Modelling Uncertainty in the Design and Planning of Sustainable Supply Chains

Gabriela Inês Gomes

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Supervisors: Prof. Ana Paula Ferreira Dias Barbosa-Póvoa
Prof. Bruna Alexandra Elias Mota

Examination Committee

Chairperson: Prof. Tânia Rute Xavier de Matos Pinto Varela
Supervisor: Prof. Ana Paula Ferreira Dias Barbosa-Póvoa
Members of the Committee: Dr. Ana Cristina dos Santos Amaro

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DECLARATION

I declare that this document is an original work of my own authorship and that it fulfils all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

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ABSTRACT

The classical form of supply chain management, on its own, faces several challenges. Decision-makers, for instance, often struggle with the level of confidence in their judgements, since several key aspects are highly affected by uncertain aspects. This, together with the recent need to consider sustainability purposes in supply chain management, have greatly increased the complexity and robustness of the network's management.

As a response, several optimization methods have been studied in the literature as suitable to the modelling of uncertainty in the supply chain network design, being stochastic programming, fuzzy programming, and robust optimization some common approaches. Uncertainty concerns in the design of supply chain networks have been fairly acknowledged in the literature. Notwithstanding, research concerning sustainable supply chain design under uncertainty often lack more rigorous and sophisticated methods, namely, dynamic optimization and hybrid optimization approaches.

Accordingly, the present dissertation focuses on the design and planning of sustainable supply chains under uncertainty, by providing a stochastic dynamic mathematical model formulation for several uncertain parameters, namely: demand, supply, products' rate of return, and construction and transportation costs.

Henceforth, the work begins by presenting the problem in study. Afterwards, the most common approaches used to model uncertainty are identified and described, followed by a thorough literature review whose purpose is to identify the relevant work being developed. Extensive considerations concerning the methodologies to apply are carefully discussed, followed by the stochastic dynamic mathematical model. The model validation is provided by accounting the representative case-study of Calzedonia Group, and final recommendations are stated.

Keywords: Supply chain; Sustainability; Uncertainty; Stochastic optimization; Dynamic optimization; Calzedonia Group

RESUMO

A gestão de cadeias de abastecimento acarreta diversos desafios, como a falta de confiança na tomada de decisão, dado que questões como a previsão da procura são afetadas por incerteza. Por outro lado, a crescente necessidade de considerar a sustentabilidade tem levado a uma mudança gradual na gestão de cadeias de abastecimento, onde questões económicas, ambientais e sociais têm sido incorporadas, levando a cadeias de abastecimento cada vez mais complexas.

Diversos métodos de otimização têm sido abordados para a modelação de incerteza nas cadeias de abastecimento, como as programações estocástica e *fuzzy,* e a otimização robusta. A modelação de incerteza no projeto de cadeias de abastecimento tem recebido atenção considerável. Contudo, em casos de cadeias de abastecimento sustentáveis, é notória a insuficiência de estudos baseados em métodos de otimização mais rigorosos e sofisticados, como as otimizações dinâmica e híbrida.

A presente dissertação foca-se na modelação de incerteza no projeto e planeamento de cadeias de abastecimento sustentáveis, com a formulação de um modelo estocástico dinâmico considerando diversos parâmetros incertos, como: procura, oferta, taxa de retorno de produtos em fim de ciclo de vida, e custos de construção e de transporte.

Deste modo, o problema em estudo é definido, e a discussão dos métodos de otimização utilizados na modelação de incerteza, bem como uma revisão da literatura que identifica os avanços na área são apresentadas. As metodologias a aplicar são discutidas, e o modelo desenvolvido e validado num caso de estudo representativo ao Grupo Calzedonia. Finalmente, considerações e recomendações finais são fornecidas.

Palavras-chave: Cadeias de abastecimento; Sustentabilidade; Incerteza; Otimização estocástica; Otimização dinâmica; Grupo Calzedonia

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ACRONYMS

ADS – Active Distribution System

BOM – Bill of Materials

CLSC – Closed-loop Supply Chain

EU – European Union

FR – Fuzzy and Robust

GSLCAP – Guidelines for Social Life Cycle Assessment of Products

LCA – Life-Cycle Approach

m-SSChain – Managing Sustainable Supply Chain

NPV – Net Present Value

OR – Operational Research

rNPV – Risk-adjusted Net Present Value

SC – Supply Chain

SCND – Supply Chain Network Design

SF – Stochastic and Fuzzy

SIP – Semi-Infinite Programs

SLCA – Social Life Cycle Assessment

SP – Sigma Point

SR – Stochastic and Robust

SSC – Sustainable Supply Chain

SSCND – Sustainable Supply Chain Network Design

TN – Transportation Network

ToBLoOM – Triple Bottom Line Operational Modelling

USA – United States of America

WEEE – Waste on Electrical and Electronic Equipment

1. INTRODUCTION

The purpose of the current chapter is to provide adequate context and information regarding the master dissertation on the decision-support tool development for sustainable supply chains under uncertainty, also highlighting both its objectives and structure. In section 1.1 a brief contextualization on supply chain, sustainability, and uncertainty is given. In section 1.2 the dissertation's proposed objectives are listed. Lastly, in section 1.3, the structure and outline of the remaining document are provided.

1.1. Problem Contextualization

The term supply chain (SC) has firstly appeared in the literature in 1982 when Oliver and Webber proposed the first definition for the management of such systems, and since then, SC have become vital for every organization (Barbosa-Póvoa, da Silva, and Carvalho 2018). Forward supply chain is the classical form of SC and thus represents the combination of processes aimed at fulfilling customers' requests at a minimum cost. Therefore, all possible network entities, such as suppliers, manufacturers, transporters, warehouses, retailers and customers are included in this system (Barbosa-Póvoa et al. 2018; Govindan, Soleimani, and Kannan 2015).

Over the years, however, there has been a growing concern in environmental issues, leading to the incorporation of reverse logistics in SC's activities, where collection and treatment of end-of-life products through recycling or remanufacturing, repairing, and/or finally disposing of used parts, have been considered within these networks (Barbosa-Póvoa et al. 2018; Cardoso, Barbosa-Póvoa, and Relvas 2013; Fleischmann et al. 1997). Consequently, closed-loop supply chain (CLSC) were also introduced as logistic systems whose goal is to maximize value creation over the entire product's life cycle, by pursuing a dynamic recovery of the product value from several types and volumes of returns (Barbosa-Póvoa et al. 2018). More recently, and apart from economic and environmental concerns, social issues, namely job creation, number of working hours, discrimination, and workers' safety and satisfaction, have also started to be accounted for in the design, planning and operation of supply chains.

Sustainable development has been defined by the Brundtland Commission (World Commission on Environment and Development, 1987) as the "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs*". This was later on associated with the three pillars of sustainability - economic, environmental, and social -, commonly known as the triple bottom line and firstly proposed by Elkington (1997). Accordingly, sustainable supply chain (SSC) refers to complex network systems involving numerous entities that manage products from suppliers to customers and their associated returns, always accounting for social, environmental and economic impacts (Barbosa-Póvoa 2014; Barbosa-Póvoa et al. 2018).

Regardless the complexity, it is a path that must be taken towards meeting current society demands and consequently governmental regulations. Thus, worldwide legislations have been adopted to phase out chemicals with ozone depleting potential, and global warming has started to be seen as a societal issue both in the public and private sector (Linton, Klassen, and Jayaraman 2007). Moreover, the European Union (EU), Canada, Japan, China and the United States of America (USA) have become highly influential proponents of sustainability and hence legislations regarding the handling responsibility of end-of-life products, such as directive 2002/96/EC on waste on electrical and electronic equipment (WEEE) have been established (Govindan et al. 2015; Linton et al. 2007; Mota et al. 2018). Additionally, public awareness has been shown to have a significant impact on big industry players which are being held responsible for practises and incidents occurring in their supply chains. Examples of this are well-established companies such as Nike, H&M, Volkswagen, Apple, and Walmart (Mota et al. 2018).

It is thus clear that industries must be capable of designing, planning and operating their entire supply chain while considering a sustainability path in a way that does not compromise the sustainability of the other players involved (Brandenburg et al. 2014; Mota et al. 2018; Seuring and Müller 2008). The main problem, however, is the inherent complexity, which can be even greater when incorporated in more demanding supply chain systems (e.g. closed-loop supply chain). Moreover, supply chain design and planning problems also involve a set of different strategic (long planning cycles for several years), tactical (shorter planning cycles) and operational (weekly planning cycles) decisions, which are highly affected by uncertainty. Examples of these are: network designing problems contemplating the number, capacity and location of facilities; decisions in the establishment of transportation links; flow of products between the installed entities so as to satisfy the clients' needs; supplier selection; inventory planning; product allocation, recovery and development; and technologies' choices (Barbosa-Póvoa et al. 2018; Govindan et al. 2015; Mota et al. 2018). Additionally, the participants of a supply chain face uncertainties regarding raw material supplies, products demands, and commodity prices and costs (Chen, Yuan, and Lee 2007). Likewise, the amount of both waste generated and CO_2 emitted to the atmosphere, as well as the number of potential hazardous products created are strong sources of environmental uncertainty (Pishvaee, Razmi, and Torabi 2012; Pishvaee, Torabi, and Razmi 2012; Saffar, Hamed Shakouri, and Razmi 2015; Tsao et al. 2018). Apart from this, situations concerning the number of job opportunities and the average number of workdays lost due to the implementation of new technologies and/or work damages portray common uncertain social issues (Pishvaee, Razmi, et al. 2012; Tsao et al. 2018).

Considering this, modelling uncertainty in sustainable supply chain systems is a challenging problem. Thus, to answer to this challenge, the use of Operational Research (OR) methods is a path to explore (Barbosa-Póvoa et al. 2018). Deterministic optimization is not the best-suited one to model uncertainty, given that these types of problems are formulated with known parameters, while real-world problems almost invariably include some uncertainties and difficulties in correctly estimating key parameters. For this reason, several methods to deal with uncertainty were discussed by Sahinidis (2004): stochastic programming where the uncertainty parameters are characterized as random variables with known probabilities, fuzzy programming which assumes that some variables are fuzzy numbers, and robust optimization.

1.2. Dissertation's Objectives

The present dissertation's goal is to contribute to the literature with the development and implementation of a model which will serve as a decision-supporting tool focused on the modelling of various forms of uncertainty commonly present upon the designing and planning of a sustainable supply chain. The current study is being developed under the scope of the m-SSChain (Managing Sustainable Supply Chain) project.

For this reason, the current dissertation targets the following intermediate objectives, which aim to support the model's definition in future dissertation stages:

- Describe the most commonly used methods to model uncertainty and respective features;
- Perform a literature review on previous works focused on modelling uncertainty in sustainable supply chains and identify the research gaps in this field;
- Define and formulate a comprehensive decision-support tool for the modelling of uncertainty in sustainable supply chains and apply it to an illustrative case-study;
- Analyse and critically discuss the obtained results.

1.3. Dissertation's Structure & Methodology

When assessing the work developed in the dissertation, and according to Figure 1, this is composed of seven distinctive stages, characterized below:

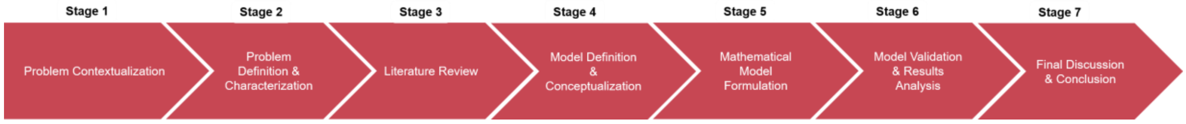

Figure 1 - Dissertation's methodology steps

Accordingly, each stage may be described as follows:

i. **Stage 1 – Problem Contextualization**

The first stage of the thesis aims at providing sufficient information about the problem being addressed. Thus, the sustainable supply chain field, along with its current challenges are identified.

ii. **Stage 2 – Problem Definition & Characterization**

The problem of modelling uncertainty in sustainable supply chains is defined and key considerations regarding how to address it are presented. Several optimization methods are identified and described, in order to characterize and support the objective of this study.

iii. **Stage 3 – Literature Review**

The third stage of the present work focuses on presenting a thorough literature review regarding the modelling of uncertainties in the supply chain network design, whether or not accounting for sustainability concerns, with the purpose of providing sufficient information regarding the advances being made in most recent years considering the uncertainty topic. Common literature considerations are identified and research gaps concerning sustainable supply chains under uncertainty exposed. Accordingly, the current challenges faced in this area are highlighted and possible research considerations presented.

iv. **Stage 4 – Model Definition & Conceptualization**

In this stage, the definition and conceptualization of the desired tools and methods to be applied in order to provide a solid and complete decision-support tool are provided. Hence, relevant literature studies are discussed and used as guidelines so as to present sufficient scientific and coherent information and level of detail. Thus, this research is based on the previously highlighted challenges, namely: the modelling of uncertain parameters; the environmental sustainability pillar model incorporation; and, the modelling of social concerns.

v. **Stage 5 – Mathematical Model Formulation**

The fifth stage of the work methodology focuses on the formulation and development of the proposed stochastic dynamic mathematical model, where several parameters are considered uncertain, and thus provides a decision-support tool for the design and planning of sustainable supply chains.

vi. **Stage 6 – Model Validation & Results Analysis**

The formulated mathematical model is applied to a representative case-study of Calzedonia Group in order to be validated. Additionally, the obtained results are analysed and discussed, so as to understand the impact of each uncertain parameter considered in the overall network. Final recommendations are given.

vii. **Stage 7 – Final Discussion & Conclusion**

The final stage of the methodology considers the analysis of the work previously presented, where a critical discussion is given concerning the work developed in the dissertation. From there, future research topics are identified as interesting to be explored.

2. Modelling Uncertainty: Methods & Applications

With the purpose of acquiring a more comprehensive knowledge on how to deal with uncertainty through Operations Research methods, and identifying the proper methodology to employ, this chapter analyses and reviews available literature about this topic. Thus, the most commonly used methodologies to model uncertainty are defined. The main advantages and limitations of each method are also given, as well as an overview on which types of uncertainties each model has been used for.

This chapter is organized as follows. In section 2.1, the stochastic programming method is presented. Section 2.2 refers to the fuzzy programming approach. Section 2.3 focuses on robust optimization. Section 2.4 describes dynamic optimization. Section 2.5 describes cases where hybrid optimization can be applied. Lastly, in section 2.6, the chapter final remarks are stated.

2.1. Stochastic Programming

Unlike deterministic mathematical programming, where data are known numbers, in stochastic mathematical programming, these numbers may be unknown. Instead, a discrete or continuous probability distribution is given (based on historical data) or estimated (Liu and Sahinidis 1996; Sahinidis 2004).

Two types of stochastic programming are considered in this study: the recourse-based stochastic programming approach, and the probabilistic or chance-constraint stochastic programming approach. The former deals with decision variables organized into two sets, *first-stage* and *second-stage* variables, where the goal is to minimize the expected recourse costs. The latter focuses on the reliability of the system, that is, the system's ability to meet feasibility in an uncertain environment, where the constraints to be optimized depend on certain probabilities.

The most commonly cited stochastic approach is the standard two-stage approach, in which, and according to Sahinidis (2004), the decision variables of an optimization problem under uncertainty are partitioned into two sets. The *first-stage* variables ("here and now" decisions) are those that have to be decided before the actual realization of the uncertain parameters. Thus, once the decision-maker takes some action upon the first-stage, random events occur, affecting the outcome of the first-stage decisions. Subsequently, once the random events have presented themselves, further design or operational policy improvements can be made by selecting, at a certain cost, the values of the *second-stage* or *recourse,* variables ("wait and see" decisions). The *second-stage* variables are interpreted as corrective measures or recourse against any infeasibilities arising due to a particular realization of uncertainty. The presence of uncertainty is reflected by the fact that both the second-stage decisions, as well as the second-stage costs are probabilistic in nature. The objective is, therefore, to choose the first-stage variables, which are deterministic, in a way that the sum of the first-stage costs and the expected value of the random second-stage costs is minimized, leading to an optimal solution that is feasible for all, or almost all, of the realizations of the uncertain parameters. Thus, the result of two-stage programming models is a single first-stage policy followed by a collection of recourse decisions (a decision rule) that indicate which second-stage policy should be implemented in response to each realization of random outcome (Mitra et al. 2009; Sahinidis 2004).

As of the chance-constrained approach, it ensures that the probability of meeting a given constraint is above a certain level, i.e., it restricts the feasible region so that the confidence level of the solution is high. Despite being quite robust, the probabilistic approach is often difficult to solve due to several challenges in transforming the chance constraints into deterministic ones, so that the solution can be reached.

The main advantage of stochastic programming methods is that it is mainly based on probabilistic terms, which are commonly known and applied concepts. Moreover, these approaches also allow decision-makers to have a complete view of the effects of uncertainties and the relationships between uncertain inputs and resulting solutions. Nonetheless, when considering real-case scenarios, it is often difficult to build a probability distribution due to the lack of historical data for the uncertain parameters and/or the high cost for acquiring it. Furthermore, the further incompleteness or impreciseness of observed information (due to market turbulence, for instance) can lead to dual uncertainties of randomness and fuzziness, given that decision-makers express different subjective judgements upon a same problem (Li, Liu, and Huang 2014).

Additionally, when there is a lack of historical data, specifically in the chance-constrained programming approach, the chance constraint can destroy the convexity properties and elevate the complexity of the original problem significantly. Besides, and as most recent works on supply chain network design under uncertainty model the uncertainty through the scenario-based stochastic programming approach, the great number of scenarios used in representing the uncertainty can lead to large-sized, computationally challenging problems (Janak, Lin, and Floudas 2007; Pishvaee, Rabbani, and Torabi 2011).

Several authors apply stochastic programming to model various types of uncertainty. One example of this is Gupta and Maranas (2003), which applied the two-stage stochastic model and where the manufacturing decisions are modelled as “here and now” decisions, and the logistics decisions postponed in a “wait and see” mode to optimize in the face of uncertainty. Furthermore, Feitó-Cespón et al. (2017) presented a stochastic model aiming to redesign a sustainable supply chain and thus allow the recycling of certain products. Once solved, feasible results were obtained, where a cost reduction of 20.9% was achieved when compared to the already existing and deterministic supply chain. Nonetheless, and even though these authors claim to have satisfactory results in using this method, others faced some difficulties, making them change their course of action. Hence, Mitra et al. (2009), shows that if the problem of modelling demand uncertainty, machine uptime and various cost components, had been performed using a scenario-based two-stage stochastic programming approach considering just “5 scenarios for each of the 34 products for a planning horizon of 12 time periods”, the problem would have been too large to solve ($5^{34x12x12}$ scenarios). As a result, another widely used approach has been applied: the fuzzy mathematical programming approach, which is described in the following subsection.

2.2. Fuzzy Programming

Fuzzy programming is another method used to model under uncertainty. This approach can be applied when situations are not clearly defined, or an exact value is not critical to the problem. Thus, fuzzy programming does not require an event to either be black or white (crisp set[1]), but instead, have a range of grey values between two given extremes, thus increasing the number of possible applications in real-case scenarios.

In a fuzzy-based approach, random parameters are considered fuzzy (uncertain) numbers and constraints are treated as fuzzy sets, that is, sets whose elements have degrees of membership. Moreover, some constraint violation is allowed and the degree of satisfaction of a given constraint is defined as the membership function of the constraint (Sahinidis 2004). As an example, one can consider a linear constraint $a^t x \leq \beta$ in terms of the decision vector x and assume that the random right-hand side β can take values in the range from b to $b + \Delta b$, with $\Delta b \geq 0$. Then, the membership function *(u)* is given by a linear function that defines the degree of satisfaction of a constraint as:

$$u(x) = \begin{cases} 1, & if\ a^t \leq b, \\ 1 - \dfrac{a^t x - b}{\Delta b}, & if\ b < a^t x \leq b + \Delta b \\ 0, & if\ b + \Delta b < a^t x \end{cases} \tag{1}$$

Although other types of membership functions are also possible, the above is typically used. Objective functions are treated as constraints with the lower and upper bounds of these defining the decision maker's expectations (Giannoccaro, Pontrandolfo, and Scozzi 2003; Sahinidis 2004).

There are two main types of fuzzy programming: flexible programming and possibilistic programming. Flexible programming deals with right-hand side uncertainties and can be applied when there is uncertainty regarding the exact values of the coefficients. Besides, some constraints violation is acceptable within a certain range. As for the possibilistic programming, it recognizes uncertainties in the objective function coefficients as well as in the constraint coefficients (Li et al. 2014; Sahinidis 2004). In both types of fuzzy programming, the membership function is used to represent the constraints satisfaction degree, the decision-maker's expectations about the objective function level, and the range of coefficients' uncertainty (Sahinidis 2004).

Unlike crisp models, fuzzy systems, combined with an interactive solution process, do not require a collection of extensive data, solving the often-existing information dilemma[2]. Consequently, the first step is to model the fuzzy system, only using easily achieved information which does not incur in high expenses. Accordingly, and based on the solution of the fuzzy model, the decision-maker must then decide which additional information has to be collected and processed. The data representation and the solution can thus be improved stepwise by gathering objective-oriented additional information, with reference to the cost-benefit relation. Since the collection of input data is cut back, its incurring costs can be considerably reduced (Rommelfanger 2004).

One key aspect of the fuzzy sets' theory, developed in 1965 by Zadeh, is that it offers a practical way to model vague and qualitative data. Hence, and instead of replacing vague data by "average data", they are modelled by fuzzy numbers and fuzzy intervals, as precisely as a decision maker will be able to explain and describe them (Rommelfanger 2004). This can thus be applied to various imprecise linguistic terms which arise from managerial subjective judgement and experience, such as: "customer

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[1] A given element can either belong or not to a given set, not allowing it to have a partly behaviour

[2] Lack of historical data and high costs for acquiring it

demand is about d_m, but definitely not less than d_l and not greater than d_u"; or "an external supplier is reliable", where no exact value of how reliable the supplier is was given. Hence, and due to their conceptual and computational simplicity, fuzzy sets can represent approximate quantifiers that correspond to natural language expressions and thus model subjective imaginations of the decision maker as precisely as he will be able to describe it, allowing for an adequate mapping of real problems (Giannoccaro et al. 2003; Petrovic, Roy, and Petrovic 1998).

Moreover, fuzzy models allow for the mixed integer programming problems to be solved relatively easily. Comparing these with classical linear programming models, where integer solutions nearby the optimum solution are often not feasible, in the case of fuzzy models, the right-hand sides are not strong (crisp) boundaries. Hence, fuzzy models also admit most of the integer solutions which are nearby the optimum solution. The decision-maker can thus choose one of the neighbour solutions, in which the advantage of a higher objective value has to be weighed against the disadvantages caused by disregarding the right-hand side of the restrictions (Rommelfanger 2004).

