AN INTEGRATED MULTI-CRITERIA DECISION-MAKING (MCDM) MODEL TO EVALUATE NEW SUPPLIERS AGAINST HISTORICAL ONES AND DEFINE ORDER ALLOCATION

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We cannot miss the chance to thank Professor Jafar Rezaei who gave us the possibility to spend three formative months at TU Delft and whose precious suggestions led us in designing the core framework of the proposed model.
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List of Abbreviations

AHP: Analytic Hierarchy Process
AI: Artificial Intelligence
ANP: Analytic Network Process
BW: Best-to-Others
BWM: Best-Worst Method
CMV: Controlled Mechanical Ventilation
DEA: Data Envelopment Analysis
DM/s: Decision Maker/s
FTS: Final Total Score
FWA: Fuzzy Weighted Average
GA: Genetic Algorithm/s
GDM: Group Decision-Making
GP: Goal Programming
GST: Grey System Theory
IFN: Intuitionistic Fuzzy Numbers
IFWA: Intuitionistic Fuzzy Weighted Averaging
JIT: Just-In-Time
LP: Linear Programming/Program
MCDM: Multi-Criteria Decision-Making
MDM: Multiple Decision Makers
MILP: Mixed-Integer Linear Programming/Program
MOP: Multi-Objective Programming
MP: Mathematical Programming
NLP: Nonlinear Programming/Program
NN: Neural Networks
OA: Order Allocation
OW: Other-to-Worst
QFD: Quality Function Deployment
RST: Rough Set Theory
R&D: Research and Development
SC: Supply Chain
SCM: Supply Chain Management
SCRM: Supply Chain Risk Management
SDM: Single Decision Maker
SP: Stochastic Programming
SS: Supplier Selection
TPC: Total Purchasing Cost
TS: Total Score
Abstract

Since the evolution of Supply Chain Management (SCM) into Supply Chain Risk Management (SCRM), Supplier Selection (SS) process has been given increasing importance as a decision capable to strongly mitigate risks related to Supply Chain itself, if taken in the right way. Many academics and practitioners have focused on SS problem over the last decades, deeply inspecting all related aspects, from solving-techniques to the implications it may have on business management and development; however, a very important point is missing, that is the selection of New Suppliers. Indeed, nowadays, the fierce market competition and increased customer expectations are pushing companies to innovate more and more products/services they offer. Since most of the time innovation passes through new materials and new technologies, the need of new suppliers results to be a current topic, today more than ever; as a direct consequence, suitable methods for the selection of the same are required. In particular, this work is aimed at presenting a method useful for the comparison between new and historical suppliers, even on those aspects that are can be evaluated only after a number of supplies has been performed. In order to enable the afore mentioned comparison, a Multi-Criteria Decision-Making (MCDM) model is proposed. Criteria are divided into two categories: Measurable and Forecastable; the former can be directly evaluated from bids submitted by involved suppliers, whereas the performances about the latter are known only for historical suppliers (which have already completed a number of supplies) and must be forecast, exploiting a scenario-based approach considering five scenarios, when it comes to new suppliers. The afore mentioned scenario-based approach also allows to take into account the DMs’ risk attitude. Criteria weights are calculated by means of the Best-Worst Method (BWM), an innovative and little information-requiring pairwise comparisons-based method. The suppliers’ ranking obtained as output from the Supplier Selection problem resolution constitutes the input for the following phase of Order Allocation. The Order Allocation problem is solved by means of a two-stage Linear Program aimed at minimizing the Total Purchasing Cost (TPC) in its first stage, then at prioritizing suppliers, according to obtained suppliers’ ranking, in its second stage. Finally, in order to prove the applicability and effectiveness of the proposed model, the same is applied to the case of an Italian leading company in the production of radiators and Controlled Mechanical Ventilation systems, which is willing to renovate its suppliers list.

**Keywords:** Supply Chain Management (SCM), Supplier Selection (SS), Order Allocation (OA), New Suppliers, Best-Worst Method (BWM), Multi-Criteria Decision-Making (MCDM), Scenario-based Approach.
In conseguenza all’evoluzione del concetto di Supply Chain Management (SCM) in quello di Supply Chain Risk Management (SCRM), il processo di Selezione Fornitori ha ricevuto sempre maggior importanza anche grazie al fatto che tale decisione, se presa correttamente, permette una drastica riduzione dei rischi associati alla Supply Chain. Negli ultimi decenni il problema di Selezione Fornitori è stato studiato a fondo e in ambito accademico e di ricerca e in quello della pratica aziendale, e tutti i suoi aspetti sono stati largamente indagati, dalle tecniche risolutive alle implicazioni che esso può avere nella gestione e nello sviluppo del business; nonostante ciò una questione molto importante non ha tutt’ora ricevuto sufficiente attenzione: stiamo parlando della Selezione di Nuovi Fornitori. Infatti, ai giorni nostri, sotto la pressione delle aumentate aspettative dei clienti e della feroce competizione che regola il mercato, le aziende sono spinte ad innovare costantemente i prodotti/servizi che offrono. Dato che la maggior parte delle volte l’innovazione passa attraverso nuovi materiali e tecnologie, la necessità di nuovi fornitori risulta essere un tema attuale, oggi più che mai; come diretta conseguenza di ciò nasce la richiesta di metodi per la selezione degli stessi. In particolare, questa tesi è volta a presentare un metodo utile per confrontare fornitori storici e nuovi, anche rispetto a quegli aspetti che possono essere valutati solo a valle di un certo numero di forniture. Al fine di permettere suddetto confronto, viene proposto un metodo appartenente alla categoria Multi-Criteria Decision-Making (MCDM). I criteri sono suddivisi in due categorie: Misurabili e Previsionali; i primi possono essere direttamente valutati a partire dalle offerte dei fornitori, mentre le prestazioni riguardo i secondi sono note solo per i fornitori storici (i quali hanno già completato un certo numero di forniture) e devono essere previsti, sfruttando un approccio a scenari che considera cinque scenari, per i nuovi fornitori. I pesi dei criteri vengono calcolati sfruttando il Best-Worst Method (BWM), un innovativo metodo basato sul confronto a coppie con il pregio di richiedere un limitato numero di informazioni. La classifica dei fornitori, ottenuta come risultato dalla risoluzione del problema di Selezione Fornitori, costituisce l’input della fase successiva di Allocazione degli Ordini. Il problema di Allocazione degli Ordini viene risolto grazie ad un Programma Lineare sviluppato in due fasi e teso, nella prima fase, a minimizzare il Costo Totale d’Acquisto, dunque, nella seconda fase, a prioritizzare i fornitori sulla base della classifica degli stessi.

Infine, per dimostrare l’abbinabilità e l’efficacia del modello proposto, lo stesso viene applicato al caso di un’azienda italiana, leader nella produzione di termosifoni e di sistemi di Ventilazione Meccanica Controllata, la quale ha intenzione di rinnovare il suo parco fornitore.

**Parole chiave:** Supply Chain Management (SCM), Selezione Fornitori (SF), Allocazione Ordini (AO), Nuovi Fornitori, Best-Worst Method (BWM), Multi-Criteria Decision-Making (MCDM), Approccio a Scenario.
Executive Summary

An integrated Multi-Criteria Decision-Making (MCDM) model to evaluate New suppliers against Historical ones and define Order Allocation

Keywords:
Supply Chain Management
Supplier Selection
Order Allocation
New Suppliers
Best-Worst Method
Scenario-Based Approach

Abstract
Nowadays Supplier Selection process plays a crucial step at the planning phase of any business organization. Since most of the time innovation passes through new materials and new technologies, the source of new suppliers becomes a challenging point for the purchasing department and new models for the evaluation of the same are required. This work is aimed at presenting a method useful for the comparison between new and historical suppliers, even on those aspects that can be evaluated only after a certain number of supplies has been performed. In order to enable the afore mentioned comparison, an MCDM model is proposed. The weights of criteria, which are divided in Measurable and Forecastable criteria, are calculated by means of the Best-Worst Method (BWM). Regarding suppliers’ scores, while for measurable criteria they can be simply extracted from suppliers’ bid, for forecastable criteria a scenario-based approach is needed, allowing to account the risk attitude of each Decision Maker (DM) in the selection process. Once the Supplier Ranking has been obtained, the Order Allocation (OA) problem is solved by exploiting a two-stage Linear Program. Finally, in order to prove the effectiveness of the model, a real application is proposed.

1. Introduction
The Supply Chain Management (SCM) is one of the most important functions in an industrial context as it addresses the inbound and outbound flows of materials, services and information of a company.

The globalization of markets, the increased awareness of consumers and the fiercer competitiveness led the concept of SCM to evolve in that of Supply Chain Risk Management (SCRM).

SCRM, that includes the processes of identification and mitigation of risks, has a more strategic role with respect to the previous SCM, particularly due to the increased dependency on suppliers.

It is clear that suppliers are the critical link to any supply chain and consequently sourcing process is one of the most important decisions to be taken at the planning stage [1]. Thus, the most challenging task of the purchasing
function regards the Supplier Selection (SS) process, i.e. the identification of the best supplier(s) that is able to provide the buyer with the right quality products and/or services at the right price, at the right quantities and at the right time [2].

Due to the great attention SS topic has received, many authors investigated this field and several frameworks were proposed. De Boer in 1998 [3] proposed a well-structured four-steps methodology to address this task: (1) problem definition, (2) formulation of criteria, (3) qualification and (4) final choice.

Another important function of the purchasing department is the Order Allocation (OA) problem among the selected suppliers, according to different objectives and policies of the company. Even this phase is nowadays characterized by the integration of the risk management concept as companies struggle to preserve their business from supply chain disruptions.

According to Faris et al. [4], buying situations can be distinguished into: (1) straight rebuy, (2) modified rebuy and (3) new task situations.

Very few authors focus on the last two types, generating a lack in the literature, especially when considering new task situations; most of the papers deal with SS in contexts where only historical suppliers are considered, thus not providing insights regarding how to carry out the decision process when it comes to the comparison between historical and new suppliers.

Moreover, when dealing with new task situations, the concept of uncertainty should be taken into account. Despite it is clear that the risk attitude of the single decision maker plays a fundamental role in the selection process, very few examples can be found in literature integrating the concept of uncertainty when addressing SS and OA problems [5].

In order to fill in the above highlighted gaps, we proposed a model aimed at making possible the comparison between new and historical suppliers, integrating the decision makers’ risk attitude by exploiting a scenario-based approach.

A MCDM model is used, where considered criteria are divided into two classes: measurable and forecastable criteria.

The criteria weights are found using a novel structured MCDM pairwise comparisons-based method by J. Rezaei, called Best-Worst Method (BWM) [6][7]. The Total Score of each candidate supplier is calculated by means of an additive weighted function, where the new suppliers’ scores about forecastable criteria are obtained applying a scenario-based approach. Finally, a two-stage Linear Programming (LP) model for the OA problem is developed.

The remainder of this dissertation is organized as follows: in section 2 an extensive literature review is reported highlighting the lack of knowledge that drove our research, in section 3 the proposed model is explained, in section 4 a real-world industrial application is described while in section 5 conclusions are reported along with suggestions for future development.

2. Literature Review

In the last decades, the risen customers’ expectations, the new communications and transportations technologies and the internationalization of markets have driven the evolution of supply chains, from the simple direct model to the extended one and, finally, to the more complex ultimate model [8]; this fact, necessarily,
has stressed the need for an accurate management of the supply chain (SCM).

The seek for greater reliability and responsiveness from suppliers has made the concept of SCM to develop in that of Supply Chain Risk Management (SCRM).

Many authors have investigated the field of SCRM, developing models intended to the identification of risk sources, the assessment of associated risks and the definition of counter-measures [9] [10]. As suppliers are the main players of any supply chain, it is clear that their performances strongly influence those of the whole process; thus, Supplier Selection (SS) performs a major role in the context of SCRM and a close link exists between them [11].

SS has a marked strategic role as the selection of the right supplier(s) can help companies to meet regulatory and quality standards, imposed by authorities and market respectively, drive customer demand and build a strong firm reputation [12]. If on one hand the SS process leads to the choice of the best supplier(s), on the other hand, Order Allocation (OA) procedure allows to assign items among the selected suppliers.

2.1 Review of SS Literature

Thanks to its leading role in structuring and managing a supply chain, SS has received extensive attention over the years. Faris et al. [4] distinguished three main categories of buying situations: straight rebuy, modified rebuy and new task. This classification, however, is not sufficient to characterize all the possible situations a buyer might face; De Boer et al. [13] integrated this classification with the Kraljic’s portfolio matrix [14], where items are classified according to two factors: supply risk and profit impact. Considering both buying situation and the position of the purchased product/service in the Kraljic’s matrix, a structured framework was created where each specific buying circumstance finds its place.

Suppliers are considered the best intangible assets of any industrial organization [12], for this reason it is not surprising that the issues related to SS process have been largely inspected by academics. Basing on the work by Chai [15], we can classify proposed methods for solving SS problem into three main groups: (1) Multi-Criteria Decision-Making (MCDM), (2) Mathematical Programming (MP) and (3) Artificial Intelligence (AI) methods.

2.1.1 MCDM Methods

In the Supplier Selection background, MCDM represents the approach that has received most attention over the years. Several reasons support this fact: (i) MCDM models are easy to use, (ii) they allow to consider not only quantitative criteria, but also qualitative ones, (iii) they can effectively integrate the opinions of the single Decision Makers (DMs) in the selection process, (iv) the integration of risk and uncertainty in estimating the suppliers’ performances, (v) while MP and AI methods are completely automated techniques and behave like a black box, MCDM approaches guarantee a high level of interaction between the DM(s) and the Decision process.

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 [16]. Some authors consider Group Decision-Making (GDM) as the most collaborative way to take a decision; in this context Chan and Chan [17] exploit the geometric average to integrate the opinions of the single DMs, Rezaei et al. [18] give the same weight to all the expert composing the decision group, Zhang et al. [19] define the weights of the single DMs by means of Vague Set Theory (VST).

Criteria

The set of criteria considered in literature is very wide and comprehends both quantitative and qualitative criteria. 

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 [20].

Kar and Pani [21] offer one of the most recent investigations about SS criteria, pointing out over 60 generic criteria that have been used in SS context.

Moreover, moved by the growing concern about environment issues and sustainable processes that have characterized recent years, many authors tried to integrate the so-called green criteria with the traditional ones.

The variety of literature not only regards the considered criteria, but also the methods applied to calculate the associated weights.


However, even other methods have been adopted; in particular, theory of fuzzy numbers is at the base of the work by Chen and Zou [25].

2.2 Review of OA Literature

Order Allocation constitutes a not so easy step to be performed by purchasing department, indeed it is expression of objectives and policies set by a company for its supply chain.

OA processes can be classified according to different points of view: (i) the number of considered suppliers, (ii) the number of purchased product-types, (iii) the time horizon of the OA itself.

As highlighted by Erdem and Göçen [22] the great majority of the studies in the literature are dedicated to supplier selection problem only. The integrated models account for a small portion of the studies in this area, even if they provide a complete framework for performing two crucial and strongly connected activities of purchasing department (Table 1).

Bohner and Minner [26] proposed a multiple product-types, multiple sourcing and single time period Mixed-Integer Linear Programming (MILP) OA model aimed to minimize the TPC.

Rezaei and Davoodi [27] utilized GA for solving both SS and OA problems in case of multiple-sourcing, multi-product and multiple period time planning horizon.

Ayhan and Kilic [28] exploit a multiple-sourcing, multi-product and single time period MILP for selecting the best suppliers and determining the OA among them.
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<td>Mafakheri et al. [46]</td>
<td>2011</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toloo and Nalchigar [47]</td>
<td>2011</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ku et al. [48]</td>
<td>2010</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sanayei et al. [49]</td>
<td>2010</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vahdani et al. [50]</td>
<td>2010</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boran et al. [51]</td>
<td>2009</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zhang et al. [19]</td>
<td>2009</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Onüt et al. [52]</td>
<td>2009</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chou and Chang [53]</td>
<td>2008</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kawtummachai and Van Hop [54]</td>
<td>2005</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chan and Chan [17]</td>
<td>2004</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sarkis and Talluri [23]</td>
<td>2002</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Total (38)</strong></td>
<td></td>
<td>24</td>
<td>2</td>
<td>12</td>
</tr>
</tbody>
</table>

**Table 1.** Classification of reviewed papers
2.3 Research Gap

Despite the great commitment dedicated to this field of SCM, many aspects still require deeper inspection. Very few authors focused on the topic of new task situations, leaving an almost unfilled gap in the SS background.

This fact seems to be quite strange in the nowadays fast changing world, where the demand for new, technologically advanced products and services keeps increasing. It is clear that the need for a framework enabling the comparison between new and/or new and historical suppliers is urgent and efforts must be directed to its development.

When considering extra-ordinary situations, risk plays a fundamental role in the decision-making process; moreover, it should be notice that single DMs are characterized by their own risk attitude, thus they will evaluate risks in different ways one from the others.

In order to integrate the opinion of each DM, something missing in literature, we think that a scenario planning approach is the best way to address this problem.

3. Model

Considering the missing points in the SS knowledge base highlighted in paragraph 2.3, we proposed a simple and effective model that allows comparing new and historical suppliers, which definitely constitutes the knowledge gap requiring the most urgent attention.

In order to propose a user-friendly tool, we think that MCDM methods constitute the best option as they are easily customizable and adaptable to even very different situations.

In Fig. 1 the general framework of MCDM in case of new task situations is presented.

The possibilities offered by internet allow to get information about a very large number of suppliers. Obviously, the evaluation process cannot be performed for all identified suppliers as time and money resources are always limited, thus a screening process should be performed in order to obtain a shortlist of suppliers that are worth being evaluated.

The structure of the model is reported in Fig. 2.

![Fig. 1. General Framework of MCDM](image)

3.1 Supplier Selection

In the following each step of the proposed MCDM framework will be exhaustively explained. We assumed that the screening methodology has already been performed and, for this reason, the shortlist has already been obtained when the model is applied.
3.1.1 Identification of Criteria

Over the years many criteria have been taken into consideration while addressing SS problem exploiting MCDM methods. Basing on the specific context of application, on their knowledge background and expertise, and even considering company’s focus, we leave DMs the freedom to identify the set of criteria (k=1,...,K) which best fit the addressed problem.

The novelty introduced by the proposed model, as it regards the criteria, is the classification of the same into two groups: **Measurable and Forecastable Criteria.** Measurable criteria are those whose performances can be directly extracted from suppliers' bids, while forecastable criteria are those whereby it is not possible
to give a score before the supply has been received.

In particular, it follows that they can be extrapolated from companies’ databases as it regards the historical suppliers, whereas, they have to be forecast when it comes to new suppliers.

3.1.2 Calculation of criteria weights

Great carefulness must be paid when selecting a suitable methodology to carry out this step.

**Best-Worst Method (BWM)**

To the end of calculating criteria weights \( (w_1, w_2, \ldots, w_K) \) we decided to apply the BWM. Two are the main drivers of this choice: the first is that it guarantees higher consistency than for example AHP thanks to the more structured way comparisons are performed, the second is its property of being less information-requiring, thus perfectly fitting new task situations which are characterized by scarcity of knowledge about some/all suppliers.

In the following the steps composing the BWM framework are introduced:

**Step 1.** Determine a set of decision criteria, which can be both qualitative and quantitative.

**Step 2.** Determine the best (most desirable) and the worst (least desirable) criteria.

**Step 3.** Determine 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:

\[
BO = (a_{B1}, a_{B2}, \ldots, a_{BK})
\]

where \( a_{Bj} \) indicates the preference of the best criterion B over criterion j. Obviously \( a_{BB} = 1 \).

**Step 4.** Determine the preference of all the criteria over the Worst criterion, using a number between 1 and 9. The resulting Others-to-Worst (OW) vector is:

\[
OW = (a_{1W}, a_{2W}, \ldots, a_{KW})
\]

where \( a_{jW} \) indicates the preference of the criterion j over the worst criterion W. Obviously \( a_{WW} = 1 \).

**Step 5.** Find the optimal weights \( w_j \). The ideally optimal weights for the criteria are those whereby, for each pair \( w_B, w_j \) and \( w_j, w_W \) it results:

\[
\frac{w_B}{w_k} = a_{Bk} \quad \text{and} \quad \frac{w_k}{w_W} = a_{kW}
\]

The aim is to determine the optimal weights, so that the maximum among the absolute differences \( \left( \left| \frac{w_B}{w_k} - a_{Bk} \right|, \left| \frac{w_k}{w_W} - a_{kW} \right| \right) \), for all \( k \), is minimized.

Considering the five steps above, the following minmax problem can be formulated:

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

subject to:

\[
\sum_k w_k = 1
\]

\[
w_k \geq 0, \quad \text{for all } k
\]

Which is equivalent to the following problem:
Min $\xi$

subject to:

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

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

$$\sum_k w_k = 1$$

$$w_k \geq 0, \text{ for all } k$$ \hspace{1cm} (2)

Solving model (1) or (2), the optimal weights $w_1, w_2, \ldots, w_K$ and $\xi^*$ are obtained.

It is also possible to linearize the original nonlinear problem, thus obtaining a much easily manageable mathematical formulation:

Min $\xi^L$

subject to:

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

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

$$\sum_k w_k = 1$$

$$w_k \geq 0, \text{ for all } k$$ \hspace{1cm} (3)

In the proposed model both linear and non-linear BWM are applied in order to get crisp weights and to define interval weights for the criteria, which are then used for the sensitivity analysis.

3.1.2.1 Application of the linear BWM

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

3.1.2.2 Application of the non-linear BWM

The challenging point is to solve the optimization problem (1) or (2) because of its nonlinearity. We addressed the problem (1) and chose Genetic Algorithms (GA) as resolution methodology.

**Genetic Algorithms (GA)**

The idea at the base of such algorithms is to evolve a population of candidate solutions to a given problem, using operators inspired by natural genetic evolution and natural selection processes. The population is formed by chromosomes, each representing one candidate solution of the problem. At each step, all the elements composing the population are evaluated with respect to the so-called fitness function, which represents the goal of the optimization problem under consideration. In order to create the next step population, the algorithm exploits the concepts of selection, crossover and mutation. Generation by generation, the algorithm aims at finding the optimal solution.

The Genetic Algorithm aimed at solving the nonlinear BWM was implemented by means of MATLAB®.

Running GAs, we got the optimal weights to be assigned to selected criteria as crisp values, along with a value of $\xi$, named $\xi^*$.

