. MCDM methods aim to provide a structured and clear approach for evaluating alternatives by considering multiple criteria and determining the most preferred option. The review of the literature has revealed 12 commonly used methods for ranking suppliers which are Simple Additive Weighting (SAW); Weighted Aggregated Sum Product Assessment (WASPAS); Technique for Order Preference by Similarity to Ideal Solution (TOPSIS); Stable Preference Ordering Towards Ideal Solution (SPOTIS); Combinative Distance-Based Assessment (CODAS); Multi-Criteria Optimization and Compromise Solution (VIKOR); Multi-Objective Optimization on the basis of Ratio Analysis (MOORA); Complex Proportional Assessment (COPRAS); Measurement of Alternatives and Ranking based on Compromise Solution (MARCOS); Elimination and Choice Expressing Reality (ELECTRE); Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE); Interactive Multi-objective Decision-Making (TODIM); and Grey Relational Analysis (GRA).

SAW and WASPAS can be considered as weighted sum and related simple aggregation methods. The SAW method is known to be simple, easy to understand and flexible for various contexts, allowing decision-makers to assign weights to criteria. This method aggregates these weights to compute a single total score for each alternative ([Haryono et al., 2024](#); [Schramm et al., 2020](#)). Similarly, WASPAS creates a more robust supplier ranking system by integrating the strengths of the weighted sum model (WSM) and the weighted product model (WPM) ([Debnath et al., 2023](#)).

Following distance-based methods, such as TOPSIS, SPOTIS and CODAS, are designed to evaluate alternatives based on their proximity to an ideal solution. TOPSIS, one of the most widely used methods, calculates the relative distance of each supplier to the ideal and worst-case solutions ([Haryono et al., 2024](#); [Hwang and Yoon, 1981](#); [Kaya et al., 2023](#); [Štilić and Puška, 2023](#)). The method's applicability in various industries is well-documented ([Meena et al., 2023](#)). Several studies have integrated TOPSIS with other decision-making tools to enhance its effectiveness. [Mohammed et al. \(2019\)](#) combined TOPSIS with DEMATEL and ELECTRE to evaluate vendors for a passport tracking system. Similarly, [Jafari-Raddani et al. \(2024\)](#) combined fuzzy TOPSIS and fuzzy AHP. [Sureeyatanapas et al. \(2018\)](#) explored extending the TOPSIS method to handle uncertainty and incomplete information, proposing a modification using the ROC method to determine criterion weights. [Yalcin et al. \(2023\)](#) presented a strategy segmentation technique that integrated TOPSIS with the Kraljic portfolio matrix and supplier relationship model. [Kaya et al. \(2023\)](#) innovated by integrating TOPSIS with Bayesian networks to handle incomplete expert knowledge, enhancing decision support in SS scenarios. SPOTIS focuses on achieving a stable and consistent ranking by comparing each alternative's performance against an ideal solution, as in [Martin \(2024\)](#) where SPOTIS was utilized to ensure that supplier rankings remain consistent despite variations in decision-maker preferences. CODAS, another distance-based method, measures the Euclidean and Taxicab distances of each alternative from the negative-ideal solution, providing a comprehensive assessment of alternatives, as applied in [Pamucar et al. \(2023\)](#).

Other methods such as VIKOR, MOORA, COPRAS and MARCOS focus on achieving a balanced solution that considers the trade-offs among different (conflicting) criteria ([Haryono et al., 2024](#)). The VIKOR method, which seeks a compromise solution by evaluating alternatives based on their proximity to the ideal and anti-ideal solutions, is applied in various studies ([Opricovic and Tzeng, 2004](#)). MOORA, on the other hand, optimizes SS by calculating a ratio to rank each alternative from the best to the worst while considering trade-offs between two or more conflicting criteria, as presented in [Magableh \(2024\)](#) and [Nemati \(2024\)](#). COPRAS evaluates alternatives based on their proportional significance, indicating how good or bad they

are relative to the other options and calculates the overall utility directly, as applied in [Erdebilli et al. \(2023\)](#) and [Masoomi et al. \(2022\)](#). Similarly, MARCOS, a method that ranks suppliers by evaluating their performance against a compromise solution, is particularly useful in situations with conflicting criteria, as demonstrated in [Mishra et al. \(2023\)](#) where MARCOS was used to balance the trade-offs between environmental sustainability and supplier performance.

Furthermore, ELECTRE, PROMETHEE and TODIM are outranking methods well-suited for handling complex decision-making scenarios where conflicting preferences among stakeholders must be managed. They work based on the dominance of the alternatives on each other ([Qu et al., 2020](#); [Tong et al., 2022](#)) and are particularly useful for handling conflicting preferences and priorities among stakeholders ([Kokaraki et al., 2019](#)). ELECTRE excels in overcoming uncertainty by considering varying preferences between criteria and eliminating alternatives that are less preferable compared to others, as demonstrated by [Mohammed et al. \(2019\)](#). The PROMETHEE method uses binary relations to compare alternatives, calculating both positive flow (how much an alternative outranks others) and negative flow (how much it is outranked), with the final ranking determined by the difference between these flows ([Chai and Ngai, 2020](#)), such as employed by [Agrawal \(2022\)](#). TODIM, which involves stakeholders directly in the decision-making process, ranks alternatives by considering both gains and losses in relation to a reference point and orders them based on their cumulative dominance scores, as demonstrated in [Sun et al. \(2024\)](#). It is particularly useful in scenarios where multiple criteria must be balanced against the subjective preferences of decision-makers ([Sun et al., 2024](#)); however, this method may require significant time and resources for stakeholder engagement, and the weights and preferences can potentially create bias or inconsistency ([Haryono et al., 2024](#)).

Finally, the GRA method is designed to rank alternatives based on their similarities and differences with a reference alternative, making it a powerful tool in contexts where data is uncertain or incomplete ([Deng, 1989](#); [Haryono et al., 2024](#)), as developed by [Haeri and Rezaei \(2019\)](#) and [Esangbedo et al. \(2024\)](#).

2.1.2.4 Fuzzy approach in MCDM models. Incorporating fuzziness into MCDM models to address the inherent uncertainties and complexities in decision-making processes has gained ground in recent years in SS ([Štilić and Puška, 2023](#)). Recent studies have introduced various fuzzy-based models to enhance the reliability and precision of supplier evaluations.

[Rabbani et al. \(2019\)](#) and [Nemati \(2024\)](#) employed interval-valued fuzzy sets and interval type-2 fuzzy sets to manage complexities and uncertainties related to sustainable SS. Similarly, [Moghaddam \(2015\)](#) dealt with such situations in reverse logistics by using Monte Carlo simulation and fuzzy goal programming. [Modibbo et al. \(2022\)](#) adopted fuzzy TOPSIS in the pharmaceutical sector, providing evidence of the utility of fuzzy methods in environments characterized by multiple uncertain factors. [Li et al. \(2022\)](#) used generalized fuzzy numbers to model the uncertainty and imprecision in decision-makers' preferences across multiple periods to reflect the influence of time and group dynamics in the supplier evaluation process. [Masoomi et al. \(2022\)](#) and [Afrasiabi et al. \(2022\)](#) are examples of fuzziness applied at the BWB to determine the importance weights of the selection criteria. [Çakır and Taş \(2023\)](#) introduced circular intuitionistic fuzzy sets, expanding the range of fuzzy approaches available for capturing uncertainties in decision-making processes. An extension of fuzzy sets recently applied in the literature are Pythagorean Fuzzy Sets ([Meng et al., 2024](#); [Mishra et al., 2023](#); [Zhou and Chen, 2023](#)) and hesitant fuzzy sets ([Zhang et al., 2022](#)). Similarly, due to the high uncertainty and incomplete information, [Pamucar et al. \(2023\)](#) used fuzzy rough numbers, an advanced form of fuzzy sets in the SS process.

2.2 Order allocation (OA)

OA is the process through which the needed order quantities are split among selected suppliers. OA embodies the objectives and policies set by a company for its supply chain. OA processes can be classified according to different points of view: (1) the number of considered suppliers

(single/multiple sourcing), (2) the number of purchased product types (single/multiple product types) and (3) the time horizon of the OA itself (single/multiple periods).

As highlighted by [Erdem and Göçen \(2012\)](#), the great majority of the studies in the literature are dedicated to the SS problem only. Following the SS, OA choices are made, which are typically performed using mathematical programming techniques for MCDM. Most of the research in the literature is only focused on the SS issue. Among the reviewed literature, a good example of a study completely dedicated to the resolution of the OA problem is represented by the work of [Bohner and Minner \(2017\)](#) who proposed multiple product types, multiple sourcing and single-period Mixed-Integer Linear Programming (MILP) model aimed to minimize the total purchasing cost. Similarly, [Song et al. \(2024\)](#) presented a MILP model to address the challenge of purchasing under disruption risks, which required balancing cost, purchase value and geographical segregation to mitigate geographically induced disruption risks. Another study by [Che et al. \(2022\)](#), proposed a robust optimization model considering two uncertainties – production and transportation reliability – emphasizing the necessity of controlling the effects of unpredictable factors in real-world OA. [Chen \(2009\)](#) developed a fuzzy-based decision support model for rebuy procurement, to account for multiple criteria and uncertain factors within the decision process. [Moghaddam \(2015\)](#) also applied fuzzy logic in reverse logistics by developing a fuzzy multi-objective model that considered supply and demand uncertainty, using Monte Carlo simulations to determine optimal OA solutions.

However, solving just the OA problem is quite restrictive as it represents a phase immediately following the SS without which it assumes just an order re-allocation meaning. That is, considering a real case where only the OA problem is solved, it means that the supplier pool remains the same whereas the order quantities change. Integrated models for SS and OA, instead, enable conducting the whole process, from the first identification of candidate suppliers to the final allocation of order quantities ([Bodaghi et al., 2018](#)).