Several authors apply fuzzy mathematical programming to model numerous forms of uncertainty, such as: (forecasted) demand uncertainty (Aliev et al. 2007; Chen and Lee 2004; Chen, Wang, and Lee 2003; Giannoccaro et al. 2003; Petrovic et al. 1998; Tsao et al. 2018), (raw material) supply uncertainty (Chen et al. 2007), product prices uncertainty in both supply and demand points (Chen and Lee 2004), inventory costs uncertainty (Giannoccaro et al. 2003), logistics and production uncertainties (Saffar et al. 2015), environmental and social uncertainties (Li et al. 2014; Saffar et al. 2015; Tsao et al. 2018), etc. Besides, fuzzy interactive methods have been widely used to solve problems related to green supply chain, closed-loop supply chain, and reversed-logistics network design (Tsao et al. 2018).

Among these authors, several reasons are given as to why this approach is being used. The main motive is its capability to estimate trough possibility rather than probability. Even though probability would be desirable, several situations can only be estimated through possibility, due to the ambiguity of the available information (Giannoccaro et al. 2003). Besides, it is also supported that the fuzzy approach does not allow the final deterministic equivalent formulation of the uncertain model to blow up in size with the increase in the number of uncertain parameters (Mitra et al. 2009).

Furthermore, and according to Giannoccaro et al. (2003), "fuzzy set theory is also used to better model the uncertainty associated to holding and backorder costs by simply using linguistic expressions". The author then continues to explain that in cases where managers must estimate costs related to the expected market demand, they find it difficult to do so through crisp numbers because these values mostly depend on factors that can be hardly quantified properly. Thus, "more reliable cost values can be obtained by modelling them through fuzzy sets and using fuzzy operators where necessary".

As of Liang (2006), in which distribution planning decision problems are being tackled, fuzzy set theory is being implemented despite the objective function and model inputs being generally assumed to be deterministic/crisp, in order to provide higher efficiency and flexibility. This approach is thus considered given that in most of real-world problems, environment coefficients and model parameters, such as available supply, forecast demand and related cost/time coefficients, are frequently imprecise/fuzzy because some information is incomplete and/or unavailable over the planning horizon.

It is also supported that the application of fuzzy logic can provide two significant advantages for sustainable supply chains. Firstly, it allows the construction of compromises between conflicting objectives usually present, by considering an overall satisfaction degree as trade-off between several objectives and constraints. Secondly, intersection of fuzzy constraints and overall objectives can be smoother (less cutting), increasing the chance to get a better solution within the overlapping areas of constraints and objectives (Aliev et al. 2007).

Crisp and fuzzy methods have also been compared in Aliev et al. (2007), where it is showed that the fuzzy model usually gives more realistic solutions in cases when the actual demand declines from forecasted values or the capacities decrease over the planning horizon. Nonetheless, the fuzzy method approach still lacks in its inability to represent the exact nature of the uncertainty, leading to results that could depend on the fuzzification[3] approach (Mitra et al. 2009).

2.3. Robust Optimization

Robust optimization is another approach used to modelling uncertainty in optimization problems. Hence, this method provides a framework capable of handling the parameters uncertainty in such a way that it is able to immunize the optimal solution for any realization of the uncertainty in a given bounded uncertainty set. Even though this approach also needs a *priori* knowledge, it does not require the actual distribution, but only the relevant distribution, leading to a much easier process (Pishvaee et al. 2011). The main purpose of the model is to find a solution which is feasible (for all data) and optimal, that is, to always satisfy the constraints, despite parametric uncertainties.

Depending on the optimization problem, and thus the structure of the uncertainty set, there can be several robust approaches. According to Drahansky et al. (2016), several concepts of robustness can be found, where the first is stricter and the others represent several ways of relaxing the former. Thus, these methods are:

i. **strict robustness**, mainly used in critical systems where a failure is not tolerable, and where it is considered that all scenarios may occur and thus have an important criticality;
ii. **cardinality constrained robustness**, which assumes the unlikelihood that all uncertainty parameters change simultaneously when analysing the worst-case scenario, hence varying only some in order to restrict the space of uncertainty and consequently relax the strict robustness;
iii. **adjustable robustness**, where the space of uncertainty of strict robustness is divided into groups of variables;
iv. **lightweight robustness**, where, instead of reducing the space of uncertainty, there is a constraints relaxation in favour of the solution's quality;
v. **regret robustness**, which relaxes the problem through the objective function;
vi. **recoverable robustness**, which uses the concept of recovery algorithm and, as in adjustable robustness, provides a two-stage solution.

Robust optimization is commonly used to address uncertainties in investment portfolio selection and is beginning to gain more attention in engineering research such as production scheduling, resource

[3] Process of changing a real scalar value into a fuzzy value through membership functions

allocation, project management, supply chain planning, and capacity expansion (Janak et al. 2007). This increasing interest in robust optimization is a consequence of being a tailored approach to the available information, relatively easy to understand intuitively and highly useful in practise (Gorissen, Yanikoğlu, and den Hertog 2015). Moreover, this method also leads to a reduction in computational costs and combines computational tractability with the structural properties of the optimal policy (Bertsimas and Thiele 2019; Gorissen et al. 2015; Janak et al. 2007).

Furthermore, and as the robust optimization approach focuses on the worst-case, if the solution is efficient for this scenario, it is thus efficient for every other possible outcome. However, because it is intrinsically a worst-case approach, feasibility often comes at a cost of performance and generally leads to overconservative solutions (Bertsimas and Thiele 2019). One example of this is Pishvaee et al. (2011), where the robust optimization approach is applied to determine the number of facilities, as well as its locations, to satisfy the returns in the worst-case scenario. Consequently, more facilities, or facilities with higher capacities have been opened when using this approach instead of the deterministic model. In other words, the robust model resulted in a more decentralized network structure, while the deterministic model obtained more efficient solutions for nominal data. Nonetheless, the latter model also resulted in infeasible solutions for the most of other realizations, concluding that the robust model for high uncertainty levels is quite acceptable in these cases.

Several other authors apply robust optimization to model numerous forms of uncertainty. Examples of this are: closed-loop supply chain uncertainties concerning both the type and quantity of returned products, and the transportation costs, (Pishvaee et al. 2011), demand uncertainties (Bertsimas and Thiele 2019), scheduling uncertainties (Janak et al. 2007; Lin, Janak, and Floudas 2004), vehicle routing uncertainties (Sungur, Ordóñez, and Dessouky 2008; Tajik et al. 2014), distributed energy systems uncertainties (Akbari et al. 2014), wind power uncertainties (Martinez-Mares and Fuerte-Esquivel 2013), surgery duration uncertainties (Marques and Captivo 2017), and supply and demand uncertainties (Miodrag Belosevic 2014).

Considering Pishvaee et al. (2011), a robust strategy has been seen as a proper method capable of handling higher uncertainty levels. By comparing such method with the determinist approach, the authors have concluded that the gap between the two approaches with respect to the performance measures widens as the problem size and uncertainty level increase, leading to believe that the robust approach appears to be capable of dealing with large-sized problems.

2.3.1. Adaptive Robust Optimization

The adaptive robust optimization approach has been proposed with the purpose of mitigating the conservatism present in the above discussed traditional version of static robust optimization method. Hence, instead of optimizing all decision variables solely in the *here-and-now* mode, this new approach incorporates two stages of decision, by using the *wait-and-see* mode, with the intent of reaching the desirable goal, while anticipating the worst-case materialization of the uncertain parameters within an uncertainty set (Drahansky et al. 2016; Shi and You 2015; Zhao, Ning, and You 2019).

When compared with the conventional stochastic programming approach, the adaptive robust optimization model is more practical, given that it only requires a deterministic uncertainty set, rather than a hard-to-obtain probability distribution on the uncertain data (Bertsimas et al. 2013). Additionally, and according to Shi and You (2015), in the "two-stage stochastic programming, the second-stage decisions are made specifically for each corresponding scenario or possible realization of uncertainty". Nonetheless, in the two-stage adaptive robust optimization, "second-stage decisions are made to hedge against the worst-case which is confined by the budgets of uncertainty and the uncertainty set".

The two-stage adaptive robust optimization approach has been widely applied to decision-making problems under uncertainty in several areas, such as: unit commitment for power systems; network flow optimization; and robust transportation problems (Shi and You 2015). In addition to this, Shi and You (2015) have proposed a two-stage adaptive robust optimization model which deals with the production scheduling problem for batch manufacturing processes facing uncertainty. Hence, decisions involving unit assignment, production sequence, and resource allocation are made *here-and-now* and so their corresponding decision variables are treated as first-stage variables. As of the remaining decision variables, such as start and end times, batch sizes, and allocated resources, these are determined in a *wait-and-see* mode after the realization of uncertain parameters and thus are second-stage variables. Lastly, and by analysing the obtained results, it is clear that, even though the deterministic model presented the most optimistic outcomes and returned the highest profit, it failed to deliver all-feasible solutions for scheduling under uncertain parameters. Moreover, and considering the conventional robust optimization technique, this led to conservative results and a lowest profit. Finally, the two-stage adaptive robust optimization approach resulted in an intermediate profit and returned a robust production schedule hedged against uncertainty. In conclusion, and according to the authors, this strategy can help increase scheduling flexibility and improve overall performance of the manufacturing system.

The work developed by Bertsimas et al. (2013) is another example of a proposed two-stage adaptive robust model. In this study, the focus is on both unit commitment, one of the most critical tasks in electric power system operations, and on the impact of a dramatical uncertainty increase in supply and demand due to the integration of variable generation resources (such as wind power and price responsive demand). Here, the model's first-stage aims at finding an optimal commitment decision, while its second-stage is focused on finding the worst-case dispatch cost under a fixed commitment solution. Afterwards, and as final remarks, the authors claim that the used method presents a better economic efficiency of the robust approach by having a lower cost average through the proper adjustment of the budget level of the uncertainty set. Moreover, it is also stated that the adaptive robust solution can reduce the volatility of the total costs significantly, as well as the inherent penalty costs. Finally, the authors also defend the approach's capability of being more robust to different probability distributions of load, as well as its capacity of amplifying its own advantages when the level of load variation is higher.

2.4. Dynamic Optimization

Generally speaking, optimization problems can be divided into two categories: static optimization problems, and dynamic optimization problems (Fu et al. 2014). Thus, while static optimization methods concentrate on reaching the optimal choice at a single point in time, dynamic approaches involve optimization over time, where the focus is on maximizing or minimizing the costs/benefits of a given objective function over a period of time. Moreover, in dynamic optimization problems, the decision-maker is responsible of making multiple decisions over time. Besides, the approach's overall performance depends on all decisions made sequentially during a given time interval, where previous decisions may have an impact on later decision-making. (Fu et al. 2014).

Furthermore, in dynamic programming optimization problems, also known as multi-stage programming optimization problems, the objective functions show a sequential structure (Hinderer, Rieder, and Stieglitz 2016). Hence, and according to Iyengar (2005), dynamic programming is the "mathematical framework that allows the decision maker to efficiently compute a good overall strategy by succinctly encoding the evolving information state". Thus, decisions are made in stages where each, besides providing an immediate reward, affects the future rewards and hence the context of future decisions (Iyengar 2005).

Given its structure, applying dynamic optimization to real-world situations may encounter several difficulties. One example is the considerable computational burden (also known as *curse of dimensionality)* of having a large number of states and actions that must be known in order to compute the optimal action in any given state. Moreover, other issues relate to the lack of proper awareness of the theory's potentials, the requirement of rather complexed models, and the possible lack of accurate data (Hinderer et al. 2016; Iyengar 2005). Nonetheless, and considering its characteristics, several authors have been combining this technique with other well-known ones, such as the stochastic and robust optimization methods, as discussed in the following subsubsections.

2.4.1. Stochastic Dynamic Optimization

While dynamic programming may be viewed as a general method aimed at solving multi-stage optimization problems, stochastic dynamic programming is seen similarly, but with its focus on solving stochastic multi-stage optimization problems. Moreover, a stochastic multi-stage optimization problem concerns cases where one or several parameters in the problem are modelled as stochastic variables or processes (Haugen 2016). Hence, with flexible state-dependent decision-making and a look-ahead capability to take future recourse actions into account, this approach balances current rewards with future option values. The principle of the stochastic dynamic programming approach is thus based on a recursive decomposition of a multi-stage problem into simpler sub-problems (characteristics of dynamic programming) that, once solved, are assembled to provide an overall solution (Schön and König 2018).

Concerning the available literature, Schön and König (2018) developed a multi-stage stochastic dynamic programming model focusing on delay management of a single train line, where the goal is to minimize the total delayed experience felt by passengers at their final destination by recursively solving Bellman equations[4]. Since railway delay management considers whether a train should wait for a delayed feeder train, the given model focuses on making wait-depart decisions in the presence of uncertain future delays. Here, the approach taken explicitly accounts for potential recourse actions at later stations in a look-ahead manner when making the decision in the current stage, and, according to the authors'

[4] Necessary condition for optimality associated with dynamic programming, which breaks the problem into a sequence of simpler sub-problems

numerical experiments, the proposed approach resulted in decisions expected to achieve lower overall delays.

Another example of this is the work developed by Li et al. (2009), based on production planning and inventory control, which, besides being a critical research point for re-manufacturing systems, often faces a great deal of uncertainty and complexity. Therefore, the authors have proposed a stochastic dynamic programming model to study the production planning, i.e. the dynamic lot sizing problem, of re-manufacturing systems, where both the demand and return amounts are stochastic over a finite planning horizon. Here, the state variable is defined by the recoverable inventory and the serviceable inventory of re-manufactured products, whereas the decision variable is defined by the number of re-manufactured products per period. The Bellman equation is constructed in order to minimize the total expected cost, including the re-manufacturing cost, the holding cost for returns and re-manufactured products, and the backlog cost. Finally, the optimal production plan of the re-manufacturing system over a finite planning horizon is said to be obtained with the policy iteration method with effective results.

Multi-stage stochastic programming is also widely used in the formulation and solution of financial problems (Consigli and Dempster 1998). One example of this is the multi-stage stochastic programming model for international portfolio management in a dynamic setting developed by Topaloglou, Vladimirou, and Zenios (2008), where uncertainty relates to asset prices and exchange rates in terms of scenario trees that reflect the empirical distributions implied by market data. According to the author's, the choice of this approach concerns its capability of helping decision-makers gain useful insights and adopt more effective decisions. For instance, by using this method, they shape decisions based on longer-term potential benefits and thus avoid myopic reactions to short-term market movements that may prove risky. Moreover, they determine appropriate dynamic recourse (contingency) decisions under changing economic conditions represented by scenario trees. Hence, interrelated decisions present in the model, which are traditionally considered separately, are cast as a unified and flexible framework that outperforms single-stage models.

2.4.2. Robust Dynamic Optimization

Similarly to the stochastic dynamic optimization approach, and according to the decision-maker context, robust methods can be divided into two categories: single-stage and multi-stage (Gabrel et al. 2014). Accordingly, in the multi-stage context, or dynamic decision-making, the information is revealed in subsequent stages. Moreover, Weinmann (1991) also defends that "robustness is the property of dynamic systems to tolerate variations of parts of the system without exceeding predetermined tolerance bounds in the vicinity of some nominal dynamic behaviour".

Given that robust dynamic optimization is a relatively recent approach to model uncertainty, few authors have explored this method. Nonetheless, and according to Puschke et al. (2018)'s studies, the *worst-case* formulations can be expressed as semi-infinite programs (SIP), despite the fact that connecting uncertain dynamic optimization problems and SIPs is somehow atypical. Besides, and according to Vallerio et al. (2016), a probabilistic framework can be used to formulate an approximate but computationally tractable solution approach for robust dynamic optimization problems involving expected value dynamic optimization and additional chance constraints. The approach is thus based on the *sigma point method* (SP) which allows the accurate approximation of the probability distribution through any nonlinear mapping via a sampling technique.

2.5. Hybrid Optimization

In hybrid optimization, more than one method is used and so the desired features of at least two approaches are combined in order to reach overall improvements. Thus, several combinations are possible, and hence, multiple drawbacks mitigated.

Several authors have been focusing on hybrid optimization approaches. One example is the study performed by Li et al. (2014), where a hybrid fuzzy-stochastic programming method has been developed for planning water trading under uncertainties of randomness and fuzziness. Therefore, this method can simultaneously deal with recourse water allocation problems generated by randomness in water availability, and tackle uncertainties expressed as fuzzy sets in the trading system. Moreover, and according to the authors, the developed method provided two main benefits that would be difficult to achieve if any other approach had been employed. Firstly, this method allows to incorporate pre-regulated water-allocation policies directly into the modelling formulation, such that an effective linkage between resources-allocation regulations and economic implications/penalties caused by improper policies due to uncertainty existence can be provided. Secondly, multiple uncertainties represented as fuzzy sets, random variables, and their combinations can be directly communicated into the optimization process, leading to enhanced system robustness for uncertainty reflection (Li et al. 2014).

Other authors have benefited from aligning the stochastic and fuzzy optimization methods. Hence, in Chen et al. (2007), the simultaneous optimization of multiple conflict objectives problem in a typical supply chain network with market demand uncertainties is investigated. Here, demand uncertainty is modelled as discrete scenarios with given probabilities for distinctive expected outcomes. Furthermore, and in order to find the degree of satisfaction of the multiple objectives, the linear increasing membership function is used. In turn, the final decision is acquired by fuzzy aggregation of the fuzzy goals, and the best compromised solution can be derived by maximizing the overall degree of satisfaction for the decision. Finally, when applying the model to the given case-study, it becomes clear that this approach can provide a compensatory solution for the multiple conflictive objectives problem in a supply chain network with demand uncertainties.

On another thought, the work developed by Bozorgi-Amiri, Jabalameli, and Mirzapour Al-e-Hashem (2013) is based on the combination of stochastic and robust optimization. Here, the authors studied the disaster relief logistics under uncertainty, where supply, demand, and costs of procurement and transportation are seen as uncertain parameters. Moreover, both the incapability of accurately knowing the demand locations, and the possibility of having some pre-positioned supplies partially destroyed by the disaster are also considered as uncertain, which was coped with by using a scenario-based approach. Furthermore, and in order to develop a robust model, two additional terms were added to the first objective: cost variability and penalty of infeasibility. As a result, the purpose of this model is not only to minimize the sum of the expected value and the variance of the total cost of the relief chain while penalizing the solution's infeasibility due to parameter uncertainty, but also to maximize the affected areas' satisfaction levels through minimizing the sum of the maximum shortages in the affected areas.

This was further applied to a case-study concerning the disaster planning for earthquake scenarios in a region of Iran.

When looking at the combination of both fuzzy and robust optimization approaches, one can state the work developed by Nie et al. (2007), where a model is developed and applied to the planning of solid waste management systems under uncertainty. Considering this, the model parameters are represented as interval numbers and/or fuzzy membership functions so that the uncertainties can be directly communicated into the optimization process and resulting solution. Furthermore, highly uncertain information for the lower and upper bounds of the interval parameters that exist due to the complexity of the real world were effectively handled by introducing the concept of fuzzy boundary interval. Complexities and uncertainties are thus explicitly addressed without unrealistic simplifications, and the obtained solutions exposed increased stability and enhanced robustness. Finally, the obtained results suggest that the proposed methodology is applicable to practical problems associated with highly complex and uncertain information. Nevertheless, the authors also state that this method can be further improved by incorporating methods of stochastic analysis.

Thus, and considering a scenario where the three methods, stochastic, fuzzy and robust, have been applied, it is vital to emphasise the work developed by Zhang, Huang, and Nie (2009). Here, a robust chance-constrained fuzzy possibilistic programming model has been developed and applied to a case-study of water quality management within an agricultural system under uncertainty. The proposed model improved upon the usage of the methods individually, by allowing fuzzy and probabilistic information in the model to be effectively incorporated within the optimization framework. Moreover, the preference form decision-makers is effectively reflected through specifying the certainty degree of the imprecise objective function, and the model enhances the robustness of the optimization process and resulting solutions by delimiting the decision space through dimensional enlargement of fuzzy constraints. Consequently, the uncertainties are directly communicated into both the optimization process and the resulting solutions, such that the generated decision schemes for agricultural activities are effectively capable of reflecting the complex system features under uncertainty. Finally, the case-study results not only indicate that useful information for providing feasible decision schemes for different agricultural activities under diverse scenarios can be obtained through the proposed model, but also that the developed approach is applicable to several practical problems where fuzzy and probabilistic distribution information simultaneously exist.

Moreover, Li et al. (2006) focus on the development of a hybrid two-stage fuzzy-stochastic robust programming model, with the purpose of applying it into the planning of an air-quality management system. Here, uncertain parameters are expressed as probability density and/or fuzzy membership functions, such that robustness of the optimization efforts could be enhanced. Besides, economic penalties as corrective measures against any infeasibilities arising from the uncertainties are considered, and the linkage to predefined policies determined by authorities that must be respected when a modelling effort is undertaken was provided by this approach. Furthermore, in the solution process, the proposed model is capable of delimiting the fuzzy decision space into a more robust one by specifying the uncertainties through dimensional enlargement of its original fuzzy constraints. Finally, the obtained results from applying this method indicate that useful solutions for planning regional air quality management practises have been generated and reflect complex trade-offs between environmental and economic considerations. Thus said, the willingness to pay a high operating cost will guarantee meeting environmental objectives, however, a strong desire to acquire a low operating cost will run into a high penalty for violating the environmental objective.

Finally, it is also relevant to emphasise the work developed by Farrokh et al. (2018), where the focus is on the closed-loop supply chain network design problem under hybrid uncertainty, namely in the processes of recycling and disposing products. The goal is thus to optimize the configuration of supply chain network with respect to both disruption and operational risks. Here, two sources of uncertainty for most parameters were treated, hence requiring fortifying the robustness of the decision. Therefore, while the first source is that some uncertain parameters may be based on the future scenarios which are considered according to the probability of their occurrence, the second source is that values of these parameters in each scenario are usually imprecise and can be specified by possibilist distributions. Moreover, and by using the simulation method, the authors compared the proposed robust model in terms of mean costs and total variability with the models developed by Mulvey and Vanderbei (1995) and Pishvaee, Razmi, and Torabi (2012), which can either control the scenario variability or the possibilistic variability, contrasting with the model proposed by Farrokh et al. (2018), which can control both variabilities. As a result, the findings indicate the superiority of the proposed model over the two others in decreasing the total variability as a measure of the optimal robustness, leading to the conclusion that it would be more suitable for most managers to control both disruption and operational risks by considering the scenario variability and the possibilistic variability simultaneously.