In case of non-linear BWM, $\xi^*$ cannot be considered as a consistency indicator by itself, and it must be divided by the Consistency Index (CI) of the correspondent class of $a_{BW}$ (Table 2), in order to get the Consistency Ratio (eq (4)), i.e. a consistency indicator:
Consistency Ratio = $\frac{\xi^*}{\text{Consistency Index}}$ \hspace{1cm} (4)

<table>
<thead>
<tr>
<th>a</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>CI</td>
<td>0</td>
<td>0.44</td>
<td>1.63</td>
<td>2.3</td>
<td>3</td>
<td>3.73</td>
<td>4.47</td>
<td>5.23</td>
<td></td>
</tr>
</tbody>
</table>

**Tab. 2.** Consistency Ratio (CR)

**Interval Weights**

If the obtained $\xi^*$ is not too small, it is possible to define an *interval weight* ($iw_k$) for each criterion. *Interval weights* ($iw_1, iw_2, ..., iw_K$) are calculated by solving the associated linear minimization/maximization problems:

**Min** $w_k$

subject to:

- $| \frac{w_B}{w_k} - a_{Bj} | \leq \xi^*$, for all $k$
- $| \frac{w_k}{w_W} - a_{kw} | \leq \xi^*$, for all $k$
- $\sum_k w_k = 1$
- $w_k \geq 0$, for all $k$ \hspace{1cm} (5)

**Max** $w_k$

subject to:

- $| \frac{w_B}{w_k} - a_{Bj} | \leq \xi^*$, for all $k$
- $| \frac{w_k}{w_W} - a_{kw} | \leq \xi^*$, for all $k$
- $\sum_k w_k = 1$
- $w_k \geq 0$, for all $k$ \hspace{1cm} (6)

Problem (5) and problem (6) give as output the lower and upper bounds of the criteria *interval weights*, respectively.

**3.1.3 Calculation of suppliers’ scores**

In relation to its performances, each supplier is assigned a score ($S_{nk}$) representing how well it performs about each criterion.

**3.1.3.1 Scoring Methodology for Measurable Criteria**

As performances related to *Measurable* criteria can be directly extrapolated from submitted bids, suppliers’ scores can be obtained by means of a simple normalization.

Equations (7) and (8) are used for *benefit* and *cost* criteria, respectively:

$$S_{nk} = \frac{v_{nk}}{\sum_k v_{nk}}$$ \hspace{1cm} (7)

$$S_{nk} = \frac{1}{\sum_k w_{nk}}$$ \hspace{1cm} (8)

**3.1.3.2 Scoring Methodology for Forecastable Criteria**

In order to deeply analyse the scoring process regarding *Forecastable* criteria, we have to divide them into two classes: *quantitative and qualitative criteria*. The formers can be evaluated by means of a value directly linked to the performances themselves (e.g. *punctuality* can be measured in terms of average delay of the supply), whereas the latters can be expressed only in terms of preference scale (e.g. *business integration capability* measured on a scale going from 1 to 10).
Then, independently of the considered criterion, values associated to suppliers’ performances have to be normalized by using equations (7) and (8).

When dealing with historical suppliers, performances related to Forecastable criteria can be directly extrapolated from company’s databases whereas, when it comes for new suppliers no previous data are available, thus a scenario-based approach is needed.

Scenario-based Approach

The number of scenarios is equal to five \((s = 1, \ldots, 5)\) and they are named: optimistic, medium-optimistic, expected, medium-pessimistic and pessimistic. The expected scenario is that characterized by the “average performances” of historical suppliers.

Each DM has to assign a probability of occurrence \(\left( p_{os} \right)\) to each scenario and to define a value characterizing the supplier under analysis in the different scenarios \(\left( v_{s} \right)\). Then, it is possible to obtain the score of the supplier about the considered criterion \(S_{nk}\) by using equation (9):

\[
S_{nk} = \sum_s p_{os} v_{ns} \quad (9)
\]

3.1.4 Integration of the Suppliers’ Scores

After having completed the suppliers’ evaluation, to the end of getting the Total Score \(TS\) of each supplier, a double integration process is required.

The first integration level regards the single DM; indeed, the Total Score \(TS_{nm}\) of the supplier \(n\) given by the DM \(m\) is obtained as a weighted average by using equation (10):

\[
TS_{nm} = \sum_k w_k \cdot S_{nk} \quad (10)
\]

The second level of integration is the one performed over all DMs, by using equation (11):

\[
TS_n = \sum_m TS_{nm} \cdot p_m \quad (11)
\]

where \(p_m\) is the weight assigned to DM \(m\).

3.2 Order Allocation

The goal of the second part of the model is the resolution of the OA problem. We used a two-stage Linear Program, as explained in the following.

1st Stage

In the first stage a minimization linear problem is formulated, aiming at minimizing the Total Purchasing Cost (TPC) and without considering the Suppliers’ Ranking.

The quantity to be purchased \(\left( Q_{tot} \right)\) is split among suppliers, taking into account constraints and policies of the company.

2nd Stage

In the second stage, the objective function is represented by the prioritization of suppliers and, thus, the Suppliers’ Total Scores \(TS_n\) are considered.

A new constraint must be now taken into account, that is the one regarding the increment assigned to the budget with respect to the minimum TPC calculated at the first stage.

By incrementing step by step the budget with respect to the calculated minimum TPC (e.g. 1% by 1%), it is possible to map
the solutions space, identifying the boundaries among different possibilities for allocating order quantities.

3.3 Sensitivity Analysis

When addressing strategic problems characterized by risk, it is not sufficient to simply obtain a solution, but rather it is necessary to verify the robustness of the found solution, by means of a proper sensitivity analysis. Variables and parameters to be changed depend on the specific case under consideration.

4. Application to Industry context

4.1 Problem definition

To the end of performing the application of the proposed model to an industry context, we developed a collaboration with a leading Italian company in the field of radiators and Controlled Mechanical Ventilation (CMV) production.

The specific case under consideration regards the purchasing of steel tubes used for the production of “Tesi radiators”, which constitute a leverage item for the company, destined to the large retailers operating in Europe.

The role of Decision Makers is played by the Purchasing Manager and by the Quality Assurance Manager, two main voices in the Procurement process of the company; the associated weights are 0.5 and 0.5, i.e. DMs have the same importance.

The company adopts a two-stage supplier selection process, constituted by the screening and evaluation phases. As already said, we assumed to apply the model once the shortlist has already been obtained.

In the presented application case two historical suppliers and one new supplier compose the current supplier park; in the following they will be recalled as Supplier 1, Supplier 2 and Supplier 3, respectively.

After a carefulness analysis conducted by DMs, five criteria were identified: Price, Quality, Delivery time, Punctuality and Flexibility.

As it regards the historical suppliers, it should be noted that despite many advantages characterize Supplier 1, Supplier 2 must be involved in the supply of the steel tubes because it is also a supplier of steel raw materials for the company, thus it acts also as logistic partner for the transportation of semi-finished radiators from Italy to the European plants.

The tubes need is evaluated in 22 shipments per month, currently assigned as follows (Table 3):

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Furniture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supplier 1</td>
<td>85%</td>
</tr>
<tr>
<td>Supplier 2</td>
<td>15%</td>
</tr>
</tbody>
</table>

Table 3. Current Supply

The application of the model is aimed at defining a redistribution of order quantities, including Supplier 3 in the procurement process.

4.2 Supplier Selection

According to the framework of the proposed model, selected criteria are divided into Measurable and Forecastable criteria, as reported in Table 4.
Then, their relative weights need to be determined. The calculation of optimal weights is performed exploiting both the linear and non-linear BWM, according to the procedure explained in paragraph 3.1.2. Judgments given by the two DMs are reported in Table 5-6, respectively.

As it could have been expected, both the interviewed managers set as Best criterion the one mostly directly-related to their field of competence.

### Table 5. Decision Maker 1' judgments

<table>
<thead>
<tr>
<th>Criterion</th>
<th>BO</th>
<th>OW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Quality</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>Del. Time</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Punctuality</td>
<td>5</td>
<td>1</td>
</tr>
</tbody>
</table>

### Table 6. Decision Maker 2’ judgments

<table>
<thead>
<tr>
<th>Criterion</th>
<th>BO</th>
<th>OW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>Quality</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>Del. Time</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Punctuality</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>Flexibility</td>
<td>5</td>
<td>1</td>
</tr>
</tbody>
</table>

Applying the Linear BWM we obtained the crisp weights reported in Table 7. As we expected they are different for the two Decision Makers.

### Table 7. Criteria Weights

<table>
<thead>
<tr>
<th>Criterion</th>
<th>DM 1</th>
<th>DM 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>0.371795</td>
<td>0.243243</td>
</tr>
<tr>
<td>Quality</td>
<td>0.211538</td>
<td>0.378378</td>
</tr>
<tr>
<td>Del. Time</td>
<td>0.211538</td>
<td>0.162162</td>
</tr>
<tr>
<td>Punctuality</td>
<td>0.141026</td>
<td>0.162162</td>
</tr>
<tr>
<td>Flexibility</td>
<td>0.064103</td>
<td>0.054054</td>
</tr>
<tr>
<td>$\xi_L$</td>
<td>0.627</td>
<td>1.5</td>
</tr>
</tbody>
</table>

By now, we focused just on the **crisp weights** which are adopted to conduct the decision-making process; **interval weights** will be introduced in the paragraph regarding the Sensitivity Analysis.

The next step concerns with the calculation of suppliers’ scores about selected criteria. From the conducted interview we gathered all the required and useful data for the application of the proposed model (Table 8).

It follows that suppliers’ scores about **Measurable** criteria can be directly calculated, taking advantage of a simple normalization technique by using eq (7) and eq (8); clearly, they are unique and do not depend on the single DM’s opinion as referred to objective performances.

The suppliers’ scores about **Measurable** criteria are reported in Table 9.

### Table 8. Data about measurable criteria

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Price [€/Ton]</th>
<th>Quality [%]</th>
<th>Del. time [days]</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier1</td>
<td>750</td>
<td>99</td>
<td>2</td>
</tr>
<tr>
<td>supplier2</td>
<td>760</td>
<td>97</td>
<td>5</td>
</tr>
<tr>
<td>supplier3</td>
<td>765</td>
<td>100</td>
<td>2</td>
</tr>
</tbody>
</table>

### Table 9. Suppliers’ scores about Measurable criteria

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Score [□]</th>
<th>Score [□]</th>
<th>Score [□]</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier1</td>
<td>0.627</td>
<td>1.5</td>
<td></td>
</tr>
<tr>
<td>supplier2</td>
<td>0.641</td>
<td>0.54054</td>
<td></td>
</tr>
<tr>
<td>supplier3</td>
<td>0.641</td>
<td>0.54054</td>
<td></td>
</tr>
</tbody>
</table>
Table 9. Suppliers’ scores about Measurable criteria

The calculation of suppliers’ scores about Forecastable criteria is different for historical and new suppliers.

For historical suppliers, performances can be directly extracted from company databases (Table 10).

Table 10. Data about forecastable criteria

Instead, concerning the new supplier, the scores calculation is performed exploiting a scenario-based approach, separately by each single DM for the two forecastable criteria (Table 11-14).

Table 11. Punctuality evaluation for DM 1

Table 12. Flexibility evaluation for DM 1

Table 13. Punctuality evaluation for DM 2

Table 14. Flexibility evaluation for DM 2

Having, at this point, the values associated to each supplier, applying equations (7) and (8), it is possible to obtain the suppliers scores about Forecastable criteria, which will be different for the two DMs (Table 15-16).

Table 15. Scores for DM1
This phase is highly characterized by the specific situation which it is referred to, thus great attention must be paid to the correct definition of constraints and company’s policies.

In Table 19-20 nomenclature and data are reported, respectively.

The OA problem is solved according to the two-stage Linear Program introduced in paragraph 3.2.

### Table 16. Scores for DM1

<table>
<thead>
<tr>
<th>Scores</th>
<th>Punctuality</th>
<th>Flexibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.33513</td>
<td>0.33997</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.33171</td>
<td>0.32624</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.33316</td>
<td>0.33791</td>
</tr>
</tbody>
</table>

Once all criteria weights and suppliers’ scores about the same criteria have been calculated, by using eq. (10) it is possible to calculate the Total Score of each supplier according to each DM’s opinion, and then with eq. (11) the Final Total Score is obtained. Results are reported in Table 17-18. The most relevant conclusion that can be directly inferred just looking at the suppliers’ ranking is the fact that Supplier 3 will be surely assigned part of the orders currently assigned to Supplier 2.

### Table 17. Total Score for DM 1 and DM 2

<table>
<thead>
<tr>
<th>Total Score</th>
<th>DM 1</th>
<th>DM 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.3531083</td>
<td>0.3488182</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.2957852</td>
<td>0.3033454</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.3511064</td>
<td>0.3478362</td>
</tr>
</tbody>
</table>

### Table 18. Final Total Score

4.3 Order Allocation

Once the suppliers’ ranking has been obtained, the Order Allocation problem is tackled in order to define the distribution of order quantities among suppliers.

### Table 19. Nomenclature

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>number of suppliers</td>
</tr>
<tr>
<td>TS (n)</td>
<td>Total Score of supplier n</td>
</tr>
<tr>
<td>x (n)</td>
<td>quantity to be allocated to supplier n</td>
</tr>
<tr>
<td>Q (n)</td>
<td>max quantity assignable to supplier n</td>
</tr>
<tr>
<td>c (n)</td>
<td>Total procurement cost of supplier n</td>
</tr>
<tr>
<td>Q2_min</td>
<td>min quantity to be assigned to supplier 2</td>
</tr>
<tr>
<td>Budget</td>
<td>TPC resulting from the found solution</td>
</tr>
<tr>
<td>budget_max</td>
<td>maximum budget available</td>
</tr>
</tbody>
</table>

### Table 20. Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>TS1</td>
<td>0.3510</td>
</tr>
<tr>
<td>TS2</td>
<td>0.2995</td>
</tr>
<tr>
<td>TS3</td>
<td>0.3495</td>
</tr>
<tr>
<td>c1 [€/ton]</td>
<td>750</td>
</tr>
<tr>
<td>c2 [€/ton]</td>
<td>760</td>
</tr>
<tr>
<td>c3 [€/ton]</td>
<td>765</td>
</tr>
<tr>
<td>Q1 [supplies]</td>
<td>18</td>
</tr>
<tr>
<td>Q2 [supplies]</td>
<td>4</td>
</tr>
<tr>
<td>Q3 [supplies]</td>
<td>11</td>
</tr>
<tr>
<td>Q2_min [supplies]</td>
<td>2</td>
</tr>
<tr>
<td>Tot supply</td>
<td>22</td>
</tr>
</tbody>
</table>

Table 20. Data
1st stage

As already explained in Chapter 2, the objective function of the 1st stage of the Linear Program is constituted by the Total Purchasing Cost which is minimized regardless the suppliers’ ranking obtained from the SS process.

\[
\text{Min } \quad TPC = x(n) \cdot c(n)
\]

subject to:

\[
\begin{align*}
Q(1) & \leq 18 \quad (1) \\
Q(2) & \leq 4 \quad (2) \\
Q(3) & \leq 11 \quad (3) \\
Q(2)_{\min} & \geq 2 \quad (4) \\
x(1) + x(2) + x(3) & = 22 \quad (5)
\end{align*}
\]

The constraints (1), (2) and (3) regard the maximum quantities assignable to suppliers, in particular no more than 80%, 15% and 50% respectively. Constraint (4) refers to the minimum quantity to be assigned to supplier 2, while constraint (5) imposes to respect the total supply required per month.

Results of the 1st stage are reported in Table 21.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>TPC [€]</td>
<td>16540</td>
</tr>
<tr>
<td>x1 [supplies]</td>
<td>18</td>
</tr>
<tr>
<td>x2 [supplies]</td>
<td>4</td>
</tr>
<tr>
<td>x3 [supplies]</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 21. Results of the 1st stage

2nd stage

The objective function characterizing the second phase is a prioritization function aimed at taking into account the suppliers’ ranking obtained downstream the SS process.

\[
\text{Max } \quad \sum_n x(n) \cdot TS(n)
\]

subject to:

\[
\begin{align*}
Q(1) & \leq 18 \quad (1) \\
Q(2) & \leq 4 \quad (2) \\
Q(3) & \leq 11 \quad (3) \\
Q(2)_{\min} & \geq 2 \quad (4) \\
x(1) + x(2) + x(3) & = 22 \quad (5) \\
budget & \leq budget_{\max} \quad (6)
\end{align*}
\]

The constraints (1-5) are the same identified for the first stage; in addition, constraint (6) is used to account for the maximum budget available for the order allocation.

With the aim of not providing just a single solution, but to offer a range of possible solutions, the maximum budget is increased 1% by 1%, until a maximum increase equal to +20% with respect to the minimum TPC calculated at the first stage.

In Fig. 3 a graphical representation of the OA solution range is presented. It should be noted that the optimal solution of the OA problem is unique even considering budget increments; this means that the found solution is independent of allocated budget, thus constituting an absolute optimal solution.

As it could have been expected analysing the suppliers’ final Total Scores, Supplier 3, i.e. the new one, is assigned part of the order quantities currently assigned to Supplier 2. However, as internal constraint, Supplier 2 is still assigned two supplies per month so to maintain the commercial relationship with European plants.
As a last consideration, Supplier 1 is assigned the 80% of the monthly supplies, a very high fraction of the total need. But considering the fact that Supplier 1 is a main player in the steel production worldwide, it is highly unlikely that it faces production problems.

In Table 22 the unique optimal solution is finally reported.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>TPC [€]</td>
<td>16550</td>
</tr>
<tr>
<td>$x_1$ [supplies]</td>
<td>18</td>
</tr>
<tr>
<td>$x_2$ [supplies]</td>
<td>2</td>
</tr>
<tr>
<td>$x_3$ [supplies]</td>
<td>2</td>
</tr>
</tbody>
</table>

**Table 22.** Optimal solution of OA problem

4.4 Sensitivity Analysis

Sensitivity analysis is a crucial step from the point of view of the operations and logistics strategy because a weak solution, not enough resilient to keep its optimality even under slight perturbances, may result in a great loss, not only in economic terms but also from the reputation point of view.

Looking at the suppliers’ scores, we can notice that Supplier 3 performs better than Supplier 1 only about criterion *Quality*; it is clear that the only possible option regards increasing the weight of criterion *Quality*, trying to find to what increasing extent of the same, if any, the final Total Score of Supplier 3 overcomes that of Supplier 1.
As already explained in section 3, the sensitivity analysis regarding criteria weights are performed exploiting the so-called *interval weights*, calculated solving the Non-Linear BWM by means of Genetic Algorithms.

The interval weights for DM1 and DM2 are reported in Table 23 and Table 24, respectively.

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Interval Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>[0.33117;0.37179]</td>
</tr>
<tr>
<td>Quality</td>
<td>[0.20523;0.27247]</td>
</tr>
<tr>
<td>Del. Time</td>
<td>[0.20557;0.21462]</td>
</tr>
<tr>
<td>Punctuality</td>
<td>[0.13711;0.14983]</td>
</tr>
<tr>
<td>Flexibility</td>
<td>[0.05847;0.06410]</td>
</tr>
</tbody>
</table>

*Table 23. Interval weights for DM1*

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Interval Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>[0.23476;0.35491]</td>
</tr>
<tr>
<td>Quality</td>
<td>[0.26685;0.37837]</td>
</tr>
<tr>
<td>Del. Time</td>
<td>[0.10690;0.18619]</td>
</tr>
<tr>
<td>Punctuality</td>
<td>[0.14643;0.21032]</td>
</tr>
<tr>
<td>Flexibility</td>
<td>[0.04042;0.05405]</td>
</tr>
</tbody>
</table>

*Table 24. Interval weights for DM2*

When the weight of criterion *Quality* is increased, obviously the weights of other criteria must be lowered in order to preserve the summation of criteria weights to be equal to 1. The idea is to equally redistribute among other criteria the required decrease. The critical point is the fact that criteria weights must be kept within their interval weights; when this is not possible we assigned the criterion under consideration a weight equal to the lower bound of its interval weight, whereas the remaining decrease is assigned to the other criteria.

Considering the case of an increment of the criterion *Quality* weight of +10%, the following criteria weights are obtained for the different DMs (Table 25-26).

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>0.3651</td>
</tr>
<tr>
<td>Quality</td>
<td>0.2327</td>
</tr>
<tr>
<td>Del. Time</td>
<td>0.2062</td>
</tr>
<tr>
<td>Punctuality</td>
<td>0.1371</td>
</tr>
<tr>
<td>Flexibility</td>
<td>0.0589</td>
</tr>
</tbody>
</table>

*Table 25. Criteria weights for DM1*

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>0.2432</td>
</tr>
<tr>
<td>Quality</td>
<td>0.3784</td>
</tr>
<tr>
<td>Del. Time</td>
<td>0.1622</td>
</tr>
<tr>
<td>Punctuality</td>
<td>0.1622</td>
</tr>
<tr>
<td>Flexibility</td>
<td>0.0540</td>
</tr>
</tbody>
</table>

*Table 26. Criteria weights for DM2*

The new Final Total Scores are reported in Table 27.

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Final Total Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.3510</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.2998</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.3492</td>
</tr>
</tbody>
</table>

*Table 27. Final Total Scores*

As we can notice, the Final Total Score of Supplier 3 is still lower with respect to that of Supplier 1, this means that the order allocation will not change. This is a good point since it means that the found solution is enough resilient to keep its optimality even under the effect of slight perturbations of the internal and/or external environments.
5. Conclusion

The main aim of this work was to offer a solution capable of making Decision Makers effectively able to compare new and historical suppliers.

The lack of works exploring the processes and methodologies typical of new task situations makes the proposal of a solving model much more difficult with respect to improving something that has already been deeply inspected; thus, the simple structure of the proposed model leaves possibilities of modification and enhancement in some aspects like the academical scenario, whereas it results to be suitable for real-world applications thanks to its linearity.

Another important point is the respect on DMs' subjectivity, giving them the possibility to express their “feelings” and risk attitude when dealing with the scenario approach, an aspect which is often not taken into account in MCDM models.

However, there are also some drawbacks that have to be highlighted.

In particular, the authors realized that the freedom given by the scenario-based approach in defining both the scenarios probabilities of occurrence and the values reflecting the new supplier’s performances in each scenario, has resulted in a certain way misleading. In order to avoid this kind of bias, different new solutions may be proposed and analysed.