[Ho et al. \(2010\)](#) claimed that the combined AHP–GP strategy for SS and OA is the most common method in an exhaustive analysis of the methodologies used in SS literature. The major reason for this is that both AHP and GP have distinct benefits. The AHP consistency verification procedure assures the DM's fair consideration of primary and subsidiary criteria. The AHP findings offer uniform weightings of different suppliers; nevertheless, the DM must consider other factors such as the total budget, supply quality, time restrictions and production technology. When allocating the yearly supply allotment to its vendors the integrated AHP–GP method is regarded as the most advantageous technique for SS and OA since GP offers an appropriate model to analyse these constraints. [Ghodyspour and O'Brien's \(1998\)](#) study was the first to explore an integrated AHP–LP model to pick the best supplier and allocate the optimal order amounts among them. Among the following, [Çebi and Bayraktar \(2003\)](#) created an integrated approach to handle SS and OA problems by combining AHP and Lexicographic Goal Programming (LGP). [Wang et al. \(2004\)](#) combined AHP with Preemptive Goal Programming (PGP). [Wang et al. \(2005\)](#) expanded the prior study by developing a technique to calculate total supply chain efficiency based on product, supply item and supplier efficacy. [Liu and Wu \(2005\)](#) integrated AHP and DEA to help them make better SS judgments for OA. Apart from the above-mentioned major studies, there is a vast number of other studies focusing on the same topic, [Yang and Chen \(2006\)](#) used GRA in conjunction with the AHP approach to finding the best suppliers for collaboration. [Bayazit \(2006\)](#) offered a sensitivity analysis for optimization and an AHP-based vendor selection model. [Jafari-Raddani et al. \(2024\)](#) offered a hybrid method using fuzzy AHP, TOPSIS and LP-metric optimization to incorporate quality policies and demand forecasting into SS and OA. For dynamic demand allocation to providers, [Liao and Rittscher \(2007\)](#) presented a non-linear mixed-integer programming model that included the effects of carrier selection and lot sizing. [Rezaei and Davoodi \(2012\)](#) utilized GA for solving both SS and OA problems in the case of a multiple-sourcing, multi-product and multiple-period time planning horizon. Similarly, [Ayhan and Kilic \(2015\)](#) exploited a multiple-sourcing, multi-product and single-period MILP for selecting the best suppliers and determining the OA among them.

Although modelling studies for SS and OA have been conducted, advanced DSS implementations are rare. Because SS and OA choices are multi-criteria problems that need to be regularly updated, it is suggested the offered approaches be implemented into computer software and web-based tools (Lee *et al.*, 2001; Pal and Kumar, 2008; Yang and Chen, 2006).

2.3 Research gaps

Despite the great commitment dedicated to this field of SCM, many aspects still require deeper inspection. In today's fast-changing world, the demand for new, technologically advanced products and services keeps increasing, pushing companies to continuously search for new suppliers able to provide the products and services, in addition to the best trade-off possible between quality and cost. In such a continuously evolving market environment, along with the increased tendency of companies to outsource part of their production, the need for a framework enabling the comparison between new and historical suppliers is urgent, and efforts must be directed toward its development. Very few authors (e.g. Aditi *et al.*, 2023; Acar Alagoz *et al.*, 2022; Tavassoli and Ghandehari, 2023) focused on the topic of new task situations, which are the most critical ones considering the associated risks and the high uncertainty degree by which they are characterized.

When considering extraordinary situations, risk plays a pivotal role in the decision-making process as DMs do not often have enough information to evaluate suppliers and they need reliable assumptions to proceed with the evaluation (Li *et al.*, 2022). Decisions are thus related to DM's perception which becomes extremely important for the success of their evaluation (Sun *et al.*, 2024). DMs are indeed characterized by a risk attitude that makes them evaluate circumstances differently.

Furthermore, as revealed in the analysis of the literature many MCDM models have been extensively studied over the years, making it impractical to identify a universally best method (Modibbo *et al.*, 2022). It might seem straightforward, but selecting the most appropriate model for SS and OA depends on the specific context in which it is applied; the nature of the industry, the availability of data, the complexity of the decision, the decision-makers' preferences and technical skills all influence the suitability of a particular method (Schramm *et al.*, 2020). Moreover, there are differences between the methods used for SS and OA. While for addressing OA problems optimization algorithms constitute the most suitable (and the main adopted) solution, they become not so efficient when it comes to SS problems. Indeed, SS usually requires taking into consideration higher-level pieces of information, that might be impossible to translate into quantitative values, therefore making the problem too complex to be solved through optimization methods.

Despite the growing interest in integrating multiple techniques to address the complexity of SS and OA problems, many proposed methods can hardly find practical application due to their inherent complexity. The integration of multiple techniques may appear promising, however, combining techniques often leads to increased model complexity, making it hard to apply in real-world situations because the manual implementation of these models can be time-intensive and complicated, requiring DMs to have specialized expertise (Bruno *et al.*, 2012). Indeed, as emphasized by Schramm *et al.* (2020), further research is needed to develop models for SS and OA that are practical for most companies, even those without advanced computational capabilities. In real situations, no optimal solution is expected, but just a good and, above all, feasible one.

3. Model

Given the research gaps stated in the previous section, we propose an MCDM model for SS and OA of several suppliers. The model includes two crucial novelties: the comparison of new and historical suppliers using measurable and forecastable decision criteria and the combination, through a scenario planning approach, of decision makers' different risk

attitudes in evaluating suppliers' performance. Moreover, other crucial elements of the proposed MCDM model include (1) the integration of both SS and OA problems; (2) the capacity to handle both qualitative and quantitative criteria, as this process often involves assessing non-quantifiable aspects; (3) adaptability to different contexts, including variations in industry types; and (4) usability in real-world situations, being easy to implement with minimal specialized expertise.

The choice of an MCDM method comes from the consideration that such methods can encompass many different aspects of the choice, through the associated criteria, thus adaptable and customizable to very complex situations. As regards the calculation of the weights to be assigned to selected criteria, a novel pairwise comparisons-based method, the BWM (Rezaei, 2015, 2016), is employed. One of the greatest advantages of this method is the fact that it is less information-demanding than other pairwise comparison-based methods (e.g. AHP) and thus it better fits new task situations, which are, by nature, characterized by a lack of information (further details in Section 3.2.1).

A more advanced approach for both criteria weighting and supplier ranking could have been selected to enhance objectivity and reduce reliance on decision-makers' evaluations. However, the choice of the proposed model prioritized reliable and effective methods that are widely applicable by most companies without specific computational capabilities. This led to the selection of simple aggregation methods for supplier ranking over more complex techniques like TOPSIS and TODIM. Similarly, BWM for criteria weighting was chosen for its balanced integration of expert insight and its ability to handle both qualitative and quantitative data in uncertain decision environments compared to methods like CRITIC and DEMATEL, which provide significant benefits in reducing subjectivity and modelling complex interdependencies but are heavily dependent on the availability of reliable numerical data and may not effectively capture qualitative aspects. From that, the decision was made to use linear BWM for SS, since it preserves, as stated by Rezaei (2016), the core philosophy of the original BWM model while ensuring a unique solution due to its linear formulation. Indeed, although multi-optimality may be desirable in some cases, in other cases, a unique solution is preferable in decision-making processes, which is why we propose a linear BWM. It constitutes – in the view of the authors – an acceptable trade-off between the goodness of results and the required computational effort, providing unique weights used consistently in the other steps of the SS process. Instead, the initial non-linear BWM model is retained in the sensitivity analysis to further validate the stability of weight allocations by deriving an optimal set of weights for the selected criteria.

The detailed structure, divided into steps, of the proposed model is reported in Figure 1. The SS, OA and sensitivity analysis are the three macro-areas covered by the model. The SS stage directly informs and influences the OA stage by providing a preference ranking of the suppliers. Each supplier is assigned a score based on the selected criteria, which reflects their overall performance and reliability. These scores are then used as key inputs in the OA process, ensuring that order quantities are distributed among suppliers in a way that the best performers will have a higher saturation of their supply and vice versa for the low-value suppliers. Additionally, a sensitivity analysis is proposed to verify the robustness of the solution. The unpredictability of some situations might change the expected outcomes, and, for this reason, it is important to evaluate the steadiness of the solution in changing conditions, especially when addressing strategic problems, characterized by risk and influenced by the company's strategic focus needs.

The proposed model develops into six steps. Some activities can be run in parallel, hence they have been arranged in common steps. Black arrows represent the flow of information from Steps 1–6, i.e. the required information before starting an activity. Grey arrows in Step 1 show that criteria should be selected after having identified DMs and potential suppliers. Dashed lines link the sensitivity analysis in Step 6 with previous steps, so determining parts of the SS and OA process to test for the robustness of the final solution.