2.6. Chapter Final Remarks

The inevitable uncertainty in supply chain systems can be modelled through several optimization methods, which can either focus on static or dynamic optimization problems. Some examples of such approaches are: (i) stochastic programming method; (ii) fuzzy programming method; (iii) robust optimization method; and (iv) dynamic optimization method. Moreover, and despite having the same purpose, these approaches work in distinctive ways, and thus several differences separate them. The main aspects, as well as main advantages and drawbacks of each of these methods are summarized in Figure 2.

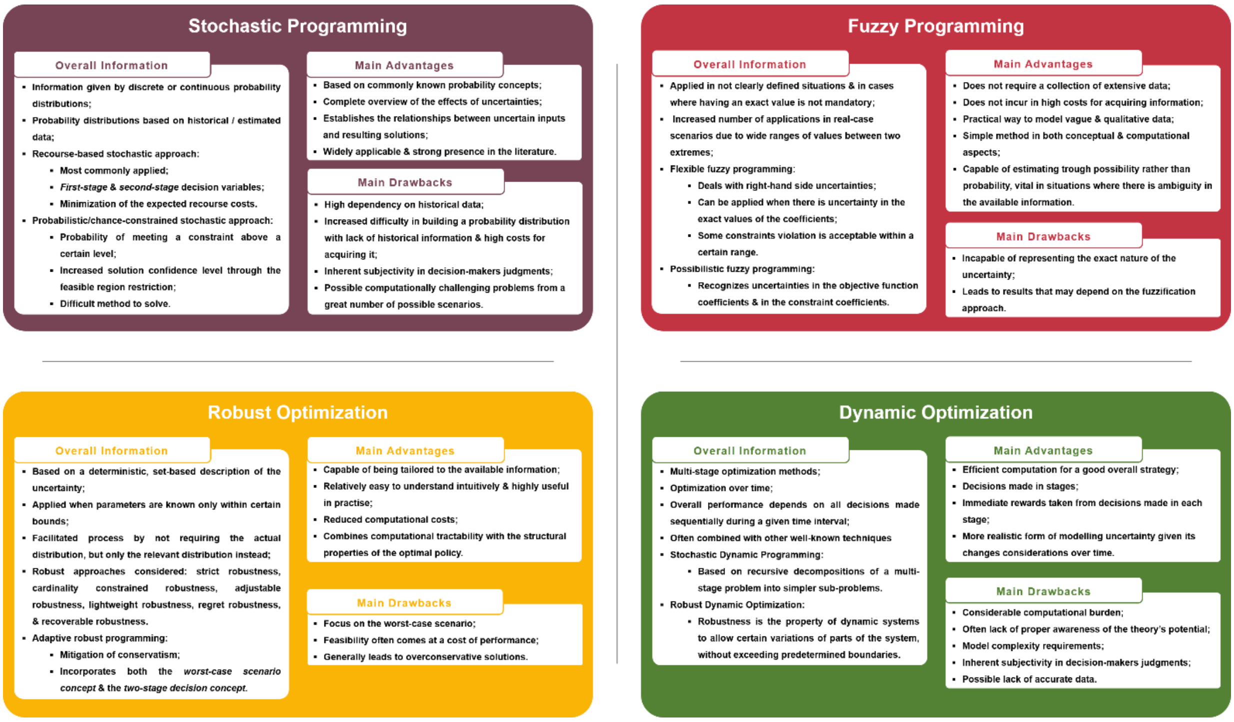

Figure 2 - Optimization methods overview

Additionally, many authors have explored the possibility of combining at least two of these methods and hence produce a hybrid approach. As a result more robust techniques are applied, and drawbacks mitigated through the combination of the best characteristics of each approach. Thus, and from the possible combinations, special emphasis should be given to the situation where the stochastic, fuzzy and robust optimization methods are used together. On that note, the work developed by Farrokh et al. (2018), should be given further attention, since its main focus is by some means related to the purpose of this study. Here, the authors develop and apply a model that considers the effects of uncertainty in a closed-loop supply chain, where economic and environmental concerns are taken into consideration. Moreover, the model's validity is also provided by a wise comparison with two other models that do not apply all three methods, leading to believe that better results can be achieved when considering a hybrid approach of this nature in the modelling of uncertainty in supply chain systems.

3. Modelling Uncertainty in Sustainable Supply Chains

The present chapter performs a comprehensive literature review on the usage of optimization methods to properly model various supply chain uncertainties, based on the methodology presented by Tranfield et al. (2003). Hence, and in order to present a more completed and thorough analysis, relevant papers considering supply chain network design under uncertainty, with and without the sustainability focus, have been accounted for, so as to provide sufficient background on the subject of uncertainty and how it may be incorporated and modelled in a (sustainable) supply chain.

This chapter is organized as follows. Section 3.1 describes the scope of this analysis and provides a general description of the collected materials. Section 3.2 focuses on the categorization of the obtained sample of papers. Section 3.3 provides a sample assessment, where a conceptual map is presented. Lastly, in section 3.4, the chapter final remarks and the identified challenges in the field are stated.

3.1. Scope and Sample Description

The main purpose of this analysis is to provide a literature review on the studies and optimization methods that have been developed for designing supply chain networks under uncertainty, in order to obtain further insights on how to properly model uncertainty in sustainable supply chains. Hence, key research questions aiming to be answered with this literature review have been developed as follows:

Q1) What type of parameters are usually considered to be uncertain when considering supply chains?

Q2) What optimization methods have been predominantly explored when addressing uncertainty in supply chains?

Q3) Which optimization method studied has predominately been applied to model each type of uncertain parameters considered?

Q4) What decision levels (strategic, tactical, or operational) have been addressed when applying the discussed methods to model uncertainty in supply chains?

Q5) What sustainability pillars (economic, environmental, and social) have been explored in the modelling of uncertainty in sustainable supply chains?

With this regard, this analysis focuses, not only on bringing new relevant data to the main findings of the work already developed by Govindan et al. (2017) concerning the supply chain network design under uncertainty, but also on further exploring the uncertainty topic incorporation into the sustainable supply chain network design and planning. Hence, key articles have been selected for this literature review that account for both sustainable and non-sustainable supply chains under uncertainty and thus provide a valid awareness on the work being developed on this subject.

Therefore, and in order to conduct the mentioned analysis, a literature review has been conducted using both Thomson Web of Knowledge and Science Direct databases, where only articles published in peer-reviewed journals and written in English have been considered. Moreover, the study has involved two main researches: one based on articles from 2016 up to 2020 whose focus is on providing an update on the work developed by Govindan et al. (2017) on supply chains under uncertainty, and another one highlighting the achieved studies since 2000 until 2020 on sustainable supply chains under uncertainty, a key issue for the purpose on the present thesis. These analyses are thus performed using the combination of the following sets of keywords, both compatible with the research conducted by Govindan et al. (2017), so that reliable conclusions can be done: (1) “supply chain”, “supply network”, “distribution network”, “logistic”, “uncertainty”, “stochastic”, “fuzzy”, “robust”, and “dynamic”; and, (2) “sustainable”, “supply chain”, ”closed-loop”, “supply network”, “distribution network”, “logistic”, “uncertainty”, “stochastic”, “fuzzy”, “robust”, and “dynamic”. Finally, and considering scenario (2), all papers concerning sustainable supply chains that do not model explicitly environmental or social concerns have been excluded, leaving only papers where at least two pillars of sustainability have been accounted for.

Using the aforementioned research description, a total of 72 extra papers (provided in Appendix A) has been identified and further explored along with the analysis developed by Govindan et al. (2017), which, on its own, analysed a total of 170 papers. The distribution of the overall sample of papers in terms of publication date is given in Figure 3, where, and according to Govindan et al. (2017), it is clear that more than 50% of the papers concerning supply chain network design (SCND) have been published since 2012. Moreover, it is also clear that, prior to 2010, little relevant work has been developed in the field of sustainable supply chain network design (SSCND). Hence, and given the obtained results, it is plausible to state that several developments have been made in the area of optimization, with a fairly recent trend on the incorporation of sustainability concerns into the design and planning of supply chains under uncertainty.

Figure 3 - Number of papers published per year since 2000 (adapted from Govindan et al. 2017)

Additionally, and according to Govindan et al. (2017)’s analysis, the European Journal of Operational Research, the Transportation Research Part E: Logistics and Transportation Review, and the International Journal of Production Research have greatly contributed to the literature in the modelling of uncertainty in supply chains. Hereafter, the additional research has considered, not only the above-mentioned journals, but also other reputable contributors, such as: International Journal of Production Economics, Journal of Cleaner Production, and Omega. Therefore, and according to Figure 4, it becomes clear that the European Journal of Operational Research has had a large contribution to the supply chain network design under uncertainty, whereas the Journal of Cleaner Production represents the higher contribution in the modelling of uncertainty in supply chains with a sustainability focus.

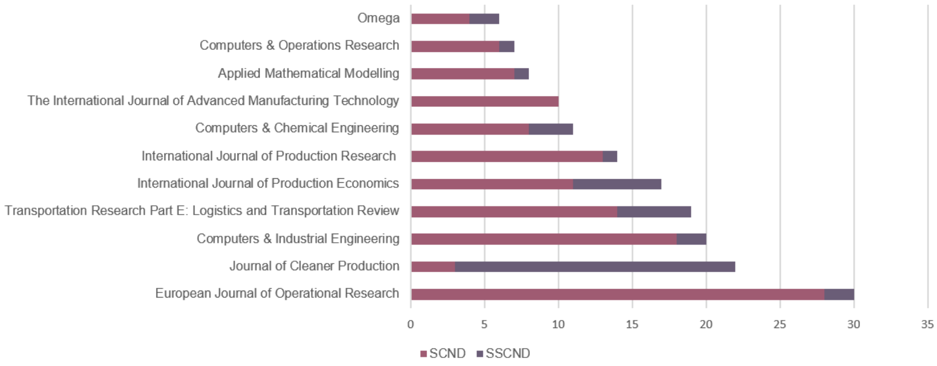

Figure 4 - Share of international journals with the highest contributions in publishing the analysed papers (adapted from Govindan et al. 2017)

Finally, and even though there is no information regarding who has been exploring the optimization methods in the design of supply chains under uncertainty in Govinan et al. (2017)'s work, when analysing the countries of origin of the corresponding authors in the remaining part of the sample of papers, China, Canada and the USA represent the countries with the highest number of contributing papers into the present analysis, where the large majority concerns the modelling of uncertainty in sustainable supply chains. Other relevant contributors are European countries, such as France, Germany, Norway, and Italy.

3.2. Sample Categorization

The present subchapter aims to categorize the several papers by considering key aspects of the developed researches. This categorization is a crucial process that requires special attention due to the variety of decisions involved in supply chain management. Thus, and by answering the questions Q1 – Q5 presented in 3.1, crucial information is presented and discussed through Figures 5 – 14, namely: uncertain parameters, optimization methods, sustainability pillars, and decisions levels considered.

Question Q1's purpose is to understand what are the main uncertainty aspects being considered when designing a supply chain network of any kind, forward, reverse, or closed-loop. Hence, and according to Govindan et al. (2017)'s work, one can conclude that demand is the uncertain parameter with the highest frequency (80%) in the forward logistics network. Following this is the numerous costs of activities, such as transportation and production (30%), as well as capacities of network facilities/transportation links (about 20%), and supply quantities for network facilities (around 10%). Moreover, and when considering the uncertain parameters frequency in the reverse logistics network, returned quantities presents the highest value (more than 80%), followed by costs of various activities, such as transportation and production (more than 40%), capacities of network facilities/transportation links (30%), and demand for reverse logistics outputs (about 20%).

Additionally, and when analysing the sample of 72 papers, the main uncertainty aspects being considered are represented in Figures 5 and 6. Hence, and from Figure 5, it is possible to conclude that demand is the parameter with the highest frequency (44%) in the SCND scenario, followed by supply (11%) and capacities of network facilities/transportation links (9%). Figure 6, on the other hand, represents the frequency of the main uncertain parameters treated in the scenario where the sustainability pillars are accounted for. Hence, it is clear that demand continues to be the uncertain parameters with the highest frequency (29%). Following that is both environmental and social impacts uncertainties, with a frequency of 16% and 14%, respectively. Concerns related to products returns, have also been considered, namely their rate of return (6%), quality (3%), and prices (2%). Capacities of network facilities/transportation links, various types of costs and supply uncertainties have also been accounted for, with a frequency of 8%, 5%, and 4%, respectively.

In light of the presented above, one can state that, concerning the SCND scenario, the obtained results of the sample of 72 papers is aligned with the findings of Govindan et al. (2017)' works. Nonetheless, and once sustainability concerns are acknowledged in the models, there is the expected shift in the frequency of the uncertain parameters towards both environmental and social impacts, as well as products return rates and characteristics. Finally, and despite having sustainability considerations or not, demand continues to be the highest parameter to be considered uncertain when modelling uncertainty in supply chains.

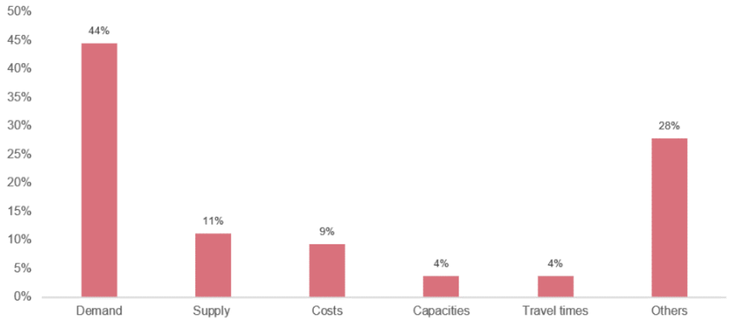

Figure 5 – Frequency of uncertain parameters in supply chain network design (SCND)

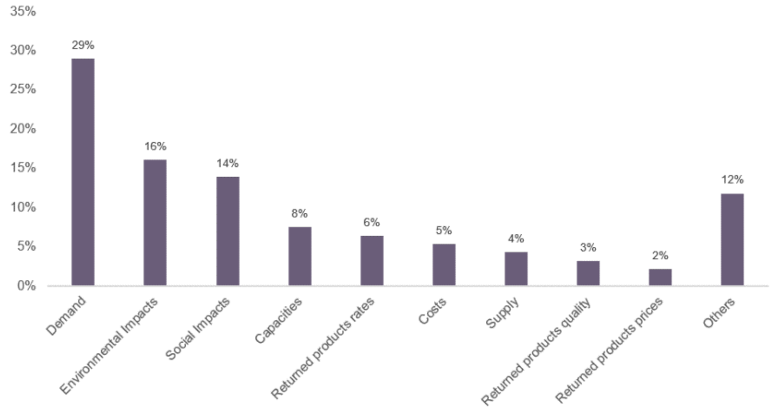

Figure 6 - Frequency of uncertain parameters in sustainable supply chain network design (SSCND)

On another note, question Q2 aims at understanding the distribution of papers among the discussed methods used to model uncertainty in supply chains: stochastic programming, fuzzy programming, robust optimization, robust adaptive optimization, and dynamic optimization, combined with stochastic programming or robust optimization. Accordingly, Govindan et al. (2017)'s research shows that a vast majority of the available literature up until 2015 have been greatly considering the usage of the stochastic optimization approach to model uncertain parameters in the supply chain network design, with a frequency of almost 73%. Following this is fuzzy programming, with about 14.7%, and robust programming, with a frequency of usage of about 5.9%. Furthermore, the authors also highlight the usage hybrid programming methods, where the combination of stochastic and fuzzy programming is the most frequent (about 3.5%), followed by stochastic and robust, and robust and fuzzy, and stochastic, robust and fuzzy.

Furthermore, when considering the sample of 72 papers, and according to Figure 7, it is clear that stochastic programming continues to be the most commonly used programming approach in both scenarios, SCND and SSCND, with 35% and 50% of frequency, respectively. Robust programming is the second most-used optimization method among the selected sample of papers (18% for SCND and 21% for SSCND), followed by fuzzy programming (6% for SCND and 11% for SSCND). Moreover, it can be noted that when considering hybrid approaches, stochastic and robust programming are the strongest combination in the SCND scenario. Nonetheless, in SSCND, both stochastic and fuzzy, and stochastic and robust are equal in a total of 5% of the sample. On the other hand, the combination of fuzzy and robust programming approaches represents only 3% of the sample in each scenario. Finally, it should also be noted that there has been a relatively acceptable interest in more advanced forms of using optimization methods, especially in the field of SCND. This is clear with the usage of robust adaptive programming in 6% of the sample of papers concerning SCND, along with the usage of dynamic programming, namely stochastic dynamic and robust dynamic, as well as with the combination of stochastic dynamic and robust programming in one paper of the studied sample.

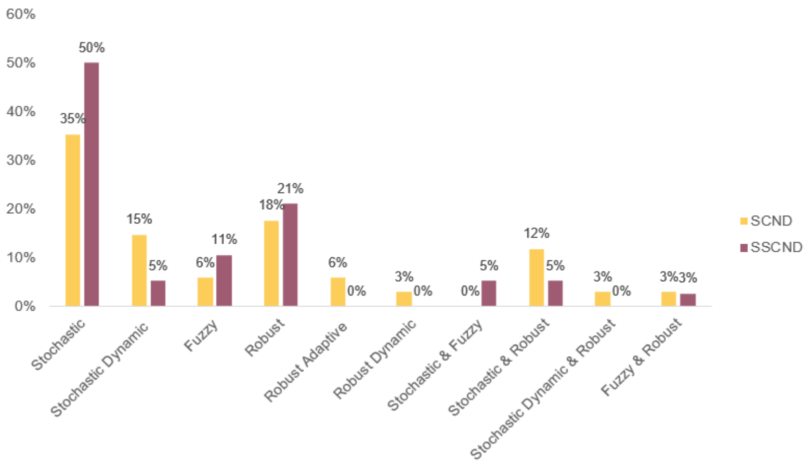

Figure 7 - Optimization methods distribution used to model uncertainty distribution

Looking more closely at some of these papers, one example of the usage of robust adaptive programming approach is the work developed by Xie, Hu, and Wang (2020), where the authors have proposed a “two-stage robust expansion planning model for a coupled ADS [Active Distribution System] and TN [Transportation Network]” while considering uncertainties regarding renewable energies, power load and traffic demand simultaneously. In the proposed two-stage model, investment decisions have been integrated in the first-stage, whereas the second-stage referred to the operation strategies for the traffic flow and active network management intended, where the overall purpose of the robust model developed was to identify the optimal first-stage solution by minimizing the total cost regarding the worst-case outcome of uncertain renewable energies and demands.

Zahiri, Suresh, and de Jong (2020), on the other hand, presented a stochastic dynamic programming approach in order to be capable of focusing on an integrated, proactive-reactive policy. This procedure thus aims at reducing hazardous materials transportation risks in a such a way that numerous decisions (e.g., locating hazardous materials response teams and warehouses for storage) were possible to be made simultaneously with inventory and allocation decisions in a multi-period, multi-product hazardous material supply chain under demand uncertainty. Stochastic dynamic programming has hence been used due to its capabilities of dealing with stochastic data in a multi-period setting, where "data uncertainty can be expressed through a scenario tree and the objective function is to represent the total risk to the sequence of decisions". Nonetheless, and in order to better portray several real-life applications where setting a certain probability to each arc, and, consequently, a certain value to each node is not realistic, the authors have presented a new multi-stage stochastic programming approach called layered multi-stage stochastic programming, where each probability arc is considered to be an uncertain parameter following a possibilistic membership function, as seen in Figure 8.

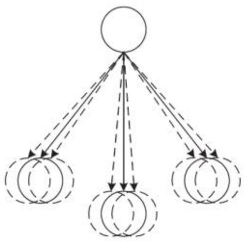

Figure 8 - Uncertain scenario tree (Zahiri, Suresh, and de Jong (2020)

Furthermore, the work developed by Shang and You (2018) is a good example of the application of the robust dynamic programming approach, where the authors have proposed an approach for solving process planning and scheduling problems under demand uncertainties and hedging against the inexactness of probability distributions of uncertainties. Thus, this study begins with a single-stage probabilistic-based robust optimization problem, which is then developed by incorporating *wait-and-see* decisions made after uncertainty realizations, in order to account for the multi-stage and multi-level decision-making structure in process operations.

Finally, the work developed by Shabani and Sowlati (2016) should also be highlighted, given its combination of stochastic dynamic programming, and robust programming with the purpose of optimizing a forest-based biomass power plant supply chain under biomass quality and availability uncertainties. Hence, the work begins by modelling the biomass quality using a robust optimization model, where the purpose was to find a robust solution, that is, a feasible solution for any realization of the uncertain parameter. Afterwards, multi-stage stochastic optimization is used in order to model the uncertainties regarding biomass availability, where a scenario tree is considered with each arc representing the rate of change from the average scenario in the available biomass from each supplier in each stage. Moreover, the scenario tree contains four stages, with each stage including three months, and where variations in biomass availability are stationary during the three months in each stage. Finally, and taking into account the authors' findings, the hybrid model has proven to provide "consistently more conservative and more stable solutions compared to the previous deterministic model" studied by them.

Now considering question Q3, this can be answered by analysing the main optimization methods used to model each of the main uncertain parameters accounted for, regardless of the considered scenario, SCND or SSCND, represented in Figure 9. Hence, it becomes clear that demand uncertainty is mainly modelled through the usage of stochastic programming, followed by robust programming and fuzzy programming. Moreover, environmental impacts uncertainties are mainly modelled through stochastic programming (mainly carbon tax rates/prices, somehow established in society) and fuzzy programming, while social impacts, costs and returned products rates uncertainties heavily rely on fuzzy programming to be accounted for. Moreover, supply uncertainties are mainly modelled through stochastic programming optimization. Capacities uncertainties (e.g., facilities, transportation), on the other hand, rely equally on stochastic and fuzzy programming methods, with little work developed using robust programming. Thus said, it is plausible to state that in cases where historical data is given and/or easily obtained (e.g., demand), stochastic programming is the preferred method. Nevertheless, in cases where historical data is difficult to obtain, fuzzy programming has been the preferred approach to use. One example of this is the consideration of environmental and/or social concerns, two relatively recent topics approached in the literature. Hence, and due to the lack of historical data and sufficient knowledge of these matters, most authors are reluctant to use a more accurate method, and thus apply fuzzy programming to take advantage of the fact that no exact values are mandatory, but instead, only a range of grey values between two given extremes. The same conclusions can be applied to situations dealing with various costs and facilities capacities uncertainties, two highly uncertain parameters often easier to be considered within a higher range of possible values rather than more specific numbers.