Moreover, another weak point identified regards the two-stage Linear Program introduced for solving the Order Allocation problem. In our opinion the definition of a proper objective function at the second stage is a crucial step for the goodness of the results; indeed, it should account other not negligible cost-aspects that are involved in the procurement process.

Lastly, the way sensitivity analysis has been performed. We focused on the weight associated to Quality criterion, decreasing the other criteria weights of a reasonable quantity so to preserve the summation of all criteria weights to be equal to 1. Even if it is a more than logic and correct way of proceeding in theory, when it comes to the practical application, it results a bit difficult to equally distribute the Δ because of the possibility to overcome the upper and/or lower bound of the interval. New solutions, instead of GA, may be applied in order to define more structured and consistent interval weights.

Obviously, the authors are conscious of the fact that the proposed model claims to be just one of the first solutions proposed for covering the highlighted research gap, but candidate itself to constitute a basis for the future research in the field of new task purchasing situations.

References


Introduction

The Supply Chain Management (SCM) is one of the most important functions in an industrial context as it addresses the inbound and outbound flows of materials, services and information of a company.

The first definition of Supply Chain Management dates back in 1982 and was reported in a white paper by the consultancy firm Booz Allen Hamilton:

"Through our study of firms in a variety of industries... we found that the traditional approach of seeking trade-offs among the various conflicting objectives of key functions -purchasing, production, distribution and sales- along the supply chain no longer worked very well. We needed a new perspective and, following from it, a new approach: Supply-chain management"

Since then, many definitions of SCM were formulated over the years, each one catching different aspects of the SCM itself.

In 1985 Jones and Riley stated “Supply chain management deals with the total flow of materials from suppliers through end users” [1], while a more recent definition is provided by Cristopher who defined the SCM as “the management of upstream and downstream relationships with suppliers and customers in order to deliver superior customer value at less cost to the supply chain as a whole” [2].

With the advent of the new millennium, the globalization of markets, the increased awareness of consumers and the fiercer competitiveness led the concept of Supply Chain Management to evolve in that of Supply Chain Risk Management (SCRM).

What distinguishes SCRM from SCM is the fact that the former includes the processes of identification and mitigation of the risks that might affect the performances of the supply chain.

Nowadays SCRM has a much more strategic role with respect to the previous SCM, firstly due to the increased dependency on suppliers and secondly because of the greater integration of business processes.

It is clear that “suppliers are the critical link to any supply chain and consequently sourcing decision is one of the most important decisions to be taken at the planning stage” (Jain et al., 2013) [3], thus the purchasing function plays a fundamental role in the SCRM.

Among all, the most challenging task of the purchasing function regards the Supplier Selection (SS) process, i.e. the identification of the best supplier(s) that is “able to provide the buyer with the right quality products and/or services at the right price, at the right quantities and at the right time” (Sonmez, 2006) [4].
Many authors investigated the field of supplier selection during the last decades since it has a great strategic impact in both the continuity and the improvement of business processes for a company. Indeed, the selection of an appropriate supplier positively affects competitive strategy and market share by providing high quality products/services to end users and favouring the reduction of both supply chain-related and operational costs.

Due to the great attention SS topic has received, several frameworks were proposed for setting the SS problem and many models were developed to deal with the different stages characterizing the process. No agreement has been found so far about the formalization of the SS problem, although De Boer in 1998 [5] proposed a well-structured four-steps methodology: (1) problem definition, (2) formulation of criteria, (3) qualification and (4) final choice.

The preliminary phase concerns with the identification of the scope of the supplier selection, i.e. what objectives the SS is aimed to. This is a very important phase since it allows to define the achievements of the Supplier Selection process, defining the direction to follow during the subsequent steps.

The second phase regards the identification of the most suitable criteria to be considered for the addressed problem. The classification of criteria and their adoption in different SS contexts has not been deeply inspected, indeed many authors focused their attention just to the very last step of the SS process, without critically examine the criteria which the final choice is based on.

The qualification stage is aimed at obtaining the so-called vendor shortlist (generally composed by 3-4 suppliers) starting from a wider set of suppliers. As highlighted by (De Boer et al., 2001) [6], the main difference between the qualification and the final choice steps is given by the sorting nature of the former with respect to the ranking nature of the latter.

Once the vendor shortlist is obtained, the final choice can be performed evaluating the qualified suppliers on the basis of the considered criteria, then the most performing one(s) is selected.

The final choice step has received much more attention than the previous ones due to its marked decision-making nature; by the way we have to consider that the correctness of this step highly depends on the goodness of the first three, indeed only well defining the problem, considering the most suitable criteria and coming to a proper vendor shortlist, it is possible to select the best supplier(s).

In order to cope with the SS problem, many decision support methods were proposed by academics, which can be grouped into three main categories: (1) Multi-Criteria Decision-Making (MCDM) techniques, (2) Mathematical Programming (MP) techniques and (3) Artificial Intelligence (AI) techniques. In the recent years, due to the increased role of SS, many authors tried to integrate multiple techniques, even belonging to different categories, in order to propose effective models for the SS issue.
Nevertheless, frequently they are not applied by practitioners in real world applications, where the SS is addressed in an unstructured and simplistic way.

Another important task of the purchasing department is the Order Allocation among the selected suppliers, according to different objectives and policies depending on the considered context.

Even this phase is nowadays characterized by the integration of the risk management concept as companies struggle to preserve their business from supply chain disruptions.

The Order Allocation procedure can be classified according to three different perspectives: (1) single sourcing or multiple sourcing, depending on the number of chosen suppliers, (2) single product or multiple product and (3) single or multiple time period, depending on the considered time horizon.

Considering the strong relation existing between Supplier Selection and Order Allocation, many authors proposed integrated models to solve both the problems adopting different techniques and considering different objectives.

According to Faris et al. [7] buying situations can be distinguished into: (1) straight rebuy situations, (2) modified rebuy situations and (3) new task situations. While the first concern with the typical process of purchasing a well-known product/service from a historical supplier, the second and the third ones are more complicated. With modified rebuy a set of purchasing situations are identified in which whether a new product/service is purchased from a historical supplier or a well-known product/service is purchased from a new supplier; new task indicates that both the purchased product/service and the supplier are new.

Very few authors focus on the last two kinds of buying situations, generating a lack in the literature, especially when considering new task situations; moreover, these are affected by a high grade of uncertainty, making the decision-making process much more challenging.

Almost always papers deal with Supplier Selection in contexts where only historical suppliers are considered, thus not providing insights regarding how to carry out the decision process when it comes to the comparison between historical and new suppliers.

Because of the lack of information that usually characterizes the knowledge of buyers about new suppliers, the risks associated to uncertainty and the established relationships with current suppliers, decision makers are frequently prone to select an historical supplier rather than a new one.

Even if on one hand this fact leads to strengthen the commercial deals with current suppliers, on the other hand it can imply additional costs, for example when the R&D function of a company is directly involved at the supplier level for the development of a new component.
Introduction

As already said, uncertainty is a characterizing feature of modified rebuy and new task situations, thus it has to be taken into account when considering such circumstances. Indeed, different decision makers differently behave in the same uncertain situation, for this reason it is clear that the risk attitude of the single decision maker plays a fundamental role in the decisions taken by the decision maker itself. However, few examples can be found in literature integrating the uncertainty about the future into the proposed models addressing SS and OA (Stewart et al., 2013) [8].

In order to fill in the above highlighted gaps, in particular the focus on new task buying situations and the integration of the decision makers’ risk attitude into the decision support system, we propose a model aimed at supporting decision makers dealing with SS and OA problems.

The novelty of our research consists in the possibility to compare the performances of new suppliers against historical ones, integrating the decision makers’ risk attitude by exploiting a scenario-based approach.

To the end of solving the issues related to the lack of knowledge characterizing new task situations, considered criteria are divided into two main classes: measurable criteria and forecastable criteria. Measurable criteria are those whose performances can be directly extracted from suppliers’ bids, while forecastable criteria are those whereby it is not possible to give a score before the supply has been received, in particular it follows that they can be extrapolated from companies’ databases as it regards the historical suppliers, whereas they have to be forecast when it comes to new suppliers.

The criteria weights are found applying a novel structured MCDM pairwise comparisons-based method by J. Rezaei, called Best-Worst Method (BWM) [9][10]. The total score of each candidate supplier is calculated by means of an additive weighted function where the new suppliers’ scores about forecastable criteria are obtained applying a scenario-based approach.

Finally, a Linear Programming (LP) model for the Order Allocation among the selected supplier(s) is integrated.

The remainder of this dissertation is organized as follows: in chapter 1 an extensive literature review is reported highlighting the lack of knowledge that drove our research, in chapter 2 the proposed model is introduced and explained, in chapter 3 the application of the proposed model to a real-world industrial case is described, in chapter 4 conclusions are reported along with suggestions for future development.
1. Literature Review

Supply Chain is defined as “a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances and/or information from a source to a customer” (Mentzer et al., 2001)[11]. The authors also proposed a classification of supply chain in three groups according to their complexity: direct supply chain, extended supply chain and ultimate supply chain (Fig. 1.1).

Direct supply chain is the simplest model of a supply chain involving just a company, a supplier and a customer, extended supply chain includes suppliers of the immediate supplier and customers of the immediate customers, ultimate supply chain comprehends all the organizations involved in all the upstream and downstream flows of products, services, finances and information from the ultimate supplier to the ultimate customer.

![Supply Chains Classification Diagram]

Figure 1.1. Supply chains classification

In the last decades, the internationalization of markets, the introduction of products characterized by a shorter life cycle, the risen customers’ expectations and new
communications and transportations technologies have driven the evolution of supply chains, from the simple direct model to the more complex ultimate model; this fact, necessarily, has stressed the need for an accurate management of the supply chain and the associated processes.

Supply Chain Management (SCM) deals with the administration, organization and control of all the processes related to supply chains, along with the relationships established with both suppliers and customers.

The scope of SCM is that of achieving a higher profit for all parties involved in the chain, and, to this purpose, relationships, co-operation among suppliers and collaboration between direct suppliers and the company are fundamental.

The seek for greater reliability and responsiveness from suppliers has made the concept of Supply Chain Management to develop in that of Supply Chain Risk Management, which represents a wider idea than the previous SCM.

SCRM includes the functionalities of SCM and extends them, incorporating those aimed to address risks identification and mitigation along the whole supply chain.

The last tendency towards outsourcing has led companies to pay much more attention to supply chain risk related issues, indeed, as highlighted by Zsidisin et al. [12], “while the benefits of outsourcing have provided many firms a competitive advantage in the marketplace, there have been corresponding increases in the level of corporate exposure to uncertain events with supplier”.

Many authors have investigated the field of SCRM, developing models intended to the identification of risk sources, the analysis and assessment of associated risks and the definition of counter-measures (e.g. Wu et al., 2006, Micheli et al., 2014) [13], [14].

As suppliers are the main players of any supply chain, it is clear that their performances strongly influence those of the whole supply chain; thus, Supplier Selection (SS) performs a major role in the context of SCRM.

Even though many authors tend to keep SCRM and SS separated concepts, actually SS can be seen as a critical component in the wider spectrum of SCRM, therefore a close link exists between them (Micheli et al., 2008) [15].

Supplier Selection is one of the critical tasks handled by purchasing department, whose objective is to obtain products/services at the right cost in the right quantity with the right quality at the right time from the right source (Sarkis and Talluri, 2002) [16]. Moreover, SS has a marked strategic role as the selection of the right supplier(s) can help companies to meet regulatory and quality standards, imposed by authorities and market respectively, drive customer demand and build a strong firm reputation (Hruška et al., 2014) [17].

If on one hand the Supplier Selection process leads to the choice of the best supplier(s), on the other hand, Order Allocation (OA) procedures allow to assign items among the selected suppliers in order to reach set objectives for a company. OA is performed integrating policies, which resemble the company attitude, and constraints, given by the business environment under consideration.
In the end it is evident that a correct selection of suppliers and subsequent order allocation is an important and essential activity for any business organization in order to minimize total purchasing costs (Trivedi et al., 2017) [18] and build a robust supply chain.
1.1 Review of Supplier Selection literature

Thanks to its leading role in structuring and managing a supply chain, SS has received extensive attention over the years. The strategic feature of SS has continuously been increasing since globalized markets, e-sourcing and improved logistics have made the supply chain to be a strong competitive aspect among companies operating in the same field; indeed, proper Supplier Selection significantly reduces the purchasing costs and improves corporate competitiveness, also allowing to reduce supply chain-related risks. (Ghodsypour and O’Brien, 2001, Hruška et al., 2014) [19] [17].

The importance of selecting the right supplier(s) becomes even more evident considering that, in industrial contexts, costs related to purchasing activity account for 50-90% of the total turnover (De Boer et al., 2001) [6].

It is clear that there exist different buying situations; Faris et al. (1967) [7] distinguished three main categories: straight rebuy, modified rebuy and new task (Table 1.1).

| **Straight rebuy**                              | Complete information about suppliers and specifications |
|                                               | Placing orders within existing contracts and agreements |
| **Modified rebuy**                             | New product/service from known suppliers |
|                                               | Existing (modified) product/service from new suppliers |
|                                               | Moderate level of uncertainty |
|                                               | No strict requirement of Group Decision-Making |
| **New task**                                   | Completely new product/service |
|                                               | Unknown suppliers |
|                                               | High level of uncertainty |
|                                               | Need of Group Decision-Making due to the complexity of the situation |

Table 1.1. Classification of buying situations by Faris et al.

While straight rebuy situations are “safe”, since a well-known product/service is purchased from a historical supplier, modified rebuy and new task situations are characterized by increasing uncertainty about the product/service to be purchased and/or the supplier that will provide the product/service. This classification, however, is not sufficient to characterize all the possible situations a buyer might face; De Boer et al. [6] integrated the classification of buying situations proposed by Faris et al. with the Kraljic’s portfolio matrix (Kraljic,
1983) [20], where items are classified according to two factors: supply risk and profit impact (Table 1.2).

The profit impact regards the contribution margin and the involved commercial volume of a commodity, while supply risk concerns the possible losses occurring from unavailability of the considered commodity.

<table>
<thead>
<tr>
<th><strong>Low-profit impact</strong></th>
<th><strong>Low-supply risk</strong></th>
<th><strong>High-supply risk</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Routine items:</strong></td>
<td>many suppliers</td>
<td>monopolistic supply market</td>
</tr>
<tr>
<td></td>
<td>rationalised</td>
<td>long-term contracts</td>
</tr>
<tr>
<td></td>
<td>purchasing</td>
<td>develop alternatives</td>
</tr>
<tr>
<td></td>
<td>procedures</td>
<td>contingency planning</td>
</tr>
<tr>
<td><strong>Leverage items:</strong></td>
<td>availability of</td>
<td><strong>Strategic items:</strong></td>
</tr>
<tr>
<td></td>
<td>many suppliers</td>
<td>few (difficult to switch)</td>
</tr>
<tr>
<td></td>
<td>competitive bidding</td>
<td>suppliers</td>
</tr>
<tr>
<td></td>
<td>short-term contracts</td>
<td>medium/long-term contracts</td>
</tr>
<tr>
<td></td>
<td>active sourcing</td>
<td>supplier development/partnership</td>
</tr>
</tbody>
</table>

### Table 1.2. Kraljic's portfolio matrix

Considering both buying situation and the position of the purchased product/service in the Kraljic’s matrix, a structured framework was created where each specific buying circumstance finds its place.

According to Hruška et al. (2014) ‘suppliers are considered the best intangible assets of any industrial organization’ [17], for this reason it is not surprising that the issues related to SS process have been largely inspected by academics, who tried to propose frameworks and techniques aimed at dealing with the same, resulting in a wide range of approaches and models.

Different classifications were suggested for schematizing into groups proposed approaches and models; inter alia, Ho et al. (2010) [21] as well as Chai et al. (2013) [22] focus on techniques adopted by authors to address the SS problem while Wetzstein et al. (2016) [23] cluster authors’ proposals according to the orientation characterizing the SS problem.
Basing on the work by Chai, we can classify proposed methods for solving SS problem into three main categories according to the adopted methodology: (1) Multi-Criteria Decision-Making (MCDM) methods, (2) Mathematical Programming (MP) methods, (3) Artificial Intelligence (AI) methods.

Figure 1.2. Methodologies to address the SS problem

1.1.1 Multi-Criteria Decision-Making methods

In the Supplier Selection background, Multi-Criteria Decision-Making represents the approach that has received most attention over the years.

Several reasons support this fact: (i) MCDM models are easy to use, (ii) they allow to consider not only quantitative criteria, but also qualitative ones, that may have great importance in the decision process, (iii) they can effectively support Multi-Decision-Maker (MDM) situations, giving the chance to integrate the opinions of the single Decision Makers (DMs), (iv) the integration of risk and uncertainty in estimating the suppliers’ performances, (v) while MP and AI methods are completely automated techniques, so once the problem has been formalized by the DM they act like a black box, MCDM approaches guarantee a high level of interaction between the DM(s) and the Decision process.

The general framework of Multi-Criteria Decision-Making methods is reported in Fig. 1.3.
Basing on this framework it is possible to analyse the extant literature about MCDM methods.

**Decision Makers**

With regard to Decision-Makers (DMs) which take part in the decision process, we can distinguish between: i) Single Decision-Maker (SDM) and ii) Group Decision-Making (GDM) (or Multiple Decision Makers (MDM)).

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 (Büyüközkan and Göçer) [24].

When considering Small and Medium Enterprises it could be the case that SS problem is addressed from an SDM point of view, given the small size of the company, by the way, when dealing with Big Enterprises and even more so with Multinational Corporations, it is unusual that such a strategically relevant problem as SS is tackled by one SDM, and situations of GDM are the routine.

Different situations have been presented in literature, some authors consider GDM as the most collaborative way to take a decision by a panel of experts. In this context Chan and Chan [25] exploit the geometric average to integrate the opinions of the single DMs, Rezaei et al. [26] give the same weight to all the expert composing the decision group, Zhang et al. [27] define the weights of the single DMs by means of Vague Set Theory (VST), Boran et al [28] find the weights of the single DMs through linguistic terms expressed as Intuitionistic Fuzzy Numbers (IFN), then they integrate different opinions adopting the Intuitionistic Fuzzy Weighted Averaging (IFWA) operator.

---

**Figure 1.3.** MCDM general framework.
We have to highlight that GDM leads to better result with respect to SDM (Kar and Pani) [29], indeed the different knowledge contributions provided by each DM allow for a more robust choice. According to our knowledge, many authors do not specify if they consider Single or Multiple DM in their works, making it ambiguous to find a practical application for proposed models.

Criteria

The set of criteria considered in supplier selection problems is very wide and comprehends both quantitative and qualitative criteria, moreover, according to the different buying situations (Faris et al., 1967) [7], different criteria have been considered.

Before ‘90s criteria were exclusively of quantitative nature (Kar and Pani, 2014) [29], while in the more recent years even qualitative ones have risen in importance; several reasons stand behind this fact: (i) the increased complexity of nowadays supply chains made buyer-supplier relationships based only on price to be no longer acceptable, especially when considering critical items (Sarkis and Talluri, 2002) [16], (ii) the grown importance of the “voice-of-customers”, which have driven buyers to focus on more qualitative aspects such as quality, flexibility and after-sale services, (iii) the greater attention to Risk Management in Supply Chain contexts led buyers to focus on criteria able to integrate risk-related considerations into the decision-making process, for instance supplier’s resiliency, conflicting interests and so on.

Analysing relevant literature about SS criteria, it is possible to notice that price, quality and delivery are the most frequently adopted criteria, but their relative importance has changed over time, indeed if once price was dominant in the background concerning SS, nowadays quality and delivery have gained a primary role (Ho et al., 2010) [21].

Being price a function of cost, profit margin and market forces and delivery dependent on the organization’s efficiency and effectiveness, it is clear that they own a marked quantitative nature, on the contrary quality is determined by the customer’s satisfaction degree so it is much more qualitative and less quantifiable, furthermore it lasts for the whole life of the product/service purchased and so it has a deeper impact in the long term with respect to price and delivery, which, conversely, are important just during the purchasing of the product/service (Cheraghi et al., 2004) [30].

Considering what afore-mentioned, it is clear that the risen importance of the voice-of-customer has made related criteria, first and foremost quality, to acquire a dominant position.

Kar and Pani [29] offer one of the most recent investigations about SS criteria, they analysed different reviews of supplier selection literature and pointed out ‘over 60
generic criteria that have been used across a variety of procurement contexts across different industries’; in Table 1.3 we report the findings of the study by Kar and Pani [29]:

<table>
<thead>
<tr>
<th>Product quality</th>
<th>Reciprocal arrangements</th>
<th>Warranties</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product pricing</td>
<td>Production capability</td>
<td>Technical capabilities</td>
</tr>
<tr>
<td>Management capability</td>
<td>Suppliers’ reputation</td>
<td>Financial position</td>
</tr>
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<td>Labour relations</td>
<td>Service quality experience</td>
<td>Past business records</td>
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<td>Communication barriers</td>
<td>Trade tariffs</td>
</tr>
<tr>
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<td>Foreign exchange rates</td>
<td>Cultural fitment</td>
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<tr>
<td>Trade restrictions</td>
<td>Value-added productivity</td>
<td>Supply variety</td>
</tr>
<tr>
<td>Quality management</td>
<td>e-transaction capabilities</td>
<td>IT standards</td>
</tr>
<tr>
<td>Documentation</td>
<td>Procedural compliance</td>
<td>Indirect costs</td>
</tr>
<tr>
<td>Lead time</td>
<td>Cost reduction capability</td>
<td>Response flexibility</td>
</tr>
<tr>
<td>Innovation</td>
<td>Intellectual property rights</td>
<td>Safety adherence</td>
</tr>
<tr>
<td>Domain experience</td>
<td>Certification and standards</td>
<td>Risk perception</td>
</tr>
<tr>
<td>Customs duties</td>
<td>Product line diversity</td>
<td>Packaging capability</td>
</tr>
<tr>
<td>Inventory position</td>
<td>Electronic data interchange</td>
<td>Buyer’s commitment</td>
</tr>
<tr>
<td>Total cost of acquisition</td>
<td>Conflict resolution systems</td>
<td>R&amp;D</td>
</tr>
<tr>
<td>Response time</td>
<td>Organizational culture</td>
<td>Availability of parts</td>
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<td>Sub-component pricing</td>
<td>Regulatory compliance</td>
<td>Self-audits</td>
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<td>Billing accuracy</td>
<td>Cost reduction performance</td>
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<td>Service quality credence</td>
<td>Suppliers’ commitment</td>
<td>Skill level of staff</td>
</tr>
<tr>
<td>Exporting status</td>
<td>Intimacy of relationship</td>
<td>Facility planning</td>
</tr>
<tr>
<td>Data administration</td>
<td>Improvement commitment</td>
<td>Design capability</td>
</tr>
</tbody>
</table>

**Table 1-3. Criteria Highlighted by Kar and Pani**

Starting from this rough set, with the support of some interviewed experts, thirteen criteria were highlighted as the ones of prime importance across the industries: **product quality, compliance with the delivery schedule, price of the product, technology capability, production capability, financials of the supplier, geographical location, buyer commitment to the supplier, management capability, e-transaction capability, responsiveness to demand fluctuations, experience in the domain and relationship.**

Büyüközkan and Göçer (2017) [24] propose a classification dividing into two main criteria: **quality and cost** and nine sub-criteria: **respect for privacy, accuracy of the delivery, delivery speed, legal responsibilities, fulfilling the urgent requirements** (related to quality) and **price dependence on purchase orders, cost comparison with market, compliance with contract terms, financial stability and strength**
(related to cost), considering the case of an international sporting goods group present in Turkey.