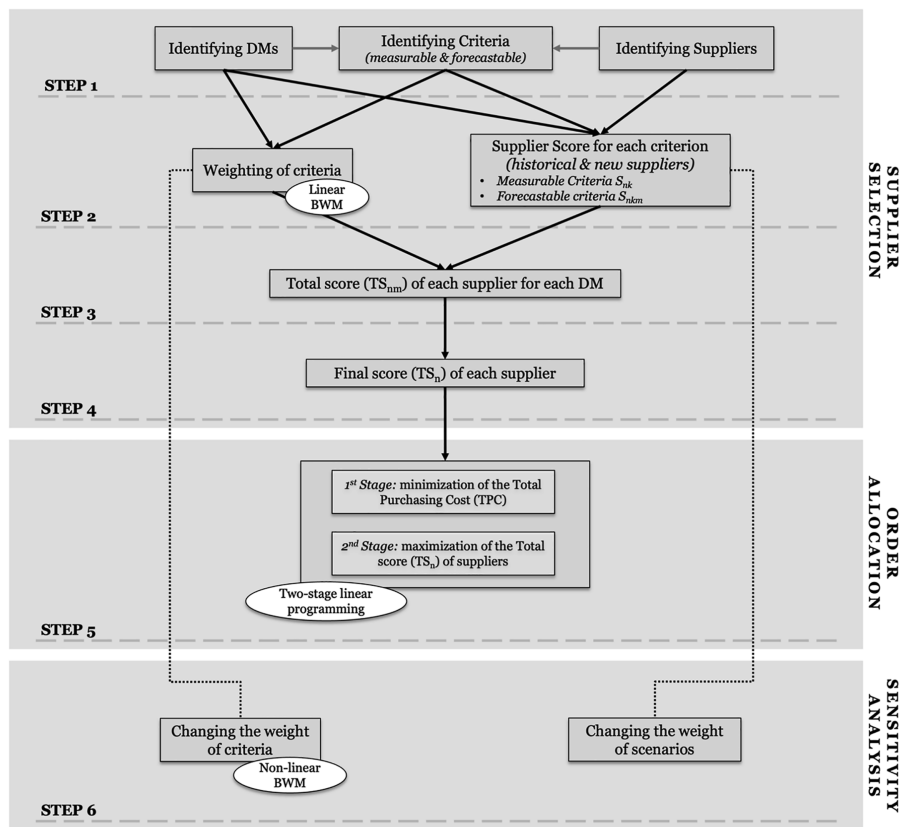


Figure 1. Complete structure of the proposed model. Note(s): Black arrows represent the flow of information from Steps 1–6; grey arrows in Step 1 show that criteria should be selected after having identified DMs and potential suppliers; dashed lines link the sensitivity analysis in Step 6 with previous steps. Source: Created by authors

3.1 Step 1

The first step will identify the main variables of the proposed model. Before starting with the computational analysis, we need to select suppliers to compare, criteria for suppliers' assessment and DMs for the evaluation. These three aspects are analysed in detail below.

3.1.1 Identification of DMs. The DM has a central role in an MCDM model. The identification of the most suitable suppliers depends on decision makers' selection and evaluation of criteria and their risk attitude. Therefore, the set of DMs ($m = 1, \dots, M$) chosen for the analysis needs to be critically discussed considering the specific SS problem.

3.1.2 Identification of criteria. Over the years many criteria have been taken into consideration to address the SS problem. The most adopted criteria have evolved, indeed, if once cost was widely considered the most important criterion in SS, quality has now got such primacy. Moreover, the tendency toward new production techniques (e.g. Just-In-Time) has made some criteria rise in importance, such as the supplier's location. Researchers, such as [Pramanik et al. \(2017\)](#), [Hruška et al. \(2014\)](#) and [Scott et al. \(2015\)](#), in the last years, have spent time defining pre-set criteria to apply in decision-making analyses. However, this limits the applicability of models that can be just implemented in those contexts where the suggested criteria are applicable. In the Authors' view, it is not worth selecting a pre-set list of criteria for

the SS. Criteria should be customized by evaluating priorities in each situation, such as the company’s focus and its field of interest. Based on the specific context of the application, we let DMs identify the most suitable set of criteria ($k = 1, \dots, K$) for the addressed problem. Moreover, a set of heuristics can guide the selection of these criteria in SS processes, providing structured methods to assess and select the most suitable criteria. The heuristics proposed by [De Boer \(2017\)](#) focus on balancing the value and cost of each criterion. Their work presented three heuristics for designing the SS process in modified rebuy situations.

- (1) Heuristic A is a basic model of procedural rationality applied to SS. It categorizes criteria based on their value-to-cost ratio, helping purchasers prioritize criteria that offer a favourable ratio. The main purpose is to facilitate a more conscious choice of SS criteria by “forcing” the purchaser to consider the value and cost of each criterion.
- (2) Heuristic B builds on Heuristic A by offering a more systematic and precise method for evaluating the value and cost of each criterion, often using AHP models.
- (3) Heuristic C uses a more formal operations research method to model satisficing behaviour, offering comprehensive guidance for selecting criteria, particularly when multiple criteria must be evaluated simultaneously. It allows for a precise balancing of value and cost and can account for precedence relations between criteria.

Finally, a peculiarity introduced by the proposed model consists of the division of the criteria into two major groups according to their nature: measurable criteria and forecastable criteria. The measurable criteria (e.g. cost and delivery time) refer to quantifiable performances that can be evaluated by analysing the bids submitted by suppliers. On the other hand, suppliers’ performance of forecastable criteria (e.g. quality, business integration and punctuality) cannot be simply extrapolated from submitted bids. Besides, a distinction is required between historical and new suppliers. As it regards historical suppliers, their performances about forecastable criteria can be measured by exploiting data contained in the company’s databases, drawing directly from suppliers’ history. When it comes to new suppliers, no historical data are available, so the performances of forecastable criteria are assessed by the DMs. This further strengthens the centrality of DMs; their background and risk attitude can lead to different estimations.

3.1.3 Identification of suppliers. Nowadays high competition and fast-changing markets have massively increased the number of suppliers. The SS problem becomes highly relevant. Although digitalization enables a fast gathering of information about a huge number of suppliers, resource and time constraints discourage DMs from evaluating all the potential suppliers. As a result, a shortlist of suppliers ($n = 1, \dots, N$) is defined to proceed with the following analyses. The screening process requires identifying a set of criteria to evaluate all the identified suppliers and decide on the best candidates. In the context of this screening process, [Hwang and Yoon \(1981\)](#) introduced systematic methods such as conjunctive, disjunctive and lexicographical screening to guide decision-makers in the choice to narrow down the pool of suppliers, as detailed in [Table 1](#). These methods are crucial in the initial screening phase, where suppliers are filtered based on their ability to meet specific criteria.

Table 1. Classification of screening processes according to [Hwang and Yoon \(1981\)](#)

Conjunctive screening	A supplier can enter the shortlist if and only if it satisfies all the set requirements
Disjunctive screening	A supplier can enter the shortlist if it satisfies at least one of the set requirements, even if they fall short on others
Lexicographical screening	Requirements are ranked in order of importance, suppliers are first evaluated on the most important and only those satisfying them, pass to the next evaluation stage and so on until a desired number of suppliers is obtained
Source(s): Created by authors	

The selection of an appropriate screening method is particularly important when industry-specific criteria are involved; for example, when some requirements are non-negotiable, conjunctive screening can be a proper approach to select the initial pool of suppliers (Linkov *et al.*, 2004; Rezaei *et al.*, 2016). Moreover, De Boer *et al.* (1998) call attention to the point that two types of decision rules can be applied in SS: compensatory and non-compensatory ones. The aforementioned screening process (Hwang and Yoon, 1981) aligns with the non-compensatory decision rules (Junior *et al.*, 2013). Non-compensatory rules are based on the premise that inadequate performance on one criterion cannot be compensated by strong performance on another, making them particularly effective for the initial screening phase. During this phase, it is crucial to ensure that all shortlisted suppliers meet the minimum requirements for key criteria, and there should be no compensation for a supplier not meeting the minimum requirement in a particular criterion. Therefore, non-compensatory rules are most appropriate at this stage, while, when comparing qualified suppliers in the final selection phase, compensatory rules may be more suitable, as all suppliers at that stage would have already met the minimum criteria (De Boer *et al.*, 1998; Rezaei *et al.*, 2014).

3.2 Step 2

Step 2 covers two independent procedures that can be run in parallel. In particular, the weight is assigned to each of the selected criteria and the score for each criterion is assigned to every supplier.

3.2.1 Criteria weights. Once we have identified the criteria for the SS analysis, we need to assign a weight ($w_1, \dots, w_k$) to each of them.

The Best-Worst Method (BWM), before mentioned in the literature review, is applied (Rezaei, 2015, 2016). It offers a structured way to conduct pairwise comparisons; it requires less information compared to the full pairwise comparison approach that perfectly fits with *new task* situations usually characterized by scarcity of available data on some/all suppliers. A few advantages are reported below.

Firstly, we need to select *a priori*, before conducting the pairwise comparisons, the best and the worst criteria. DMs have a clear understanding of how to evaluate criteria that imply more consistent pairwise comparisons. Secondly, the use of two opposite references (*best* and *worst*) to determine the two pairwise comparison vectors reduces possible anchoring biases during DMs' pairwise comparison process. Thirdly, BWM stands in the middle between methods that use a single vector (e.g. Swing and SMART family) and those that use a full matrix (e.g. AHP). By using pairwise comparisons, we can check the consistency of DM's evaluations, which instead is not possible with one-vector methods. At the same time, it is data (and time)-efficient as it does not require a full-matrix evaluation. Asking too many and not independent questions might produce confusion and inconsistency in DMs' answers. The steps of the BWM (Rezaei, 2015, 2016) for criteria weighting are below described.

Step 1

Once the criteria are defined, every DM has to determine the *best* (most desirable, most important) and the *worst* (least desirable, least important) criteria.

Step 2

The Best-to-Others (BO) vector determines the preference of the best criterion over all the other criteria, using a number between 1 and 9. The resulting Best-to-Others (BO) vector is $BO = (a_{B1}, a_{B2}, \dots, a_{BK})$; where a_{Bj} indicates the preference of the *best criterion* B over criterion j .

Step 3

The Others-to-Worst (OW) vector determines the preference of all the criteria over the worst criterion, using a number between 1 and 9. The resulting OW vector is

$OW = (a_{1W}, a_{2W}, \dots, a_{KW})$; where a_{jW} indicates the preference of criterion j over the worst criterion W .

Once the BO and OW vectors are determined, the consistency of the DM's preferences can be assessed through the recent method identified by [Liang et al. \(2020\)](#), i.e. the Input-based Consistency Ratio (CR^I):

$$CR^I = \max_k CR_k^I$$

where:

$$CR_k^I = \begin{cases} \frac{a_{Bk} \times a_{kW} - a_{BW}}{a_{Bk} \times a_{Bk} - a_{Bk}}; & \text{if } a_{Bk} > 1 \\ 0; & \text{if } a_{Bk} = 1 \end{cases} \quad (1)$$

The consistency thresholds for CR^I were defined by [Liang et al. \(2020\)](#), which consider the number of criteria (from 3 to 9) and the scale, i.e. the value assumed by a_{BW} (from 3 to 9). In case of significant inconsistencies, the analyst could aid the DM in revising the pairwise comparison systems (local inconsistencies can be used for guiding the revision process; see [Liang et al. \(2020\)](#)).