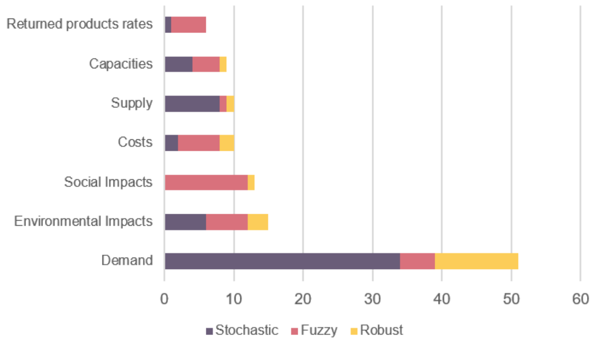

Figure 9 - Uncertain parameters and optimization methods studied relation

On another note, question Q4's purpose is to understand the main focus of the sample of papers regarding the different decision levels in a supply chain: strategic; tactical; and operational. Hence, a paper to be considered strategic should address a long planning cycle for several years out, which may be accomplished at an executive management level. On the contrary, a tactical paper deals with a shorter planning cycle, more focused on inventory, demand and/or supply planning. Finally, papers related with operational supply chain include demand fulfilment, production and distribution, as well as scheduling and monitoring activities that are current planning tasks measured weekly (Barbosa-Póvoa et al. 2018).

According to Govindan et al. (2017)' findings, 30% of all papers considered in their study have accounted for capacity decisions for supply chain facilities. Following this is the technology selection (13%), as well as transportation modes' decisions (10.5%), and supplier selection for raw materials/components

(9.5%). Moreover, and considering the sample of the 72 papers being analysed, Figure 10 presents the distribution of such papers per decision level, where the first number in each group represents the SCND scenario, and the second the SSCND. Accordingly, one can conclude that these papers have been mainly focused on both strategic and tactical aspects, with a total of 45 (62.5%) and 44 papers (61.1%), respectively. Considering the former, most decisions relate to the supply chain network design of any kind, that is, forward, reverse, and closed-loop. As of the latter, some of the considered decisions relate to inventory management, and scheduling and production planning. Operational aspects, on the other hand, represent the decision level with the least amount of consideration in the selected papers, appearing in only 8 papers (11.1%). Furthermore, it is also possible to conclude that 18 papers considered both strategic and tactical aspects, while only five looked at both strategic and operational levels. As of tactical and operational aspects, these have been combined in two papers. Finally, no paper has considered all three decision levels.

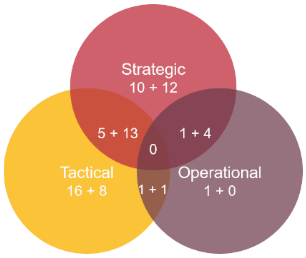

Figure 10 - Number of papers covering the different decision levels in supply chain

Finally, question Q5 aims at focusing specifically on the sample of papers that account for sustainability concerns, with the purpose of understanding the main sustainability focuses considered. The findings to answer this question are portrayed in Figure 11. Moreover, and as previously stated, due to the sustainability emphasis of the research, papers that take into consideration only one of the three pillars of sustainability have not been accounted for. Thus, and due to the high number of situations where economic purposes are considered on their own, all papers that did not model explicitly environmental or social concerns were excluded, leaving only papers where at least two pillars of sustainability have been accounted for.

Therefore, and in view of the information obtained in Figure 11, it is clear that the selected researches have a major focus on both economic and environmental concerns, where all papers consider this combination of sustainability pillars. Additionally, there is a lack of attention towards social concerns, which is only considered when combined with the remaining sustainability pillars, in a total of 8 papers. In light of this, one can state that, when addressing sustainability concerns, most authors only focus on the more studied and researched pillars, that is, economic and environmental, leaving a large research gap in the incorporation of social concerns.

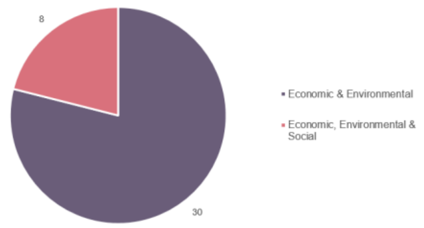

Figure 11 - Number of papers per Sustainability Pillar

Bearing in mind this analysis, one can further detail the information provided and present the major aspects considered in each sustainability pillar (Figures 12 – 14). Thus, the assessment of each sustainability pillar is given as follows.

i. **Economic Pillar**

Figure 12 shows the distribution of the economic indicators used in the selected papers to assess the economic pillar. Given its information, it is possible to verify that cost reduction has been the main economic objective function (71% of the total papers), while profit has been considered in 26% of the papers. The Net Present Value (NPV), however, is only considered in the remaining 3% of the papers. In light of this, when accounting for investment decisions, where high levels of risks are involved, the Net Present Value should be the primary indicator to be used, given its capabilities of incorporating such risks in the future cash flows. Thus, it is plausible to state that the distribution of indicators given in Figure 12 is uneven. Moreover, and in order to mitigate this, the percentage of papers addressing the NPV as the right economic indicator should rise, especially when considering network design decisions.

ii. **Environmental Pillar**

When considering the environmental pillar assessment given in Figure 13, it becomes clear that the majority of papers cover the global warming factor (74% of the total papers treating environmental concerns), represented by aspects related to carbon dioxide (CO_2) emissions and greenhouse gases. Hence, it is possible to state that the environmental studies have been exploring a narrow perspective, where only aspects concerned with the carbon footprint have been measured.

Additionally, utilities consumption is considered in 7% of all papers, whereas, waste reduction is considered in another 5% of all papers. However, and considering that waste is not an environmental impact category, but instead a flow, these authors have been trying to measure the environmental impact indirectly. As of biodiversity, this indicator is considered in 5% of all papers, while products recovery and fuel and energy consumption, in 2% each.

Finally, the use of the Life-Cycle Assessment (LCA) approach is verified in only 5% of the papers. This approach, which has been described as the most scientifically reliable method currently available for studying and evaluating the impacts of a certain product or process, quantifies all relevant emissions and resources consumed, as well as the related environmental and health impacts and resource depletion issues that are associated with any goods or services. Hence, this approach takes into consideration the entire life cycle of the good or service, from the extraction of resources, through production, use, recycling and disposal (Mota, Gomes, et al. 2015). Moreover, some literature exists where authors apply LCA methodologies to supply chain design, such as the Eco-Indicator 99 and the ReCiPe 2008, each employed in only one of the selected papers. Thus, while the former reports several environmental impacts through a multi-echelon perspective, the latter is a further development of Eco-Indicator 99 and hence a more appropriate method. Thus said, and with LCA being a more complete methodology to assess environmental impacts, it should be further applied when studying the environmental pillar within supply chain, where the extended characteristics of LCA should be explored.

iii. Social Pillar

Regarding the social pillar, it is possible to verify from Figure 14 that job creation (either fixed, variable or both) has been the most common indicator, with a total of 47%. Afterwards, aspects related to regional development represents 27% of all papers concerning the social pillar of sustainability. Following this is the consideration for the safety and health of workers, with a total of 20% of all papers concerning the social pillar of sustainability. This number is calculated by the sum of both health & safety (13%) and number of lost workdays due to damages and workplace hazards (7%). Finally, the remaining 7% focus on the overall satisfaction of consumers.

Considering this analysis, it is clear that only single issues have been applied and hence there is no integrated approach. Moreover, and given the relative diversity of indicators used, it is plausible to state that authors are still looking for a clear definition of social sustainability. Nonetheless, the GSLCAP (Guidelines for Social Life Cycle Assessment of Products) is a product-oriented social impact assessment method based on LCA that appropriately addresses social issues by following the supply chain logic and utilizing an environmental assessment method, such as the ReCiPe 2008, to further facilitate the model development and formulation (Ghaderi, Moini, and Pishvaee 2018; Messmann et al. 2020). Thus, the incorporation of a similar integrated approach might lead to the better modelling of social concerns and hence lead to feasible results.

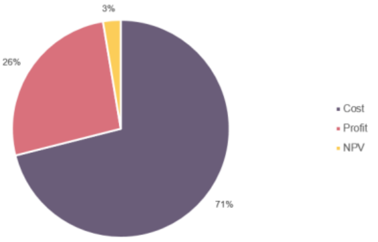

Figure 12 - Economic pillar assessment

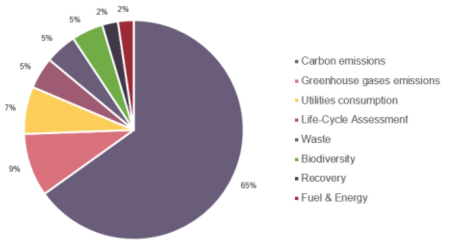

Figure 13 - Environmental pillar assessment

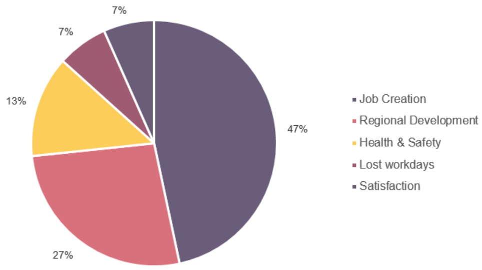

Figure 14 - Social pillar assessment

3.3. Sample Assessment – Conceptual Map

The purpose of this review is to comprehend the usage of optimization methods to model uncertainty specifically in sustainable supply chains, where the focus of this research lies on. Thus, it is now clear that, according to subchapters 3.1 and 3.2, this is a relatively recent issue in the literature, with a diversification of the type problems addressed. Therefore, and to graphically portray the literature focus and the interest devoted to the research community to each one of the sustainable supply chain dimensions analysed, Figure 15 represents a conceptual map. Hence, one can conclude the importance of each dimension from the explicit information provided in each square. Moreover, and being sustainable supply chain (SSC) under uncertainty the motivation of this analysis, it is represented as the central point in this map. Afterwards, this central point ramifies into three main research streams representing the decision levels: Strategic; Tactical; and Operational. In turn, the sample of 38 papers concerning specifically sustainable supply chain network design is then further divided depending on each sustainability pillar: Economic; Environmental; and Social. Lastly, the sample of papers is further divided according to the final layer of division related to the optimization methods used to model uncertainty: Stochastic; Fuzzy; Robust; and Hybrid, which can either be through the combination of both stochastic and fuzzy optimization methods (SF), stochastic and robust methods (SR), or fuzzy and robust optimization methods (FR). It is also relevant to state that the usage of stochastic dynamic optimization is represented through the '+1' present in some stochastic boxes.

Considering the decision levels dimension, the strategic level has been the most studied one, where attention is mainly focused on network design problems in forward, reverse, and closed-loop supply chains. Among these papers, both the economic and the environmental pillars have been assessed at all times. Social concerns, on the other hand, have only been accounted for in about 27.6% (a total of 8) of the papers with strategic purposes. Besides, and by further looking into this analysis, it is clear that stochastic programming has been the most used approach to model uncertainty while considering strategic decisions and economic and environmental concerns, followed by robust optimization and fuzzy programming. Regarding the strategic-social group, it is clear thar both stochastic and fuzzy programming are the most used methods, followed by robust optimization. Lastly, it should also be acknowledged the usage of more than one programming method in this strategic group, where all sustainability pillars have been covered by, at least, two papers using hybrid programming, where two of the studied methods have been combined.

On another note, the tactical level has been essentially addressed in conjunction with strategic decisions, with less than 41% of its total sample of papers considering tactical decisions, either on its own, or together with the operational decision level. It is also clear that all papers covering tactical decisions have accounted for both the economic and environmental pillars. The social pillar, on the other hand, has only been addressed in five of all papers concerning tactical decisions. Once again, stochastic programming is considered in the largest amount of papers in this group, with one case related to stochastic dynamic programming, followed by robust optimization and fuzzy programming. Additionally, three papers considering both economic and environmental concerns relate to the usage of hybrid programming methods, with the combination of stochastic programming and either fuzzy programming or robust optimization. Nonetheless, the hybrid programming cases reduces to only two papers in the social pillar of sustainability, where stochastic programming has been combined with fuzzy programming.

Lastly, the operational level has been the least studied one, with only five papers considering this type of decisions. Besides, there is no paper addressing both operational decisions and the three pillars of sustainability altogether, leaving the social pillar with zero records. As expected, stochastic programming continues to be widely used, with one record of stochastic dynamic programming, whereas fuzzy programming has not been accounted for in this subgroup. Besides this, there is also one record of the usage of hybrid programming through the combination of both stochastic and robust programming methods.

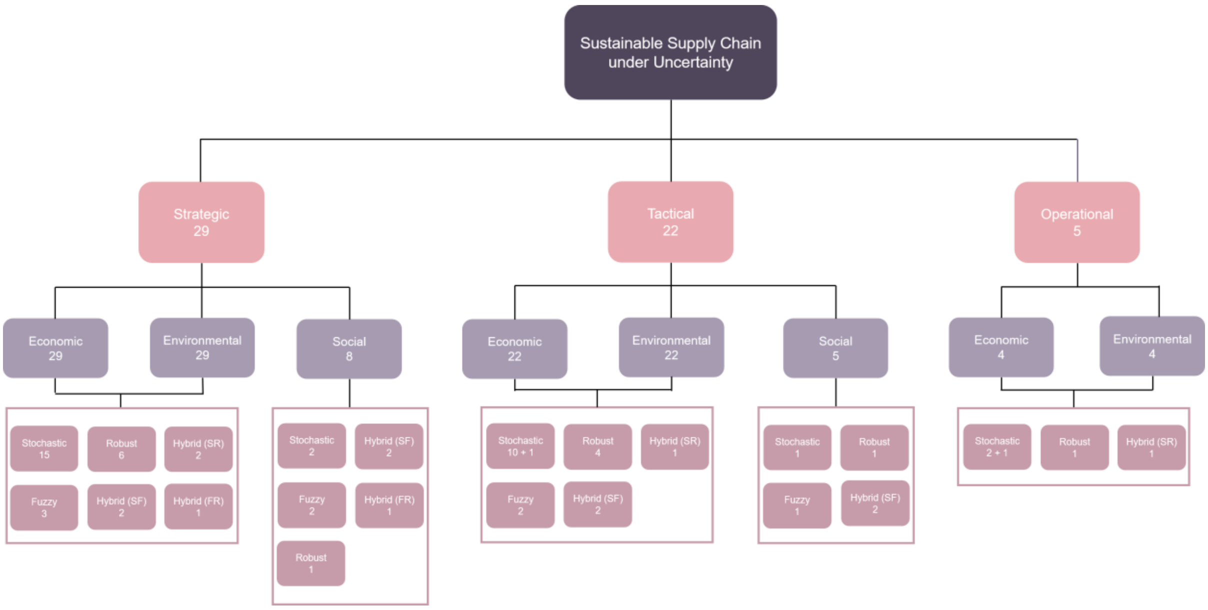

Figure 15 - Conceptual Map on modelling uncertainty in sustainable supply chains

Looking closely at some relevant work developed in this area, the study developed by Mota et al. (2018) is an example where both strategic and tactical decisions have been accounted for, while also considering the three pillars of sustainability (economic, environmental, and social), leading to believe to be one of the most complete papers in the studied sample. Thus, this paper has presented a ToBLoOM –Triple Bottom Line Optimization Modelling, that is, a decision support tool for the design and planning of sustainable supply chains. It consists of a multi-objective mixed integer linear programming model integrating several interconnected decisions, such as: facility location and capacity determination;

supplier selection and purchase levels definition; technology selection and allocation; transportation network definition, including both unimodal and intermodal options; supply planning; and product recovery and remanufacturing. Moreover, the three pillars of sustainability have been addressed as objective functions with the overall goals of: (i) profit maximization, measured through the Net Present Value; (ii) environmental impact minimization, assessed through the LCA approach, with the ReCiPe 2008 methodology; and (iii) social benefit maximization, measured through the development of a GDP-based (Gross Domestic Product) metric relating the number of jobs created by the supply chain with the maximization of job creation in countries with lower economic development. Finally, demand uncertainty has been considered using the stochastic optimization approach.

Tsao et al. (2018) is another good example of a paper addressing strategic-tactical problems together with economic, environmental and social concerns. Hence, the goal is to determine the number and location of facilities (i.e., production and distribution centres), as well as the product flows in the network, while bearing in mind the key objective functions: (i) minimize the total costs of the sustainable supply chain network; (ii) minimize the environmental impacts of the network, through the consideration of, not only the total equivalent emissions of CO_2 caused by production and transportation, but also the amount invested in environmental protection at the production centres; and (iii) maximize the number of social benefits earned from establishing the network, measured through the number of job opportunities created, as well as through the amount of hazardous by-products associated with the selection of production technology and materials, and through the number of workdays lost due to workplace hazards. The main difference of this paper, however, lies on the usage of a hybrid approach, through the combination of both stochastic and fuzzy programming models, in order to model various uncertain parameters, such as: demand, cost, capacity, CO_2 emissions, number of job opportunities, generation of hazardous by-products, and the average number of workdays lost due to the implementation of new technologies. Therefore, the two-phase stochastic programming approach has been used to divide the decision variables into two sets: (i) recourse-related variables, such as technologies, materials, and the number of facilities, determined using random variables; and (ii) output variables, namely the amount of product that is produced and shipped, determined using the realized value of random variables and which may have be influenced by stochastic variables in the model, such as demand in specific costumer zones. Finally, and through the usage of fuzzy possibilist programming, the multi-objective mixed-integer linear programming model obtained to formulate the sustainable supply chain network has been transformed into an equivalent crisp model, significantly reducing the problem's complexity by adjusting the objective functions and constraint.

Finally, the work developed by Purohit et al. (2016) has presented a novel approach of modelling demand uncertainty in sustainable supply chains using stochastic dynamic programming optimization. According to the authors, real-life supply chains face stochastic and non-stationary demand, but most studies on inventory lot-sizing with emission concerns consider deterministic demand. Therefore, the purpose of this research is to "deal with the inventory lot-sizing problem of a firm under non-stationary stochastic demand with carbon emission constraints", where cycle service level has been considered as a customer service measure in order to state that the demand process is not deterministic. By solving the mixed integer linear programming model presented, the authors have determined the optimal replenishment schedule that could minimize the systemwide cost in advance of the planning horizon. Environmental concerns, on the other hand, are stated as emission constraints, where carbon emissions are controlled under the carbon cap-and-trade regulatory mechanism applied over the planning horizon. Finally, the authors also state that a “static-dynamic uncertainty” strategy has been considered, where replenishment timing and corresponding stock levels are fixed at the beginning of the planning horizon and the order sizes for coming periods are determined after realization of the demands of previous periods.

3.4. Chapter Final Remarks

Considering that uncertainty incorporation into the design, plan and operation of a sustainable supply chain has been a fairly recent subject in the literature, the present literature review has considered the main contributors, not only to this issue, but also to the supply chain network design under uncertainty in general, together with the already developed work of Govindan et al. (2017) in this field. Moreover, the European Journal of Operations Research and the Journal of Cleaner Production, together with China, Canada, the USA, and several European countries, have proven to have done strong contributions to these studies.

When observing in detail the main parameters to be considered as uncertain in the modelling of supply chains, demand has the highest frequency of occurrence, followed by concerns related with both environmental and social impacts (in the SSCND scenario), supply, various costs and capacities. Furthermore, and when considering the main optimization methods used, it is clear that stochastic programming has greatly contributed to this field, followed by fuzzy and robust programming approaches. Moreover, it should also be noted the utilization of more advanced methods, namely, robust adaptive programming, and dynamic programming, combined with either stochastic or robust programming. Finally, and when accounting for the relation of uncertain parameters acknowledged and the optimization methods used, one can note that, in cases where historical data is given and/or easily obtained (e.g., demand), stochastic programming is the preferred method.

Additionally, it is clear that the strategic decision level has been the most addressed, followed by tactical and operational levels, being the former the least explored in the literature. Moreover, among the three sustainability pillars, both economic and environmental concerns have been accounted for at all times, leaving social aspects with less consideration. By further looking into the assessment of these pillars, economic concerns are mainly dealt by, either the minimization of costs, or the maximization of profit. Nonetheless, and considering the high risks associated with investments, a shift towards the usage of the NPV should be considered in the literature. In the environmental indicators’ distribution there is a strong focus on the global warming consideration and a lack of attention towards the usage of LCA-based approaches, which have been described as the most scientifically reliable methods currently available for studying and evaluating the impacts of a certain product/process. Regarding the social pillar of sustainability, there has been a wide range of parameters being addressed, such as the number of job opportunities created, and the regional development. However, no integrated approach has been proposed, leading to believe that authors are still looking for a clear definition of social sustainability.

3.4.1. Uncertainty in Sustainable Supply Chains: Current Challenges

Considering the main findings of the literature review provided above, it is possible to characterize the current challenges faced when modelling uncertainty in sustainable supply chains. Hence, aspects concerning the uncertain parameters to consider, as well as how to properly model them is emphasised. Moreover, attention towards sustainable and decision levels considerations is also provided.

Accordingly, and considering Figure 16, several uncertain parameters that have proven to be highly considered should be accounted for, namely: demand; environmental and social data; supply and resources availability; various costs (e.g., production, transportation); and numerous capacities (e.g., facilities, transportation). Considering this, it is crucial to understand which optimization method(s) to use, where proper and efficient solution approaches should be applied in order to provide feasible and valid results. Thus, the choice of optimization method should be aligned with the type of uncertain parameter considered. For instance, in cases where historical data is given or can easily be obtained, optimization approaches dealing with more exact values and results should be investigated. Moreover, multi-stage (dynamic) programming should also be further studied, which, by considering a longer planning horizon, can provide decision-makers with more complete and reliable information.

Concerning sustainability modelling, a holistic economic assessment, as well as a sound assessment of environmental and social aspects represent another challenge that should also be reached. Thus, economic objectives should be carefully selected depending on the type of analysis under consideration, where problems involving investments should consider project assessment indicators, such as the NPV, where the inherent associated risk is contemplated. Moreover, and given their characteristics, the use of LCA-based methods presents a research potential for the environmental pillar assessment. Likewise, the social pillar assessment, which has not yet been fully considered nor properly modelled, may benefit from an integrated approach, where social-LCA methods may prove to be successful. Finally, the integration of the different decision levels should also be acknowledged, in order to explore the multi-functional activities of any supply chain (forward, reverse, or closed-loop) contemplating sustainability issues in a comprehensive manner, while fostering a supply chain holistic view.

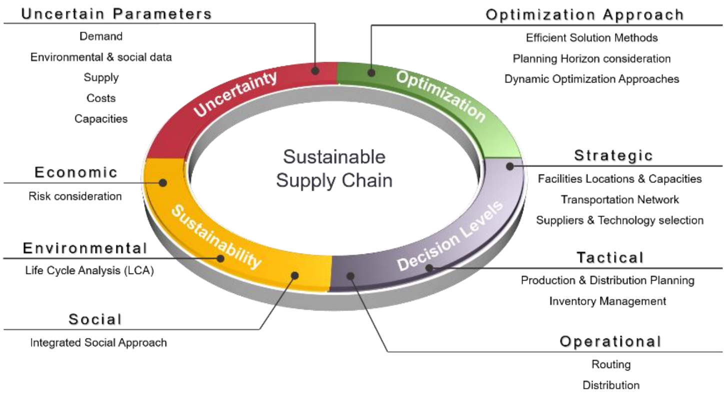

Figure 16 - Research Framework on sustainable supply chain under uncertainty

4. MODEL DEFINITION & CONCEPTUALIZATION

The present chapter aims to present both the model definition and conceptualization, based on previously highlighted challenges. Thus, and due to their relevance in the literature, significant studies are discussed and reviewed with the purpose of serving as guidelines for the future model formulation, namely on the uncertainty incorporation, and on the proper environmental and social assessments.