Chen and Zou [31], by means of a detailed survey of the literature and a questionnaire submitted to the managers of a company operating in the manufacturing business, identified five critical criteria: low overall cost, high quality, good for service performance, goodness of supplier's profile and low risk. After having interviewed many experts from the field of academics, finance, production and material management, Jain et al. [3] propose a hierarchical model for applications in supply chain management. The main level is constituted by four criteria: cost, quality, delivery and flexibility for each of which a set of sub-criteria was also identified.

Moved by the growing concern about environment issues and the continuous search for designing environmentally sustainable processes that have characterized recent years, many authors tried to integrate the so-called green criteria with the traditional ones. Different approaches for taking into account green criteria have been proposed; some authors keep the green criteria separated from traditional ones, the weight of each set is separately computed and then the overall score of a supplier is obtained integrating its performances about each set of criteria (e.g. Hamdan and Cheaitou [32]), others do not operate this distinction, considering together both traditional and green criteria (Rezaei et al. [26]), still others focus only on green criteria, basing the SS only on them (e.g. Shen et al. [33]).

The variety of literature not only regards the considered criteria, but also the methods applied to calculate the associated weights. Since each MCDM approach to SS problem involves the consideration of multiple criteria and therefore the calculation of the corresponding weights, it is clear that, given the great abundance of examples of such approaches, many methods have been proposed. The vast majority of authors adopt pairwise comparisons-based methodologies for calculating the weights to be assigned to considered criteria, for instance Erdem and Göçen [34] utilise AHP, Sarkis and Talluri [16] exploit Analytic Network Process (ANP), Gupta and Barua [35] employ a novel pairwise comparisons-based method named Best-Worst Method (BWM) [9] [10].

However, other methods have been adopted in order to address the calculation of criteria weights, in particular, theory of fuzzy numbers is at the base of the work by Chen and Zou [31], Karsak and Dursun [36] calculate criteria weights in an imprecise environment by means of Fuzzy Weighted Average (FWA) method, Ayhan and Kilic [37] integrate fuzzy logic with AHP (FAHP) while Chou and Chang [38] integrate fuzzy logic with SMART.
Another differentiation point is that some authors keep the two processes of calculating criteria weights and suppliers scores separated (e.g. Pramanik et al. [39]), while others exploit techniques (like AHP) that allow to perform the two steps with the same methodology (e.g. Hruška et al. [17]).

A valuable work by De Boer [40] concerns how to rank criteria rather than how to assign each criterion a correspondent weight. In this research, the author proposes three heuristics for identifying the “order of application” of the selected criteria basing on the trade-off between the benefit and the cost characterizing the single criterion in the supplier evaluation process.

**MCDM techniques**

“All decision-making problems have several criteria to evaluate and select one candidate among several alternatives. As the number of alternatives and criteria increases, decision making becomes more complicated, which is the reason for continuous efforts by researchers for finding a solution to these problems.” [24]

Regarding the techniques proposed to address MCDM SS problems, we can start differentiating, according to Ho et al. [21] and Chai et al. [22], between independent and integrated techniques.

Independent techniques are said those composed of a single tool, while by integrated techniques are intended those in which two or more tools are combined together.

Hruška et al. [17], as well as Dweiri et al. [41] adopt AHP to address SS problem, Gencer and Gurpinar [42] exploit ANP, Cheraghalipour and Farsad [43] take advantage of a novel pairwise comparisons-based method, named Best-Worst Method [9] [10], Vahdani et al [44] extend ELECTREE method applied to SS considering interval weights for the criteria and interval score for alternative suppliers with respect to each criterion, Chou and Chang [38] propose a fuzzy SMART model both for calculating criteria weights and assessing suppliers on selected criteria, Sanaye et al. [45] employ VIKOR method in a fuzzy environment, Boran et al. [28] introduce intuitionistic fuzzy TOPSIS. Other independent MCDM techniques that can be found in the literature concerning SS problem are SWING, DEMATEL and PROMETHEE.

While in all the afore-mentioned papers independent MCDM techniques are adopted, the more recent tendency is that of integrating different tools in order to create more effective models for solving SS problems of increased complexity.

Hamdan and Cheaitou [32] as well as Fallahpour et al. [46] integrate AHP and TOPSIS in a fuzzy environment, Luthra et al. [47] combine AHP and VIKOR in the context of Sustainable Supplier Selection (SSS), Önütt et al. [48] propose the integration of Fuzzy ANP, to calculate the criteria weights, and Fuzzy TOPSIS, to rank the alternatives, Gupta and Barua [49] introduce a joint BWM-Fuzzy TOPSIS model.
The risen importance of *quality*, as an extended concept that goes beyond the simple technical quality, have pushed many authors to include the Quality Function Deployment (QFD), integrating it with different decision-support MCDM techniques. Pramanik et al. [39] integrate AHP with QFD for calculating the criteria weights and adopt TOPSIS methodology for ranking the suppliers, Tavana et al. [50] combine ANP with QFD, Dursun and Karsak [51] propose a QFD-based approach exploiting Fuzzy Weighted Averaging (FWA) method for calculating criteria weights boundaries and rating candidate suppliers, Haldar et al. [52] introduce a model exploiting QFD, TOPSIS and AHP.

### 1.1.2 Mathematical Programming methods

Another approach employed by a number of authors to address SS problem is Mathematical Programming (MP). This field includes many sub-techniques that can be divided, according to Chai et al. [22], into: Linear Programming (LP), Nonlinear Programming (NLP), Multi-Objective Programming (MOP), Goal Programming (GP), Stochastic Programming (SP) and Data Envelopment Analysis (DEA).

LP is a mathematical optimization tool used for determining a way to achieve the best outcome possible for a given mathematical model, this is done by minimizing or maximizing a linear objective function under a set of linear constraints. An example of implementation of LP in SS literature is given by Ghodsypour and O’Brien [53] who combined it with AHP.

NLP is similar to LP, but it allows for some of the constraints and/or the objective function to be nonlinear. Ware et al. [54], after having highlighted the fact that SS problem is highly dynamic in real practice, propose a mixed-integer NLP model to address SS.

MOP is characterized by multiple, and usually conflicting, objective functions that can be optimized over a set of feasible solutions; in the context of SS and OA Yücel and Güneri [55] develop a MOP model integrating fuzzy logic.

GP can be regarded as an extension of MOP, indeed, as the latter, it deals with multiple and possibly conflicting objectives, but setting for each measure a target value to achieve. Ku et al. [56] combine Fuzzy GP with Fuzzy AHP to build a SS-OA model, in particular, after having found the weights of each goal adopting AHP, suppliers and related order quantities are selected by solving the GP problem.

SP is a framework for modelling optimization problems characterized by uncertainty, which is taken into account by means of probability distributions.
Hammami et al. [57] propose a mixed integer scenario-based two stage stochastic programming model where the scenarios are related to uncertainty about exchange rate fluctuations.

DEA is a nonparametric MP technique for comparing the efficiencies of entities in terms of decision-making units (DMUs). It is a largely used technique for dealing with SS problems because of its suitability for evaluating multi-criteria problems and giving improvement hints for the same. Many authors adopted DEA in order to tackle SS problems, among all, Kumar et al. [58] propose DEA for solving an environment-friendly SS problem, taking into account the carbon footprint of suppliers, Toloo and Nalchigar [59] adopt DEA for SS in presence of both cardinal and ordinal data, Karsak and Dursun [36] integrate DEA with QFD following the current trend of paying much more attention to quality issues when addressing SS problems.

MP techniques lead to find the optimal solution (or one of the optimal solutions) of the given problem, but they are unable to account for qualitative criteria, thus limiting the application possibilities of the same.

1.1.3 Artificial Intelligence methods

AI tools are advanced mathematical tools that exploit the intelligence demonstrated by machines for solving complex problems, as SS is. The main benefits of AI techniques with respect to the others is that they do not need assumptions in the decision-making process, in addition they can provide predictive models basing on historical data set. The major AI techniques are Genetic Algorithms (GA), Neural Networks (NN), Grey System Theory (GST) and Rough Set Theory (RST). Because of the complexity of AI methods, they are little utilised for addressing SS problems, since this kind of problems can be efficiently solved adopting more manageable techniques like MCDM and MP. However, some authors implement AI techniques for solving SS problems taking into account multiple aspects; for instance, Rezaei and Davoodi [60] employ GA for structuring a joint pricing, lot-sizing and supplier selection model.
1.2 Overview on Order Allocation

In real world practice, the step following the choice of the best suppliers is the allocation of the quantities to be purchased among selected suppliers. Order Allocation constitutes a not so easy step to be performed by purchasing department, indeed it is expression of objectives and policies set by a company for its supply chain. In addition, it has also a strategic importance, in fact it allows to prevent and/or minimize risks that can affect the supply chain integrity for example by splitting the supply of a critical item among different suppliers so that if one faces some disruptions, the supply chain keeps intact, without being blocked by the occurred interruption.

Order Allocation processes can be classified according to different points of view: (i) the number of considered suppliers, (ii) the number of purchased product-types, (iii) the time horizon of the OA itself.

According to the number of suppliers chosen we can distinguish between single sourcing, in case just one supplier provides the whole requested quantity, and multiple sourcing, in case the supply is split among two or more suppliers. While single sourcing usually guarantees a less complex, thus more easily manageable supply chain, along with greater quantity discounts with respect to multiple sourcing, the latter, despite its higher administration costs and more time-consuming contract negotiations, can ensure the supply chain a safer coverage from disruptions. Finding a trade-off between these two aspects constitutes the most challenging decision in the Order Allocation context.

Considering the number of purchased product-types, we talk about single product, in case the supply regards just one product-type, or multiple product, in case two or more product-types are considered within the OA process.

The last distinction is about the considered time horizon, dividing OA processes into single time period OA and multiple time period OA.

While single time period OA is mostly considered by academics in order to simplify real world situations, these are actually characterized by a multiple time period nature mainly due to the uncertainty about the demand.

As highlighted by Erdem and Göçen [34] the great majority of the studies in the literature are dedicated to supplier selection problem only. The integrated models, which support both supplier evaluation and order allocation, account for a small portion of the studies in this area, even if they provide a complete framework for performing two crucial and strongly connected activities of purchasing department (Table 1.4).

Some authors focused only on the OA problem, without integrating it with the SS one. This means that they started from a predefined set of selected suppliers which order quantities must be assigned to in order to satisfy the production demand. This approach is quite limiting as it considers just a portion of the SS-OA problem, but it can be useful in case a company just needs to revise its order allocation process, for instance due to changed production needs, without changing its suppliers’ list.
In particular, Bhoner and Minner [61] propose a multiple product-types, multiple sourcing and single time period MILP OA model aimed to minimize the total purchasing cost, starting from a predefined set of suppliers, taking into account failure risk and quantity and business volume discounts.

Trivedi et al. [18] introduce a MOLP model for OA, considering a given suppliers set, in a multiple product-types, multiple sourcing and single time period context; the goal is the minimization of the total purchasing cost and the main contribution consists in the integration of the Bill of Materials (BOMs) in the model.

Kawtummachai et al. [62] suggest an algorithm in order to examine the effectiveness of the OA system in terms of service level and company’s total purchasing cost, in a multiple items, multiple sourcing and multiple time period scenario.

Many other authors, on the contrary, tackled the whole problem, namely the joint SS and OA problem, developing frameworks useful for performing the OA process after having found a set of suitable (best) suppliers. The great amount of models dealing with both supplier selection and order allocation processes prove the strong relation between these two aspects.

Mafakheri et al. [63] propose a Bi-Objective Linear Programming optimization that aims at maximizing a utility function for the company as well as minimizing the total supply chain costs. It considers the case of multiple-sourcing, multi-product types and multiple time periods.

Nazari-Shirkouhi et al. [64] develop a Fuzzy Multi-Objective Linear Programming (FMOLP) for solving both SS and OA problems in case of multiple-sourcing, multi-product and single time period situation, aiming at the minimization of the ordering cost, number of the rejected items from the suppliers and net number of late delivered items.

Ayhan and Kilic [37] exploit a multiple-sourcing, multi-product and single time period Mixed-Integer Linear Programming (MILP) for selecting the best suppliers and determining the order allocation among them.

Hamdan and Cheaitou [32] implement a Bi-Objective Integer Programming model aimed at maximizing the weights of green criteria and minimizing the total purchasing cost in a multiple-sourcing, single product and multiple time period context.

Erdem and Göçen [34], after evaluating the suppliers by means of the AHP, employ a Goal Programming method for dealing with the Order Allocation problem, by considering a multiple-sourcing, multiple-product and multiple time period environment.

Rezaei and Davoodi [60] utilize Genetic Algorithms for solving both SS and OA problems in case of multiple-sourcing, multi-product and multiple period time planning horizon.

Vahidi et al. [65] propose a novel bi-objective two-stage mixed possibilistic-stochastic programming model, exploiting a combined SWOT-QFD approach, to address sustainable supplier selection and order allocation problem under operational and disruption risks.
<table>
<thead>
<tr>
<th>Authors</th>
<th>Year</th>
<th>SS</th>
<th>OA</th>
<th>SS&amp;OA</th>
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**Table 1.4.** Classification of reviewed papers basing on the addressed field.
1.3 Research Gaps

Supplier Selection and Order Allocation problems have received extensive attention by academics, researchers and practitioners over the last decades due to their strategic importance for companies, especially in nowadays complex supply chains. Most of the works have been focused on the SS problem, seen as a critical starting point for building up efficient and effective supply chains, while much less concern has been given to OA problem; indeed, it is rising in importance only in the last years with some authors focusing on the lonely, specific OA process and many others proposing integrated models for addressing the joint SS and OA problem.

Despite the great commitment dedicated to this field of SCM, many aspects still require deeper inspection in order to frame a complete knowledge base for addressing SS problems.

Even though, already in 2001, De Boer et al. [6] highlighted the lack of attention directed to the so-called new task situations, since then, only very few authors focused on this topic leaving an almost unfilled gap in the previously mentioned knowledge base.

To our best knowledge no literature reviews exist proposing a classification of papers according to the specifically addressed buying situation, namely straight rebuy, modified rebuy and new task, making it even more difficult to find works concerning new task buying situations.

From our search conducted on major on-line scientific libraries, in particular Google Scholar®, Scopus® and ScienceDirect®, filtering by means of keywords new suppliers and new task it came out that only Rezaei et al. [26] and Hruška et al. [17] deal with the selection of new suppliers in a new and in an existing market respectively.

This fact seems to be quite strange in the nowadays fast changing world where the demand for new, technologically advanced products and services keeps increasing, leading companies to the need of finding new solutions and developing new products, able to cope with customers’ requirements. It is clear that in such a continuously evolving market environment, along with the increased tendency of company to outsource part of their production, the need for a framework enabling the comparison between new and/or new and historical suppliers is urgent and efforts must be directed to its development.

When considering extra-ordinary situations, risk plays a fundamental role in the decision-making process as the realization of a particular situation with respect to another one could determine the successfulness of the choice.

Consequently to the consideration of risk in the whole supply chain, fact that led the term Supply Chain Management to turn into Supply Chain Risk Management, also SS process calls for the integration of risk while evaluating and selecting suppliers.
Moreover, when the decision-making process involves more than one DM, we have to take into account the fact that the single DMs are characterized by their own risk attitude, thus they will evaluate the risks related to SS in different ways one from the others.

In the last years many decision-support methods were proposed integrating fuzzy logic with the traditional methodologies in order to account for vagueness and imprecision of both available information and DMs’ judgements; by the way they aim at modelling, as already said, uncertainty rather than risk attitude.

For this reason, we think that a scenario planning approach could be more effective than fuzzy numbers for modelling the DMs’ risk attitude, integrating it in the decision-making process as the application of fuzzy logic allows to, but empowering the subjective perception of risk characterizing the decisions taken by the single DMs.

In the end we argue that many of the methods proposed in the literature can hardly found practical application due to their complexity; in particular, while for addressing OA problems, optimization algorithms constitute the most suitable (and actually the main adopted) solution, they are 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 be translated into quantitative values, therefore making the problem too complex for being solved by means of optimization methods; moreover, it should be underlined that in real situations no optimal solution is expected, but just a good and, above all, feasible one.
1.4 Proposal

Considering the missing points in the SS knowledge base highlighted in paragraph 1.3, we want to propose a simple and effective method for dealing with the joint SS and OA problem, which can be readily applied by practitioners thanks to its linear and clear structure.

The main contribution of the methodology we are going to introduce is the fact that it allows comparing new suppliers one with the others and also with historical ones which definitely constitutes the knowledge gap requiring the most urgent attention.

In order to propose a user-friendly tool, we think that MCDM methods constitute the best option as they are easily customizable and adaptable to even very different situations. Group Decision-Making is considered as the reference context, indeed in nowadays complex structured companies it is very uncommon that a decision is taken by a single DM.

The suitable criteria identified by the DMs are distinguished into two categories, namely *Measurable Criteria* and *Forecastable Criteria*, according to how the related suppliers’ performances can be evaluated. *Measurable Criteria*-related suppliers’ performances can be evaluated simply from bids submitted by both historical and new suppliers, while *Forecastable Criteria*-related suppliers’ performances assessment is more challenging, indeed, when considering historical suppliers, they can be directly extracted from company’s databases, whereas, when it comes to new suppliers, they require the exploitation of a scenario planning approach.

In particular, the integration of a scenario planning approach within MCDM methods was already suggested by Stewart et al. [8] in a paper dated back to 2013, where the authors stated that many quantitative decision analytic models do not adequately deal with the many uncertainties and risks that arise in long-term strategic decision-making contexts.

Starting from this consideration, the utilization of a scenarios-based score method for the quantification of the performances of new suppliers with respect to *Forecastable Criteria* allows taking into account the *risk attitude* of each DM, that is another of the main missing point in the SS literature.

As it regards the calculation of the weights to be assigned to selected criteria, a novel pairwise comparisons-based method, named Best-Worst Method (BWM) [9] [10], is employed. One of the greatest advantages of this recently-developed method is the fact that it is less-information requiring than other pairwise comparisons-based methods (e.g. AHP) and thus it better fits a *new task* situation, which is, by nature, characterized by lack of information. For an exhaustive explanation of the BWM we refer to chapter 2 of this work.
Once criteria weights and scores of each supplier with respect to each criterion have been found, it is possible to obtain the total score of each supplier, from the point of view of each DM, by simply applying an Additive Weighted Function. It results that there will be as much total scores for each candidate supplier as the number of DMs.

Then the integration of the DMs’ opinions is performed by means of a weighted average of the scores obtained by each supplier basing on the weights assigned to the single DM, so obtaining the final rank of suppliers. As it is clear the integration of DMs’ opinions takes place at the end of the Decision-making process performed by each Decision Maker, this is required by the need of taking into account the risk attitude of the single Decision Maker.

The last step concerning with SS is the verification of the robustness of the choice coming out from the decision process described above. Indeed, exploiting the nonlinear formulation of the BWM it is possible to define an optimality range for each criteria weight, thus allowing to perform a sensitivity analysis aimed to provide further suggestions about suppliers’ final rank.

Once the suppliers’ ranking has been obtained from previous steps, it is possible to define the order quantities to allocate to a selected number of suppliers (e.g. the best two or the best three).

In analyzing the OA problem, we decide to consider a multi-sourcing, multi-item and multi-time period situation. Particular attention should be paid to the multi-sourcing feature of the addressed problem, indeed, as new task buying situations are the object of our study, it results risky to assign the whole supply to just one supplier; for this reason, upper bounds for the supply fraction allocated to each selected supplier have been set. Moreover, we should consider that it is not worth starting a new business relationship just for a small supply quantity, due to associated starting costs; this is the reason why lower bounds for the supply fraction assigned to each selected supplier have been set too.

The proposed resolution methodology consists in a two-stage Linear Program: in the first stage orders are allocated in such a way to minimize the Total Purchasing Cost (TPC) without considering the prioritization of suppliers according to the obtained ranking, while in the second stage a positive variation range of the minimum TPC is considered so to get a range of possible solutions, prioritizing selected suppliers.

The inspiring factors leading to our proposal are schematized in Fig. 1.4.
**Figure 1.4.** Inspiring factors leading to our proposal
2. Model

In paragraph 1.3 the research gaps affecting SS knowledge base were highlighted, stressing the need for a model enabling the comparison between new and/or new and historical suppliers so to cope with nowadays fast changing market and the increased tendency to outsourcing.

In order to fill-in these gaps, in paragraph 1.4 we introduced our proposal of a model, addressing the joint SS and OA problem, capable to cover the underlined missing points.

As it regards the SS problem, we decided to adopt an MCDM method. This choice comes from the consideration that such methods are more easily applicable and customizable with respect to MP and AI methods, which require advanced mathematical skills. In addition to this, MCDM methods allows to take into consideration many different aspects of the choice by means of the associated criteria; for this reason, they can be applied even to very complex situations in which MP and AI methods are hardly applicable, the former due to the impossibility to get an optimal solution for such complicated problems and the latter because of the burdensome computational effort required.