Step 4

The aim of the final step is to determine the optimal weights for each criterion k so that the maximum absolute differences $\left| \frac{w_B}{w_k} - a_{Bk} \right|$ and $\left| \frac{w_k}{w_W} - a_{kW} \right|$ for all k is minimized. This translates into a min-max problem as follows:

$$\min \max_k \left(\left| \frac{w_B}{w_k} - a_{Bk} \right|, \left| \frac{w_k}{w_W} - a_{kW} \right| \right)$$

subject to:

$$\sum_k w_k = 1$$

$$w_k \geq 0, \text{ for all } k \quad (2)$$

This is equivalent to the following problem (3):

$\min \xi$
subject to:

$$\left| \frac{w_B}{w_k} - a_{Bk} \right| \leq \xi, \text{ for all } k$$

$$\left| \frac{w_k}{w_W} - a_{kW} \right| \leq \xi, \text{ for all } k$$

$$\sum_k w_k = 1$$

$$w_k \geq 0, \text{ for all } k \quad (3)$$

Solving model (3), the optimal weights $w_1, w_2, \dots, w_K$ and ξ^* are obtained.

Model (3) might result in multiple optimal solutions for problems with more than three criteria. It is possible to linearize the original nonlinear problem, which results in a unique solution (Rezaei, 2016):

$\min \xi^L$
subject to:

$$|w_B - a_{Bk} w_k| \leq \xi^L, \text{ for all } k$$

$$|w_k - a_{kW} w_W| \leq \xi^L, \text{ for all } k$$

$$\sum_k w_k = 1$$

$$w_k \geq 0, \text{ for all } k \quad (4)$$

The optimal weights ($w_1^*, w_2^*, \dots, w_k^*$) and ξ^{L*} are obtained.

The linear BWM (4) constitutes a very good trade-off between the goodness of results and the required computational effort. It can be simply implemented in widely available software such as Microsoft Excel, thus enhancing the possibilities for a practical application.

The linear model of BWB (4) will be applied at this step of the model development. Instead, the non-linear model of BWB (3) will be utilized for the sensitivity analysis (see Section 3.6.1).

Consistency ratio

The Consistency Ratio (5), subsequently called the Output-based Consistency Ratio (CRO) by Liang *et al.* (2020), shows the extent to which the provided pairwise comparison system is consistent. The lower the consistency ratio the higher the consistency of the pairwise comparison system. Consistency Ratio $\in [0, 1]$, values close to 0 show more consistency, while values close to 1 show less consistency.

$$CR^O = \frac{\xi^*}{\text{Consistency index}} \quad (5)$$

Table 2 shows the maximum possible ξ , i.e. the consistency index, for different values of $a_{BW} \in \{1, 2, \dots, 9\}$.

Table 2. Consistency index

a_{BW}	1	2	3	4	5	6	7	8	9
CI	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

Source(s): Rezaei (2015)

As seen above for the CR^I , the consistency thresholds for CR^O were determined by considering the number of criteria (from 3 to 9) and the scale, i.e. the value assumed by a_{BW} (from 3 to 9) (Liang *et al.*, 2020).

3.2.2 Supplier score. Concerning the performances of the selected criteria, each supplier is assigned a score (S_{nk}), where n and k are respectively the supplier and the criterion indexes, representing how well it performs about each criterion. The main novelty introduced by the proposed model is the distinction between *measurable* and *forecastable* criteria, which gives

the possibility to completely evaluate also *new suppliers* by means of two different scoring processes depending on the considered criterion, i.e. *benefit* and *cost* criteria below detailed (Figure 2).

3.2.2.1 Scoring for measurable criteria. As performances related to measurable criteria (v_{nk}) can be directly extrapolated from submitted bids, suppliers' scores can be obtained using a simple normalization. The normalization process will be different according to the nature of the criterion under consideration.

A direct normalization is used for benefit criteria (Equation (6)):

$$S_{nk} = \frac{v_{nk}}{\sum_k v_{nk}} \tag{6}$$

while for cost criteria an *inverse normalization* must be adopted (Equation (7)):

$$S_{nk} = \frac{1}{\sum_k \frac{1}{v_{nk}}} \tag{7}$$

3.2.2.2 Scoring for forecastable criteria. As it comes to the evaluation of new suppliers for *forecastable* criteria, things become challenging. Forecastable criteria can be also *quantitative* or *qualitative*. Quantitative criteria refer to values directly linked to the performances (e.g. punctuality can be measured in terms of the average delay of the supply). Qualitative criteria are expressed in Likert scales (e.g. business integration capability measured on a scale from 1 to 10). Then, independently of the considered criterion, values associated with suppliers' performances are normalized, by using Equations (6) and (7), equal to measurable criteria. Such intangible criteria might lead to discrepancies in the evaluation of the performances of different companies.

When dealing with historical suppliers, the values representing performances related to quantitative and qualitative forecastable criteria can be directly extrapolated from the company's databases, hence the evaluation is objectively detached from DMs' evaluations. As it regards new suppliers, we need instead to leverage the expertise of DMs who refer to existing available data and forecasts. Similarities with existing/historical suppliers can support the assessment of the performance of new ones. A scenario-based approach is applied to make data more consistent and reduce DMs' biases.

3.2.2.3 Scenario-based approach – new suppliers. The scenario-based approach sets some scenarios to represent possible future situations and integrates the risk attitude of the DMs into the decision process. The number of scenarios is set equal to five ($s = 1, \dots, 5$) and they are

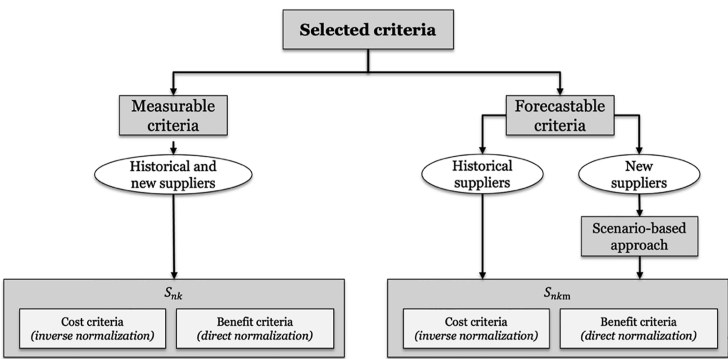


Figure 2. Framework of the suppliers' scoring processes. Source: Created by authors

named: *optimistic*, *medium-optimistic*, *expected*, *medium-pessimistic* and *pessimistic*. The *expected* scenario takes as a reference the “average performances” of historical suppliers, i.e. in this scenario new suppliers are expected to behave as the historical ones, while the other scenarios capture best-case, worst-case and intermediate conditions to better cover the spectrum of possible supplier performances, ensuring a balanced assessment of different risk levels.

Each DM must assign a probability of occurrence (po_s) to each scenario and define a value characterizing the supplier under analysis in the different scenarios (v_s), i.e. the normalized values of the supplier’s performances in each scenario. Then, each DM (m) evaluates the score of each supplier (n) for a considered criterion (k) (S_{nkm}) by applying first Equation (8) and then Equations (9) or (10):

$$v_{nkm} = \sum_s po_{nsk} \cdot v_{nsk} \quad (8)$$

$$S_{nkm} = \frac{v_{nkm}}{\sum_k v_{nkm}} \text{ (direct normalization)} \quad (9)$$

$$S_{nkm} = \frac{1}{\sum_k \frac{1}{v_{nkm}}} \text{ (inverse normalization)} \quad (10)$$

3.3 Step 3

Defining S_{nk} and S_{nkm} (only for forecastable criteria of new suppliers), we got an evaluation by every DM of criteria associated with suppliers. Now we want to gather these evaluations and obtain the Total Score (TS_{nm}) of the n -th supplier given by the m -th DM. It is obtained as a weighted average of the scores of a considered supplier on a selected criterion (S_{nk} or S_{nkm}) and the criteria weights (w_k) (Equation (11)):

$$TS_{nm} = \sum_k w_k \cdot S_{nk} + \sum_k w_k \cdot S_{nkm} \quad (11)$$

3.4 Step 4

Once the Total Score (TS_{nm}) of each supplier has been obtained for each DM, the Total Score (TS_n) for each supplier n , considering DM’s opinions, is calculated by aggregating values through a geometric mean (Equation (12)):

$$TS_n = \sqrt[m]{\prod_m TS_{nm}} \quad (12)$$

[Note: steps 3 and 4 become the same when there are no forecastable criteria and/or new suppliers].

3.5 Step 5

The previous step closed the analysis for SS and we obtained a preference ranking of the suppliers. From this step, the OA problem is explored by assigning to each supplier the order quantities considering its performance. It implies that the best performers will have a higher saturation of their supply and vice versa for the low-value suppliers.

We used a two-stage LP to solve an optimization problem, as clarified in Figure 3. Linear equations ($c_1, c_2, \dots, c_C$) address different aspects of the OA problem by including constraints and policies of the company and the suppliers. They take into account physical constraints (e.g. suppliers’ capacities, company’s inventory capacity) as well as supplier-buyer relationship policies, from the company’s side (e.g. not assigning more than a fraction of the whole supply

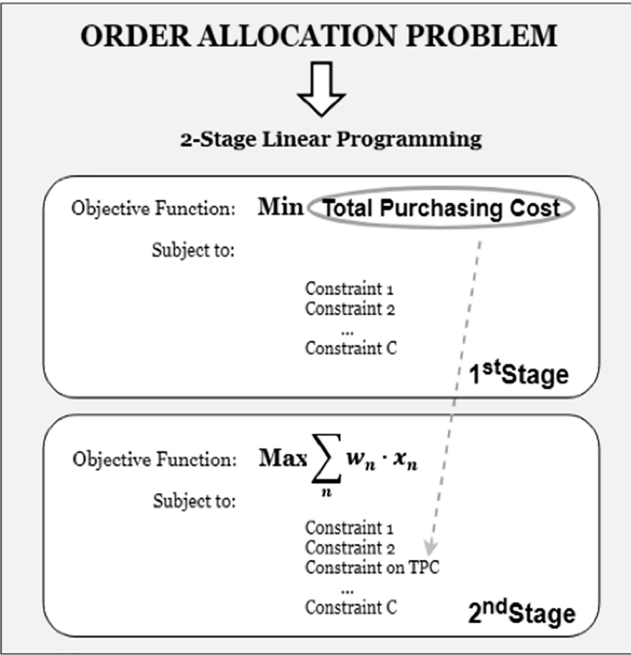


Figure 3. Two-stage linear programming problem. Source: Created by authors

to a single supplier, setting a lower bound for starting a commercial relationship) and from suppliers' side (e.g. setting a lower bound for starting a commercial relationship, not selling more than a certain fraction of the total production capacity to a single buyer).