This chapter is organized as follows. In section 4.1, the selected optimization method to model uncertainty is presented and discussed considering key literature studies. Section 4.2 focuses on relevant work dedicated to the proper assessment of the three pillars of sustainability. Lastly, in section 4.3, the chapter final remarks are stated.

4.1. Optimization Method Selection

Considering previously highlighted information and data related to the optimization methods often used to model uncertainty in supply chains (chapters 2 and 3), it becomes clear that dynamic optimization approaches bring robustness and generalization when compared to static optimization methods. Moreover, and given its relative lack of usage in the modelling of sustainable supply chains under uncertainty, it is plausible to state that this should be further explored.

Subsequently, stochastic dynamic optimization has been selected as the optimization approach to be used. This choice, which mainly lies on the characteristics of the method, leads to the further selection of the proper technique to apply in order to describe uncertainty. Hence, and according to Sazvar et al. (2014), there are two distinctive approaches: i) the distribution-based approach, which is applied when a continuous range of potential future outcomes can be anticipated; and ii) the scenario-based method, which is applicable when the uncertainty is illustrated by a set of discrete scenarios forecasting how it might take place in the future, being each scenario associated with a probability level signifying the decision maker's expectations of the occurrence of a particular scenario. On that account, and taking into consideration the relevant literature's contributions and insights on the subject, the stochastic dynamic optimization approach is to be applied in the upcoming model through the scenario-based technique, applicable when a continuous range of future outcomes is not available.

In the scenario-based approach, the uncertainty is represented by a scenario tree, where, at each stage, a discrete number of nodes represents points in time where realizations of the uncertain parameters take place and decisions must be made. Moreover, each node of the tree, apart from the root, is connected to both a unique node at the previous stage, known as the ancestor node, and to other nodes at the following stage, called the successors (Ben Mohamed, Klibi, and Vanderbeck 2020). As of the stages, these correspond to a time when the decision-maker updates the information with new available data, and not necessarily to specific time periods (Sazvar et al. 2014).

A recent study developed by Ben Mohamed et al. (2020) portrays a proper example of the usage of stochastic dynamic optimization in the modelling of demand uncertainty. In this research, the authors' purpose is thus to define a two-echelon distribution-network design problem under both uncertain and time-varying demand, as well as time-varying distribution platforms opening costs. In the presented modelling framework, it is considered that the planning horizon is composed by a set of planning periods shaping the evolution of the uncertain ship-to-point demand over time. Furthermore, it is also assumed that the number and location of distribution platforms are not fixed *a priori* and must be decided at the strategic level along the set of planning periods.

Thus said, the studied problem considers the business context of a retail company that sources a range of products from a number of supply sites, such as suppliers and manufacturing plants, and stores them at primary warehouses. Additionally, under a make-to-stock policy, the company operates a set of primary warehouses designed to "centralize inventories and ensure distribution to demand zones periodically". Nonetheless, the locations of the company warehouses are not necessarily designed to provide next-day and/or same-day delivery. To do so, the company needs to deploy an advanced set of distribution resources to serve ship-to-points with an adequate service level, namely capacitated distribution platforms. Accordingly, the location of such platforms, as well as the links capacity between the warehouses and the ship-to-locations, compose the model's strategic decisions. Moreover, and given that ship-to-point orders vary in quantity of product demanded on a daily basis, once a given set of distribution platforms is deployed, the company periodically determines the quantity of goods to be allocated to each distribution platform, translating into a number of full-load trucks required from warehouses to deliver products to a distribution platform. Afterwards, and on a daily basis, the goods are delivered to ship-to-locations through common or contract carriers for each single ship-to-point.

Considering this, the proposed model studies a long-term planning horizon that covers a set of successive design planning periods, which are defined in accordance with the operational dynamics such that a planning period corresponds to a year, a typical scenario in the context of leasing distribution platforms. Additionally, each planning period covers a set of operational periods which are generally represented in a discrete way by common business days. Moreover, location and capacity decisions can be periodically adapted at each design period in order to align the distribution network to its business environment, especially when operating under uncertainty. Nonetheless, design decision must be made prior to their deployment period with partial information on the future business environment, which is available after the implementation period.

Given the above, the model thus assumes information asymmetry between the design level and the operational level, mainly due to the fact that the decisions are not made simultaneously. Consequently, the model displays a multi-stage decision structure, where *here-and-now* decisions are made at the beginning of the planning horizon and thus considered as the first-stage design decisions of the distribution platforms. Afterwards, at the beginning of each subsequent period, and based on the current available information, a new opportunity to adapt the distribution network structure to its future environment is provided. Therefore, decisions made at the beginning of a period depend on the design decisions made up to such period.

As of the uncertain daily demand of ship-to-points, this is represented by a random variable, which is estimated by a given probability distribution and has a mean value, estimated from historical data until time period zero. Furthermore, the random demand process is seen as time-varying, since "a multi-period plausible future allows capturing factor transitions (inflation-deflation, population density, etc) that perturb the *a priori* estimation of demand behaviour and could thus impact the design decisions".

Therefore, a trend function is associated with the random variable and its distribution probability and mean value, in order to shape demand realization.

Hence, the uncertainty is characterized by a set of plausible future scenarios. Each scenario encompasses the demand realization for each period as well as for all the ship-to-points during a typical business day. Then, at the beginning of each period, the information available is updated according to the additional data revealed up to such time period. Therefore, and given the entire planning horizon, a scenario tree is built in order to characterize the realization of demand for each planning period, where scenario instances may be generated by Monte Carlo methods. Furthermore, and given its history up to the ancestor node, each node of the scenario tree is associated with a conditional probability of the random process in such instance. Moreover, the path from the root node to a terminal (leaf) node corresponds to a scenario, and represents a joint realization of the problem parameters over all periods. According to the authors, and as depicted in Figure 17 (a), in a typical multi-stage scenario tree, the scenario probability is obtained by multiplying the conditional probabilities through the path. Additionally, the authors have implemented the non-anticipatively principle[5] by requiring that the decisions related to identical scenarios up to a given stage are considered the same and can thus be represented by a single variable. Nonetheless, and in order avoid writing the non-anticipatively constraints explicitly, restricted scenarios have been used, which are represented by each scenario tree's branch, used to define recourse variables.

Finally, and due to the complexity of solving large and complex problems as the one described above, the authors have presented two mechanisms that, through reduction and relaxation, can transform the "multi-stage stochastic program into a two-stage stochastic program that is sufficiently accurate to capture the essence of the problem while being solvable in practice". Hence, the first mechanism consists on transferring from the original model all the design decisions of all periods to the first-stage, in order to be set at the beginning of the horizon. Therefore, only first-stage design decisions are made *here-and-now,* but subsequent design decisions are essentially used as an evaluation mechanism, which are deferrable in time according to their deployment period. The alternative mechanism, on the other hand, transfers from the original model and into the first-stage only the periods whose design decisions are related to the location decisions, whereas all capacity-allocation decisions are relaxed and allocated into the second-stage, for all periods. Thus, the latter capacity-allocation decisions become part of the recourse problem and hence scenario-dependent.

Accordingly, when transforming a multi-stage stochastic model into a two-stage stochastic one, the scenario building approach is impacted since, from stage two onwards, the scenario tree construction algorithm can reduce the number of nodes to a fan of individual scenarios that prescribes the random parameter value for the full-time horizon with a given probability. Hence, and as depicted in Figure 17 (b), scenarios are independent of the number of periods. Finally, Figure 18, provides a representative scheme of the methodology and considerations employed by the authors.

[5] Additional and necessary constraints to ensure that scenarios with a common history must have the same set of decisions and that future outcomes cannot be anticipated

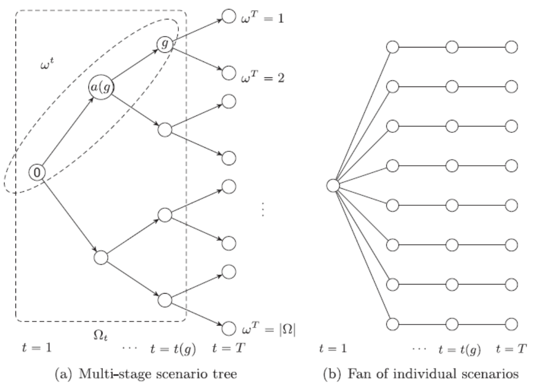

Figure 17 - Scenario tree representation and notations (Ben Mohamed et al. 2020)

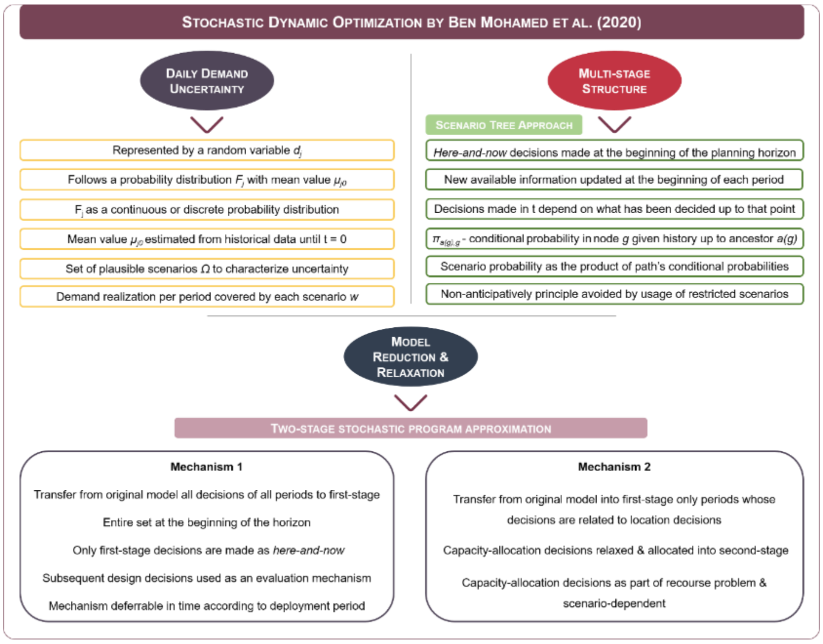

Figure 18 - Representative scheme of the employed methodology by Ben Mohamed et al. (2020)

On another note, Shabani and Sowlati (2016) have presented an alternative approach to modelling uncertainty in supply chains, through the combination of robust optimization and stochastic dynamic optimization, where the scenario tree method has been considered as well. Hence, the provided model is based on “a forest biomass power plant whose supply consists of several different suppliers that provide distinct types of forest-based biomass to the plant, an open storage yard for storing the mix of biomass, and a power plant that generates electricity”. Moreover, and even though the plant has fixed contracts with some suppliers and hence purchases the residues they produce with a fixed cost, such suppliers have no obligation to produce biomass for the power plant when they do not product their main products. Having said that, the presented study focuses on the modelling of uncertainty in both biomass quality and availability.

Considering this, the power plant must generate sufficient electricity to meet its costumer’s demand throughout the year. Alternatively, the power plant also has the option of generating more electricity than the strictly needed and hence sell it on the open market price whenever it is profitable. Thus, and despite the decision of whether to produce the surplus amount of electricity or not, the company must determine this action in the beginning of each year and not change it throughout this period. Moreover, and taking into account the generated biomass, this depends on the type of product that is supplied, which, once received, is mixed and stored in a storage yard until combusted. Additionally, the biomass storage may have two distinctive upper limits and one lower limit, being the latter a reference point for the deterioration of biomass quality, a product property that can be highly variable.

According to the authors, and considering the goal of employing an appropriate method to model uncertainty, there were faced with problems regarding both the insufficient data concerning the probability distribution of the biomass quality, and issues concerning the dimensionally of the problem, factors to be critical to the usage of certain approaches, namely stochastic programming. Subsequently, and in order to model both uncertainties (biomass quality and availability) adequately, the authors have proposed a hybrid multi-stage stochastic programming-robust optimization model, where the biomass quality uncertainty is modelled through robust optimization, and its availability uncertainty incorporated into the hybrid approach.

Therefore, and considering the modelling of biomass's quality uncertainty, this was incorporated into the linear optimization model through the robust optimization method, where a robust solution is defined as "one that must be feasible for any realization of the uncertain parameter". Afterwards, and in order to propose the hybrid multi-stage stochastic programming-robust optimization model, the scenario tree approach has been used. Hence, the scenario tree contains four stages, where each includes three successive months. It has been also assumed that variations in biomass availability are stationary during the three months in each stage, and that each arc represents the rate of change from the average scenario in the available biomass from a given supplier in each stage. Finally, and according to the authors results, the present hybrid model has provided consistently more conservative and more stable solutions when compared to a previously studied deterministic model. Figure 19 provides the considerations and overall scheme employed by the authors in the incorporation of both robust and stochastic dynamic optimization.

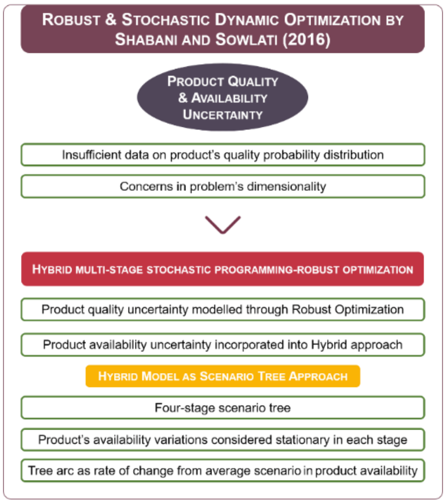

Figure 19 - Representative scheme of the employed methodology by Shabani and Sowlati (2016)

4.2. Sustainable Integrated Approaches Selection

As previously stated, when accounting for sustainability concerns, one should consider the application of integrated approaches for both environmental and social concerns, in order to better provide accurate and significant results. Thus said, the present subchapter further explores two integrated approaches proven to be appropriate for this matter, namely the Life Cycle Assessment, and the Social Life Cycle Assessment approaches, with the purpose of providing additional information, and to be latter incorporated in the model.

4.2.1. Environmental Assessment

When considering the several existing methods and frameworks available to assess the environmental impact, the LCA approach is described as the most scientifically reliable option currently available for studying and evaluating the environmental impacts of a certain product of process, allowing both retrospective and prospective assessment (Mota, Isabel, et al. 2015; Ness et al. 2007). Accordingly, LCA is an environmental impact assessment method that quantifies all relevant emissions and resources consumed, as well as the related environmental and health impacts and resource depletion issues that are associated with any goods or services. Moreover, it takes into consideration the entire life cycle of the good or service, from extraction of resources, through production, use, recycling, and disposal (Commission 2010).

According to Mota, Isabel, et al. (2015), and as depicted in Figure 20, a typical LCA method follows a generic structure, where the initial step considers the collection of the life-cycle inventory of a given good or service. Following this is the characterization step, where the environmental impact of each emitted substance or resource consumed is determined and categorized in either a midpoint and/or endpoint environmental impact category, which, in turn, correspond to the environmental mechanism itself and to the subsequent damage, respectively. This structure continues with both the normalization and weighting steps (step 3 and 4, respectively), and finishes in step 5, with the arrival at a single score.

Figure 20 - Typical structure of LCA methods (Mota, Isabel, et al. 2015)

Within the LCA approach, there are several distinctive methods available and being developed, which may use different models in the characterization step, different normalization assumptions and/or different weighting factors (Carvalho et al. 2014). However, and given the broad usage and utilization of such method in several areas, it is challenging to conclude which is more appropriate. Nonetheless, and according to Mota, Isabel, et al. (2015), the ReCiPe methodology, not only portrays a follow up of the Eco-Indicator 99 method, but also combines the CML 2002, while following the typical LCA structure provided in Figure 20. Therefore, and also considering that the European Commission defends this is the most developed methodology currently available, the authors have selected the ReCiPe methodology to assess the environmental impact in the developed study.

Thus said, and when taking a closer look at the work developed by Mota, Salema, et al. (2015), it can be noted that, by using the ReCiPe 2008, the study's supply chain as a system has been used as a functional unit in order to be compared. Hence, a Life Cycle Analysis has been performed on the products, transportation mode and entities (warehouses and factories) existent within the defined boundaries of the supply chain studied. Moreover, the Life Cycle Inventory (LCI) of each product, transportation mode and entity has been retrieved from the Ecoinvent database, which the authors have assessed through the software SimaPro 7.3.2. From this resulted an inventory list (e.g. pollutants, resources depleted) and the corresponding quantities, which have used to determine the environmental impact of each activity (production, transport and installation of entities) on each impact category. Furthermore, the resulting environmental impacts have been used as input data (parameters) to the mathematical model formulation.

Lastly, and now considering the following steps of the LCA structure presented (3,4 and 5), these have been performed within the developed function, where the obtained values of the overall impact of each activity in each category have been aggregated into a single score (*NI*) using the normalization and/or weighting factors of the ReCiPe 2008 methodology. Finally, the obtained single score has become the model's objective function, whose goal is to be minimized.

4.2.2. Social Assessment

Regarding the social pillar of sustainability, it has been concluded in chapter 3 that the overall literature's contribution does not follow an integrated approach, but only several distinctive social indicators instead. Considering the numerous advantages of using an approach of this kind, namely the holistic view of the social indicators, it is thus crucial to account for this issue and hence propose a possible method to be followed. Hence, and according to Ramos Huarachi et al. (2020), the Social Life Cycle Assessment (SLCA) is presented as the most effective technique, within the Life Cycle Sustainability Assessment (LCSA)[6], to assess the social impacts of products throughout their life cycles.

Accordingly, the SLCA is defined as an assessment technique of social and socioeconomic aspects of products and their positive and negative impacts (and potential impacts) along their entire life cycles. Moreover, it should also be noted that the ultimate objective for conducting the SLCA is to promote improvement of social conditions and of the overall socio-economic performance of a product throughout its life cycle for all of its stakeholders (Benoît et al. 2013; Ramos Huarachi et al. 2020).

Additionally, and taking into consideration the work developed by Benoît et al. (2013), the SLCA follows a similar framework as the (environmental) LCA, and is thus organized in four steps as follows:

i. **Goal and scope definition**

   In the first step of the SLCA framework, several concepts should be considered and defined. Hence, the first step is to define the goals of the study, which refer to its description, where questions such as the reason to conduct such study, its intended use, what is meant to be assessed, and who is meant to use the results, are answered. Moreover, and in order to specify

[6] Evaluation of all environmental, social, and economic negative and positive impacts in decision-making processes towards more sustainable products throughout their life cycle

the scope of the study, it should be clear that it encompasses issues of depth and breadth, where limits are placed and defined not only on the product's life cycle, but also on the detail of information to be collected and analysed.

The function of the product and the functional unit, on the other hand, represent the role of the product for its customers, and the quantified description of the performance requirements that the product system fulfils, respectively. Considering this, and in order to clearly specify the functional unit, practitioners must firstly describe the function of the product. Additionally, and so as to properly define a valuable functional unit, several steps should be considered as follows: (i) description of the product and its properties; (ii) market segmentation of the product; (iii) identification of relevant product alternatives; (iv) definition and quantification of the product's functional unit, in terms of the obligatory product properties required by the relevant market segment; and, (v) reference flow[7] determination for each of the product systems.

Other key actions to conduct in this stage refer to the determination of the activity variable to use and the unit processes to include, the planning and specifying of the data collection, and the identification of the stakeholders involved in each process, where five categories have been considered: workers, local community, society, consumers, and value chain actors.

ii. **Social Life Cycle Inventory analysis**

The second part of the framework relates to the data collection, the modelling of the systems, and the obtention of results. Thus, several actions may be considered, namely: (i) data collection (for prioritizing and screening, generic data, and hotspot assessment); (ii) main collection preparation; (iii) main data collection; (iv) impact assessment preparation for necessary data; (v) data validation; (vi) main data relation establishment to functional unit and unit process (when applicable); (vii) system's boundary refinement; and, (viii) data aggregation (when applicable).

iii. **Social Life Cycle Impact assessment**

This section aims at selecting the impact categories and subcategories and characterizing methods and models, relating the inventory data to particular subcategories and impact categories (classification), and, determining and/or calculating the results for the subcategory indicators (characterization). Hence, impact categories can be defined as logical groupings of SLCA results, related to social issues of interest to stakeholders, whereas the subcategories represent the socially relevant characteristic or attribute to be assessed (e.g., fair salary).

iv. **Social Life Cycle Interpretation**

The final stage of the framework aims at identifying significant issues, evaluate the study in hand, identify the level of engagement with stakeholders, and provide relevant conclusions, recommendations, and reporting.

Hence, the discussed assessment system is based on the identified stakeholder categories (workers, local community, society, consumers, and value chain actors), and, consequently, on the appropriate indicators, that is, subcategories, for each relevant stakeholder. Once considered all appropriate

[7] Quantified amount of product(s), including product parts, necessary for a specific product system to deliver the performance described by the functional unit

stakeholders and issues to address for the case-study in hands, the subcategories are selected from a vast list of 31 subcategories provided by Benoit-Norris (2013), where each considered indicator is carefully defined and explained (complete list available in Appendix BAppendix). Finally, once all indicators are selected, these are accounted for in the modelling of the decision-support tool.

4.3. Chapter Final Remarks

When accounting for the several challenges proposed, and taking into consideration the numerous methods for modelling uncertainty in sustainable supply chains, it is vital to apply more generalized and robust methods. Thus said, dynamic programming optimization approaches are seen as the more appropriate, not only due to their characteristics, but also due to its relative lack of usage in this field. Additionally, and among these methods, the stochastic dynamic programming approach has been selected as the optimization approach to be applied.

Accordingly, there are two distinctive approaches within the stochastic dynamic programming method: the distribution-based approach, and the scenario-based approach. Thus, and while the former is applied when a continuous range of potential future outcomes can be anticipated, the latter is applicable when the uncertainty is illustrated by a set of discrete scenarios forecasting how it might take place in the future. On that account, and given that the scenario-based technique has been selected as the most appropriate approach, two key literature articles considering this method have been carefully described as thus portrayed as proper examples to be followed in the modelling of uncertainty in sustainable supply chains.

Finally, and when accounting for sustainability concerns, the application of integrated approaches for both environmental and social concerns are crucial in order to better provide accurate and significant results. Thus, two integrated approaches, namely the Life Cycle Assessment, and the Social Life Cycle Assessment methodologies have been described and acknowledged as appropriate for this matter.