In case of new task situations, which are by nature riskier with respect to straight rebuy and modified rebuy ones, the general framework of MCDM methods presented in paragraph 1.1.1 can be extended, leading to the following (Fig. 2.1):

![MCDM framework for new task situations](image)

**Figure 2.1.** MCDM framework for new task situations
Along with the traditional framework of MCDM methods applied to SS problems, two “new” steps are added, characterizing the specific addressed situations, i.e. new task.

Indeed, the possibilities offered by the internet allow to get information about a very large number of suppliers which are usually all considered as possible candidates at first glance. Obviously, the evaluation process cannot be performed for all identified suppliers as time and money resources are always limited, thus a screening process should be performed in order to obtain a shortlist of suppliers that are worth being evaluated.

The screening process is based on the evaluation of each identified supplier on the base of a set of requirements which, if satisfied, allow the analysed supplier to enter the shortlist.

Even though the selection of the most appropriate screening methodology lies outside of the scope of this work, for the sake of completeness we report three different ways to conduct the screening process according to Hwang and Yoon [66] (Table 2.1):

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conjunctive screening</td>
<td>A supplier can enter the shortlist if and only if it satisfies all the set requirements</td>
</tr>
<tr>
<td>Disjunctive screening</td>
<td>A supplier can enter the shortlist if it satisfies at least one of the set requirements</td>
</tr>
<tr>
<td>Lexicographical screening</td>
<td>Requirements are ranked in order of importance, suppliers are first evaluated on the most important, only those satisfying it pass to the next evaluation stage and so on, until a desired number of suppliers is obtained</td>
</tr>
</tbody>
</table>

Table 2.1. Classification of screening processes according to Hwang and Yoon

Once the suppliers shortlist is obtained then only qualified suppliers are deeply investigated and evaluated, coming to the final rank.

The adoption of an MCDM method allows also to take into account the risk attitude of each single DM; in the proposed model this is done integrating a scenario-based approach.

Coming to the OA problem, we considered a general situation characterized by multiple sourcing, single item and single time-period.

The proposed model addresses the OA problem by means of a two-stage Linear Program; in the first stage the minimum Total Purchasing Cost (TPC) is obtained while in the second stage, after having set a maximum budget increment with
respect to the minimum TPC, orders are allocated respecting the prioritization of suppliers according to their ranking.

The structure of our model is reported in Fig. 2.2, in the following each step of the proposed model will be exhaustively explained.

Figure 2.2. Proposed model
2.1 Supplier Selection

Following the proposed MCDM framework in case of a new task situation, the first step concerns with the identification of the criteria which the evaluation process is based on, the second step regards the calculation of the weights to be associated to selected criteria, the third step deals with the calculation of the scores of each supplier about each criterion for each DM, the fourth step consists in the calculation of the total score of each supplier according to each DM, in the fifth step the integration of the evaluation processes conducted by each DM is performed, considering the weights associated to DMs themselves, so to obtain the ranking of suppliers, and finally, in the sixth step, a sensitivity analysis is carried out in order to evaluate the robustness of the choice.

As already said, the selection of the screening methodology exploited to get the suppliers shortlist starting from all identified suppliers is not object of our work, for this reason, we start from the assumption that the shortlist has already been obtained when the model is applied.

2.1.1 Identification of criteria

Over the years many criteria have been taken into consideration while addressing SS problem exploiting MCDM methods. As highlighted in the literature review conducted in chapter 2, the most adopted criteria have evolved over time, indeed if once cost was widely considered the most important criterion in SS, quality has now got such primacy. Moreover, the tendency to particular production techniques (e.g. Just-In-Time) has made some criteria to rise in importance (e.g. supplier’s location).

In their papers many academics propose a set of criteria to be considered, such as Pramanik et al. [39], Hruška et al. [17] and Scott et al. [67]; this fact, however, limits the applicability of proposed models, finding application only in those contexts where the suggested criteria are applicable.

In our opinion it is not worth to select a priori a set of criteria for the SS because each particular situation is regulated by its own criteria (e.g. company’s focus, field of interest etc.), for this reason we leave to the DMs the identification of the most suitable criteria according to the specific addressed situation.

Basing on the specific context of application, on their knowledge background and expertise, and even considering company’s focus, DMs identify a set of criteria (k=1,...,K) which best fit the addressed problem and allow the DMs themselves to perform a complete evaluation, taking into consideration all relevant features (Fig. 2.3).
The novelty introduced by the proposed model, as it regards the criteria at the base of the evaluation process, consists in the division of the latter into two groups according to their nature, *Measurable Criteria* and *Forecastable Criteria*, respectively. The *Measurable Criteria* (e.g. cost, delivery time) are those the performances about which can be evaluated just analysing the bids submitted by suppliers; on the contrary performances about *Forecastable Criteria* (e.g. quality, business integration, punctuality) cannot be simply extrapolated from submitted bids, moreover a distinction is required between historical and new suppliers. As it regards historical suppliers, their performances about *Forecastable Criteria* can be measured exploiting data contained in company’s databases, indeed they directly come from the supplies history. On the other hand, when it comes to new suppliers no historical data are available so the performances about *Forecastable Criteria* have to be forecast by the DMs; this estimation process, performed by each DM, allows us to take into account the risk attitude of the DM itself by means of a scenario-based approach.

### 2.1.2 Calculation of criteria weights

Once the criteria best fitting the addressed situation and allowing to take into consideration all the aspects playing a role in the decision process, have been identified, it is necessary to determine the weight to be associated to each criterion. The criteria weights express the importance of the criterion to which they are associated, in particular they define how much the suppliers’ performances related to a particular criterion will influence the final choice. The calculation of the optimal weights to be associated to selected criteria is of fundamental importance because they play a crucial role in the definition of the total score of suppliers thus of the final ranking. For this reason, great carefulness must be paid when selecting a suitable methodology to carry out this step. Lots of MCDM methods allowing the calculation of criteria weights have been developed over the years and, as reported by Ho et al. [21], the most adopted one is the AHP.
Pairwise comparisons-based methods are of simple use, moreover they give the possibility to clearly compare, in a pairwise way, all the alternatives under analysis.

**Best-Worst Method**

To the end of calculating criteria weights \((w_1, w_2, \ldots, w_K)\) we decided to adopt the Best-Worst Method (BWM), a novel pairwise comparison method. Two are the main drivers of this choice: the first is that it guarantees higher consistency than the AHP thanks to the more structured way comparisons are performed, the second is its property of being less information-requiring thus perfectly fitting *new task* situations which are characterized by scarcity of knowledge about some/all suppliers.

According to its pairwise comparison structure, BWM requires the DMs to express judgements about the comparison of two elements each time, giving both the *direction* and the *strength* of the comparison. While the former can be easily stated, the latter can lead to ‘lack of rationality’, thus increasing the inconsistency of comparisons.

In order to prevent this hidden danger, BWM streamlines the comparison process (Fig. 2.4), demanding the DM to identify the Best and Worst elements of the given elements set and then to compare just the Best with all Others and all Others against the Worst.

![Figure 2.4. Representation of the comparisons required by BWM](image)

The outcome of the comparison process is constituted by two vectors, namely Best-to-Others and Others-to-Worst, which are the inputs of the optimization problem at the core of BWM.
By solving the just mentioned optimization problem it is possible to obtain the optimal criteria weights, both in the form of interval weights, by solving the nonlinear BWM, and in the form of crisp weights, linearizing the original nonlinear problem.

In the following the steps composing the BWM framework are introduced:

- **Step 1.** Determine a set of decision criteria, which can be both qualitative and quantitative.

- **Step 2.** Determine the best (most desirable, important) and the worst (least desirable, important).

- **Step 3.** Determine 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:
  \[
  BO = (a_{B1}, a_{B2}, ..., a_{BK})
  \]
  where \( a_{Bj} \) indicates the preference of the best criterion B over criterion j. Obviously \( a_{BB} = 1 \).

- **Step 4.** Determine the preference of all the criteria over the Worst criterion, using a number between 1 and 9. The resulting Others-to-Worst (OW) vector is:
  \[
  OW = (a_{1W}, a_{2W}, ..., a_{KW})
  \]
  where \( a_{jW} \) indicates the preference of the criterion j over the worst criterion W. Obviously \( a_{WW} = 1 \).

- **Step 5.** Find the optimal weights \( w_j \). The ideally optimal weights for the criteria are those whereby, for each pair \( w_B, w_j \) and \( w_f, w_W \) it results:
  \[
  \frac{w_B}{w_k} = a_{Bk} \quad \text{and} \quad \frac{w_k}{w_W} = a_{kW}
  \]
  The aim is to determine the optimal weights to be assigned to the considered elements, so that the maximum among the absolute differences
  \[
  \left| \frac{w_B}{w_k} - a_{Bk} \right|, \left| \frac{w_k}{w_W} - a_{kW} \right|
  \]
  for all k, is minimized.
Considering the five steps above, the following minmax problem can be formulated:

\[
\begin{align*}
\min & \quad \max_k \left( \left| \frac{w_B}{w_k} - a_{Bk} \right|, \left| \frac{w_k}{w_W} - a_{kW} \right| \right) \\
\text{subject to:} \quad & \quad \sum_k w_k = 1 \\
& \quad w_k \geq 0, \quad \text{for all } k
\end{align*}
\]

Which is equivalent to the following problem:

\[
\begin{align*}
\min & \quad \xi \\
\text{subject to:} \quad & \quad \left| \frac{w_B}{w_k} - a_{Bk} \right| \leq \xi, \quad \text{for all } k \\
& \quad \left| \frac{w_k}{w_W} - a_{kW} \right| \leq \xi, \quad \text{for all } k \\
& \quad \sum_k w_k = 1 \\
& \quad w_k \geq 0, \quad \text{for all } k
\end{align*}
\]

Solving the reported mathematical formulation for the optimization problem, the optimal weights \(w_1, w_2, \ldots, w_K\) and \(\xi^*\) are obtained.

It is also possible to linearize the original nonlinear problem, thus obtaining a much more easily manageable mathematical formulation for the resolution of BWM. The linear model of the BWM is based on the minimization of the maximum distance among the set \(\left(\left| w_B - a_{Bk} \cdot w_k \right|, \left| w_k - a_{kW} \cdot w_W \right| \right)\) instead of \(\left(\left| \frac{w_B}{w_k} - a_{Bk} \right|, \left| \frac{w_k}{w_W} - a_{kW} \right| \right)\); the resulting problem is the following:

\[
\begin{align*}
\min & \quad \xi^L \\
\text{subject to:} \quad & \quad \left| w_B - a_{Bk} \cdot w_k \right| \leq \xi^L, \quad \text{for all } k \\
& \quad \left| w_k - a_{kW} \cdot w_W \right| \leq \xi^L, \quad \text{for all } k \\
& \quad \sum_k w_k = 1 \\
& \quad w_k \geq 0, \quad \text{for all } k
\end{align*}
\]
In the proposed model BWM is applied both in its linear and nonlinear form, in order to get ready-to-use crisp weights and to define interval weights for the criteria which constitute the starting point for the sensitivity analysis performed in order to assess the robustness of the choice (Fig. 2.5).

**Figure 2.5.** Input-Action-Output step ‘Calculation of criteria weights’

### 2.1.2.1 Application of the linear Best-Worst Method model

The linear model of the BWM constitutes a very good trade-off between the goodness of results and the required computational effort. Its form of a simple linear optimization problem allows the implementation of the model itself in a widespread software as Microsoft Excel is, thus enhancing the possibilities for a practical application. According to the framework of the BWM, each DM must establish the Best and the Worst criterion according to its knowledge, function, expertise and background, then the comparisons to build the Best-to-Others and the Others-to-Worst vectors are carried out, giving judgements according to a Likert scale from 1 to 9 (where 1 indicates the compared elements have the same importance and 9 indicates the first element is extremely more important than the second one). Once the vectors $BO$ and $OW$ have been obtained it is possible to solve the model getting the optimal weights $(w_1, w_2, \ldots, w_K)$ to be assigned to selected criteria as well as $\xi^L$, which, in the linear form of the BWM, can be directly considered as a consistency indicator; we remark that this process needs to be applied to each DM.

### 2.1.2.2 Application of the nonlinear Best-Worst Method model

Starting from vectors $BO$ and $OW$, it is possible to apply also the nonlinear model of the BWM. The challenging point is to solve the optimization problem (1)-(2) right because its nonlinearity.
We addressed the problem in the form (1) and chose Genetic Algorithms (GA) as resolution methodology thanks to their suitability for nonlinear optimization problems.

**Genetic Algorithms (GA)**

The origins of GA date back to 50’s when many computer scientists started to study evolutionary systems with the assumption that evolution could be used as an optimization tool for engineering problems.

As it specifically regards GA, they were developed by John Holland in 60’s whose original goal was not to design algorithms to solve specific problems, but rather to study the phenomena of adaptation and evolution as they occur in nature, then to find a way to import such mechanisms into computer systems.

The idea at the base of such algorithms was to evolve a population of candidate solutions to a given problem, using operators inspired by natural genetic evolution and natural selection processes.

The population is formed by chromosomes, i.e. artificial elements composed by bits, each representing one candidate solution to the addressed problem.

At each step of the algorithm, all the elements composing the population are evaluated with respect to the so-called **fitness function**, which represents the goal of the optimization problem under consideration.

In order to create the next step population, the algorithm exploits the concepts of **selection, crossover** and **mutation**.

**Selection**: not all the elements from the current population are selected to be parents of the offspring elements composing the next step population, indeed they are selected by the **selection operator** with a probability directly proportional to their scaled score representing how well they fit the **fitness function**. Thus, the better an element of the population fits the **fitness function** the higher its reproduction probabilities.

**Crossover**: the **crossover operator** randomly chooses a location and exchanges the sub-sequences before and after that location between two selected chromosomes belonging to the current population to create two offspring elements.

**Mutation**: the **mutation operator** randomly changes some of the bits in a parent chromosome to generate an offspring element.

Both processes of **crossover** and **mutation** are essential to the genetic algorithm. Indeed, **crossover** enables the algorithm to extract the best genes from different individuals and recombine them into potentially superior children, while **mutation**
adds to the diversity of a population thus increasing the likelihood that the algorithm will generate individuals with better fitness values.

By exploiting the afore-mentioned operators, the reproductive process gives origin to the next generation which will be composed by elite children, crossover children and mutation children.

*Elite children* are the individuals in the current generation with the best fitness values; these individuals automatically survive to the next generation (Fig. 2.6).

![Figure 2.6. Elite child](image)

*Crossover children* are the individuals of the next generation generated by crossover between two parent individuals (Fig. 2.7).

![Figure 2.7. Crossover child](image)

*Mutation children* are the individuals of the next generation generated by mutation of a selected parent individual (Fig. 2.8).

![Figure 2.8. Mutation child](image)

From one generation to the other a certain fraction of the population is kept unaltered (*elite children*); of the remaining individuals composing the new generation, a set fraction (*crossover fraction*) is made to evolve by crossover whereas the others are made to evolve by mutation.
Generation by generation, the algorithm aims at finding the optimal solution to the given problem. This is a very tricky task, indeed, being GA heuristics, it is not possible to know if the found solution is whether the global or just a local one.

In order to explain this fact, the concept of search space, must be introduced: the search space represents the collection of all possible candidate solutions, moreover, it has as many dimensions as the number of variables characterizing the problem. The fitness function can be represented in the search space as a succession of peaks and valleys, representing maxima and minima respectively, and individuals, as little balls tending to settle in such valleys.

Considering a minimization problem (which can of course identify a maximization problem too), the ideal is that one of the little balls composing the evolving population falls into the deepest valley, however this is not what happens every time due to limited time for making the initial population to evolve, i.e. runtime of the algorithm.

In most cases, when the optimum is not reached, results are satisfying as well.

The Genetic Algorithm aimed at solving the nonlinear BWM was implemented by means of MATLAB®, exploiting the built-in function “ga”.

As it regards the parameters regulating the evolution of the population, the following were adopted:

- the population size is set equal to 300
- the number of generations is set equal to 100
- the fraction of elite children kept unaltered to the next generation is equal to the 0.05 of the population size (default value)
- the crossover function is “crossoverheuristic” being the problem characterized by linear constraints; this kind of crossover function returns a child that lies on the line containing the two parents, a small distance away from the parent with the better fitness value in the direction away from the parent with the worse fitness value
- the crossover fraction is equal to 0.8 (default value)
- the mutation function is “mutationadaptfeasible”, which is the default mutation function when there are constraints; it randomly generates directions that are adaptive with respect to the last successful or unsuccessful generation; the mutation chooses a direction and step length that satisfies bounds and linear constraints.

The fitness function represents the minmax problem (1); at each generation, all the absolute differences \( |w_B^a - a_{B_k}| \), \( |w_k^{w_W} - a_{kW}| \) are computed, then the largest one represents the quantity to be minimized by the next generation.

Running the Genetic Algorithm, we get the optimal weights to be assigned to selected criteria as crisp values, along with a value of \( \xi \), named \( \xi^* \).
In case of the nonlinear BWM, $\xi^*$ cannot be considered as a consistency indicator by itself, and it must be divided by the Consistency Index of the correspondent class of $a_{BW}$ (Table 2.2), in order to get the Consistency Ratio (eq. (1)), i.e. a consistency indicator:

$$\text{Consistency Ratio} = \frac{\xi^*}{\text{Consistency Index}}$$

<table>
<thead>
<tr>
<th>$a_{BW}$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>CI</td>
<td>0</td>
<td>0.44</td>
<td>1.63</td>
<td>2.3</td>
<td>3</td>
<td>3.73</td>
<td>4.47</td>
<td>5.23</td>
<td></td>
</tr>
</tbody>
</table>

**Table 2.2.** Consistency Index (CI) table for the Best-Worst Method.

**Interval Weights**

If the obtained $\xi^*$ is not too small, ideally different from zero, it is possible to define an interval weight ($iw_k$) for each criterion. *Interval weights* ($iw_1, iw_2, \ldots, iw_K$) are calculated by solving the associated linear minimization/maximization problems:

\[
\begin{align*}
\text{Min} & \quad w_k \\
\text{subject to:} & \\
\left|\frac{w_B}{w_k} - a_{Bj}\right| & \leq \xi^*, \text{ for all } k \\
\left|\frac{w_k}{w_W} - a_{kW}\right| & \leq \xi^*, \text{ for all } k \\
\sum_k w_k & = 1 \\
w_k & \geq 0, \text{ for all } k
\end{align*}
\] (4)
Max \quad w_k

subject to:

\[
\begin{align*}
\left| \frac{w_B}{w_k} - a_{Bk} \right| & \leq \xi^*, \text{ for all } k \\
\left| \frac{w_k}{w_W} - a_{kw} \right| & \leq \xi^*, \text{ for all } k \\
\sum_k w_k &= 1 \\
w_k &\geq 0, \quad \text{for all } k
\end{align*}
\]

Problem (4) and problem (5) give as output the lower and upper bounds of the criteria interval weights, respectively.

As we will see in paragraph 4.3 the definition of such interval weights enables to conduct some sensitivity analyses, which in turn, allows for a robustness assessment of the choice taken basing on the resulting suppliers’ ranking.

2.1.3 Calculation of suppliers’ scores about selected criteria

In this phase each DM has to perform the suppliers’ evaluation, assessing their performances with regard to selected criteria. In relation to its performances, each supplier is assigned a score \( S_{nk} \) representing how well it performs about each criterion (Fig. 2.9).

At this point the main novelty introduced by the proposed model, i.e. the distinction between Measurable and Forecastable criteria, gives the possibility to completely evaluate also new suppliers, by means of two different scoring processes depending on the considered criterion.

Figure 2.9. Input-Action-Output step ‘Calculation of suppliers’ scores about selected Criteria’
2.1.3.1 Scoring methodology for Measurable criteria

As performances related to Measurable criteria can be directly extrapolated from submitted bids, the criteria belonging to this category are clearly of a quantitative nature. For this reason, it results quite easy to assign the suppliers scores about Measurable criteria, indeed, it is sufficient to normalize the performances of suppliers regarding them in such a way that, for each considered Measurable criterion, the sum of the scores assigned to suppliers is equal to 1.

Clearly, the normalization process will be different according to the nature of the criterion under consideration; as it regards benefit criteria a direct normalization is used (eq.(2)):

$$S_{nk} = \frac{v_{nk}}{\sum_k v_{nk}}$$  \hspace{1cm} (2)

while when dealing with cost criteria, an inverse normalization must be adopted (eq.(3)):

$$S_{nk} = \frac{1}{\sum_k \frac{1}{v_{nk}}}$$  \hspace{1cm} (3)

2.1.3.2 Scoring methodology for Forecastable criteria

Conversely to what afore said regarding scores about Measurable criteria, as it comes to the evaluation of suppliers with regard to Forecastable criteria, things become more challenging.

In order to deeply analyse the scoring process regarding Forecastable criteria, we have to divide them into two classes, according to the nature of judgement: quantitative Forecastable criteria and qualitative Forecastable criteria.

The formers are characterized by the possibility to evaluate related performances by means of a value directly linked to the performances themselves (e.g. punctuality can be measured in terms of average delay of the supply), whereas the performances related to the latters can be expressed only in terms of preference scale (e.g. business integration capability measured on a scale going from 1 to 10).

Independently of the considered criterion, values associated to suppliers’ performances have to be normalized in the same way as already explained for the case of Measurable criteria-related performances (eq. (2) and eq. (3)).

Regarding Forecastable criteria another distinction needs to be made according to the case in which DMs are evaluating historical suppliers or new suppliers.
When dealing with historical suppliers the values representing performances related to quantitative Forecastable criteria can be directly extrapolated from company’s databases whereas, when coming to performance about qualitative Forecastable criteria, sufficient information is available in order to assign a preference value in a scale set a priori. It is important to underline that different companies may differently evaluate performances related to such intangible criteria, for example by defining different scale or even by adopting verbal preferences. For the sake of simplicity, we remark that, according to our model, the predefined preference scale for evaluating suppliers’ performances with regard to qualitative Forecastable criteria goes from 1 to 10, where 1 means ‘horrible’ and 10 means ‘perfect’; moreover, the preference scale can vary from criterion to criterion, according to the required detail-level.

As it regards new suppliers, since no previous data are available, DMs have to forecast, as the name itself suggests, their performances on Forecastable criteria. This step has a fundamental importance, indeed by means of the DMs’ forecasts about new suppliers it is possible to compare them with the historical ones.