3.5.1 First stage. In the first stage, a minimization linear problem is formulated, aimed at minimizing the Total Purchasing Cost (TPC) without considering the suppliers' ranking. The quantity to be purchased (Q_{tot}) is split among suppliers by undergoing constraints and policies of the company and the suppliers. At this stage, the order quantities are assigned not considering the best suppliers, therefore this minimization problem might cause a violation of the suppliers' ranking. Indeed, it may be the case when the cheapest suppliers do not correspond to the best suppliers according to the suppliers' ranking.

3.5.2 Second stage. Nonetheless, the suppliers' ranking cannot be ignored, and this second stage enables the integration in the OA problem of the suppliers' prioritization according to their Total Score (TS_n). The objective function represents the prioritization of suppliers by solving a maximization linear problem. The suppliers' Total Scores (TS_n) constitute the base for the prioritization of suppliers in being assigned order quantities ($x_1, \dots, x_n$). As before, the problem is subject to constraints and policies of the company and the suppliers. A new constraint is now considered; not minimizing the TPC at this stage, we decided to introduce a constraint related to the maximum TPC a company can afford. Depending on how compelling this constraint is, we might observe variations from the initial maximization linear problem, which does not consider this new budget constraint and keeps unchanged the constraints of the first stage.

By increasing the budget step by step considering the calculated minimum TPC (e.g. 1 by 1%), it is possible to map the solution space by identifying the boundaries among different possibilities to allocate order quantities. DMs will thus acquire knowledge on possible scenarios of OA among suppliers, given the normal variation of the company's budget and

performance. This empowers DMs to select a preferred solution, for a variety of reasons, among comparable alternatives.

3.6 Step 6

When addressing strategic problems characterized by risk, as SS and OA problems are, it is not sufficient to simply propose a solution, rather it is necessary to verify the robustness of the found solution. The unpredictability of some situations might change the expected outcomes, and, for this reason, it is important to evaluate the steadiness of the solution in changing conditions. It is not just a matter of risk; the company's strategic focus needs to be considered too. Different strategies may lead to diverse suppliers' evaluations and modified rankings in the SS problem.

We will handle the sensitivity analysis by studying the possible variation of two parameters defined in Step 2 of the proposed model: the criteria weights (w_k) assigned through the BWM (Section 3.6.1), the probabilities of occurrence (po_s) assigned by DMs for scenarios of forecastable criteria of new suppliers (Section 3.6.2).

3.6.1 Weights of criteria. The sensitivity analysis regarding the criteria weights is performed by solving the non-linear BWM. The outcome of a non-linear BWM is a set of optimal weights for selected criteria. A range of optimal weights is obtained for each criterion by running the non-linear BWM 100 times. Each run corresponds to one feasible solution, and we can select one optimal-weight vector depending on the sensitivity analysis we want to perform. This sensitivity analysis enables assessing the robustness of the selected solution according to the company's focus and determining to what extent criteria can be prioritized over the others. We can indeed investigate the effects on the final OA solution, with respect to the linear BWM solution, by increasing the weight of a criterion. Hence, the optimal weights for each run are identified through the non-linear BWM, as formulated above in Equation (3).

3.6.2 Weights of scenarios. In evaluating new suppliers against forecastable criteria, as explained in Section 3.2.2.2, the DMs are required to define a set of probabilities of occurrence (po_s) and assign the suppliers a score (v_s). Changing po_s might affect the goodness of the final solution. To understand the influence of DMs' risk attitude, it is indeed possible to increase or decrease the probabilities of occurrence (po_s). Increasing the po_s in the *optimistic zone* puts a DM in a more risk-taker position, thus rewarding the most promising suppliers; on the contrary, increasing the po_s in the *pessimistic zone* determines a more risk-averse perspective.

4. Real-world case study and discussion

We now move to the application of the proposed model in a real industrial context. A case study of a leading Italian company in the field of radiators and Controlled Mechanical Ventilation (CMV) production was chosen. The reference case has specific contours, typical of the engineering industry, which, in turn, represents a characteristic environment, led by fierce competitiveness, high stress on quality and continuous improvement. Moreover, the adopted Just-In-Time (JIT) production philosophy remarks the need of searching for suppliers able to supply required materials in short times and to be flexible in terms of purchased quantities and delivery times. The specific case under consideration regards the purchasing of steel tubes used for radiators' production, which constitutes a leveraged item for the company, destined for large European retailers. The tubes have high-quality standards because they are welded with radiator heads to compose the elements constituting the radiator, thus defective tubes can cause significant problems during the production process. The case study will follow step-by-step the proposed model in the previous section. Finally, Section 4.7 will provide an in-depth discussion of the overall implications of the study, focusing on how the proposed MCDM model for SS and OA bridges theory and practice, based on insights from the case study.

4.1 Step 1

4.1.1 Identification of DMs. The roles of the DM are played by the *purchasing manager* and by the *quality assurance manager*, two main voices in the procurement process of the company.

4.1.2 Identification of criteria. The DMs, after an accurate analysis by [De Boer \(2017\)](#), have identified five criteria: *price*, *quality*, *delivery time*, *punctuality* and *flexibility*. Except for *price* and *quality*, which are the most used criteria in SS problems, identified criteria are aimed at evaluating the suppliers from the point of view of their compliance with production pace, being able to apply variation to order quantities and delivery date when necessary. The identified criteria, according to their nature, have been divided by the DMs into measurable and forecastable criteria, as reported in [Table 3](#).

4.1.3 Identification of suppliers. The company adopts a two-stage SS process, constituted by the screening and evaluation phases. During the screening phase, the revenue and financial stability of potential suppliers are assessed, moreover, according to the company's policies, only large companies (+200 workers) are considered potential suppliers. The *conjunctive screening* process was adopted, i.e. a supplier must satisfy all basic requirements to enter the shortlist. The evaluation process is applied only to the candidates grouped in the shortlist, obtained downstream of the screening phase. Two historical suppliers (*Supplier 1*, *Supplier 2*) and one new supplier (*Supplier 3*) compose the current supplier pool. *Supplier 1* is an Italian historical company active at all levels of steel production. *Supplier 2* is a Serbian steel producer. *Supplier 3* is a specialized company in the production of steel rods and formed steel, which has expanded its business from North-East Italy to Central Europe.

As regards the historical suppliers, it should be noted that, despite many advantages characterizing *Supplier 1*, *Supplier 2* must be involved in the supply of the steel tubes because it is a steel supplier for the company, and it acts as a logistic partner for the transportation of semi-finished radiators from Italy to the European plants. The total demand of tubes of the company is evaluated in 22 shipments per month, currently assigned as follows ([Table 4](#)).

Supplier 3, by its side, can offer almost the same delivery time as that guaranteed by *Supplier 1* and the same can be said for punctuality. As regards flexibility, the production capacity and storing space of *Supplier 3* are quite lower than *Supplier 1*, thus the flexibility will be lower too. The following application of the model aims at defining a redistribution of order quantities, including *Supplier 3* as it is thought that it can partially substitute *Supplier 2* and also get a portion of the order quantities required by *Supplier 1*.

Table 3. Criteria classification for the real-world case

Criterion	Type
Price	Measurable
Quality	Measurable
Delivery time	Measurable
Punctuality	Forecastable
Flexibility	Forecastable
Source(s): Created by authors	

Table 4. Current supply

Supplier	Materials
Supplier 1	85%
Supplier 2	15%
Source(s): Created by authors	

4.2 Step 2

4.2.1 Criteria weights. Once criteria have been identified (Section 4.1.2), their relative weights need to be determined. The calculation of optimal weights is performed by exploiting the linear BWM, according to the procedure explained in Section 3.2.1. Judgements given by the two DMs, each working on its own to avoid any sort of influence, are reported in Table 5.

DM1 set price as the most important criterion (best) whereas DM2 selected the quality criterion. Both identified flexibility as the least important criterion (worst). This fact can be associated with the great market stability reached over the years, i.e. a small number of clients accounts for most of the production. This, in turn, means that very few variations usually occur to the sales forecast, thus suppliers' flexibility is not considered that important, yet relevant.

It is worth noticing that both the purchasing manager and the quality assurance manager gave almost the same importance to the criteria of delivery time and punctuality, which indeed represent the basis for the JIT production philosophy in the company's culture.

We have checked the consistency of the criteria and all the CR^I are below the consistency threshold (Liang *et al.*, 2020), as explained in Section 3.2.1.

Then, applying the linear BWM, we obtained the unique weights (w_1, w_2, w_3, w_4, w_5) reported in Table 6.

The CR^O for each DM is below the threshold, thus both the DMs were consistent in their evaluations. The application of the linear BWM has determined unique weights that are now applied in the following steps. Instead, weights determined with the non-linear BWM will be introduced for the sensitivity analysis (Section 4.6).

4.2.2 Supplier score. The next step concerns the calculation of suppliers' scores on selected criteria. Different procedures were set depending on the nature of the considered criterion (i.e. measurable or forecastable).