5. MODEL FORMULATION & DEVELOPMENT

The present chapter focuses on providing a solid and complete mathematical model portraying a generic sustainable supply chain under uncertainty, through its formulation and development. Hence, previously highlighted considerations, namely the uncertainty parameters incorporation, as well as the economic, environmental, and social considerations are accounted for.

This chapter is organized as follows. Section 5.1 focuses on the problem definition. In section 5.2, the mathematical formulation of the model is provided with the incorporation of crucial and previously highlighted aspects. Lastly, in section 5.3 the chapter final remarks are stated.

5.1. Problem Definition

The development and formulation of the decision-support tool for the design and planning of a sustainable supply chain under uncertainty follows the developed work accomplished by Mota et al. (2018), where the authors have proposed a decision-support tool for the design and planning of closed-loop supply chains by focusing on strategic-tactical problems. The present work models the same generic supply chain representation, which follows a four-echelon structure, as depicted in Figure 21.

Thus said, and by following the provided network structure, it becomes clear that raw materials flow from suppliers to factories in order to be transformed into final products. Production technology (i.e., process) selection is available at the factories, where each can have a maximum of one production technology allocated. Once the final products are obtained, these can either flow to warehouses or directly to markets to be sold. Concerning the inventory of final products, this is allowed at both factories and warehouses. As for the end-of-life products, these are recovered at the markets and sent back to either warehouses or directly to factories, and, once at the factories, are remanufactured and transformed once more into final products. Following the same pattern as earlier, remanufacturing technology selection is only allowed at the factories and with a maximum of one remanufacturing technology per factory. Furthermore, transhipment between warehouses is allowed, and the transportation between different entities can be performed by either unimodal or intermodal transportation, where the latter may include road, air and sea transportation options. Regarding outsourced and insourced options, the former is modelled for air and sea transportation, while the latter for road transportation. Rail transportation, on the other hand, is not explicitly modelled given its lack of presence in the case-study to be considered. Nonetheless, this option can easily be included by adding/modifying the model inputs. Moreover, hub terminals are modelled as supply chain entities since they connect and allow for the material transfer from one transportation mode to another. Concerning the three pillars of sustainability, these are introduced as objective functions, while the uncertainty often present in a sustainable supply chain is associated with parameters such as: product demand; raw materials supply; recovered products' rate of return; and, significant costs, related, for instance, to transportation and facilities construction. The boundaries for this analysis are set to only include company-internal costs, and both environmental and social impacts.

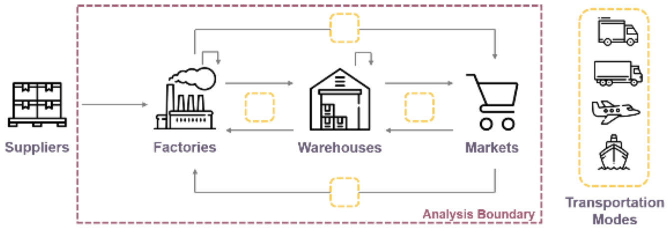

Figure 21 - Network representation (adapted from Mota et al. 2018)

Henceforth, and taking into account the provided information, the present study is focused on adding the following contributions on the defined goals set by Mota et al. (2018):

- Uncertainty consideration in parameters considered to be more critical in the design and planning of a sustainable supply chain, such as: product demand; raw materials supply; transportation and facilities construction costs; and, recovered products rate of return;
- Risk consideration in the economic objective function, so as to better portray the economic investment liability;
- Environmental assessment based on the ReCiPe 2016 LCA methodology;
- Social assessment though the incorporation of social indicators related to the contribution to economic development, equal opportunities/discrimination, and health and safety of workers.

5.2. Mathematical Formulation

As previously stated, the mathematical formulation of the proposed sustainable supply chain model under uncertainty follows the work developed by Mota et al. (2018) and further develops it in order to incorporate the stochastic dynamic programming approach so as to model the uncertainty often faced in key aspects considered to be challenges in subchapter 3.4. Hence, this incorporation is based on the main literature findings described in chapter 4, and is thus applied to product demand, raw materials supply, transportation and facilities construction costs, and, recovered products rate of return.

In order to better comprehend the multistage working logic applied in the stochastic dynamic approach, one can firstly study the simpler form of stochastic programming, that is, the two-stage stochastic programming, since it follows the same principles as the former. Henceforth, in the first-stage of the two-stage stochastic programming approach, a decision must be made before the realization of the uncertain data is clear. Hence, the optimal solution of the first-stage is fixed and only afterwards it is known which values have the uncertain parameters assumed. Subsequently, and given both the fixed solution of the first-stage and the new available data, a recourse action can be taken in the second-stage, and hence the optimal solution determined. Therefore, each possible realization of the uncertain parameters is represented by a scenario, and the overall purpose is to reach a feasible solution that minimizes the total costs, namely the sum of the first-stage costs, and the expected second-stage costs.

Having said that, the logic behind the two-stage stochastic approach can be easily extended to a multi-stage stochastic model, where, at the beginning of each stage the uncertainty is resolved, and recourse decisions and adjustments are made after the information becomes available. Hence, at the point where decisions are made, only outcomes of the current and previous stages are provided. Figure 22 schematically represents the logic behind the multi-stage stochastic programming, where the representative example of demand uncertainty is provided for better comprehension. Accordingly, at *stage 1*, the initial decision of the amount of product to produce is set, which may be challenged once *stage 2* begins and the actual demand, provided by its random variable, is known, leading to the need of having a recourse action. Hence, all random variables (e.g., demand) realized in stage *k* are fixed parameters in stage *k+1.* As for the *stage 1* random variables (e.g., demand), these are given by deterministic values.

Figure 22 - Multistage working logic

Therefore, the model uncertainty incorporation follows the stochastic programming approach through the usage of the scenario tree concept, followed by several authors and described in subchapter 4.1. As depicted in Figure 23, the scenario tree is composed of several stages t, where each does not necessarily correspond to a specific time period but instead to a time when the decision-maker updates the given information with new data. Moreover, a discrete number of nodes *e* is set at each stage of the scenario tree, and represents points in time where realizations of the uncertain parameter(s) take place and decisions are made. Finally, the scenario *s* is given by the path from the root node to a terminal node (leaf) and represents a joint realization of the problem parameters over all periods $t \in T$.

As of the uncertain parameters, these are represented by a random variable, which is estimated by a given probability distribution, and where the set Ω identifies the plausible future scenarios characterizing the uncertainty. The probability distribution to employ may be chosen considering the type of uncertain parameter and situation in study, where a wide range of probability distributions are a possibility. Additionally, $\pi_{b(e),e}$ represents the conditional probability of the random process of a given parameter in node *e* given its history and path up to ancestor node *b(e).* Hence, and from the multiplication of the conditional probabilities obtained through the path, the scenario probability is obtained.

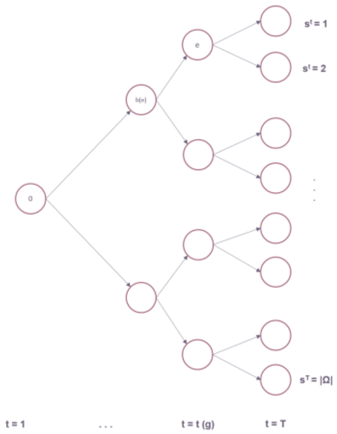

Figure 23 - Generic scenario tree representation for parameters uncertainty (adapted from Ben Mohamed et al. (2020))

Considering the above, and according to subchapter's 3.4 main conclusions, the following model formulation considers the uncertain parameters to be the demand, the supply and various supply chain's costs. Hence, these are represented by random variables estimated by probability distributions. The scenario tree concept is employed considering the time period t = 1, … ,T, with a total of *e* nodes and a set of plausible future scenarios given by *Ω*. Finally, and as required when working under the scenario logic, the non-anticipatively equations are also accounted for, in order to ensure that scenarios with a common history have the same set of decisions and that future outcomes cannot be anticipated. The complete multistage stochastic model formulation is provided and detailed in 5.2.1 as follows.

5.2.1. The Stochastic Dynamic Model Formulation

Indices and related sets

i, j	Entities or locations	$I = I_{sup} \cup I_f \cup I_w \cup I_c \cup I_{air} \cup I_{port} = I_{loc1} \cup I_{loc2} \cup \ldots$	
		I_{sup}	Suppliers
		I_f	Factories
		I_w	Warehouses
		I_c	Markets/Clients
		I_{air}	Airports
		I_{port}	Seaports
		I_{loc1} , I_{loc2}	Location 1, Location 2, …
a	Transportation Modes	$A = A_{truck} \cup A_{plane} \cup A_{ship}$	
		A_{truck}	Truck
		A_{plane}	Airplane
		A_{ship}	Ship
g	Technologies (i.e., processes)	$G = G_{prod} \cup G_{rem}$	
		G_{prod}	Production technologies
		G_{rem}	Remanufacturing Technologies
m, n	Products	$M = M_{rm} \cup M_{fp} \cup M_{rp}$	
		M_{rm}	Raw Materials
		M_{fp}	Manufactured Products
		M_{rp}	Recovered Products
t	Stages		
s	Scenarios		
γ	Investments (1 = entities, 2 = technologies, 3 = transportation)		
c	Environmental midpoint categories		
U	Allowed entity-entity connections	$U = \{(i,j) : i, j \in I\}$	
V	Allowed product-entity relations	$V = \{(m,i): m \in M \wedge i \in I\}$	
H	Product-technology pairs	$H = \{(m,g): m \in M \wedge g \in G\}$	

H_{prod} – product-technology pairs for production technologies

H_{rem} – product-technology pairs for remanufacturing technologies

F	Allowed flows of materials between entities	$F = \{(m,i,j): (m,i) \in V \wedge (i,j) \in U\}$

The description of each subset considers the given examples:

F_{INFFP} – final product (FP) that enters (IN) factories (F) and comes from entity i

F_{OUTFFP} – final product (FP) that leaves (OUT) factories (F) and goes to entity i

F_{OUTW} – allowed flows of products leaving (OUT) warehouses (W)

Net	Allowed transport modes between entities	$\mathrm{Net} = \{(a, i, j) : a \in A \wedge (i, j) \in U\}$
NetP	All allowed network	$\mathrm{NetP} = \{(a, m, i, j) : (a, i, j) \in \mathrm{Net} \wedge (m, i, j) \in F\}$

Parameters

The considered parameters are grouped by type (entity, product, technology, transportation mode, environment, stochastic, and others), as follows.

Entity related parameters

sc_{mi}^{min}	Minimum supply quantity of product m at supplier i
ec_{i}^{max}	Maximum flow capacity in entity i
ic_{mi}^{max}	Maximum inventory capacity for product m in entity i
ic_{mi}^{min}	Minimum inventory level for product m in entity i
ins_{mi}	Stock of product m in entity i in stage 1
ea_{i}^{max}	Maximum installation area of entity i
ea_{i}^{min}	Minimum installation area of entity i
hhc_{i}	Handling costs at the hub terminals
w_{i}	Workers needed when opening entity i
lc_{i}	Labour cost at location i
$wpsq_{i}$	Necessary number of workers per square meter for entity i

Product related parameters

BOM_{mn}^{f}	Bill of materials at the factory for non-transformed products
BOM_{mng}^{prod}	Production bill of materials
BOM_{mng}^{rem}	Remanufacturing bill of materials
BOM_{mn}	Bill of materials at warehouses, airports and seaports
BOM_{mn}^{recov}	Bill of materials at clients for recovered products
apu_{m}	Necessary area per unit of product m
$apur_{m}$	Necessary area per unit of product m assuming product rotation
psu_{m}	Price per sold unit of product m
rmc_{mi}	Cost of raw material m supplied by supplier i
rpc_{m}	Cost of recovered product m
pw_{m}	Weight of product m
sc_{m}	Inventory cost of product m

Technology related parameters

pc_{g}^{max}	Maximum production capacity of technology g
pc_{g}^{min}	Minimum production level of technology g

opc_g Operational costs of technology g

w_g Fixed workers per technology g

tec_g Installation cost of technology g

<u>Transportation related parameters</u>

ct_a^{max} Maximum capacity of transportation mode a

ct_a^{min} Minimum cargo to be transported by transportation mode a

cca_a^{max} Contracted capacity with airline/freighter

avs Average speed (km/h)

mhw Maximum driving hours per week

ftc_a Fixed transportation cost for transportation mode a

$invt$ Maximum investment in trucks

avc_a Average vehicle consumption (1 per 100 km)

fp Fuel price (€/l)

vmc Vehicle maintenance costs (€/km)

cfp_i Contracted payment to the airline or freighter for allocated capacity per stage and/or for hub terminal use

w_a Workers per transportation mode a for the case of road transportation. For the cases of air and sea transportations, it represents the average number of jobs created in airlines and freighters per kg km

<u>Environmental related parameters</u>

ei_{mgc} Environmental impact characterization factor of producing product m with technology g at midpoint category c (per product unit)

ei_{ac} Environmental impact characterization factor of producing product m with transportation mode a at midpoint category c (per kg km)

ei_{ic} Environmental impact characterization factor of installing entity i at midpoint category c (per square meter)

η_c Normalization factor for midpoint category c

<u>Social related parameters</u>

wed Importance weight of social impact indicator related to the contribution to economic development subcategory

wgr Importance weight of social impact indicator related to the equal opportunities/discrimination subcategory through the wage level between genders

$wacc$ Importance weight of social impact indicator related to the health and safety of workers subcategory through the number of accidents occurred

si_{min}^{ed} Minimum possible value of social impact related to the contribution to economic development subcategory

si_{max}^{ed} Maximum possible value of social impact related to the contribution to economic development subcategory

si_{min}^{gr} Minimum possible value of social impact related to the equal opportunities subcategory

si_{max}^{gr} Maximum possible value of social impact related to the equal opportunities subcategory

si_{min}^{acc} Minimum possible value of social impact related to the health and safety subcategory

si_{max}^{gr} Maximum possible value of social impact related to the health and safety subcategory

ev_i Economic value of entity i

rd_i Regional development level at location i

faw_i Average female wage in entity i

maw_i Average male wage in entity i

ra_i Number of accidents reported in entity i

ce_i Contribution factor of entity i to the supply chain

fsc_i Contribution of entity i to the supply chain

tfv_i Total value of entity i in the supply chain

Stochastic parameters

sc_{mis}^{max} Maximum supply capacity for product m by supplier i under scenario s

$sqmc_{is}$ Construction cost of entity i per square meter under scenario s

dmd_{mits} Demand of product m by client i in stage t under scenario s

$retF_{ms}$ Minimum return fraction of end-of-life products under scenario s

tc_{as} Variable transportation cost of transportation mode a per kg.km under scenario s

ρ_s Probability of occurrence of scenario s, where $\sum_{s\in S} \rho_s = 1$

Others

d_{ij} Distance between entities i and j (km)

$BigM$ Large number

wpt Number of weeks per stage

wwh Weekly working hours

ir Interest rate

sv_γ Percentage salvage value of investment γ

tr Tax rate

∂ Cash flow certainty estimation percentage

Decision Variables

Continuous variables

S_{mits} Amount of inventory of product m in entity i in stage t under scenario s

P_{mgits} Amount of product m produced with technology g at entity i in stage t under scenario s

R_{mgits} Amount of product m remanufactured with technology g at entity i in stage t under scenario s

X_{maijts} Amount of product m transported by transportation mode a from entity i to entity j in stage t under scenario s

YC_i Capacity of entity i

YCT_{its} Used capacity in entity i in stage t under scenario s

K_{aits}	Upper bound for the number of transportation mode a leaving entity i in stage t under scenario s

Integer variables

K_{ai}	Number of transportation modes in entity i
Q_{aijts}	Number of trips with transportation mode a between entities i and j in stage t under scenario s

Binary variables

Y_i	= 1 if entity i is installed
Z_{gmi}	= 1 if technology g that produces product m is installed in entity i

Auxiliary variables at objective functions

$rNPV$	Risk-adjusted net present value
CF_{ts}	Cash flow in stage t under scenario s
NE_{ts}	Net earnings in stage t under scenario s
FCI_{γ}	Fixed capital investment of investment γ
DP_t	Depreciation of the capital at stage t
si_{nor}^{ed}	Normalized value of social impact related to the contribution to economic development subcategory
si_{nor}^{gr}	Normalized value of social impact related to the equal opportunities subcategory
si_{nor}^{acc}	Normalized value of social impact related to the health and safety subcategory
$EnvImpact$	Environmental impact indicator
$SocBenefit$	Social impact indicator

Constraints

In order to better comprehend the applied constraints, these are grouped into five categories, namely: material balances; entity capacity; transportation; technology; and, non-anticipatively. These are thus defined and characterized as follows.

Material Balances

Material balance at the factories:

$$S_{mi(t-1)s} + \sum_{g:(m,g)\in H_{prod}} P_{mgits} + \sum_{g:(m,g)\in H_{rem}} R_{mgits} = S_{mits} + \sum_{\substack{n,j:(n,i,j)\in F_{OUTFFP} \\ a:(a,n,i,j)\in NetP}} BOM_{mn}^{f} X_{naijts}, t \in T \wedge m \in M_{fp} \wedge i \in I_f \wedge s \in S$$

(2)

$$\sum_{\substack{j\in I_{sup} \\ a:(a,m,j,i)\in NetP}} X_{majits} = \sum_{(n,g)\in H_{prod}} BOM_{mng}^{prod} P_{ngits}, m \in M_{rm} \wedge i \in I_f \wedge t \in T \wedge s \in S$$

(3)

$$\sum_{\substack{j:(m,j,i)\in F_{INFRP} \\ a:(a,m,j,i)\in NetP}} X_{maijts} = \sum_{(n,g)\in H_{rem}} BOM_{mng}^{rem} R_{ngits}, m \in M_{rp} \wedge i \in I_f \wedge t \in T \wedge s \in S$$

(4)

Material balance at the warehouses:

$$S_{mi(t-1)s} + \sum_{\substack{n,j:(n,j,i)\in F_{INW} \\ a:(a,n,j,i)\in NetP}} BOM_{mn} X_{najits} = S_{mits} + \sum_{\substack{n,j:(n,i,j)\in F_{OUTW} \\ a:(a,n,i,j)\in NetP}} BOM_{mn} X_{naijts}, t \in T \wedge \in \left(M_{fp} \cup M_{rp}\right) \wedge i \in I_w \wedge \ s \in S$$

(5)

Cross-docking at the airports:

$$\sum_{\substack{n,j:(n,j,i)\in F_{INAIR} \\ a:(a,n,j,i)\in NetP}} BOM_{mn} X_{najits} = \sum_{\substack{n,j:(n,i,j)\in F_{OUTAIR} \\ a:(a,n,i,j)\in NetP}} BOM_{mn} X_{naijts}, \ \ m \in (M_{fp} \cup M_{rp}) \ \wedge i \in I_{air} \ \wedge t \ \in T \wedge \ s \in S$$

(6)

Cross-docking at the seaports:

$$\sum_{\substack{n,j:(n,j,i)\in F_{INPORT} \\ a:(a,n,j,i)\in NetP}} BOM_{mn} X_{najits} = \sum_{\substack{n,j:(n,i,j)\in F_{OUTPORT} \\ a:(a,n,i,j)\in NetP}} BOM_{mn} X_{naijts}, \ \ m \in (M_{fp} \cup M_{rp}) \ \wedge i \in I_{port} \ \wedge t \in T \wedge \ s \in S$$

(7)

Demand and return at the markets:

$$\sum_{\substack{j:(m,i,j)\in F_{INCFP} \\ a:(a,m,j,i)\in NetP}} X_{majits} = \ dmd_{mits}, \qquad i \in I_c \ \wedge t \ \in T \wedge \ s \in S$$

(8)

$$\sum_{\substack{j:(m,i,j)\in F_{INCFP} \\ a:(a,m,,i,j)\in NetP}} X_{majits} \geq \ retF_{ms} \sum_{\substack{n,j:(n,j,i)\in F_{INCFP} \\ a:(a,n,j,i)\in NetP}} BOM_{mn}^{recov} X_{maji(t-1)s}\,, \qquad t > 1 \wedge m \in M_{rp} \ \wedge \ i \in I_c \wedge \ s \in S$$

(9)

$$\sum_{\substack{j:(m,i,j)\in F_{OUTCRP} \\ a:(a,m,i,j)\in NetP}} X_{majits} \leq \sum_{\substack{n,j:(n,j,i)\in F_{INCFP} \\ a:(a,n,j,i)\in NetP}} BOM_{mn}^{recov} X_{maji(t-1)s}\,, \qquad t > 1 \wedge m \in M_{rp} \ \wedge \ i \in I_c \wedge \ s \in S$$

(10)

Considering the constraints above, and according to Mota et al. (2018), constraint (2) models the material balance constraints at factories during each time unit. Hence, it assures that the existing stock of final products (first term of the equation) plus the new and remanufactured products (second and third equation terms, respectively) must equal the amount kept in stock plus the outgoing product flow. For sake of simplicity, the authors have not included this constraint for the first stage, and thus, when t = 1, the variable $S_{mi\,(t\,-\,1)}$ should be replaced by parameter ins_{mi}, the initial stock of product *m* in entity *i.*

Additionally, both production and remanufacturing operations are taken into consideration by constraints (3) and (4), respectively. Hence, while the former sets the necessary amount of raw materials to be sent by suppliers, the latter relates to all ingoing flows of recovered products to the factory.

On another note, the warehouse balance is assured by equation (5), where products kept in stock at the previous time unit plus the inbound flows must equal the current stock volume plus the outbound flows. As of the material balance constraints at factories, and considering the first stage (t = 1), the variable $S_{mi\,(t-1)}$ should be replaced by parameter ins_{mi}.

Furthermore, airports and seaports operate in a cross-docking mode, where the stocks amounts are not made available at these sites. Considering equations (6) and (7), these ensure that, for each product and time unit, the inbound flow at each location equals the outbound flow.

As of the demand at markets, this must be totally satisfied, as staged through constraint (8). Additionally, the present model assumes that products have a usage period of a time unit, leading to having no returns available at stage t = 1. This is reflected in constraint (9), where the return amount is at least a fraction of the volume supplied in the previous time unit, and at most the quantity delivered to the markets, as provided in equation (10).