**Scenario-based approach**

The forecasts are performed by DMs by exploiting a scenario-based approach which allows to integrate the risk attitude of the same in the decision process. The number of scenarios is equal to five ($s = 1, \ldots, 5$) and they are named: optimistic, medium-optimistic, expected, medium-pessimistic and pessimistic. The expected scenario is that characterized by the “average performances” of historical suppliers, i.e. in this scenario new suppliers are expected to behave more or less as the historical ones.

Each DM has to assign a probability of occurrence ($p_o$) to each scenario and to define an increment or decrement for the performances of the supplier under evaluation with respect to the average performances about considered criterion.

This way the DM gets the possibility to express twice its risk attitude by both defining the probabilities of occurrence and the performances increments/decrements.

Even in this context the distinction between quantitative and qualitative Forecastable criteria is needed, indeed for the formers the variation of the performances from the average ones can be expressed as a percentage of increment/decrement, whereas for the latters it is required to assign a value from the predefined preference scale associated to considered criterion.
Once a DM has defined both probabilities of occurrence for scenarios \((p_{os})\) and the scores characterizing the supplier under analysis in the different scenarios \((v_{s})\), that are nothing but the normalized values of supplier’s performances in each scenario, it is possible to obtain the score of the supplier about the considered criterion \((S_{nkm})\) by applying a simple weighted average of the scores, being the probabilities of occurrence the weights (eq. (4)):

\[
S_{nkm} = \sum_s p_{os_{nkm}} \cdot v_{nkm}
\]  

(4)

In Fig. 2.10 a schematic representation of the scenario-based approach is reported.

![Risk Attitude Integration](image)

**Figure 2.10.** Scenario-based approach.

In conclusion we report the complete framework of the scoring process for both new and historical suppliers about both *Measurable* and *Forecastable* criteria (Fig. 2.11).
Figure 2.11. Complete framework of the scoring processes
2.1.4 Integration of the suppliers’ scores

After having completed the suppliers’ evaluation, each DM has assigned each supplier a score on each criterion, to the end of getting the Total Score (TS) of each supplier, a double integration process is required (Fig. 2.12-13).

The first integration level regards the single DM, indeed the Total Score ($TS_{nm}$) of a supplier according to the m-th DM, is obtained as a weighted average of the scores obtained by the considered supplier on selected criteria ($S_{nk}$), being the weights the previously calculated criteria weights ($w_k$) (eq. (5)).

$$TS_{nm} = \sum_k w_k \cdot S_{nk}$$  
(5)

The second level of integration is the one performed over all DMs, once the Total Score ($TS_{nm}$) of each supplier has been obtained by each DM, then the Total Score ($TS_n$) of a supplier is calculated by means of a weighted average, being the weights the DMs’ weights ($p_1, \ldots, p_M$) (eq. (6)).

$$TS_n = \sum_m TS_{nm} \cdot p_m$$  
(6)

**Figure 2.12.** Input-Action-Output step ‘Calculation of Suppliers’ Total Scores’
2.1.5 Suppliers’ ranking

Basing on the characterizing Total Score ($TS_n$), suppliers can be ranked according to the same, thus obtaining the Suppliers’ Ranking, which constitutes the final outcome of the model as it regards the SS problem.

As it will be clear in section 4.2, the prioritization of the suppliers in solving the OA problem is based on the weight (i.e. $TS_n$) of each supplier, in such a way the highest ranked ones will be assigned the whole/most of order quantity.
2.2 Order Allocation

The goal of the second part of the model is the resolution of the OA problem, i.e. the definition of the order quantities to be assigned to each of the considered suppliers.

The pieces of information needed in order to address the OA problem are: cost-related voices from suppliers' bids, Suppliers' Ranking, representing the ultimate result of the SS problem resolution, suppliers' and company's constraints and policies \((c_1, c_2, \ldots, c_C)\) (Fig. 2.14).

![2-Stage Linear Programming](image)

**Figure 2.14.** Input-Action-Output Order Allocation problem

It is worth paying particular attention to the last two inputs, i.e. constraints and policies operated by both sides, company and suppliers, indeed they shape the feasibility region of the solutions space, taking into account physical constraints (e.g. suppliers' capacities, company's inventory capacity, etc.) as well as supplier-buyer relationship policies, that are present both from company's side (e.g. willingness not to assign more than a fraction of the whole supply to one single supplier or set lower bound for starting a commercial relationship) and from suppliers' side (e.g. set lower bound for starting a commercial relationship or willingness not more than a certain fraction of the total production capacity to be committed to one single buyer).

A Linear Programming model was designed considering two stages, each one constituted by a linear optimization problem; indeed, such a resolution strategy is aligned to the general scope of the research, that is not just giving a unique “optimal” solution for the joint SS-OA problem, but allowing the DMs to integrate in the decision higher-level information, which cannot be translated into quantitative terms.
Chapter 2

1st stage

In the first stage a minimization linear problem is formulated, aiming at minimizing the Total Purchasing Cost (TPC). The quantity to be purchased ($Q_{tot}$) is split among suppliers with regard to suppliers’ and company’s constraints and policies following the “as cheap as possible” rule.

Proceeding in such a way could cause the violation of the Suppliers’ Ranking, indeed it may be the case that the cheapest suppliers, i.e. those which the order quantities are assigned to in the 1st stage, do not correspond with the best suppliers according to the Suppliers’ Ranking.

Since it represents the global evaluation of each supplier, considering even a lot of criteria other than cost, the Suppliers’ Ranking cannot be violated, thus it is required to integrate the prioritization of suppliers according to their Total Score.

2nd stage

The second stage is constituted by the definition and resolution of a maximization linear problem.

In this phase the Suppliers’ Total Scores ($TS_n$) constitute the base for the prioritization of suppliers in being assigned order quantities ($X_1, X_1, \ldots, X_n$).

As previously done, the suppliers’ and company’s constraints and policies are integrated in order to obtain a feasible solution, however a new constraint must be now considered, that is the one regarding the increment assigned to the budget with respect to the minimum TPC calculated at the first stage.

The introduction of this additional constraint allows the board of DMs to integrate in the decision about assigned order quantities higher-level pieces of information (e.g. the budget increment may depend on the overall performance of the project as well as on the strategic role of the items to be purchased).

Indeed, by incrementing step by step the budget with respect to the calculated minimum TPC (e.g. 1% by 1%), it is possible to map the solutions space, identifying the boundaries among different possibilities for allocating order quantities.

This way the DMs have the freedom to select the preferred solution, with the consciousness of what happens in the neighbourhood of the same, instead of being given a unique solution, which is claimed to be the optimal one.

A schematic representation of the two-stage linear programming is reported in Fig. 2.15
Figure 2.15. Two-stage Linear Programming model.
2.3 Sensitivity Analysis

When addressing strategic problems characterized by risk, as SS and OA problems are, it is not sufficient to simply obtain a solution, but rather it is necessary to verify the robustness of the found solution. Indeed, the unpredictability of the risk developments are likely to make the outcomes to change with respect to what forecast, and for this reason it is important to assess to what extent of changes the selected solutions is still a good one.

In addition to risk, also company’s focus needs to be integrated in the robustness assessment as it influences the weights assigned to criteria, representing the global importance of the suppliers’ performances on each selected criterion.

At this point we can distinguish between two different ways to perform sensitivity analysis: one acting on scenarios probabilities of occurrence, which means in turn, on the forecast about new suppliers’ performances, and the other modifying the weight of one or more criteria, according to company’s strategy (Fig. 2.16).

![Diagram of Sensitivity Analysis](image)

**Figure 2.16.** Input-Action-Output Sensitivity Analysis

*Sensitivity Analysis – Forecasts on new suppliers’ performances*

In evaluating new suppliers against *Forecastable criteria*, the DMs are required to define a set of probabilities of occurrence $(p_{o})$, one for each scenario, then to assign the suppliers a score $(v_{s})$ according to the forecast of their performances in each scenario.

Then the score of a new supplier on a specific *Forecastable criterion* is obtained as the weighted average of the scores obtained in each scenario where the weights are the scenarios probabilities of occurrence. It is clear that changing the weights of the weighted average, the result of the same may change, but it is much more interesting how it changes, and how this change may influence the goodness of the selected final solution. In order to understand the influence of DMs’ *risk attitude* it is possible to increase/decrease the probabilities of occurrence of a particular scenario type in order to introduce a more risk-averse/risk-taker point of view.
By increasing the probabilities of occurrence of scenarios in the ‘optimistic-zone’ it is possible to be more risk-taker, in particular rewarding most promising suppliers; on the contrary, an increase in the probabilities of occurrence of scenarios in the ‘pessimistic-zone’ allows to act from a risk-averse perspective.

**Sensitivity Analysis – Interval Weights**

As afore mentioned, the outcome of the resolution of the nonlinear BWM is a set of *interval weights* for selected criteria, that is each criterion is assigned a range of optimal weights, comprehended between a *lower bound* \( w_{k\text{min}} \) and an *upper bound* \( w_{k\text{max}} \), the results of optimization problems (4) and (5), respectively. Varying criteria weights inside their respective intervals, it is guaranteed that still an optimal solution is obtained, but it may result in a change of the *Suppliers’ Ranking*, thus of the order quantities allocation. This fact makes possible to assess the robustness of the selected solution according to the company’s focus and allows to determine to what extent criteria representing it can be prioritized with respect to the others.

For the sake of simplicity, the variation applied to one or more criteria is equally distributed among the others, in order to preserve the summation of criteria weights to be equal to 1.

In the end we propose a further type of sensitivity analysis, which is much simpler, but it can give powerful insights about the equilibrium of the choice. We are talking about a sensitivity analysis on *Decision Makers’ Weights*, indeed, starting from a realistic case where the DMs have different weights, we can further investigate how the final solution would change assigning all the DMs the same weight. Having equal weights for the DMs means that they give the same contribution to the choice independently of their position in the company’s hierarchy, which means, in turn, they are equally “expert”. This is done in order not to let a particular DM’s point of view to take over the others when associated to a high DM’s weight.
3. Application to industry context – case study

After the introduction of the whole structure of the proposed model and the detailed explanation of its constituting steps in chapter 2, we now move to the application of the same to an industrial context. This is done in order to demonstrate how the model should be applied, i.e. to give an exemplification; moreover, the authors want to prove the easiness of applicability of the model itself, highlighting its linearity in the schematization of the joint SS and OA problem, in the subdivision in smaller, thus more easily manageable, problems and finally in the resolution process.

In addition to what afore said, while conducting our literature review we noticed that many authors restrict themselves to the introduction and the description of the proposed method, without presenting an application of the same to a real context, so to prove its practical employability and easiness of use. Indeed, the latter aspect is not a negligible one as we have to remember that we aim at building an effective and user-friendly method which can be easily applied to practical cases.
3.1 Problem Definition

To the end of performing the application of the proposed model to an industry context, we developed a collaboration with Irsap S.p.a., a leading company in the field of radiators and Controlled Mechanical Ventilation (CMV) production.

The company was founded in 1963 in Arquà Polesine (RO) with a particular focus in the production of pressed steel radiators. The company grew over the years, expanding its business to design radiators and entering new markets as East European ones. Its position in the East Europe was strengthened by the delocalization of part of the production in Romania in 2005. At the very beginning of the new millennium (2000) Irsap acquired Rhoss S.p.a., historic company based in Codroipo (UD) and active in the field of cold climatization. Nowadays Irsap S.p.a. is a well structured international company, winner of many awards in both the technology innovation (home automation) and design fields, representative of Italian excellence.

As it clearly notable from what afore said, 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 as it regards purchased quantities and delivery times.

The methodology designed by the authors is applied to the purchasing of steel tubes used for the production of Tesi radiators (Fig. 3.1), which constitute a leverage item for the company, destined to the large retailers operating in Europe. The tubes compliance with quality standards is of fundamental importance because they have to be welded with radiators heads in order to compose the elements constituting the radiator, thus defects of the tubes from the metallurgical point of view can cause very significant problems during the production process.

![Figure 3.1. Tesi radiator by Irsap](image)
The role of Decision Makers is played by the Purchasing Manager and by the Quality Assurance Manager, two main voices in the Procurement process of the company; the associated weights are 0.5 and 0.5, i.e. DMs have the same importance. Moreover, they are representative of the two principal aspects taken into account while evaluating the performances of a supplier.

The company adopts a two-stage supplier selection process, constituted by the screening and evaluation phases. During the screening phase, revenue and financial stability of potential suppliers are assessed, moreover, only large companies (+200 workers) are considered as potential suppliers, accordingly to company’s policies. The screening process is of conjunctive type, i.e. a supplier must satisfy all basic requirements in order to enter the vendor shortlist. The evaluation process is applied only to the candidates grouped in the vendor shortlist, obtained downstream the screening phase.

In the presented application case two historical suppliers compose the current suppliers’ list, in the following they will be recalled as Supplier 1 and Supplier 2. Supplier 1 is an Italian historic company active at all levels of steel production. Supplier 2 is a Serbian steel producer, offering a good trade-off between quality of the tubes and their price. In addition to the afore-mentioned historical suppliers, also one new supplier is considered while solving the joint SS and OA problem. This, in the following named as Supplier 3, is a company specialized in the production of steel rods and formed steel, which has expanded its business from North-East Italy to the Central Europe (Fig. 3.2).

![Figure 3.2. Geographical position of Irsap S.p.a. and of suppliers](image)
During the formalization of the problem, the involved DMs highlighted three main categories: Price, Quality and Service. After a further analysis the criteria were identified in 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, be able of applying variation to order quantities and delivery date when necessary.  
As it regards the historical suppliers, we have to highlight that the geographical location of Supplier 1 put the same in a better position compared to Supplier 2 as Delivery time is lower and Punctuality is favoured by the short distance dividing it from Irsap. Despite the listed advantages characterizing Supplier 1, Supplier 2 must be involved in the supply of the steel tubes for the production of Tesi radiators because it is also a supplier of steel raw materials for the Romanian production plant, thus it acts also as logistic partner for the transportation of semi-finished radiators from the Italian to the Romanian plant and the other way around. This fact leads Irsap to keep a portion of the total order quantity assigned to Supplier 2 in order to maintain the advantage in the management of interplants logistics guaranteed by the same. Supplier 3, by its side, can offer the more or less the same Delivery time as that guaranteed by Supplier 1 and the same can be said for the punctuality; as it regards Flexibility, we have to consider that its production capacity and storing space is quite lower with respect to that of Supplier 1, thus, most likely, its flexibility will be lower too.

The tubes need is evaluated in 22 shipments per month, currently assigned as follows:
- 85% to Supplier 1
- 15% to Supplier 2

The application of the model is aimed at defining a redistribution of order quantities, including Supplier 3 as it is thought that it can partially substitute Supplier 2 and even be assigned also a portion of the order quantities required to Supplier 1.
3.2 Supplier Selection

According to the framework of the proposed model, selected criteria are divided into two categories, namely Measurable and Forecastable (Table 3.1).

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>Measurable</td>
</tr>
<tr>
<td>Quality</td>
<td>Measurable</td>
</tr>
<tr>
<td>Del. time</td>
<td>Measurable</td>
</tr>
<tr>
<td>Punctuality</td>
<td>Forecastable</td>
</tr>
<tr>
<td>Flexibility</td>
<td>Forecastable</td>
</tr>
</tbody>
</table>

Table 3.1. Categorization of selected criteria

Once criteria have been identified, their relative weights need to be determined. The calculation of optimal weights is performed exploiting both the linear and non-linear formulation of the BWM, according to the procedure explained in paragraph 2.1.2. Judgments given by both DMs are reported in Table 3.2 and Table 3.3.

**Decision Maker 1 (Purchasing Manager)**

<table>
<thead>
<tr>
<th></th>
<th>Best</th>
<th>Price</th>
<th>Worst</th>
<th>Flexibility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>price</th>
<th>quality</th>
<th>del. time</th>
<th>Punctuality</th>
<th>flexibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>BO</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>OW</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3.2. BWM inputs according to DM1’s opinion

**Decision Maker 2 (Quality Assurance Manager)**

<table>
<thead>
<tr>
<th></th>
<th>Best</th>
<th>Quality</th>
<th>Worst</th>
<th>Flexibility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>price</th>
<th>quality</th>
<th>del. time</th>
<th>Punctuality</th>
<th>flexibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>BO</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>OW</td>
<td>6</td>
<td>8</td>
<td>4</td>
<td>5</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3.3. BWM inputs according to DM2’s opinion
As it could have been expected, both the interviewed managers set as Best criterion the one mostly directly-related to their field of competence.

Regarding the Worst criterion, both managers defined as the least important criterion Flexibility; this fact can be associated to the great market stability reached over the years, with a small number of clients absorbing most of the production. This, in turn, means that usually very little variations occur to the sales forecast, thus suppliers’ Flexibility is not a much relevant feature.

In addition to what afore said about Best and Worst criteria, it is worth noticing that both the Purchasing Manager and the Quality Assurance Manager gave almost the same importance to criteria Delivery time and Punctuality, which indeed represent the establishment of the JIT production philosophy in the company’s culture, as well as the attention put in respecting shipment dates promised to client, especially to long-term ones.

Applying the Linear BWM we obtained the crisp weights to be assigned to selected criteria according to the opinion of each of the two Decision Makers; in the following the same are reported (Table 3.4 and Table 3.5):

**Decision Maker 1 (Purchasing Manager)**

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Price</th>
<th>Quality</th>
<th>Del. time</th>
<th>Punctuality</th>
<th>Flexibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight</td>
<td>0,371795</td>
<td>0,211538</td>
<td>0,211538</td>
<td>0,141026</td>
<td>0,064103</td>
</tr>
</tbody>
</table>

*Table 3.4. Crisp weights according to DM1’s opinion*

**Decision Maker 2 (Quality Assurance Manager)**

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Price</th>
<th>Quality</th>
<th>Del. time</th>
<th>Punctuality</th>
<th>Flexibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight</td>
<td>0,243243</td>
<td>0,378378</td>
<td>0,162162</td>
<td>0,162162</td>
<td>0,054054</td>
</tr>
</tbody>
</table>

*Table 3.5. Crisp weights according to DM2’s opinion*

By now, we focus just on the crisp weights which are adopted to conduct the decision-making process; interval weights will be introduced in the section regarding the Sensitivity Analysis conducted on the presented application case.

Along with crisp weights, another output is given by the application of the Linear BWM, that is the parameter $\xi^L$, which, as already known, can be considered by itself a measure of the consistency of the obtained results.

The value of this parameter is 0,627 for the results associated to the comparisons judgements expressed by the Purchase Manager, and 1,50 for the results associated to the comparison judgements given by the Quality Assurance Manager.
As a direct conclusion, we can infer that the Purchase Manager was much more consistent with respect to the Quality Assurance Manager in performing the pairwise comparisons that led to the building up of the BO and OW vectors.

The next step concerns with the calculation of suppliers' scores about selected criteria; different procedures are exploited depending on the nature of the considered criterion (Measurable or Forecastable).

From the conducted interview we gathered all the required and useful data and information for the application of the proposed model, from the voices of interest of suppliers' bids, to performance data contained in company databases and DMs' opinions about the forecasts regarding the performance of the new supplier.

The data regarding suppliers' performances about Measurable criteria are reported in Table 3.6.

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Price [€/ton]</th>
<th>Quality [%]</th>
<th>Del. Time [€/ton]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supplier 1</td>
<td>750</td>
<td>99</td>
<td>2</td>
</tr>
<tr>
<td>Supplier 2</td>
<td>760</td>
<td>97</td>
<td>5</td>
</tr>
<tr>
<td>Supplier 3</td>
<td>765</td>
<td>100</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 3.6. Suppliers' performances about Measurable criteria

From gathered data, suppliers' scores about Measurable criteria can be directly calculated, taking advantage of a simple normalization technique, by using eq. (2) and eq. (3); clearly, they are unique and do not depend on the single DM’s opinion as referred to objective performances.

The suppliers' scores about Measurable criteria are reported in Table 3.7.

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Price [€/ton]</th>
<th>Quality [%]</th>
<th>Del. Time [€/ton]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supplier 1</td>
<td>0,337014</td>
<td>0,33258</td>
<td>0,330406</td>
</tr>
<tr>
<td>Supplier 2</td>
<td>0,334459</td>
<td>0,327703</td>
<td>0,337838</td>
</tr>
<tr>
<td>Supplier 3</td>
<td>0,416667</td>
<td>0,166667</td>
<td>0,416667</td>
</tr>
</tbody>
</table>

Table 3.7. Suppliers’ scores about Measurable criteria

As explained in detailed in Chapter 2 dedicated to the Model presentation, the calculation of suppliers’ scores about so-called Forecastable is different according to the type of considered supplier (historical or new). For historical suppliers,
performances, thus scores, about such criteria can be directly extracted from company databases; whereas regarding New Supplier the scores calculation is performed exploiting a scenario-based approach which allows to take into account the DMs’ risk attitude while they are expressing their judgments about the possible performances characterizing new suppliers themselves.

Regarding historical suppliers, indexes about both Punctuality and Flexibility are available (Table 3.8):

<table>
<thead>
<tr>
<th>Data</th>
<th>Punctality [%]</th>
<th>Flexibility [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>98</td>
<td>97</td>
</tr>
<tr>
<td>supplier 2</td>
<td>99</td>
<td>95</td>
</tr>
</tbody>
</table>

| Table 3.8. Indexes about Punctuality and Flexibility for historical suppliers |

Concerning the New Supplier, according to the model framework, it is necessary to give estimation about its performances related to identified Forecastable criteria.

This process is performed by each single Decision Maker and is required upstream the calculation of the suppliers’ scores about the criteria under consideration, since the normalization technique needs a value to be defined for each supplier regarding each criterion.