4.2.2.1 Scoring for measurable criteria. From the company's interviews, we gathered all the required and useful information to assess measurable criteria. It follows that (historical and new) suppliers' scores for the measurable criteria can be directly calculated, taking advantage

Table 5. Judgements of DM1 and DM2

Criterion	DM1			DM2		
	BO (Price)	OW (Flexibility)	CR_k^I $CR_{max}^I = 0.2306$	BO (Quality)	OW (Flexibility)	CR_k^I $CR_{max}^I = 0.2958$
Price	1	5	0	2	6	0.0714
Quality	2	4	0.15	1	8	0
Del. time	2	4	0.15	3	4	0.0714
Punctuality	3	3	0.2	3	5	0.125
Flexibility	5	1	0	8	1	0

Source(s): Created by authors

Table 6. Criteria weights

Criterion	DM1	DM2
Price	0.371795	0.234783
Quality	0.211538	0.408696
Del. time	0.211538	0.156522
Punctuality	0.141026	0.156522
Flexibility	0.064103	0.043478
Ksi*	0.051282	0.060870
CR^O	0.022297	0.013617
CR_{max}^O	0.3019	0.4029

Source(s): Created by authors

of a simple normalization technique, by using Equations (6) and (7) (Section 3.2.2.1). The suppliers' scores (S_{nk}) for measurable criteria are reported in Table 7.

4.2.2.2 Scoring for forecastable criteria. The calculation of suppliers' scores for forecastable criteria is different for historical and new suppliers.

For historical suppliers, performances can be directly extracted from company databases (Table 8).

In contrast, for the new supplier, the calculation of the scores for the two forecastable criteria is performed by exploiting a *scenario-based approach* from every single DM (Table 9 and 10).

As it can be easily inferred by looking at the resulting scores for the new supplier, a general optimism characterizes the perception of DMs on the new supplier. As regards punctuality according to DM1's opinion, Supplier 3 is expected to work better than Supplier 1 and at least

Table 7. Suppliers' scores on measurable criteria

Supplier	Price [€/ton]	Price score	Quality [%]	Quality score	Del. time [days]	Del. time score
Supplier 1	750	0.33701	99	0.33446	2	0.41667
Supplier 2	760	0.33258	97	0.32770	5	0.16667
Supplier 3	765	0.33041	100	0.33784	2	0.41667

Source(s): Created by authors

Table 8. Data about forecastable criteria for historical suppliers

Supplier	Punctuality [%]	Flexibility [%]
Supplier 1	98	97
Supplier 2	99	95

Source(s): Created by authors

Table 9. Data of DM1 about forecastable criteria for the new supplier

Punctuality	Prob	Val_scen	Flexibility	Prob	Val_scen
P	0.1	96%	P	0.05	95%
MP	0.1	97%	MP	0.1	96%
E	0.2	97.5%	E	0.3	97%
MO	0.4	98.5%	MO	0.3	98%
O	0.2	99.5%	O	0.25	99%
Value		98.1%	Value		97.6%

Note(s): P: pessimistic; MP: medium-pessimistic; E: expected; MO: medium-optimistic; O: optimistic

Source(s): Created by authors

Table 10. Data of DM2 about forecastable criteria for the new supplier

Punctuality	Prob	Val_scen	Flexibility	Prob	Val_scen
P	0.15	95%	P	0.1	94%
MP	0.15	97%	MP	0.1	96%
E	0.25	97.5%	E	0.4	97%
MO	0.3	98%	MO	0.2	98%
O	0.15	99%	O	0.2	99%
Value		97.4%	Value		97.2%

Note(s): P: pessimistic; MP: medium-pessimistic; E: expected; MO: medium-optimistic; O: optimistic

Source(s): Created by authors

comparably to Supplier 2, and even DM2 is confident that the new supplier is expected to work at least comparably to Suppliers 1 and 2. About the flexibility forecast, we can notice that both DMs assigned the new supplier an expected value (97%) higher than the average between historical suppliers (97 and 95%).

Having obtained the values of the criteria associated with each supplier, applying Equation (8), it is possible to obtain the suppliers' scores (S_{nkm}) for forecastable criteria (Equation (9)), which will be different for the two DMs (Tables 11 and 12).

4.3 Step 3

Once all the criteria weights and suppliers' scores for each criterion have been calculated, by using Equation (11), we can calculate the Total Score of each supplier according to each DM's opinion (TS_{nm}) (Table 13).

4.4 Step 4

The Total Score (TS_n) for each supplier is obtained with Equation (12) (Table 14) by aggregating the values of the two DMs through the geometric mean. Looking at the resulting suppliers' ranking, it can be inferred that Supplier 3 will probably get part of the orders currently assigned to Supplier 2.

4.5 Step 5

Once the suppliers' ranking has been obtained, the OA problem is tackled to define the distribution of order quantities among the three suppliers. The OA problem is strongly characterized by the specific situation it relates to, thus great attention must be paid to the correct definition of the company's policies and other constraints. Table 15 reports the

Table 11. Scores for DM1 (S_{nkm})

Supplier	Punctuality	Flexibility
Supplier 1	0.33209	0.33494
Supplier 2	0.33548	0.32804
Supplier 3	0.33243	0.33702
Source(s): Created by authors		

Table 12. Scores for DM2 (S_{nkm})

Supplier	Punctuality	Flexibility
Supplier 1	0.33288	0.33541
Supplier 2	0.33628	0.32849
Supplier 3	0.33084	0.33610
Source(s): Created by authors		

Table 13. Total score of each supplier for DM1 and DM2 (TS_{nm})

Supplier	DM 1	DM 2
Supplier 1	0.352496	0.347720
Supplier 2	0.296569	0.305018
Supplier 3	0.350937	0.347263
Source(s): Created by authors		

Table 14. Total score of each supplier (TS_n)

Supplier	Total score
Supplier 1	0.350100
Supplier 2	0.300764
Supplier 3	0.349095
Source(s): Created by authors	

Table 15. Nomenclature for the OA analysis

Notations	Description
n	Index of supplier
$TS(n)$	Total score of suppliers n
$x(n)$	Quantity to be allocated to suppliers n
$c(n)$	Total procurement cost of suppliers n
$Min x(n)$	Min quantity to be assigned to Supplier n
$Max x(n)$	Max quantity to be assigned to Supplier n
TPC	Total purchasing costs
TPC_{max}	Maximum budget available
Source(s): Created by authors	

nomenclature used in the following OA analysis. Table 16 provides all the necessary data (constraints and requirements) for the development of the OA problem.

The OA problem is solved according to the two-stage LP introduced in the previous section (Section 3).

4.5.1 First stage. In the first stage, a minimization linear problem is formulated, aimed at minimizing the TPC without considering the suppliers' ranking.

$$\begin{aligned} \min TPC &= \sum_{n=1}^3 [x(n)c(n)] \\ \text{subject to:} \end{aligned}$$

$$x(1) \leq 18 \text{ (i)}$$

$$x(2) \leq 4 \text{ (ii)}$$

$$x(3) \leq 11 \text{ (iii)}$$

$$x(1) + x(2) + x(3) = 22 \text{ (iv)}$$

$$x(1) \geq 0 \text{ (v)}$$

$$x(2) \geq 2 \text{ (vi)}$$

$$x(3) \geq 0 \text{ (vii)} \tag{14}$$

The constraints (i), (ii) and (iii) regard the maximum quantities assignable to suppliers, which, considering the total supply, must be no more than 81.8% for Supplier 1, 18.2% for Supplier 2 and 50% for Supplier 3. As a result, we guarantee at least two suppliers and avoid assigning all the orders just to one supplier. The constraint (iv) establishes the total supply required per month. The constraint (vi) refers to the minimum quantity to be assigned to Supplier 2 (as there is a minimum order quantity for the reasons explained at the beginning of this section). The results of the first stage are reported in Table 17.

Table 16. Data to set the OA problem

Parameters	Value
TS1	0.350100
TS2	0.300764
TS3	0.349095
c1 [€/ton]	750
c2 [€/ton]	760
c3 [€/ton]	765
Max x(1) [supplies]	18
Max x(2) [supplies]	4
Max x(3) [supplies]	11
Min x(1) [supplies]	0
Min x(2) [supplies]	2
Min x(2) [supplies]	0
Tot. supply	22
Source(s): Created by authors	

Management
Decision**421****Table 17.** Results of the 1st stage

Variable	Value
TPC [€]	16,540
x(1) [supplies]	18
x(2) [supplies]	4
x(3) [supplies]	0
Source(s): Created by authors	

At the end of this stage, no order quantities are assigned to the new supplier. It was expected since, just by looking at the prices offered by the three suppliers, Supplier 3 was the most expensive one.

4.5.2 *Second stage.* However, the suppliers' ranking cannot be ignored, and this second stage enables the integration in the OA problem of the suppliers' prioritization according to their Total Score (TS_n) defined in Step 4 (Section 4.4).

$$\begin{aligned} &\max \sum_{n=1}^3 [x(n)TS(n)] \\ &\text{subject to:} \end{aligned}$$

$$x(1) \leq 18 \text{ (i)}$$

$$x(2) \leq 4 \text{ (ii)}$$

$$x(3) \leq 11 \text{ (iii)}$$

$$x(1) + x(2) + x(3) = 22 \text{ (iv)}$$

$$x(1) \geq 0 \text{ (v)}$$

$$x(2) \geq 2 \text{ (vi)}$$

$$x(3) \geq 0 \text{ (vii)}$$

$$\sum_{n=1}^3 [x(n)c(n)] \leq TPC_{max} \text{ (viii)} \quad (15)$$

The constraints (i–vii) are the same as identified for the first stage; in addition, constraint (viii) is used to account for the maximum budget available for the OA problem. Therefore, the available budget must be greater than the minimum TPC calculated in the 1st stage, otherwise, the solution space would become empty. This maximization linear problem can be first solved without the budget constraint (viii) to see the value resulting from TPC, by just maximizing the suppliers’ score and not considering the cost of the solution. If the obtained TPC is lower than the maximum TPC available, this first solution to the maximization linear problem will not be affected by the introduction of the new constraint on the budget. Therefore, the budget constraint results in a non-discriminating factor. Whereas a resulting TPC higher than the maximum TPC will change the solution space by reallocating supplies to comply with the requirement.