<u>Entity capacity constraints</u>

Supply capacity:

$$\sum_{\substack{a,j:(a,m,i,j)\in NetP \\ (m,i,j)\in F_{OUTSUP}}} X_{maijts} \le sc_{mis}^{max} Y_i, \qquad i \in I_{sup} \wedge m \in M_{fp} \wedge t \in T \wedge s \in S \tag{11}$$

$$\sum_{\substack{a,j:(a,m,i,j)\in NetP \\ (m,i,j)\in F_{OUTSUP}}} X_{maijts} \ge sc_{mi}^{min} Y_i, \qquad i \in I_{sup} \wedge m \in M_{fp} \wedge t \in T \wedge s \in S \tag{12}$$

Flow capacity:

$$\sum_{a,m,j:(a,m,i,j)\in NetP} X_{maijts} \le ec_i^{max} Y_i, \qquad i \in I \wedge t \in T \wedge s \in S \tag{13}$$

$$\sum_{a,m,j:(a,m,i,j)\in NetP} X_{maijts} \le ec_j^{max} Y_j, \qquad j \in I \wedge t \in T \wedge s \in S \tag{14}$$

Stock capacity:

$$S_{mits} \le ic_{mi}^{max} Y_i, \qquad m \in M_{fp} \wedge i \in (I_f \cup I_w) \wedge t \in T \wedge s \in S \tag{15}$$

$$S_{mits} \ge ic_{mi}^{min} Y_i, \qquad m \in M_{fp} \wedge i \in (I_f \cup I_w) \wedge t \in T \wedge s \in S \tag{16}$$

Entity capacity:

$$YCT_{its} = \sum_{m,a,j:(m,a,j)\in NetP} apur_m X_{majits} + \sum_{m:(m,i)\in V} apu_m S_{mits} \ , \qquad i \in (I_f \cup I_w) \ \wedge \ t \ \in T \wedge \ s \in S \tag{17}$$

$$YC_i \geq YCT_{its} \ , \qquad i \in (I_f \cup I_w) \wedge \ s \in S \tag{18}$$

$$YC_i \leq ea_i^{max} Y_i \ , \qquad i \in (I_f \cup I_w) \tag{19}$$

$$YC_i \geq ea_i^{min} Y_i \ , \qquad i \in (I_f \cup I_w) \tag{20}$$

Entity existence constraints:

$$\sum_{a,m,i,t:(a,m,i,j)\in NetP} X_{maijts} \ \geq Y_j, \qquad j \in I \ \wedge \ t \ \in T \wedge \ s \in S \tag{21}$$

$$\sum_{a,m,i,t:(a,m,i,j)\in NetP} X_{maijts} \ \geq Y_i, \qquad i \in I \ \wedge \ t \ \in T \wedge \ s \in S \tag{22}$$

Constraints (11) – (20) set capacity limits, namely: maximum and minimum supply of raw materials (equations (11) and (12) and; flow amounts between each pair of entities in the network (constraints (13) and (14)); and, minimum and maximum stock capacity at factories and warehouses (equations (15) and (16)). Considering this, it should also be noted that these constraints ensure the related variables can only differ from zero if the facilities integrate the supply chain, that is, when $Y_i = 1$.

Moreover, and while the above entities capacities are pre-established, the installation area of warehouses and factories is modelled differently. Thus said, and considering these two facilities, capacities are matter of decisions. Hence, with equation (17), the capacity required at each time unit at each facility is determined by ensuring that it is sufficient to accommodate the incoming flow and the current stock levels. Constraint (18) on the other hand, sets the maximum capacity needed over the time horizon. Considering this, it should be noted that, and according to Mota et al. (2018), the authors have followed a minmax approach, since variable YC_i is minimized at the economic objective function (addressed below). As of the equations (19) and (20), these limit the installation area at each location, with a maximum and minimum, respectively.

Additionally, an in order to guarantee that entities are only installed if there is material flow going through them, constraints (21) and (22) have been included in the model, which can also be portrayed as minimum flow constraints. Finally, for such an extension, one should define the minimum flow parameter, which should be multiplied to variable Y_i (similarly to constraint (14)).

<u>Transportation constraints:</u>

Physical constraints:

$$\sum_{\substack{a,j(a,m,j,i)\in NetP \\ j\in I\setminus(I_{air}\cup I_{sup})}} X_{majits} \ \geq \sum_{\substack{a,j(a,m,i,j)\in NetP \\ j\in I_{air}}} X_{maijts} \ , \qquad m \in (M_{fp} \cup M_{rp}) \wedge i \in I_{air} \ \wedge \ t \ \in T \wedge \ s \in S$$

(23)

$$\sum_{\substack{a,j(a,m,j,i)\in NetP \\ j\in I\setminus(I_{port}\cup I_{sup})}} X_{majits} = \sum_{\substack{a,j(a,m,i,j)\in NetP \\ j\in I_{port}}} X_{maijt}, \qquad m \in (M_{fp} \cup M_{rp}) \wedge i \in I_{port} \wedge t \in T \wedge s \in S$$

(24)

Necessary number of trips:

$$\sum_{m:(a,m,i,j)\in NetP} X_{maijts} \leq ct_a^{max} Q_{aijts}, \qquad (a,i,j) \in Net \wedge t \in T \wedge s \in S$$

(25)

$$\sum_{m:(a,m,i,j)\in NetP} X_{maijts} \geq ct_a^{min} Q_{aijts}, \qquad (a,i,j) \in Net \wedge t \in T \wedge s \in S$$

(26)

$$Q_{aijts} \leq BigM.Y_i, \qquad (a,i,j) \in Net \wedge t \in T \wedge s \in S$$

(27)

$$Q_{aijts} \leq BigM.Y_j, \qquad (a,i,j) \in Net \wedge t \in T \wedge s \in S$$

(28)

Contracted capacity with air and sea carrier:

$$\sum_{m:(a,m,i,j)\in NetP} X_{maijts} \leq cca_a^{max}, \qquad (a,i,j) \in Net \wedge a \in (A_{plane} \cup A_{boat}) \wedge t \in T \wedge s \in S$$

(29)

Necessary number of transportation modes:

$$KT_{ait} = \frac{\sum_j 2.d_{ij} Q_{aijts}}{avs.mhw.wpt}, \qquad (a,i,j) \in Net \wedge a \in A_{truck} \wedge t \in T \wedge s \in S$$

(30)

$$KT_{ai} \geq KT_{aits}, \qquad a \in A_{truck} \wedge i \in I \wedge t \in T \wedge s \in S$$

(31)

$$\sum_{\substack{a:\, a\in A_{truck} \\ i:\, i\in I}} ftc_a K_{ai} \leq invt$$

(32)

$$K_{ai} \leq BigM.Y_i, \qquad a \in A_{truck} \wedge i \in I$$

(33)

$$K_{ai} \leq BigM. \sum_{\substack{m,j:(a,m,i,j)\in NetP \\ t\in T}} X_{maijts}, \qquad a \in A_{truck} \wedge i \in I \wedge s \in S$$

(34)

Considering the above, constraints (23) and (24) state that the material flow entering an airport/seaport, respectively must be transported by plane/boat to another airport/seaport, respectively. Furthermore, the network superstructure, established when defining the provided sets, ensures that intercontinental trips can only make use of air or sea transportation.

Furthermore, through constraint (25) it is ensured that the number of trips between entities times the capacity of the corresponding transportation mode is larger than the flow between entities. Additionally, equation (26) imposes minimum cargo in each transportation mode.

On another note, constraints (27) and (28) assure that variable Q_{aijt} is only activated if both the entities of origin and destination are installed, respectively.

Considering equation (29), this establishes that the transportation performed by either air or sea in each stage is limited by a contracted capacity with the airline or freighter, respectively.

Additionally, constraint (30) defines an upper bound for the number of trucks in each entity of origin in each stage, K_{ait}. In the model, each truck is assumed to be assigned to one truck driver. Therefore, trucks must be enough to obey the European Union Rules on Driving Hours, which state that an average maximum of 45 h per week is allowed. The denominator of the equation, on the other hand, reflects the number of kilometres that are actually travelled per stage, having as starting point entity *i* and considering that trucks must return to the entity of origin. Similarly to the definition of the entities' capacities, equation (31) defines the number of trucks necessary in each stage over the time horizon. Moreover, and following the same pattern as in entities capacities, the minmax approach has been followed in order to model the number of workers allocated to transportation activities. Constraint (32) on the other hand, imposed a maximum investment in road transportation, defined by the company decision makers. Finally, and while constraint (33) ensures trucks are only purchased if the entity of origin is installed, equation (34) guaranties trucks are only purchased if there is flow to be transported with those same trucks.

<u>Technology constraints:</u>

Technology capacity:

$$P_{mgits} \leq pc_g^{max} Z_{gmi}, \qquad i \in I_f \wedge (m,g) \in H_{prod} \wedge t \in T \wedge \ s \in S \tag{35}$$

$$R_{mgits} \leq pc_g^{max} Z_{gmi}, \qquad i \in I_f \wedge (m,g) \in H_{rem} \wedge t \in T \wedge \ s \in S \tag{36}$$

$$P_{mgits} \geq pc_g^{min} Z_{gmi}, \qquad i \in I_f \wedge (m,g) \in H_{prod} \wedge t \in T \wedge \ s \in S \tag{37}$$

$$R_{mgits} \geq pc_g^{min} Z_{gmi}, \qquad i \in I_f \wedge (m,g) \in H_{rem} \wedge t \in T \wedge \ s \in S \tag{38}$$

Technology installation:

$$\sum_{g:(m,g)\in H_{prod}} Z_{gmi} \leq Y_i, \qquad m \in M_{fp} \wedge i \in I_f \tag{39}$$

$$\sum_{g:(m,g)\in H_{rem}} Z_{gmi} \leq Y_i, \qquad m \in M_{fp} \wedge i \in I_f \tag{40}$$

Equations (35) – (40) represent the technology constraints. Particularly, equations (35) and (36) model production and remanufacturing maximum capacity, respectively, while constraints (37) and (38) impose minimum production levels in each stage. Additionally, they also ensure that, if the technology is not established (Z_{mgi} = 0), the corresponding manufacturing and remanufacturing volumes are set to zero. Consequently, at most one technology can be allocated to open facilities (when Y_i = 1), for both production and remanufacturing technologies, as stated in equations (39) and (40). It should also be noted that different technologies, i.e., production/remanufacturing processes, can differ in the number of necessary workers to operate them, production/remanufacturing capacity, environmental impact, and involved costs.

Non-anticipatively constraints:

$$S_{mits} = S_{mits'}\,, P_{mgits} = P_{mgits'}\,, R_{mgits} = R_{mgits'}\,, X_{maijts} = X_{maijts'}\,, YCT_{its} = YCT_{its'}\,,$$
$$K_{aits} = K_{aits'}\,, Q_{aijts} = Q_{aijts'}\,,$$

$$m \in M, \quad i,j \in I, \quad g \in G, \quad a \in A, \quad t \in T \quad \wedge \quad s,s' \in S\, x\, (s \neq s') \tag{41}$$

$$P_{mgits}\,, R_{mgits}\,, X_{maijts}\,, S_{mits}\,, YC_i\,, YCT_{its}\,, KT_{aits} \geq 0$$
$$K_{ai}\,, Q_{aijts} \geq 0 \; and\ integer$$
$$Y_i\,, Z_{gmi} \in \{0,1\} \tag{42}$$

Equation (41) represents the non-anticipatively constraints of the stochastic dynamic model, necessary when modelling under the multistage concept, by ensuring that scenarios with a common history must have the same set of decisions and that future outcomes cannot be anticipated. Lastly, the decision variables domains are provided in constraint (42).

Objective Functions

Economic Objective Function

The economic objective function provided in equation (43) is obtained through the maximization of the expected risk-adjusted NPV (rNPV) of all scenarios considered. Hence, and through this adaptation of the commonly applied NPV, the rNPV accounts for the associated economic risk often present on future cash flows associated with the design and planning of a sustainable supply chain, thus leading to an extended work of Mota et al. (2018)'s findings.

$$max\ rNPV = \sum_s \rho_s \left(\sum_{t \in T} \frac{CF_{ts} . \partial}{(1 + ir)^t} - \sum_\gamma FCI_\gamma \right) \tag{43}$$

$$CF_{ts} = \begin{cases} NE_{ts}\,, & t = 1, \dots, NT-1 \wedge s \in S \\ NE_{ts} + \sum_\gamma \left(sv_\gamma FCI_\gamma\right), & t = NT \wedge s \in S \end{cases} \tag{44}$$

$$
\begin{aligned}
NE_{ts} = (1 - tr) \Bigg[& \sum_{\substack{(m,i,j) \in F_{INCFP} \\ (a,m,i,j) \in NetP}} psu_m X_{maijts} \\
& - \Bigg(\sum_{\substack{(m,i,j) \in F_{OUTSUPRM} \\ (a,m,i,j) \in NetP}} rmc_{mi} X_{maijts} + \sum_{\substack{(m,g) \in H_{prod} \\ i \in I_f}} opc_g P_{mgits} \\
& + \sum_{\substack{(m,i,j) \in F_{OUTCRP} \\ (a,m,i,j) \in NetP}} rpc_m X_{maijts} + \sum_{\substack{(m,g) \in H_{rem} \\ i \in I_f}} opc_g R_{mgits} \\
& + \sum_{\substack{(a,m,i,j) \in NetP \\ a \in A_{truck}}} \left(\frac{avc_a}{100} fp + vcm \right) . 2 d_{ij} Q_{aijts} + \sum_{\substack{(a,m,i,j) \in NetP \\ a \in (A_{plane} \cup A_{boat})}} tc_{as} . pw_m . d_{ij} . X_{maijts} \\
& + \sum_{\substack{(a,m,i,j) \in NetP \\ (j \in I_{air} \wedge i \notin I_{air}) \cup (j \in I_{port} \wedge i \notin I_{port})}} hhc_j . X_{maijts} + \sum_{i \in I_{air} \cup I_{boat}} cfp_i . Y_i \\
& + \sum_{(m,i) \in V} sc_m S_{mits} + \sum_{i \in I_f \cup I_w} w_i . lc_i . wwh . wpt . Y_i + \sum_{i \in I_f \cup I_w} wpsq . lc_i . wwh . wpt . YC_i \\
& + \sum_{\substack{(m,g) \in H \\ i \in I_f}} w_g . lc_i . wwh . wpt . Z_{mgi} + \sum_{\substack{i \in I \\ a \in A_{truck}}} w_a . lc_i . wwh . wpt . K_{ai} \Bigg) \Bigg] + tr . DP_t
\end{aligned}
\tag{45}
$$

$$
DP_t = \sum_{\gamma} DP_{\gamma t} FCI_{\gamma} \tag{46}
$$

$$
FCI_{\gamma} = \begin{cases} \sum_{i \in I_f \cup I_w} sqmc_{is} . YC_i \,, & \gamma = 1 \\ \sum_{\substack{(m,g) \in H \\ i \in I_f}} tec_g Z_{gmi} \,, & \gamma = 2 \\ \sum_{\substack{(a,i,j) \in Net \\ a \in A_{truck}}} ftca_a . K_{ai} \,, & \gamma = 3 \end{cases} \tag{47}
$$

According to equation (43), the risk-adjusted Net Present Value (rNPV) is calculated similarly to the commonly applied NPV, being the only difference the parameter ∂, which represents the cash flow certainty estimation percentage, that is, the certainty level in reaching expected future cash flows, calculated as the ratio of the current risk meditated and the risk meditated after several stages t have passed with success (Stewart, Allison, and Johnson 2001). Hence, and considering the typical NPV formula, the remaining represents the sum of the discounted cash flows of each stage, at interest rate ir. Thus, and in order to obtain the necessary data, auxiliary equations have been considered, namely equation (44), which represents the cash flow calculation for each stage, obtained through the net earnings, NE_{ts} for every stage excluding the final one, where the recovery of the salvage value, sv_{γ}, of each type of investment, FCI_{γ}, is also accounted for. Additionally, the net earnings for each stage are considered in equation (45), and thus obtained through the difference between incomes and overall costs, where the former is represented by the amount of products sold times the price per unit, psu_m, and the latter by the following cost considerations:

- raw material costs (first term) – amount of products purchased from suppliers times the unit raw material cost, rmc_m;
- operating production costs (second term) – amount of final products produced, P_{mgits}, times the unitary operating costs of each available production technology, opc_g;
- product recovery costs (third term) – amount of end-of-life products recovered from clients times the unit recovered product cost, rpc_m;
- remanufacturing operating costs (fourth term) – amount of final products obtained through remanufacturing, R_{mgits}, times the unitary operating costs of each available remanufacturing technology, opc_g;
- transportation costs for road transportation (fifth term) – number of trips between entities, Q_{aijts}, times twice the distance travelled, $2d_{ij}$, in order to account for the round trip, times the transportation cost per km, given by the vehicle average fuel consumption, avc_a, the fuel price, fp, and the vehicle maintenance costs, vmc;
- transportation costs for air and sea transportation (sixth term) – flow of products transported through transportation mode *a*, X_{maijts}, times the transportation cost per kg.km, tc_a, times the weight of each unit of product transported, pw_m, times the distance travelled, d_{ij};
- hub terminal handling costs (seventh term) – flow of products through hub terminals at the airports/seaports times the unit handling costs at such terminals, hhc;
- airline/freighter contracted costs (eight term) – contracted costs with the airliner/freighter, cfp_i, for the allocated transportation capacity and/or for hub terminal use per stage, assuming that a contract is established with companies operating at hub terminals;
- inventory costs (ninth term) – amount of product in stock, S_{mits}, times the unitary stock cost, sc_m;
- labour costs at entities (tenth and eleventh terms), labour costs for production and remanufacturing technologies (twelfth term), and labour costs for owned transportation modes, namely road transportation (thirteenth term) – varying costs according to the fixed (w_i) and variable ($wpsq$) number of workers necessary at each entity, the number of workers required for each technology (w_g), and to the number of workers per transportation mode (w_a), respectively. Additionally, the labour cost at each location, lc_i, the weekly working hours, wwh, and the number of weeks per stage, wpt, are also considered in these calculations.

As of the final term of equation (45), it describes the depreciation of the invested capital, DP_{ts}, with the tax rate represented by tr. Subsequently, the depreciation is calculated for each type of investment considered, γ, as represented in equation (46).

Finally, the fixed capital investment, FCI, is described in equation (47) and thus obtained considering the following terms:

- facilities investment (first term) – necessary installation area, YC_i , times the varying construction costs, which depend on the facilities' locations, $sqmc_i$;
- technologies investment (second term) – number of installed technologies times the installation cost of each technology, tec_g;
- transportation links investment (third term) – fixed investment in road transportation, ftc_a, assuming the company's fleet purchase.

Environmental Objective Function

The environmental objective function is obtained through the minimization of the environmental impact represented in equation (48), and modelled by the ReCiPe methodology, thus following the work developed by Mota et al. (2018), and according to subchapter 4.2's main findings. Therefore, and as the functional unit is the supply chain, the aggregated obtained results should only be used to compare distinctive supply chain designs and decisions and not as a tool to accurately determine the environmental impact of the supply chain.

$$min\ EnvImpact\ = \sum_{s} \rho_s \left(\sum_{c} \eta_c \left(\sum_{\substack{t \in T, i \in I_f \\ (m,g) \in H}} ei_{mgc}.pw_m.\left(P_{mgits} + R_{mgits}\right) + \sum_{\substack{t \in T \\ (a,m,i,j) \in NetP}} ei_{ac}.pw_m.d_{ij}.X_{maijts} + \sum_{i \in I_f \cup I_w} ei_{ic}.YC_i \right) \right) \tag{48}$$

Thus, and according to equation (48), the environmental impact of four supply chain activities is calculated for each midpoint category *c,* namely:

- production and remanufacturing environmental impact (first term) – environmental impact per kg produced of remanufactured with technology *g,* ei_{mgc}, times the weight of product *m* times the amount of final products produced, P_{mgits}, or remanufactured, R_{mgits};
- transportation environmental impact (second term) – environmental impact per kg.km transported with transportation mode *a,* ei_{ac} , times the weight of each unit of product transported, pw_m, times the distance travelled, d_{ij}, times the product flow, X_{maijts};
- entity installation environmental impact (third term) – environmental impact per square meter of entity *i* installed, ei_{ic}, times the installed area, YC_i.

Social Objective Function

The social objective function takes into consideration the main findings described in subchapter 4.2, through the application of the SLCA, the indicators (i.e., subcategories) defined and proposed by Benoit-Norris (2013) (Appendix B), and a critical analysis on the relevance of each for the social assessment. Thus, this social analysis can easily be extended to any other studying focus, by adding and adapting the most appropriate indicators for the case, while considering the list provided of well-defined subcategories, as well as the necessary data collection and viability for each.

Considering this, and following the described steps to conduct a proper SLCA, the goal of the present social study is to provide the sustainable supply chain model formulation with a proper mechanism to evaluate the social pillar while applying an adequate methodology that, even though is yet to be fully developed, can bring great importance to the model. Hence, three subcategories have been selected for this analysis and thus concern two distinctive stakeholders: (i) stakeholder *workers,* with focus on both equal opportunities/discrimination, and health and safety indicators; and, (ii) stakeholder *society*, with the incorporation of the contribution to economic development subcategory.

The choice of each subcategory indicated highly focuses on the indicators overall relevance in any sustainable supply chain evaluation. Saying this, today's society heavily struggles to fight discrimination, namely gender discrimination, an issue still present worldwide, even in the most developed countries (United Nations Developments Report 2018). Thus, the wage level between genders ratio has been selected as the most appropriate indicator to use to evaluate this problem, since it better portrays the discrepancy between both genders. Additionally, the health and safety of workers has also been selected as a relevant social problem to analyse, through the occurred number of injuries and accidents. This choice of analysis aims to appropriately study the workers safety, and whether or not companies are taking every measure to ensure it, given that large amounts of accidents may be a signal of poor safety concerns. Finally, the contribution to the economic development indicator intents to acknowledge the positive impact of establishing entities in certain areas and countries, and consequently, on the inhabitants of such region.

Therefore, the above-mentioned subcategories are incorporated into one social objective function, obtained through the maximization of the social benefit, as represented in equation (49).

$$
\begin{aligned}
max\ SocBenefit\ &= \sum_{s} \rho_s \left(wed\,.\,si_{nor}^{ed} + \mathrm{wgr}\,.\,si_{nor}^{gr} - wacc\,.\,si_{nor}^{acc} \right) \\
&= \sum_{s} \rho_s \left(wed\,.\ \frac{\sum_{\mathrm{i}\,\in\, I_f \cup I_w} \frac{\mathrm{fsc_i}}{\mathrm{tfv_i}} ev_i (1 - rd_i).Y_i\ - si_{min}^{ed}}{si_{max}^{ed} - si_{min}^{ed}} \right. \\
&\left. + \ wgr\,.\ \frac{\sum_{\mathrm{i}\,\in\, I_f \cup I_w} ce_i.\frac{faw_i}{maw_i}.Y_i\ - si_{min}^{gr}}{si_{max}^{gr} - si_{min}^{gr}} + wacc\,.\frac{si_{max}^{acc} - \sum_{\mathrm{i}\,\in\, I_f \cup I_w} \frac{\mathrm{fsc_i}}{\mathrm{tfv_i}} \mathrm{ra_i}.Y_i}{si_{max}^{acc} - si_{min}^{acc}} \right)
\end{aligned} \tag{49}
$$

Hence, and according to equation (49), the social benefit is calculated taking into account the following subcategories and subsequent developed indicators:

- contribution to economic development (first term) – aggregation factor of each entity i, $\frac{\mathrm{fsc_i}}{\mathrm{tfv_i}}$, times the difference between the economic value of each entity (€), ev_i, and the economic value of each entity times the regional development level of the corresponding area, rd_i;
- equal opportunities/discrimination (second term) – measured through the wage level between genders ratio, calculated by the multiplication of the contribution factor of each entity, ce_i, with the ratio of the female average wage (€), faw_i, and the male average wage (€), maw_i, per entity i;

- health and safety of workers (third term) – measured through the number of injuries and accidents, obtained by the aggregation factor of each entity i, $\frac{\mathrm{fsc_i}}{\mathrm{tfv_i}}$, times the number of accidents reported per location i, $\mathrm{ra_i}$.