The application of the scenario-based approach is reported, separately for each Decision Maker (Table 3.9-12):

**Decision Maker 1 (Purchasing Manager)**

<table>
<thead>
<tr>
<th>Punctuality</th>
<th>Prob</th>
<th>Val_scen</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>0.1</td>
<td>96%</td>
</tr>
<tr>
<td>MP</td>
<td>0.1</td>
<td>97%</td>
</tr>
<tr>
<td>E</td>
<td>0.2</td>
<td>97.5%</td>
</tr>
<tr>
<td>MO</td>
<td>0.4</td>
<td>98.5%</td>
</tr>
<tr>
<td>O</td>
<td>0.2</td>
<td>99.5%</td>
</tr>
<tr>
<td>Value</td>
<td></td>
<td>98.1%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Flexibility</th>
<th>Prob</th>
<th>Val_scen</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>0.05</td>
<td>95%</td>
</tr>
<tr>
<td>MP</td>
<td>0.1</td>
<td>96%</td>
</tr>
<tr>
<td>E</td>
<td>0.3</td>
<td>97%</td>
</tr>
<tr>
<td>MO</td>
<td>0.3</td>
<td>98%</td>
</tr>
<tr>
<td>O</td>
<td>0.25</td>
<td>99%</td>
</tr>
<tr>
<td>Value</td>
<td></td>
<td>97.6%</td>
</tr>
</tbody>
</table>

Tables 3.9, 3.10. Scenario-based approach performed by DM1
Decision Maker 2 (Quality Assurance Manager)

<table>
<thead>
<tr>
<th>Punctuality</th>
<th>Prob</th>
<th>Val_scen</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>0.15</td>
<td>95%</td>
</tr>
<tr>
<td>MP</td>
<td>0.15</td>
<td>97%</td>
</tr>
<tr>
<td>E</td>
<td>0.25</td>
<td>97.5%</td>
</tr>
<tr>
<td>MO</td>
<td>0.3</td>
<td>98%</td>
</tr>
<tr>
<td>O</td>
<td>0.15</td>
<td>99%</td>
</tr>
<tr>
<td>Value</td>
<td></td>
<td>97.425%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Flexibility</th>
<th>Prob</th>
<th>Val_scen</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>0.1</td>
<td>94%</td>
</tr>
<tr>
<td>MP</td>
<td>0.1</td>
<td>96%</td>
</tr>
<tr>
<td>E</td>
<td>0.4</td>
<td>97%</td>
</tr>
<tr>
<td>MO</td>
<td>0.2</td>
<td>98%</td>
</tr>
<tr>
<td>O</td>
<td>0.2</td>
<td>99%</td>
</tr>
<tr>
<td>Value</td>
<td></td>
<td>97.2%</td>
</tr>
</tbody>
</table>

Tables 3.11, 3.12. Scenario-based approach performed by DM2

As it can be easily inferred looking at resulting scores for the New Supplier, we can notice that a general optimism characterizes the perception the Decision Makers have about the evaluated New Supplier. Indeed, as it regards the Punctuality it is expected to work better than both historical suppliers, according to DM1’s opinion, and even DM2 is much confident in the New Supplier, giving it a score slightly lower than that characterizing Supplier 1 (i.e. the best one). Moreover, it has to be underlined that for the Purchasing Manager the Punctuality forecast index for the New Supplier is 0.5% higher with respect to that according to the Quality Assurance Manager’s opinion.

About the Flexibility forecast, we can notice that both managers assigned the New Supplier a value higher than the average between historical suppliers, however, in this case, none judged this to have the possibility to perform better than Supplier 1 (again the best one).

Having, at this point, the values associated to each supplier, applying again a simple normalization, as done for the case of Measurable criteria scores, it is possible to obtain the suppliers scores about Forecastable criteria, which will be different for the two DMs due to the subjective influence expressed by means of the scenario-based approach (Table 3.13 and Table 3.14):

Decision Maker 1 (Purchasing Manager)

<table>
<thead>
<tr>
<th>Scores</th>
<th>Punctuality</th>
<th>Flexibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.33436</td>
<td>0.33951</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.33094</td>
<td>0.32579</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.33469</td>
<td>0.33470</td>
</tr>
</tbody>
</table>

Table 3.13. Suppliers’ scores about Forecastable criteria according to DM1’s opinion
**Decision Maker 2** (Quality Assurance Manager)

<table>
<thead>
<tr>
<th>Scores</th>
<th>Punctuality</th>
<th>Flexibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.33513</td>
<td>0.33997</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.33171</td>
<td>0.32624</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.33316</td>
<td>0.33791</td>
</tr>
</tbody>
</table>

*Table 3.14.* Suppliers’ scores about *Forecastable* criteria according to DM2’s opinion

Once all criteria weights and suppliers’ scores about the same criteria have been calculated, it is possible first to calculate the Total Score of each supplier according to each DM’s opinion (*Table 3.15-16*), then to merge the results obtained for the single DMs to obtain the Final Total Score and thus the suppliers’ ranking (*Table 3.17*).

**Decision Maker 1** (Purchase Manager)

<table>
<thead>
<tr>
<th>Total Score</th>
<th>DM 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.3531083</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.2957852</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.3511064</td>
</tr>
</tbody>
</table>

*Table 3.15.* Suppliers’ Total Scores according to DM1’s opinion

**Decision Maker 2** (Quality Assurance Manager)

<table>
<thead>
<tr>
<th>Total Score</th>
<th>DM 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.3488182</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.3033454</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.3478362</td>
</tr>
</tbody>
</table>

*Table 3.16.* Suppliers’ Total Scores according to DM2’s opinion
From Table 3.17, we can notice that Supplier 1 results to be the best one, immediately followed by Supplier 3 (the new one), whereas Supplier 2 is rather left behind. The difference in the Final Total Scores of Supplier 1 and Supplier 3 is very small, representing almost an equivalence between the two afore mentioned suppliers.

In this case it is important to integrate higher-level pieces of information in order to define the priority between the two suppliers. For the sake of simplicity, along with the difficult to take into account these higher-level pieces of information, usually integrated in the decision while the same is discussed with the top management, in performing the following steps of the proposed model, we consider the obtained Final Total Scores.

The most relevant conclusion that can be directly inferred just looking at the suppliers’ ranking is the fact that Supplier 3 will be surely assigned part of the orders currently assigned to Supplier 2. To the latter only a number of orders sufficient to maintain the commercial relationship useful for exploiting the courier function of Supplier 2, will be kept assigned.
3.3 Order Allocation

According to the proposed model, once the suppliers’ ranking has been obtained, thus when the Supplier Selection phase is completed, the Order Allocation problem is tackled in order to define the distribution of order quantities among suppliers. The OA problem is solved according to the two-stage Linear Program introduced at the end of Chapter 2.

This phase is highly characterized by the specific situation which it is referred to, indeed every case is subjected to constraints set by the external and internal environments, i.e. by the company’s policies and by the business in which the same operates. The definition of the constraints is the way the particular situation under consideration is reproduced; as a matter of fact, the objective functions (one for the first step and one for the second step) are the same for every problem the model is applied to, what differs from situation to situation is the set of constraints. For what afore said great attention must be paid to the correct definition of constraints as it means an accurate representation of the actual situation and environment in which it is contextualized, favouring the achievement of a really optimal solution.

In Table 3.18 and Table 3.19 nomenclature and data of the OA problem are reported, respectively.

The OA problem is solved according to the two-stage Linear Program introduced in paragraph 2.2.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$</td>
<td>number of suppliers</td>
</tr>
<tr>
<td>$TS (n)$</td>
<td>Total Score of supplier $n$</td>
</tr>
<tr>
<td>$x (n)$</td>
<td>quantity to be allocated to supplier $n$</td>
</tr>
<tr>
<td>$Q (n)$</td>
<td>max quantity assignable to supplier $n$</td>
</tr>
<tr>
<td>$c (n)$</td>
<td>Total procurement cost of supplier $n$</td>
</tr>
<tr>
<td>$Q_{2\text{-}min}$</td>
<td>min quantity to be assigned to supplier 2</td>
</tr>
<tr>
<td>Budget</td>
<td>TPC resulting from the found solution</td>
</tr>
<tr>
<td>budget_max</td>
<td>maximum budget available</td>
</tr>
</tbody>
</table>

Table 3.18. Nomenclature of the OA problem
### Application to industry context – case study

#### Table 3.19. Data of the OA problem

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>TS1</td>
<td>0.3510</td>
</tr>
<tr>
<td>TS2</td>
<td>0.2995</td>
</tr>
<tr>
<td>TS3</td>
<td>0.3495</td>
</tr>
<tr>
<td>c1 [€/ton]</td>
<td>750</td>
</tr>
<tr>
<td>c2 [€/ton]</td>
<td>760</td>
</tr>
<tr>
<td>c3 [€/ton]</td>
<td>765</td>
</tr>
<tr>
<td>Q1 [supplies]</td>
<td>18</td>
</tr>
<tr>
<td>Q2 [supplies]</td>
<td>4</td>
</tr>
<tr>
<td>Q3 [supplies]</td>
<td>11</td>
</tr>
<tr>
<td>Q2_min [supplies]</td>
<td>2</td>
</tr>
<tr>
<td>Tot supply</td>
<td>22</td>
</tr>
</tbody>
</table>

1st stage

Min \( TPC = x(n) \cdot c(n) \)

subject to:

\[
\begin{align*}
Q(1) & \leq 18 & (1) \\
Q(2) & \leq 4 & (2) \\
Q(3) & \leq 11 & (3) \\
Q(2)_{min} & \geq 2 & (4) \\
x(1) + x(2) + x(3) & = 22 & (5)
\end{align*}
\]

As already explained in Chapter 2, the objective function of the 1st stage of the Linear Program is constituted by the Total Purchasing Cost which is minimized regardless the suppliers’ ranking obtained from the SS process. The constraints regard the quantities to be assigned to different suppliers, in particular:

- Constraint (1) regards the order quantity to be assigned to Supplier 1 that must be lower or equal to 18 supplies per month, i.e. the 80% of the total supplies required per month
- Constraint (2) regards the order quantity to be assigned to Supplier 2 that must be lower or equal to 4 supplies per month, i.e. the 15% of the total supplies required per month
- Constraint (3) regards the order quantity to be assigned to Supplier 3 must be lower or equal to 11 supplies per month, i.e. the 50% of the total supplies required per month
- Constraints (4) refers to the minimum order quantity to be assigned to Supplier 2 that is equal to 2, in order to maintain the commercial relationship and exploit its courier function
- Constraint (5) refers to the summation of the order quantities assigned to the different suppliers that must be equal to the monthly need equal to 22 supplies

The value assumed by the objective function is equal to 16540 € whereas the order quantities are:
- \( x(1) = 18 \)
- \( x(2) = 4 \)
- \( x(3) = 0 \)

Thus, downstream the first stage, the situation remains the current one, with the New Supplier which is assigned no order quantities (this fact could be expected looking at the prices offered by the three suppliers and noting that Supplier 3 is the most expensive one).

\[ 2^{nd\ stage} \]

\[ \text{Max} \quad \sum_n x(n) \cdot TS(n) \]

subject to:

\[ Q(1) \leq 18 \quad (1) \]
\[ Q(2) \leq 4 \quad (2) \]
\[ Q(3) \leq 11 \quad (3) \]
\[ Q(2)_{\text{min}} \geq 2 \quad (4) \]
\[ x(1) + x(2) + x(3) = 22 \quad (5) \]
\[ \text{budget} \leq \text{budget}_{\text{max}} \quad (6) \]
The objective function characterizing the second phase is a prioritization function aimed at taking into account the suppliers’ ranking obtained downstream the SS process. The constraints are the same identified for the first stage with an additional one (constraint (6)) used to account for the maximum budget available for the order allocation.

Considering a positive situation for the company and for the suppliers’ list renovation project, we considered the company can afford a higher expense with respect to the minimum TPC.

With the aim of not providing just a single solution, but to offer a range of possible solutions, the maximum budget is increased 1% by 1%, until a maximum increase equal to +20% with respect to the minimum TPC calculated at the first stage.

In the following the results are reported in schematic way (Table 3.20).

<table>
<thead>
<tr>
<th>Budget Max</th>
<th>% increment</th>
<th>x(1)</th>
<th>x(2)</th>
<th>x(3)</th>
<th>Budget Sol</th>
</tr>
</thead>
<tbody>
<tr>
<td>16705,4 €</td>
<td>1%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>16870,5 €</td>
<td>2%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>17036,2 €</td>
<td>3%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>17201,6 €</td>
<td>4%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>17367 €</td>
<td>5%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>17532,4 €</td>
<td>6%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>17697,8 €</td>
<td>7%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>17863,2 €</td>
<td>8%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>18028,6 €</td>
<td>9%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>18194 €</td>
<td>10%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>19021 €</td>
<td>15%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
<tr>
<td>19848</td>
<td>20%</td>
<td>18</td>
<td>2</td>
<td>2</td>
<td>16550 €</td>
</tr>
</tbody>
</table>

Table 3.20. Solutions for the OA problem according to budget increment with respect to minimum TPC
Moreover, in Fig. 3.3 a graphical representation of the Order Allocation solution range is presented.

**Figure 3.3.** Graphical representation of the OA range of solution

The solution to the OA problem is characterized by the following order quantities distribution:

- $x(1) = 18$
- $x(2) = 2$
- $x(3) = 2$

with a total cost equal to 16550 €.

Looking at both Table 3-20 and Fig. 3-3, we can notice that the optimal solution of the OA problem is unique even considering budget increments; this means that the found solution is independent of allocated budget, thus constituting an absolute optimal solution. Moreover, it is worth highlighting that it is also a very cheap solution being more expensive with respect to minimum TPC by just 10 €.

The main drawback of such a situation is the fact that in case higher-level information, integrated downstream the model application, determines a change in the order allocation, the new solution will be out of the optimality range.

As it could have been expected analysing the suppliers’ final Total Scores, Supplier 3, i.e. the new one, is assigned part of the order quantities currently assigned to
Supplier 2. However, as internal constraint, Supplier 2 is still assigned two supplies per month so to maintain the commercial relationship useful for continuing exploiting the courier function between Italy and Romania performed by Supplier 2 itself.

As a last consideration regarding assigned order quantities, we can notice that Supplier 1 is assigned the 80% of the monthly supplies, this is a very high fraction of the steel tubes need and it could result in a risky situation in case Supplier 1 face production problems. By the way, considering the fact that Supplier 1 is a main player in the steel production worldwide, it is highly unlikely that such a situation will come true.

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 an order quantity equal to two supplies per month, then to increase it at the expense of Supplier 1, leveraging on synergies that might arise more easily between two medium-big companies deeply rooted in the territory of the North-East Italy rather than with a multinational company which operates in other business fields in addition to steel production. Furthermore, we have to consider that Supplier 3 is the best one as it regards the Quality, which is a very important feature for Irsap S.p.a.; thus, starting a long-lasting collaboration with Supplier 3 might also mean continuous improvement in the quality of radiators, a significance strategic advantage with respect to competitors.
3.4 Sensitivity Analyses

Following the framework of the proposed model presented in Chapter 2, once the joint SS and OA problem has been solved and the order quantities have been assigned to involved suppliers, some sensitivity analyses can be performed in order to evaluate the robustness of the obtained solution. This constitutes a very important step of the proposed model as it allows to evaluate to what extent found optimal solution/s remains valid and eventual changes in the internal and/or external environment, which reflect in the DMs' vision of the problem, and/or in DMs' risk attitude, and consequently in the definition of scenarios probabilities of occurrence, do not affect the final result. Following what said just above, the sensitivity analyses are conducted making criteria weights and scenarios probabilities of occurrence to vary; obviously, according to the definition of sensitivity analysis, only one parameter at a time is made to vary.

To the end of performing meaningful sensitivity analyses, firstly we have to accurately analyse what are the variable that, changing their value, may lead the final result to change. This analysis is of crucial importance as it constitutes the basis for a "strategic" sensitivity analysis; indeed, we have to remember that the renovation of the suppliers' list is one of the most important decisions from the point of view of the operations and logistics strategy, thus a weak solution, not enough resilient to kept its optimality even under slight perturbances of the internal and/or external environment, may result in a great loss, not only in economic terms but also from the reputation point of view.

We focused our attention on Supplier 3, comparing its performances with those of Supplier 1 (it is clear that Supplier 2 is a step below the other two suppliers). Looking at the suppliers' scores, we can notice that Supplier 3 performs better than Supplier 1 about only one criterion, that is Quality (0.337837838 of Supplier 3 versus 0.334459459 of Supplier 1); another strong point of the New Supplier is the Punctuality, however only in the perception of the Purchase Manager it may perform better than Supplier 1 and the difference between the two scores results to be lower than that observable looking at the judgements of the Quality Assurance Manager, this time in favour of Supplier 1.

All in all, the only thing that makes sense to do regarding criteria weights is to increase the weight of criterion Quality, trying to find to what increasing extent of the same, if any, the final Total Score of Supplier 3 overcomes that of Supplier 1. As already explained in Chapter 2, the sensitivity analyses regarding criteria weights are performed exploiting the so-called interval weights, calculated solving the Non-Linear BWM by means of a Genetic Algorithm.
The interval weights for both DMs are reported (Table 3.21 and Table 3.22).

**Decision Maker 1** (Purchase Manager)

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Interval Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>[0.33117;0.37179]</td>
</tr>
<tr>
<td>Quality</td>
<td>[0.20523;0.27247]</td>
</tr>
<tr>
<td>Del. Time</td>
<td>[0.20557;0.24162]</td>
</tr>
<tr>
<td>Punctuality</td>
<td>[0.13711;0.14983]</td>
</tr>
<tr>
<td>Flexibility</td>
<td>[0.05847;0.06410]</td>
</tr>
</tbody>
</table>

*Table 3.21. Interval weights according to DM1’s opinion*

**Decision Maker 2** (Quality Assurance Manager)

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Interval Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>[0.23476;0.35491]</td>
</tr>
<tr>
<td>Quality</td>
<td>[0.26685;0.37837]</td>
</tr>
<tr>
<td>Del. Time</td>
<td>[0.10690;0.18619]</td>
</tr>
<tr>
<td>Punctuality</td>
<td>[0.14643;0.21032]</td>
</tr>
<tr>
<td>Flexibility</td>
<td>[0.04042;0.05405]</td>
</tr>
</tbody>
</table>

*Table 3.22. Interval weights according to DM2’s opinion*

In the following conducted sensitivity analyses about the variation of criterion *Quality* are reported. When the weight of this criterion is increased, obviously the weights of other criteria must be lowered in order to preserve the summation of criteria weights to be equal to 1. The rule for lowering the weight of other criteria, as a consequence of the weight increase of *Quality*, is to equally redistribute among other criteria weights the required decrease, according to what stated just above. The critical point is the fact that criteria weights must be kept within their interval weights according to the logic at the base of the proposed model; for this reason, it is not always possible to decrease all other criteria weights by the same quantity, as one or more may overcome the boundaries of their interval weight. When this is the case we assigned the criterion under consideration a weight equal to the lower bound of its interval weight, whereas the remaining decrease is assigned to another
criterion characterized by a sufficient margin with respect its interval weight lower bound. In doing this, we tried to compensate the cases above introduced by lowering criteria characterized by lowest weights (Flexibility, above all, but also Punctuality and Delivery Time).

**Variation of criterion Quality weight by +10%**

Consider the case whereby quality issues are more stressed from the top management in order to create a competitive advantage towards competitors, or customers’ awareness about quality has increased so to force the company to pay a greater attention to this aspect; the effect on the subjectivity of the Decision Makers will be expressed in the importance they give to criterion Quality. Supposing an increment of the criterion Quality weight equal to +10%, we obtain the following criteria weights (Table 3.23 and Table 3.24).

**Decision Maker 1 (Purchase Manager)**

<table>
<thead>
<tr>
<th><strong>Criterion</strong></th>
<th><strong>Weight</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>0.3651</td>
</tr>
<tr>
<td>Quality</td>
<td>0.2327</td>
</tr>
<tr>
<td>Del. Time</td>
<td>0.2062</td>
</tr>
<tr>
<td>Punctuality</td>
<td>0.1371</td>
</tr>
<tr>
<td>Flexibility</td>
<td>0.0589</td>
</tr>
</tbody>
</table>

*Table 3.23. Criteria weights for DM1 due to a 10% increase of criterion Quality weight*

**Decision Maker 2 (Quality Assurance Manager)**

<table>
<thead>
<tr>
<th><strong>Criterion</strong></th>
<th><strong>Weight</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>0.2432</td>
</tr>
<tr>
<td>Quality</td>
<td>0.3784</td>
</tr>
<tr>
<td>Del. Time</td>
<td>0.1622</td>
</tr>
<tr>
<td>Punctuality</td>
<td>0.1622</td>
</tr>
<tr>
<td>Flexibility</td>
<td>0.0540</td>
</tr>
</tbody>
</table>

*Table 3.24. Criteria weights for DM2 due to a 10% increase of criterion Quality weight*
For DM2, the weight for criterion Quality, found by applying the Linear form of BWM, coincides with the upper bound of the found interval weight; for this reason, no variation occurs to the criteria weights for DM2.

The new Final Total Scores obtained consequently to this variation in criteria weights are (Table 3.25):

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Final Total Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.3510</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.2998</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.3492</td>
</tr>
</tbody>
</table>

Table 3.25. Suppliers’ final Total Scores according to a 10% increase of criterion Quality weight

As we can notice from Table 3.25, the final Total Score of Supplier 3 is still lower with respect to that of Supplier 1, this means that the order allocation will not change as the value assumed by the 2nd stage objective function under maximization condition will remain equal to the base-case.

Thus, we can conclude that the distribution of order quantities consequently to an increase by 10% of criterion Quality weight, is still the following:

- \( x(1) = 18 \)
- \( x(2) = 2 \)
- \( x(3) = 2 \)

with a total cost equal to 16550 €.

Variation of criterion Quality weight up to the upper bound of its interval weight

The aim of this sensitivity analysis is to inspect what happens to the obtained results if the weight of criterion Quality is set equal to the upper bound of the found interval weights, for both Decision Makers, as a consequence of a major stress on quality aspects; this might be determined by an identified lack of quality of tubes currently supplied, causing, for example, production difficulties in the welding between tubes themselves and radiators heads.

Following this idea, the criteria weights obtained for each Decision Maker are reported (Table 3.26 and Table 3.27):
**Decision Maker 1** (Purchase Manager)

<table>
<thead>
<tr>
<th><strong>Criterion</strong></th>
<th><strong>Weight</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>0.3312</td>
</tr>
<tr>
<td>Quality</td>
<td>0.2676</td>
</tr>
<tr>
<td>Del. Time</td>
<td>0.2056</td>
</tr>
<tr>
<td>Punctuality</td>
<td>0.1371</td>
</tr>
<tr>
<td>Flexibility</td>
<td>0.0585</td>
</tr>
</tbody>
</table>

Table 3.26. Criteria weights for DM1 consequently to the setting of criterion *Quality* weight equal to the upper bound of its interval weight

As we can notice the weight of criterion *Quality* is not exactly equal to the upper bound of its interval weight, this is due to the fact that setting it perfectly equal to the upper bound of its interval weight would mean to make some other criteria weight to exceed the lower bound of the respective interval weight, thus exiting the optimality condition.