The available budget was set to 16,600€. The optimal solution is first obtained without the budget constraint (i.e. keeping the same constraint of the 1st stage). In Table 18, the optimal solution is finally reported.

The resulting TPC (i.e. 16,550€) is lower than the available budget, then, in this case, it is needless to introduce the budget constraint. In Figure 4, a graphical representation of the OA solution range is presented. It is worth noting that the optimal solution to the OA problem is unique even considering budget increments. This means that the found solution is an optimal solution independent of the allocated budget.

4.5.3 Discussion. Analysing the OA solution, part of the order quantities currently assigned to Supplier 2 are allocated to Supplier 3. Not all the initial quantities of Supplier 2 have been relocated due to the constraint required for Supplier 2, at least two supplies per month to maintain the commercial relationship with European plants.

Looking at Supplier 3 and considering its willingness to establish a long-lasting relationship with the company, it could be a great solution to start testing it with small order

Table 18. Optimal solution to the OA problem

Variable	Value
TPC [€]	16,550
x1 [supplies]	18
x2 [supplies]	2
x3 [supplies]	2

Source(s): Created by authors

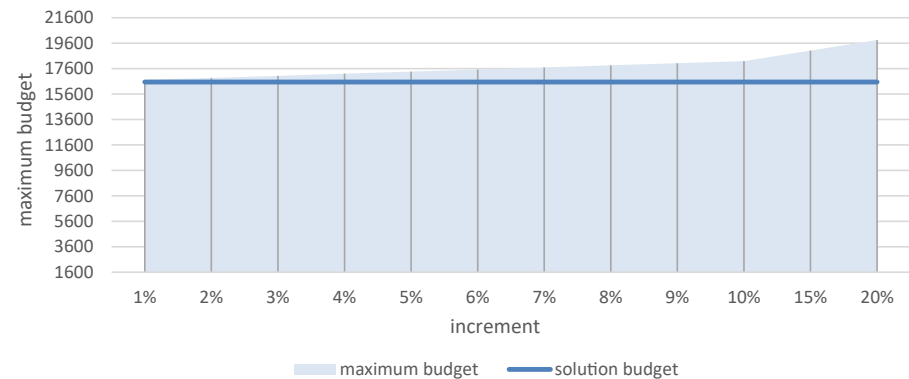


Figure 4. Graphical representation of the OA range of solutions. Source: Created by authors

quantities, and then, increase them at the expense of Supplier 1, by leveraging on synergies that might arise between the company and Supplier 3, which is deeply rooted in the territory of North-East Italy. Furthermore, Supplier 3 is the best one in terms of quality, which is a very important feature for the considered company. Therefore, starting a long-lasting collaboration with Supplier 3 might also lead to continuous improvement in radiators' quality, which would become a significant strategic advantage to competitors. As a final consideration, Supplier 1 is assigned a high fraction of the total requirement, i.e. more than 80% of the monthly supplies, which is equal to the initial constraint set. Supplier 1 is indeed the main player in steel production worldwide.

4.6 Step 6

The sensitivity analysis is a crucial step from the point of view of the operations and logistics strategy because it enables evaluating the steadiness of the obtained optimal solution if variables' values change. A weak solution, which is not sufficiently resilient to maintain its optimality even under slight perturbations, may result in a great loss, in economic and reputation terms. As explained in the previous section (Section 3.6), two types of sensitivity analysis are applicable by varying weights of criteria and scenarios. One example below shows the sensitivity analysis performed on the criteria weights by using the non-linear BWM.

4.6.1 Criteria weights. We focused our attention on Supplier 3 comparing its performances with those of Supplier 1. Looking at the suppliers' scores, we can notice that Supplier 3 performs better than Supplier 1 in one measurable criterion, that is *quality* (0.33784 of Supplier 3 versus 0.33446 of Supplier 1; Table 7). We wanted to test a feasible solution with greater weights for the quality criterion with respect to the resulting ones from the linear BWM (Section 4.2.1) to see whether the score of Supplier 3 would have exceeded Supplier 1. Therefore, we ran the non-linear BWM 100 times to get a range of optimal weights, and then, selected the vector with the maximum weight for the quality criterion. The task was repeated for DM1 and DM2's weights.

We investigated the "boundary" condition by analysing the effects on the obtained results when we selected greater, but still feasible, weights for the quality criterion of Supplier 3. Following this idea, the criteria weights obtained for each DM are reported in Table 19.

The new Total Scores (TS_n) for each supplier, resulting from Equation (12), are reported in Table 20.

4.6.2 Discussion. The Total Score of Supplier 3 is still lower than Supplier 1, which means that the OA will not change. This is a good point since it means that the found solution is robust enough to keep its optimality even under the effect of slight perturbations of the internal and external environments.

The robustness of the found solution is anchored on the price guaranteed by Supplier 1, lower by about 15 €/ton, i.e. almost 2%, than Supplier 3. Figure 5 reports the behaviour of Supplier 1 when varying their price per ton of Supplier 3. If Supplier 3 guarantees a price equal

Table 19. Criteria weights for DM1 and DM2

Criterion	Weight for DM1	Weight for DM2
Price	0.307947	0.129314
Quality	0.280168	0.422902
Del. time	0.212537	0.181645
Punctuality	0.137759	0.213277
Flexibility	0.061589	0.052862
Ksi*	0.000012	0.000026

Source(s): Created by authors

Table 20. Total score of each supplier

Supplier	Total score
Supplier 1	0.350926
Supplier 2	0.298501
Supplier 3	0.350561

Source(s): Created by authors

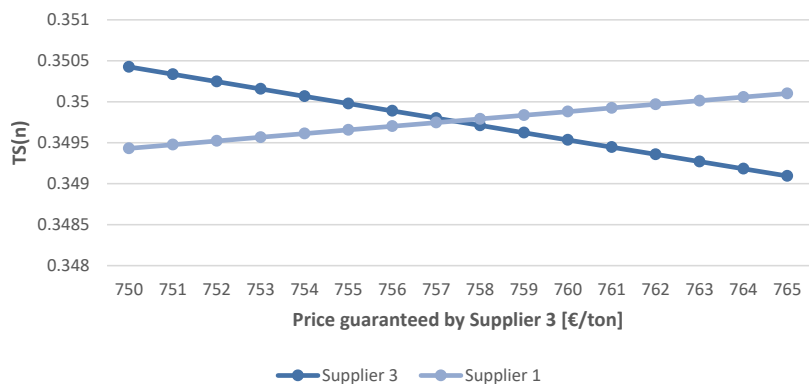


Figure 5. Behaviour of Supplier 1 when varying the price per ton of Supplier 3. Note(s): Considered the optimal solution found by the linear BWM. Source: Created by authors

to 757.5 €/ton, instead of the current 765 €/ton, its Total Score becomes equal to that characterizing Supplier 1. This kind of analysis is very useful to the company that can use it as a means of negotiation with the new supplier, by promising the purchase of greater quantities in exchange for a discount on the purchasing price. Starting from this point, it is quite easy to solve again the OA problem and find the most appropriate allocation of order quantities and the required budget for the new solution.

As another sensitivity analysis, we also played by varying the constraint of the maximum quantity assignable to Supplier 1 and keeping the others unchanged, including the budget constraint. The results of the maximization linear problem are shown in Table 21. Quantities assigned to the suppliers, TPC and the maximized objective function are displayed. Figures 6 and 7 are graphical representations of the values in Table 21. It is worth noting that reducing the maximum quantity assignable to Supplier 1 increases the TPC up to the budget constraint (i.e. 16,600). Falling below 14 units, as the maximum quantity assignable to Supplier 1, will get the total required supply not fulfilled. Hence, the feasible range of such constraint, while keeping the rest unchanged, is between 20 and 14.

4.7 Overall implications: connecting theory and practice

The proposed MCDM model for SS and OA in uncertain environments was tested through a case study at a leading Italian company in the industry of radiators and CMV production. The evaluation considered the procurement of steel tubes for two historical suppliers (Supplier 1, Supplier 2) and one new supplier (Supplier 3). The goal was to determine whether Supplier 3 should be added to the supply base and how order quantities might have been redistributed among the suppliers.

Supplier 3 was supposed to partially replace Supplier 2 and, over time, even absorb some of Supplier 1's order share, as Supplier 3's performance was nearly equivalent to that of Supplier

Table 21. Changes in the maximization linear problem when varying the constraint of the maximum quantity assignable to Supplier 1

$x(1) \leq$	20	19	18	17	16	15	14	13	12
$x(1)$	20	19	18	17	16	15	14	13	12
$x(2)$	2	2	2	2	2	2	4	4	4
$x(3)$	0	1	2	3	4	5	4	4.98	5.96
Tot. supply	22	22	22	22	22	22	22	21.98	21.96
TPC	16,520	16,535	16,550	16,565	16,580	16,595	16,600	16,600	16,600
$\sum_n x(n)TS(n)$	7.60352	7.60252	7.60152	7.60051	7.59951	7.59850	7.50084	7.49299	7.48514

Note(s): Considered the optimal solution found by the linear BWM

Source(s): Created by authors

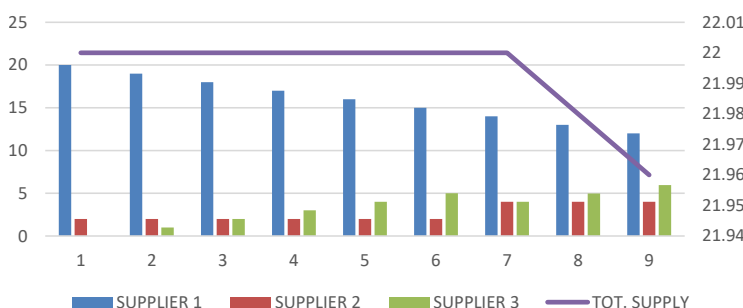


Figure 6. Supplies when varying the constraint of the maximum quantity assignable to Supplier 1. Note(s): Considered the optimal solution found by the linear BWM. Source: Created by authors