For what afore said, the weight of criterion *Quality* is set equal to the highest value possible allowing to keep other criteria weights within the bounds of their interval weights.

*Decision Maker 2* (Quality Assurance Manager)

For DM2 we remark once more that the weight for criterion *Quality*, found by applying the Linear form of BWM, coincides with the upper bound of the found interval weight; for this reason, no variation occurs to the criteria weights for DM2.

<table>
<thead>
<tr>
<th><strong>Criterion</strong></th>
<th><strong>Weight</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>0.2432</td>
</tr>
<tr>
<td>Quality</td>
<td>0.3784</td>
</tr>
<tr>
<td>Del. Time</td>
<td>0.1622</td>
</tr>
<tr>
<td>Punctuality</td>
<td>0.1622</td>
</tr>
<tr>
<td>Flexibility</td>
<td>0.0540</td>
</tr>
</tbody>
</table>

Table 3.27. Criteria weights for DM2 consequently to the setting of criterion *Quality* weight equal to the upper bound of its interval weight
The new Final Total Scores obtained consequently to this variation in criteria weights are reported in Table 3.28:

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Final Total Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.3507</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.2999</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.3494</td>
</tr>
</tbody>
</table>

Table 3.28. Suppliers’ Final Total Scores consequently to the setting of criterion *Quality* weight equal to the upper bound of its interval weight

From Table 3.28 we can easily conclude that the allocation of order quantities does not change with respect to the base-case, thus it will be again the following:

- \( x(1) = 18 \)
- \( x(2) = 2 \)
- \( x(3) = 2 \)

with a total cost equal to 16550 €.

It is important to notice how close the Final Total Scores of Supplier 1 and Supplier 3 are in this case; moreover, we have to consider that we are post-processing data obtained from interviewed Decision Makers, but if the needs presented as introduction of each sensitivity analysis took place, we have to take into account that the DMs’ judgements themselves would change, following the push of market environment. This push might lead even the Purchase Manager to elect *Quality* as the Best criterion which, in turn, would bring, most likely, Supplier 3 to be the best one (indeed it is under the quality point of view).

We have shown how the suppliers’ ranking is not affected by the variation of the criterion *Quality* weight, at least from a purely mathematical post-processing point of view.

As explained in the introduction to *Sensitivity Analyses*, another way to test the possibility that Supplier 3 overcomes Supplier 1 in the suppliers’ ranking is to make the scenarios probabilities of occurrence to vary. Since, as said, the objective of our sensitivity analysis is to test the conditions that may lead Supplier 3 to overcome Supplier 1, what makes sense to do regarding scenarios probabilities of occurrence is to increase the optimistic view of the New Suppliers, that is to assign a higher probability of occurrence to medium-optimistic and optimistic scenarios.

Considering the fact that Decision Maker 1 already expressed a great confidence towards the performances of the New Supplier about *Forecastable* criteria, we decided to make its approach common, i.e. to assign the scenarios probabilities of
occurrence set by DM1 even to DM2. Indeed, the difference between the confidence towards the New Supplier is mainly related to the fact that the Purchase Manager has been contacted many times from the latter with the aim of offering its supply; on the contrary the Quality Assurance Manager is more distant from Supplier 3, so its knowledge about the same is scarcer. For this reason, by adopting a “common approach” regarding the forecasts about New Supplier’s performances, we tried to simulate the same knowledge level for both Decision Makers, thus the same confidence is thought to be given by the latter towards the New Supplier.

In the following the scenarios probabilities of occurrence proper of DM1, and made common to both, are reported (Table 3.29 and Table 3.30).

<table>
<thead>
<tr>
<th>Punctuality</th>
<th>Prob</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>0,1</td>
</tr>
<tr>
<td>MP</td>
<td>0,1</td>
</tr>
<tr>
<td>E</td>
<td>0,2</td>
</tr>
<tr>
<td>MO</td>
<td>0,4</td>
</tr>
<tr>
<td>O</td>
<td>0,2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Flexibility</th>
<th>Prob</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>0,05</td>
</tr>
<tr>
<td>MP</td>
<td>0,1</td>
</tr>
<tr>
<td>E</td>
<td>0,3</td>
</tr>
<tr>
<td>MO</td>
<td>0,3</td>
</tr>
<tr>
<td>O</td>
<td>0,25</td>
</tr>
</tbody>
</table>

*Table 3.29-3.30.* “Common” scenarios probabilities of occurrence

In order to preserve the *risk attitude* proper of each Decision Maker, the values associated to identified scenarios are kept unaltered (Table 3.31-3.34).

**Decision Maker 1 (Purchase Manager):**

<table>
<thead>
<tr>
<th>Punctuality</th>
<th>Val_scen</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>96%</td>
</tr>
<tr>
<td>MP</td>
<td>97%</td>
</tr>
<tr>
<td>E</td>
<td>97,5%</td>
</tr>
<tr>
<td>MO</td>
<td>98,5%</td>
</tr>
<tr>
<td>O</td>
<td>99,5%</td>
</tr>
<tr>
<td><strong>Value</strong></td>
<td><strong>98,1%</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Flexibility</th>
<th>Val_scen</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>95%</td>
</tr>
<tr>
<td>MP</td>
<td>96%</td>
</tr>
<tr>
<td>E</td>
<td>97%</td>
</tr>
<tr>
<td>MO</td>
<td>98%</td>
</tr>
<tr>
<td>O</td>
<td>99%</td>
</tr>
<tr>
<td><strong>Value</strong></td>
<td><strong>97,6%</strong></td>
</tr>
</tbody>
</table>

*Table 3.31-3.32.* Values and Scores about *Punctuality* and *Flexibility* in DM1’s opinion
**Decision Maker 2** (Quality Assurance Manager)

<table>
<thead>
<tr>
<th>Punctuality</th>
<th>Val_scen</th>
<th>Flexibility</th>
<th>Val_scen</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>95%</td>
<td>P</td>
<td>94%</td>
</tr>
<tr>
<td>MP</td>
<td>97%</td>
<td>MP</td>
<td>96%</td>
</tr>
<tr>
<td>E</td>
<td>97,5%</td>
<td>E</td>
<td>97%</td>
</tr>
<tr>
<td>MO</td>
<td>98%</td>
<td>MO</td>
<td>98%</td>
</tr>
<tr>
<td>O</td>
<td>99%</td>
<td>O</td>
<td>99%</td>
</tr>
<tr>
<td>Value</td>
<td>97,7%</td>
<td>Value</td>
<td>97,55%</td>
</tr>
</tbody>
</table>

*Table 3.33-3.34.* Values and Scores about Punctuality and Flexibility in DM2’s opinion

Considering the suppliers’ scores regarding Measurable criteria and the ones about Forecastable criteria for the two historical suppliers, reported in Paragraph 3.2, we obtained the following Final Total Scores (*Table 3.35*):

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Final Total Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>supplier 1</td>
<td>0.3509</td>
</tr>
<tr>
<td>supplier 2</td>
<td>0.2995</td>
</tr>
<tr>
<td>supplier 3</td>
<td>0.3496</td>
</tr>
</tbody>
</table>

*Table 3.35.* Suppliers’ Final Total Scores according to the variation of scenarios probabilities of occurrence

Looking at suppliers’ Final Total Score, we can directly infer that, from a mathematical point of view, the situation is unmutated with respect to the base-case; thus, the allocation of order quantities will be still the same:

- \( x(1) = 18 \)
- \( x(2) = 2 \)
- \( x(3) = 2 \)

with a total cost equal to 16550 €.

We can notice that, as underlined for the sensitivity analysis in which the criterion Quality weight has been maximized, the Total Scores of Supplier 1 and 3 are really close one to the other.

Again, we want to remark that in such a case higher level pieces of information integrated in the decision downstream the mathematical model application, may
lead to favour Supplier 3, being it almost equal to Supplier 1 and bringing with it all the advantages already discussed in conclusion to the base-case (synergies, common growth, joint research for a better quality and so on).

From the results obtained by applying the described Sensitivity Analyses, we can notice that no variation occurs with respect to the solution characterizing the base-case; this is a good news since it means that the found solution is enough resilient to keep its optimality under the effect of more or less slight perturbations of the internal and/or external environments.

However, the robustness of the found solution is anchored on the price guaranteed by Supplier 1, which is 15 €/ton, i.e. almost 2%, lower with respect to that offered by Supplier 3.

In Fig. 3.4 the behaviour of the comparison between Supplier 1 and Supplier 3 is reported, depending on the price per ton guaranteed by Supplier 3.

![Graph showing Supplier 1 vs Supplier 3](image)

**Figure 3.4.** Behaviour of New Supplier’s Final Total Score according to the supplying price of the same and comparison with the Total Score of Supplier 1

As we can notice from the Fig. 3.4, in correspondence of a price equal to 754 € per ton guaranteed by Supplier 3 its Total Score becomes equal to that characterizing Supplier 1; in addition to this, if the New Supplier offered its supplies at the same price of Supplier 1, its Total Score would be even higher with respect to that of this latter.

This kind of analysis is very useful for the company which can use it as a mean of negotiation towards the New Supplier, promising the purchase of greater quantities.
provided that a discount is applied on the purchasing price, in such a way the New Supplier results to be more “convenient” than Supplier 1. Starting from this point, it is quite easy to perform again the resolution of the Order Allocation problem, so to find the most appropriate allocation of order quantities and the required budget for the new solution.
Conclusions, limitations, hints for future research

Supply Chain Management is a concept that dates back in 1982 when the consultancy firm Booz Allen Hamilton gave a first definition of the same, in the perspective of a renovation of the industry practice about the process constituting the Supply Chain itself; from the seeking of a trade-off among the different functions playing a role in the Supply Chain, the idea of Supply Chain Management arose, as a more complex system of controlling and optimizing Supply Chains. Later on, a new, wider concept was born, named Supply Chain Risk Management. SCRM embeds within itself the identification of risks that could disrupt the Supply Chain and of possible mitigation measures for the afore mentioned risks. Considering the high strategic value of the Supplier Selection and Order Allocation problems, such topics received extensive and increasing attention from both academics and practitioners, especially since the globalization of markets and the birth of the concept of international economy started leading the nowadays way of doing business.

In conducting the literature review, the authors focused on the production of the last two decades in order to inspect what are the recent tendencies in approaching and solving both SS and OA problems. The analysis started from some recently-published reviewing papers, then extended to papers proposing innovative approaches, with a particular focus on:

- MCDM methods, as the methodology category which the proposed model is referred to, as it regards SS
- Linear Programming, as one of the mainly adopted solving approaches, as it concerns OA.

After having reviewed all the papers reported in Table 1.4 and others cited, but not reported in the afore mentioned table for the sake of brevity, we realized that a very important point is almost missing in the overview of SS processes, that is a method enabling an effective comparison between historical and new suppliers, especially about those criteria named as Forecatastable in the model proposed by the authors. This fact results to be quite strange in a world-based market where the watchword is “innovation”; indeed, in many cases innovate means searching for new materials, components and technologies thus for new suppliers. If a method capable to put on the same footing historical and new suppliers is not available, how can the decision to leave one supplier to start the collaboration with another one be taken? The main aim of this work is to offer a solution capable of making Decision Makers effectively able to compare new and historical suppliers, so to take aware decisions when renovating the suppliers list. Obviously, the authors are conscious of the fact that the proposed model claims to be just one of the first solutions proposed for covering the highlighted research gap, but candidate itself to constitute, along with
other few works (e.g. Rezaei et al. [26] and Hruška et al. [17]), a basis for the future research in the field of \textit{new task} (according to the classification proposed by Faris et al. [7]) purchasing situations.

The lack of works exploring the processes and methodologies typical of such situations, makes the proposal of a solving model much more difficult with respect to improving something that has already been deeply inspected and formalized; thus, the simple structure of the proposed model leaves possibilities of modification and enhancement in agreement with the academical scenario, whereas it results to be suitable for real-world applications thanks to its linearity.

A second gap identified regards the scarcity of papers aimed at proposing a model for solving the joint SS and OA problem; as a matter of fact, most of reviewed papers deal either with one topic or the other. However, since the consequential link between SS and OA, we think that an effective model should tackle both the topics, and this is the reason why the proposed model is aimed at solving the joint SS and OA problem. In our work the resolution of the OA problem is directly linked with the output obtained from the resolution of the SS problem as clearly demonstrated by the definition of the objective function characterizing the second stage of the Linear Program adopted to solve the OA problem itself.

Another important point is the respect on DMs’ subjectivity, giving the same the possibility to express not only their opinions, peculiar characteristic of MCDM, and in particular pairwise comparisons-based methods, but also their \textit{risk attitude}, an aspect which is often not taken into account, relegating DMs to express their “sensations” only when expressing judgments about the afore-mentioned pairwise comparisons.

We think that the adopted scenario-based approach, in addition to enabling the comparison between historical and new suppliers, gives the DMs also the possibility to express their vision and even “feelings” about the considered situation. Even if scenario-based approach is not so commonly employed, it allows to take into account the shades that reality may assume, allowing to incorporate in the proposed model the uncertainty affecting the forecasts made about something which is unknown by nature (in our case the performances of new suppliers about criteria that are usually evaluated after a number of supplies has been performed).

All in all, the proposed model is characterized by three features that allow to tackle Supplier Selection problems where new and historical suppliers have to be compared:

- categorization of selected criteria in \textit{Measurable} criteria and \textit{Forecastable} criteria
- adoption of the Best-Worst Method, as pairwise comparisons-based method exploited for calculated criteria weights
- scenario-based approach for forecasting new suppliers’ performances about \textit{Forecastable} criteria.
The distinction made between *Measurable* and *Forecastable* criteria is fundamental to keep separated what is known from what is not, moreover, it allows to adopt different processes for scoring the suppliers’ performances, basing on the nature of both specific criterion and supplier considered.

From the novelty regarding criteria, it directly follows the application of the scenario-based approach as a very effective methodology for forecasting new suppliers’ performances according to different scenarios that could take place, also considering, as already said, the perceptions and feelings of Decision Makers.

The adoption of the BWM is perfectly in accordance with the purchasing situations the proposed model refers to, indeed, it guarantees much less pairwise comparisons with respect to the mostly adopted pairwise comparisons-based methods (e.g. AHP), thus better adapting to situations characterized by a high degree of uncertainty.

With the aim of proving the applicability of the proposed methodology, a case study is introduced; the environment is the manufacturing one where a medium-big company producing radiators and with a family-management tradition, even if with a structured organization, wants to renovate its suppliers’ list. The reference case is characterized by two historical suppliers, and a new one; the three suppliers are evaluated on five criteria, according to the MCDM approach and Total Scores are obtained allowing to draft the suppliers’ ranking. After the SS process is completed, the OA problem is tackled so to define the allocation of order quantities among involved suppliers.

The presented case study allowed to verify the suitability and applicability of the proposed model, regarding both the SS and OA problems resolution; in addition to this also sensitivity analyses were conducted so to verify the robustness of the solution found solving the base-case, which resulted to be resilient enough to keep itself unaltered when subjected to small perturbations coming from either the internal or external environments.

Considering the obtained results, it can be asserted that the proposed model constitutes a good response to the call for methodologies capable to guide the Supplier Selection in case of *new task* purchasing situations, which are gaining increasing importance nowadays, moved by globalization and, above all, by innovation on products and services.

As already said, the proposed work wants to be part of the knowledge base useful for opening a new investigation stream in the field of the Supplier Selection literature, a field that is calling for more attention since the very beginning of the new millennium, when De Boer et al. [6] highlighted the lack of attention directed to *new task* purchasing situations, and the need to put greater efforts in analysing the same. However, the authors are aware of the fact that some steps of the proposed model require deeper inspection, and, in some cases, they could result to be simplistic.

One weak point is represented by the *scenario-based approach* itself, indeed, beyond all the already underlined advantages of this approach, there are also some drawbacks.

First of all, while performing the application of the proposed model to the presented case study, the authors realized that the freedom given by the scenario-based approach in defining both the scenarios probabilities of occurrence and the values
reflecting the new supplier’s performances in each scenario, has resulted in a certain way misleading. In particular what resulted to be particularly difficult is to maintain a certain “balance” between probabilities of occurrence and values expressing the performance levels. Indeed, sometimes, the sensations and perceptions have a negative influence in the rationality that must characterize the judging process, for example a Decision Maker may be pushed not only to assign a low value to a new supplier on a certain criterion in correspondence of the pessimistic scenario, but also to give the afore mentioned scenario a relatively high probability of occurrence; in such a way the supplier under analysis results to be penalized by the influence the emotivity of the Decision Maker has played during the evaluation process. Obviously, the same thing may happen in the opposite sense, in such a way a supplier takes advantage both from the high value assigned to its performances and from the elevated probability of occurrence related to the considered (optimistic) scenario.

In order to avoid this kind of bias while evaluating new suppliers about so-called Forecastable criteria, alternative solutions may be undertaken. A first, simple, relief could be to set scenarios probabilities of occurrence so that Decision Makers’ freedom is restricted to the definition of the value corresponding to each considered scenario; clearly, this is not an easy task as each situation, even in the same business and market environments, is characterized by its own peculiar features and a rigid, schematic, definition of scenarios probabilities of occurrence might not be able to correctly represent the possible developments of the specific considered situation.

Another possible solution is the adoption of triangular and/or trapezoidal fuzzy numbers and so of fuzzy logic; in such a way the scenarios probabilities of occurrence are, in a certain way, set as in the logic of fuzzy numbers they are represented by the vertices of the fuzzy number itself. This solution seems to be more appropriate from a mathematical/academic point of view, indeed it guarantees a higher formalization level of the resolutive process; on the other hand, it supposes the Decision Makers to have knowledge of fuzzy numbers and fuzzy logic, or at least the skills and a knowledge background sufficient to comprehend these concepts.

The second weak point identified regards the two-stage Linear Program introduced for solving the Order Allocation problem. In our opinion the structure is anchored on a solid base, composed by the division in two stages and by the prioritization function constituting the objective function of the second stage; what, on the contrary, needs to be deeply inspected is the objective function proper of the first stage. Indeed, it is presented simply as the Total Purchasing Cost, that contains also indication of the transportation and quality-checks costs (in most of the cases), but it does not account for other not negligible cost-aspects, for example stock-keeping costs. Given the general purpose of the proposed model, we propose the integration of other relevant cost-terms usually considered independently of the specific industry field addressed, in order to offer a solution able to keep into consideration other cost-related aspect beyond the simple TPC.
The third, and last, at least according to our knowledge, weak point is constituted by
the way sensitivity analyses have been performed in the resolution of the presented
case-study.
As far as it regards the sensitivity analyses regarding the scenarios probabilities of
occurrence, we can refer to what afore said about the difficulty perceived in
managing the great amount of freedom given by the scenario-based approach itself.
Considering, instead, the sensitivity analyses conducted on criteria weights, we
focused on the weight associated to Quality criterion, decreasing the other criteria
weights of a reasonable quantity so to preserve the summation of all criteria weights
to be equal to 1. Even if it is a more than logic and correct way of proceeding in
theory, when it comes to the application of such a way of performing sensitivity
analyses, it results a bit difficult to equally distribute the Δ due to the increase of a
specific criterion weight among other criteria weights. This issue is mainly due to
the fact that:

- 1) the authors, as stated in Paragraph 3.4, wanted to keep all the criteria
weights within the boundaries defined by relative interval weights
- 2) interval weights calculation starts from the results obtained as outputs of
the non-linear model of the Best-Worst Method which, in turn, has been
solved by means of a Genetic Algorithm.

Point 1) is related to the authors’ willingness of keeping the whole problem
resolution within the boundaries of optimality.
Point 2) requires deeper investigation: being the BWM, in its native form, nonlinear,
it requires advanced solving methods in order to get the optimal weights to be
assigned to selected criteria. Among the number of solving methodologies for
addressing nonlinear problems, the authors chose Genetic Algorithms as a tool able
to find a sub-/optimal solution in a multidimensional solution space. The output of
the nonlinear BWM, solved by applying the customized Genetic Algorithm, is
constituted by criteria weights and ξ, a parameter representing the consistency of
pairwise comparisons used as input to the resolution of the BWM itself. As already
explained in Paragraph 2.1.2.2, starting from criteria weights and ξ, it is possible to
define the interval weights which are at the base of the sensitivity analyses
conducted on criteria weights.
As it should be clear, the definition of the afore mentioned interval weights largely
depends on the calculated criteria weights and parameter ξ resulting from the
resolution of the nonlinear BWM; for this reason, even the adopted solving
methodology plays an important role. As it regards Genetic Algorithms, they allow
to found not the optimal, but a sub-optimal solution (which can even be the optimal
one, but without guarantee about that), thus criteria weights and parameter ξ found
by means of the application of the customized Genetic Algorithm may not constitute
the optimal solution to the problem, but a sub-optimal one. This fact, in turn, reflects
in the calculation of optimal weights, thus in the way sensitivity analyses about
criteria weights are conducted.
According to our opinion two possibilities exist in order to more precisely define
interval weights and, consequently, conduct more accurate sensitivity analyses:
1) solve the nonlinear BWM with another suitable solving methodology, allowing to find univocally the optimal solution to the addressed problem
2) refine the parameters characterizing the customized Genetic Algorithm, such as Crossover and Mutation fractions, initial Population Size and number of generations.

Adopting one of the proposed solutions, the calculation of interval weights should be more structured and less aleatory so that also sensitivity analyses based on the optimality range defined by interval weights themselves should be more meaningful and easier to perform, especially as it regards the redistribution of the Δ consequently to the increase of a criterion weight of interest.

Lastly, it is worth underlining that the case study refers to a particular situation, characterized by the typical features of a mechanic, family-managed medium-big Italian company. For this reason, even if the proposed model has given evidence of its applicability and effectiveness in such a context, typical of Italian manufacturing industry landscape, it may present some other limitations when applied to a multinational company, operating in very different countries and with a more complex suppliers' list renovation process.

According to what said just above, it could be appropriate to verify the adaptability and effectiveness of the model even to more structured industrial realities, where the resolution of the joint SS and OA problem involves a greater number of Decision Makers, coming from very different functions within the company, thus with very different visions of the problem.

In concluding this research, the authors want to remark the goodness of the work done, from both a theorical and a practical point of view; indeed, it claims to be a trailblazer for future research on New Supplier Selection and to find application in the industry context thanks to its simple and linear structure ensuring easiness of use.
Bibliography