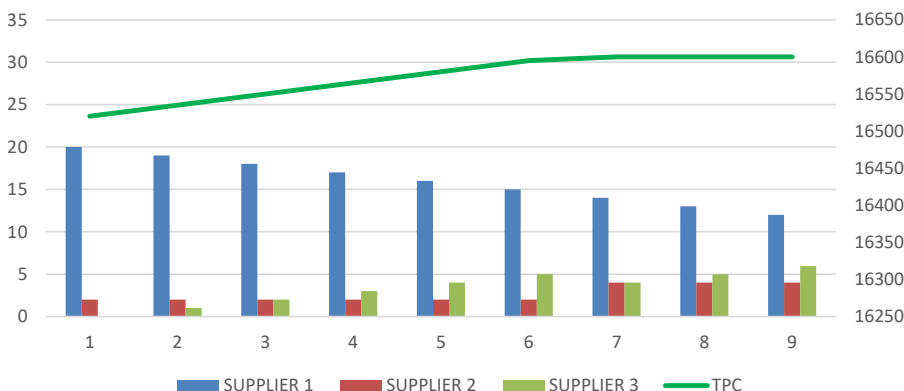


Figure 7. Total purchasing cost when varying the constraint of the maximum quantity assignable to Supplier 1. Note(s): Considered the optimal solution found by the linear BWM. Source: Created by authors

1. The SS and OA solution confirmed the inclusion of Supplier 3, showing the introduction of the new supplier in the supply base. At the end of the fourth step, the final scores of Suppliers 1 and 3 were close with a short advantage for Supplier 1 based on its pricing power as a major global steel supplier. Supplier 2, meanwhile, maintained only the minimum order quantity as required by the OA constraints, and we can guess that – without this constraint – Supplier 2 would have been removed from the supply base.

The findings from this application highlight, besides the model's strengths in evaluating suppliers and performing sensitivity analysis, its key advantages over existing approaches. As described, this model enables comparing new and historical suppliers by relying on multiple DMs; this represents a significant step forward over current research. Existing models, according to [Li et al. \(2022\)](#) and [Sun et al. \(2024\)](#), are inadequate in comparing new and historical suppliers, particularly in high-risk, new task situations, where low reliable data are available and DMs' perceptions and attitudes toward risk make the difference in SS and OA choices. The proposed MCDM model addresses this gap by leveraging the expertise of DMs who in the absence of historical data through a scenario-based approach evaluate new suppliers by comparing them with the performance of existing/historical suppliers, as was done with Supplier 3 in the case study. This approach also reduces evaluation biases linked to the DMs' varying risk attitudes and perceptions, as illustrated in the case study by incorporating the perspectives of both the purchasing manager and the quality assurance manager, the two key voices in the procurement process.

Another main advantage of this model is its accessibility to companies without advanced computational capabilities. Targeting more complex problems by integrating multiple techniques may seem appealing but raises the question of whether these approaches are actually useful, given that they are more concerned with sounding sophisticated than with delivering tangible, impactful results ([Bruno et al., 2012](#)). These complex models can also be time-intensive and require specific expertise, making them impractical for many companies ([Bruno et al., 2012](#); [Schramm et al., 2020](#)). The simplicity of the steps of the proposed MCDM model, as demonstrated in the case study, allows for straightforward implementation with minimal computational resources. This is guaranteed by using BWM for criteria weighting, over methods like CRITIC and DEMATEL, and simple aggregation methods for supplier ranking, instead of more complex techniques like TOPSIS and TODIM.

5. Conclusions

The main aim of this work is to formulate an approach to mitigate risks coming from the procurement process. SS and OA tasks, especially in extraordinary situations such as modified rebuy and new task situations, become critical if we consider the associated risks and the high uncertainty degree by which they are characterized. In several circumstances, not enough information is available to the DMs, thus reasonable assumptions are needed to proceed with the evaluation of suppliers. Decisions are thus related to DMs' perceptions and their risk attitude, which become pivotal in their evaluation. Models in the literature considering these major aspects are still limited and are necessary, in particular when we deal with historical and new suppliers in highly uncertain situations. In this work, we propose an MCDM model for SS and OA that enables DMs to effectively compare new and historical suppliers and to make informed decisions when renovating the suppliers' list. The limited knowledge of the new suppliers is mitigated by using a combination of measurable and forecastable decision criteria through a scenario planning approach that considers DMs' different risk attitudes in evaluating suppliers' performance. The BWM for the SS problem and the two-stage LP model for the OA problem have been selected for the purpose. Moreover, this MCDM model enables sensitivity analyses that help in testing the robustness of the solutions. When we deal with unpredictable situations, the steadiness of the solution is indeed crucial.

This work provides relevant theoretical (5.1) and managerial (5.2) contributions, while also recognizing certain limitations (5.3) that, in turn, pave the way for future research.

5.1 Theoretical contributions

This work contributes to the theoretical understanding of integrated MCDM models for SS and OA processes under uncertainty, addressing significant gaps in existing literature. Firstly, it proposes a model that adequately considers uncertainty in SS and OA problems in new task

situations, particularly when comparing historical and new suppliers – a critical aspect in SS often overlooked in previous research. By filling this gap, this work introduces a scenario-based approach based on DMs' evaluation to assess the supplier score when forecastable criteria are considered, bypassing the scarcity of information and forecasts available on new suppliers. Secondly, this work includes, as often stated as a limitation in previous studies in the literature, the variability in DMs' risk attitudes and utilizes a scenario-based approach to weigh forecastable criteria, handling both qualitative and quantitative criteria. This inherent bias is mitigated by incorporating five (optimistic, medium-optimistic, expected, medium-pessimistic and pessimistic) scenarios and DMs assign a probability of occurrence to each scenario, considering as a reference the "average performances" of historical suppliers. Thirdly, a novel pairwise comparisons-based method, the BWM (Rezaei, 2015, 2016), is employed, which offers advantages over traditional methods like the AHP by requiring less information, making it particularly suitable for new task situations characterized by lack of information. Overall, despite the growing complexity of techniques to address SS and OA problems, the literature has emphasized (Bruno *et al.*, 2012; Schramm *et al.*, 2020) that further research is needed to develop models for SS and OA that are practical for most companies without advanced computational capabilities, thus not requiring DMs to have specialized expertise. More complex methods like TOPSIS (e.g. Jafari-Raddani *et al.* (2024) and Mohammed *et al.* (2019)) or VIKOR (e.g. Opricovic and Tzeng (2004)), while powerful, which involve more complex procedures such as determining distances from an ideal solution or compromise solutions, may not always be necessary or desirable, particularly when time and resource constraints are significant considerations. In this regard, the proposed MCDM model operates on less computational effort, which makes it suitable for a wide range of companies.

5.2 Managerial contributions

This work has also strong managerial implications in line with previous theoretical contributions, offering an MCDM model for SS and OA processes designed to be adaptable – easy to use and flexible – across various procurement contexts. Its usability and flexibility would facilitate efficient decision-making, empowering DMs to make informed choices. In this regard, the proposed MCDM model enables strategic supplier management and takes into account the different risk attitudes of DMs, hence reducing the bias given by the subjectivity of their judgements. Managers would gain a valuable model that could support them in their decision-making process, enabling the evaluation of historical and new suppliers by leveraging the expertise of internal or external DMs, to anticipate and address potential risks inherent in SS and OA decisions. This enables companies to proactively identify and leverage supplier capabilities, enhancing supply chain resilience and agility in dynamic market environments. Moreover, this model does not require advanced mathematical or programming knowledge or extensive IT infrastructure; therefore, companies of all sizes dealing with SS and OA processes could use this model by just applying simple language programming and software tools. The model's practical strength is further highlighted by its capacity to perform sensitivity analyses, as illustrated in the case study in Section 4. Specifically, the analysis investigated the impact of variations in the price offered by Supplier 3 and the maximum quantity assignable to Supplier 1 on the overall solution. Therefore, this sensitivity analysis enables DMs to evaluate the robustness of their decisions and make more informed and adaptable choices in dynamic procurement scenarios. Additionally, such analyses are highly beneficial for companies that can use them as a means of negotiation with their suppliers, e.g. as presented in the case study, by promising increased order quantities in exchange for a discounted price.

5.3 Limitations and future research

This work, being somehow a pioneer in the field, leaves much room for improvement. The proposed model, although satisfactory, can be refined to enhance its applicability in

real-world scenarios. It still requires comprehensive testing across various procurement contexts and industries to validate its feasibility and effectiveness beyond the case study presented here.

Potential improvements include incorporating fuzzy logic to better address uncertainties in criteria weights, such as through fuzzy BWM or fuzzy AHP. Additionally, integrating more objective weighting methods, like the CRITIC method, could further reduce subjective biases and improve the model's accuracy. Future research should also consider how to better incorporate forecastable criteria into the decision-making process. Alternative approaches, such as those for assessing the scores of new suppliers based on forecastable criteria, could also be investigated beyond the scenario-based method proposed here. Other supplier ranking methods, such as TOPSIS, COPRAS and TODIM, could provide valuable insights into alternative approaches. For instance, applying TODIM can help capture the behavioural aspect in the decision-making process, better aligning with human behaviour in uncertain conditions. TOPSIS, one of the most widely used methods, selects suppliers closest to an ideal benchmark solution across all criteria, and similarly, COPRAS, which balances positive and negative attributes to achieve a well-rounded solution, could be particularly advantageous in complex and conflicting procurement environments. Enhancing the two-stage LP model for OA, especially in defining the TPC, could be another key issue for optimizing resource allocation and achieving cost efficiency.

It must be acknowledged, as already said before, that while more sophisticated and versatile models could better address the complexities and uncertainties of modern procurement environments, their implementation in real-world situations remains challenging, and often not feasible in companies due to limited resources or expertise. Therefore, practicality and ease of implementation should be always taken into consideration when developing new MCDM models for SS and OA.

Overall, the authors hope that the proposed model, with its pivotal characteristics of mitigating risks under uncertain situations, will encourage companies to adopt it in their operations, as well as academics to consider it as a reference for their research.

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