Considering the above, and in order to distinct both the positive and negative impacts of each indicator considered, different signals have been assigned to the different subcategories chosen. Thus, while both the contribution to economic development, and the equal opportunities/discrimination indicators have been considered in the equation with a plus signal ("+"), in order to have the highest value for each as possible, the health and safety of workers subcategory has been given a minus signal ("-"), so as to minimize the number of accidents in the workplace.

Moreover, it is clear all indicators have been multiplied by either an aggregation factor, $\frac{\mathrm{fsc_i}}{\mathrm{tfv_i}}$, or by a contribution factor, ce_i. According to Popovic et al. (2018), these are necessary so as to relate the obtained value of the indicator to the actual size and impact of each entity in the overall network. Thus, the aggregation factor represents the ratio between the entity's contribution to the supply chain, $\mathrm{fsc_i}$, (e.g.: production volume, turnover) and the overall total value in such entity, $\mathrm{tfv_i}$, (e.g.: total production, turnover). The contribution factor, ce_i, on the other hand, are commonly determined by the entity itself, however, some other possibilities rely on the turnover that the supply chain entity makes to the overall supply chain (Schöggl, Fritz, and Baumgartner 2016).

On another note, one should notice that all three social indicators have been incorporated into one single social objective function. This choice, over the possibility of studying each indicator separately, aims to tackle several issues, being one of them the avoidance of having one social network for each indicator. Hence, instead of having, in this case, three separate social networks, only one overall social network is given, thus preventing the decision-maker to ultimately having to choose one social network, related to one specific indicator, over the remaining ones, upon having to evaluate all three objective functions (economic, environmental, and social) together, since there is not an entirely logical or unbiased answer for such decision. Moreover, another valid point that lead into the development of one overall social objective function is aligned with the goal of having a properly designed SLCA closest to the LCA methodology as much as possible. Hence, and given that the original LCA seeks for a single-score for the environmental impact assessment, it is correct to have the social LCA following the same line of thought and hence having a single-score solution to properly evaluate the social pillar of sustainability.

Therefore, in order to do so, and aligned with step three of the LCA methodology, all social indicators must be normalized, that is, having their originally obtained value translated into a new value, so as to, instead of having incompatible and distinctive types of values, one can have a common range for all. In order to do so, the decision-maker must have sufficient knowledge concerning the minimum, si^*_{min}, and maximum, si^*_{max}, values each indicator can reach within their company. Thus, the normalization of each indicator follows the below mentioned expressions, used when minimization and maximization are desired, respectively (Ghaderi et al. 2018; Pishvaee, Razmi, and Torabi 2014):

- $si^*_{nor} = \frac{si^* - si^*_{min}}{si^*_{max} - si^*_{min}}$;

- $si_{nor}^{*} = \frac{si_{max}^{*} - si^{*}}{si_{max}^{*} - si_{min}^{*}}$.

Finally, once all indicators have been normalized, weights are assigned according to step four of the LCA methodology. Therefore, and considering equation (49), these are multiplied with each corresponding normalized social impact value obtained. However, and even though this is a logical step to follow in order to consider the impact of each indicator differently, depending on its core and importance, it should be noted that, as of today, all weighting values are to be assigned by the decision-maker according to their beliefs and common sense, which may, at times, be somehow subjective.

5.3. Chapter Final Remarks

The present chapter builds on the several challenges identified concerning the subject in study, that is, the modelling of a decision-support tool for the design and planning of sustainable supply chains under uncertainty. Thus, a mathematical formulation has been provided for several key points, such as the integrated supply chain design and planning optimizations model that incorporates numerous different interconnected supply chain decisions, namely: supplier selection; raw material purchase planning; facility location and capacity installation; technology selection; production and remanufacturing planning; product recovery strategies; transportation network definition; and, inventory planning.

Additionally, the demand uncertainty incorporation has also been accounted for, through the application of the stochastic dynamic optimization approach based on the scenario tree concept, where nodes representing each stage of the scenario tree are considered.

Finally, three distinctive objective functions have been presented in order to consider all three pillars of sustainability. Thus, the economic pillar has been accounted for through the application of the risk-adjusted NPV, in order to assess the economic risk associated. On the other hand, the environmental concerns have been tackled through the application of the Life Cycle Assessment, an integrated approach for the environmental valuation. Finally, the social pillar has been studied based on the fairly recently developed SLCA, an integrated approach based on the already well-established LCA, and whose focus is the social aspects that must be considered when aiming for a sustainable supply chain.

6. Model Validation & Results Analysis

The present chapter focuses on the application of the formulated model to a representative case-study of the Calzedonia Group. Thus, the obtained results of its implementation are analysed and discussed in order to provide valuable conclusions and relevant insights on the work developed.

This chapter is organized as follows. Section 6.1 focuses on the case-study definition and characterization. In section 6.2, the obtained results are analysed and discussed. Lastly, in section 6.3, the chapter final remarks are stated.

6.1. Case-Study Definition & Characterization

The model presented in chapter 5 is now applied into a representative case-study so as to serve as a basis for results analysis and, consequently, model validation. Therefore, in the present chapter, a study concerning the supply chain network of Calzedonia Group, an Italian company focused on the apparel industry, is performed based on the company's provided reports of year 2019, as well as on further available and public information provided by the group. It should be noted, however, that due to the lack of substantial data, the present case-study serves only as a representative study of the group's network.

Calzedonia Group comprises seven distinctive brands, namely: (i) Calzedonia, the historical brand of the group, whose focus in mainly on the socks sector, and which is present in 53 countries across de world; (ii) Intimissimi Italian Lingerie, a brand positioned in the lingerie and underwear market established in a total of 47 countries; (iii) Intimissimi Uomo, a fairly recent underwear brand created specifically for the needs of male customers, established in a total of 8 countries worldwide; (iv) Tezenis Underwear, a brand focused on affordable and trendy underwear present 31 countries; (v) Falconeri Superior Cashmere, a brand focused on creating top quality cashmere knitwear, established in 17 countries across the world; (vi) Atelier Emé, with a strong focus on wedding and ceremonial dresses, and with only 2 stores to date; and, (vii) Signorvino, the most particular brand of the group, as its market concerns Italian wines across 17 distinctive stores (Group Calzedonia 2019).

When looking further into the details concerning the group's supply chain network, it is clear that Calzedonia Group has a strong presence worldwide, particularly within the European region, where the company holds more than 4500 stores. Henceforth, and given its large presence and focus on the European market, the present representative case-study focuses on the European region, and particularly in the set of countries where the brand has its strongest presence. Additionally, from Calzedonia Group large range of brands, only two have been considered, namely Calzedonia and Tezenis Underwear. This decision is supported by the fact that these represent the vast majority of stores across the European region, while having a fairly compatible array of products.

Considering this, and in order to select the set of countries that represent the company's strongest presence among the Calzedonia and Tezenis Underwear stores array, the approximate total number of stores for both brands combined have been accounted for. From these, and according to Figure 24, all countries that comprise, at least 100 stores of both brands, have been selected as vital for this analysis, leading to a total of six markets. It should be noted that, even though the approximate total number of stores in Poland is less than 100 (99 stores), this country has been considered nonetheless, due to clear values approximation. Finally, and as depicted in Figure 24, the products considered in the study represent a standard pair of cotton mid-calf socks, as well as a pair of seamless totally invisible sheer tights, two widely sold products worldwide under both of these brands, and thus clear key contributors for this study.

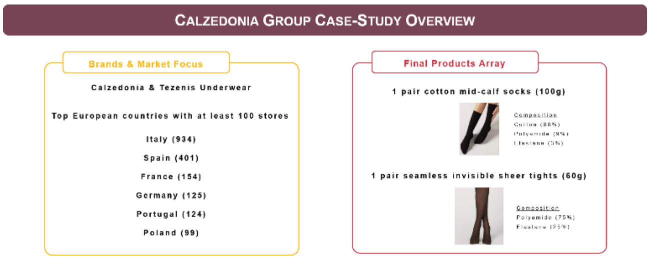

Figure 24 - Calzedonia Group case-study general considerations

As depicted in Figure 25, and based on Group (2019)'s main findings, the Calzedonia Group supply chain network, apart from the already selected markets, has been defined as follows: (i) two suppliers, Italy and China; (ii) three factories, located in Avio (Italy), Grissi (Italy), and Croatia; and, (iii) three warehouses, established in Vallese di Oppeano (Italy), Castagnaro (Italy), and Varazdin (Croatia). Concerning the selection of transportation modes, this comprises three options: (i) truck, to move between European entities; (ii) airplane, to move from a warehouse to a market, in cases where demand must be met within a short amount of time (only applicable in further countries, namely Portugal, and Poland); and, (iii) ship, whose goal is to move raw materials from the China supplier to the factories established in Europe. Finally, and given the closed-loop approach considered in this study, it is also assumed to have established two different types of technologies per factory: (i) production technology, aiming to produce the final products from raw materials; and, (ii) remanufacturing technology, which manufactures final products from recovered products (i.e.: once the final product has no value to the client, it is sent back to the network to serve as a basis for a new and remanufactured final product). All values related to the parameters considered in this analysis are provided in Appendix C.

Considering the above, an analysis of the group's supply chain network is performed for a time horizon of five years, so as to understand whether or not the considered network, under the influence of uncertainty in several parameters, is the optimal configuration for this case-study. Thus, considerations such as the necessity, or lack of it, of maintaining all pre-existent entities/establishing additional entities (i.e.: warehouses established in all of the countries' markets) are taken in this analysis.

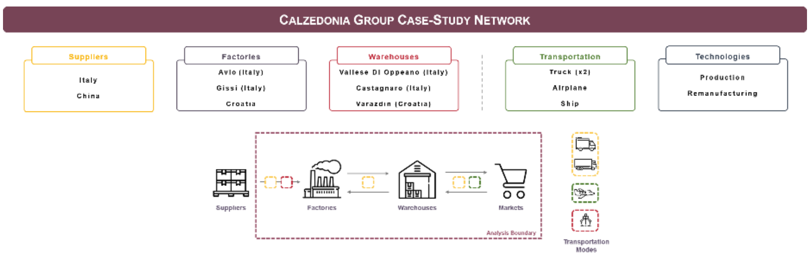

Figure 25 - Calzedonia Group case-study overall network

6.2. Results Analysis & Discussion

Given the information presented above, and in order to validate and take relevant remarks of the decision-support tool presented in subchapter 5.2, this has been implemented in GAMS 31.1, and the case-study solved using CPLEX 12.1, in an Intel Core i7-8550U, 1.80 – 1.99 GHz processor with 16GB RAM. Moreover, and apart from validating the model presented, this section aims to provide sufficient evidence on how a sustainable supply chain under uncertainty behaves depending on the type of uncertainty faced, so that more critical uncertain parameters may be identified. Hence, all considerations of uncertainty here presented are compared with the deterministic version of the sustainable supply chain under consideration (case A), so that one can better understand the changes and the impacts of having a given parameter as uncertain. From there, it will thus be possible to comprehend how much does a given uncertain parameter (e.g.: demand) influences the network and, consequently, the decision-makers actions. Accordingly, the parameter(s) that portray the more significant changes are then considered while accounting for a time horizon, from which conclusions regarding the stochastic dynamic nature of the model can be made. Finally, it should also be noted that, during implementation, it has been acknowledged that all three objective functions are considered to have equal relevance to the decision-makers and have hence been normalized and assigned identical relevance weights (normalized values per objective function available in Appendix D). This decision lies with the belief that the final purpose of any sustainable supply chain should be the equal consideration of each pillar.

On that note, the following results analysis is divided into three parts: i) tactical uncertainty (section 6.2.1); ii) objective function uncertainty (6.2.2); and, iii) dynamic uncertainty (6.2.3). Hence, and considering part i), parameters such as demand, supply, and end-of-lifecycle products' rate of return have been considered as uncertain, due, not only to their high relevance to the network, but also because these portray some of the most common uncertain aspects faced (subchapter 3.2). As of part ii), this includes costs that highly impact any supply chain network, that is, both construction and (variable) transportation costs. It should be noted that, despite considering three distinctive objective functions in the model developed, only the economic objective function has been considered for the uncertainty characterization, due to the fact that, for both environmental and social parameters, historical/estimated data is hard to obtain, leading to difficulties in applying the stochastic dynamic optimization approach here discussed. Considering this, for both the tactical and the objective function uncertainty analysis, a two-stage approach was firstly acknowledged. Afterwards, a final results analysis is then provided in iii), where the parameter(s) with the highest influence on the overall model network are considered in a stochastic dynamic approach. The choice of such strategy lies in the large problem complexity in hands, thus allowing, through this approach, to have a more comprehensive analysis of the uncertainty consequences on the design and planning of a sustainable supply chain.

Considering this, for each case being discussed, several aspects are taken into consideration and compared, namely: (1) entities and corresponding capacities, which displays all entities that are part of the network and their respective capacities; (2) suppliers selection and allocation, where all suppliers considered in each network are identified; (3) production and remanufacturing technologies, which highlight the relationship between each production/remanufacturing technology in each considered factory, for each final product; (4) inventory per product, with a connection between each final product and each opened warehouse regarding inventory levels; (5) transportation modes, which represents all transportation modes selection; and, (6) sustainable indicators, where the final score for each objective function is given.

6.2.1. Tactical Uncertainty

The tactical uncertainty evaluation's purpose is to analyse and comprehend the network changes that occur when there is some uncertainty associated to one (or more) of the following key aspects: demand, supply, and, end-of-life products' rate of return. Hence, a total of five distinctive cases have been considered, where three correspond to each parameter on its own, and the remaining two to the combination of more than one simultaneously, as follows: (B) uncertain demand; (C) uncertain supply; (D) uncertain products' rate of return; (E) uncertain demand and uncertain supply; and, (F) uncertain demand, uncertain supply, and uncertain products' rate of return. Thus, each is to be analysed and compared to the deterministic case, that is, case A, where no uncertainties are considered. The uncertainty variation for each case B to F is depicted in Figure 26, where, for each case, five distinctive scenarios are accounted for with the respective probabilities of occurrence.

	B. Uncertain Demand	C. Uncertain Supply	D. Uncertain Products Rate of Return	E. Uncertain Demand & Supply	F. Uncertain Demand, Supply & Rate of Return
Scenario 1	Demand Variation = 0% Scenario Probability = 20%	Supply Variation Italy / China = 0% / 0% Scenario Probability = 20%	Products Rate of Return Variation = 0% Scenario Probability = 35%	Demand Variation = 0% Supply Variation Italy / China = 0% / 0% Scenario Probability = 20%	Demand Variation = 0% Supply Variation Italy / China = 0% / 0% Products Rate of Return Variation = 0% Scenario Probability = 25%
Scenario 2	Demand Variation = -10% Scenario Probability = 10%	Supply Variation Italy / China = -5% / 0% Scenario Probability = 10%	Products Rate of Return Variation = -10% Scenario Probability = 20%	Demand Variation = -10% Supply Variation Italy / China = -5% / 0% Scenario Probability = 10%	Demand Variation = -10% Supply Variation Italy / China = -5% / 0% Products Rate of Return Variation = -10% Scenario Probability = 15%
Scenario 3	Demand Variation = +5% Scenario Probability = 35%	Supply Variation Italy / China = -5% / +5% Scenario Probability = 20%	Products Rate of Return Variation = -5% Scenario Probability = 30%	Demand Variation = +5% Supply Variation Italy / China = -5% / +5% Scenario Probability = 30%	Demand Variation = +5% Supply Variation Italy / China = -5% / +5% Products Rate of Return Variation = -5% Scenario Probability = 30%
Scenario 4	Demand Variation = +10% Scenario Probability = 25%	Supply Variation Italy / China = -10% / +10% Scenario Probability = 25%	Products Rate of Return Variation = +5% Scenario Probability = 10%	Demand Variation = 10% Supply Variation Italy / China = -10% / +10% Scenario Probability = 25%	Demand Variation = 10% Supply Variation Italy / China = -10% / +10% Products Rate of Return Variation = +5% Scenario Probability = 20%
Scenario 5	Demand Variation = +15% Scenario Probability = 10%	Supply Variation Italy / China = -15% / +15% Scenario Probability = 15%	Products Rate of Return Variation = +10% Scenario Probability = 5%	Demand Variation = 15% Supply Variation Italy / China = -15% / +15% Scenario Probability = 15%	Demand Variation = 15% Supply Variation Italy / China = -15% / +15% Products Rate of Return Variation = 10% Scenario Probability = 10%

Figure 26 - Tactical uncertainty results analysis - scenario probability per case B – F

The obtained results are given in Figures Figure 27Figure 32, where all cases are considered and compared to the deterministic version, for all six relevant aspects mentioned above (1 - 6). Hence, and firstly considering uncertain demand considerations (case B), it becomes clear that several aspects differ from the deterministic version (case A). For instance, and while in case A the network consists of a total of eight entities, where each is established to its maximum permitted installation area (100%), in cases where the demand is uncertain, this number increases to twelve, four of each only accounting for a small percentage of the total allowed installation area per entity, leaving only one entity unconsidered, as depicted in Figure 27. As of the suppliers selection and allocation, represented in Figure 28, this remains unchanged, since only the supplier from Italy is acknowledged in both cases. Moreover, in the deterministic case, all products are produced/remanufactured in all three factories, with the exception of product 2 (pair of seamless invisible shear tights), which is only remanufactured in two facilities. On the contrary, Figure 29 shows that, in case B, all factories are associated with the production/manufacturing of both products. Additionally, and while in case A both factories from Avio and Gissi represent the most percentage of production and remanufacturing, in case B, the facility established Croatia greatly impacts the overall production and specially remanufacturing processes, while the Avio factory portrays much smaller percentage values. As of the amount of inventory per facility, represented in Figure 30, the Poland warehouse is a key player in case A, whereas in case B, this is combined with the contributions of the warehouses from Spain and Portugal. Another distinctive characteristic is the product with the overall highest inventory representation, which differs from the one in case A. Furthermore, when accounting for the transportation modes per network considered, depicted in Figure 31, and while in case A trucks are the only option selected, in case B, airplane intracontinental links are considered between Italy and Portugal. Moreover, and even though smaller trucks are preferred in both situations, in case B, there is a much higher investment of large-sized trucks, with a total difference of eight. Finally, and considering Figure 32, the economic sustainability indicator has seen a decrease of 65.4% in the NPV in case B. This number may be explained by, among others, the following considerations: (i) higher construction and labour costs due to the increased number of facilities in the network, even without having all entities constructed to the maximum permitted installation area; (ii) higher installation and labour costs for the remanufacturing technology in the Avio factory; (iii) larger investment in the number of trucks, leading to larger fixed and variable costs; and, (iv) higher costs for the incorporation of air transportation options. As of the environmental impact assessment, there is a positive decrease of 20.85% in environmental impacts, even while considering more entities and airplane connections. This may be explained by the fact that, not only are some entities not large in size, and the airplane connections very rare in the overall products flow in the network, but also because there has been made an improvement regarding the incorporation of remanufacturing process in all three factories. Finally, and even though no significant changes have been considered in the social assessment, it should be noted that, with the increased number of entities and transportation modes in the network, it should be expected that the social impact would be positively impacted.

Now considering case C, that is, uncertain supply, and as depicted in Figure 27, only one extra entity is accounted for in comparison to case A, which is the warehouse in Portugal. Moreover, and even though this new incorporation is established to the maximum allowed installation area, several other facilities are only being considered in a much smaller percentage of the total permitted capacity. Additionally, Figure 28 shows that the suppliers' selection and allocation solely relies on the supplier form Italy in both cases since no other supplier is considered in neither network. On another note, in the final products production process, represented in Figure 29, it is possible to state that the Avio factory does not contribute in the same amount as the remaining. As of the remanufacturing process, this heavily relies on the efforts made by the Croatian factory. Furthermore, and even though product 2 (pair of seamless invisible shear tights) represents the highest product in inventory in both cases A and C, the Portuguese warehouse is seen as the key contributor in the storage levels considerations under uncertain supply, as depicted in Figure 30. As represented in Figure 31, transportation modes considerations do not represent major differences between both cases, thus being trucks are the only mode selected, with a slight decrease in the amount of small-sized trucks purchase. Finally, and as of the economic assessment, there is a total decrease of 87.80%, thus representing a much smaller NPV (even smaller than in cases where demand is the uncertain parameter), depicted in Figure 32. This value may be explained by, among other, the following topics: (i) high construction costs for the Portuguese warehouse at 100% of the permitted capacity; (ii) higher labour costs following the establishment of a new facility; and, (iii) establishment of production/remanufacturing technologies that are idle, leading to higher investment and labour costs. Moreover, and as of the environmental assessment, this represents a positive decrease of 44.20%, higher that the above discussed case B, which may rely on the following considerations: (i) smaller amount of entities in the network, leading to a smaller environmental impact per m^2; (ii) smaller amount of both small and large-sized trucks; and, (iii) zero airplane connections being considered. Lastly, and as of the social assessment, there has been a decrease of 10%, which may rely on the economic development of the regions being considered.

Case D, on the other hand, represents situations where the end-of-life products' rate of return is uncertain in a given closed-loop supply chain network. Accordingly, and following the data provided by Figure Figure 27, one can state that, for the overall entities inclusion in the network, there is one less facility being established, namely, the warehouse from Poland. Still on this topic, it is also relevant to acknowledge the high decrease in the installation areas per facility, where most are under 50% of the total permitted installation area per building type (see Appendix C for further details). Furthermore, and as depicted in Figure 28, given the fact that the Italian supplier is the only one considered in the network, there are no differences in the suppliers allocation. Nonetheless, and when accounting for the production and remanufacturing of the final products represented in Figure 29, it is clear that, for product 2, that is, the pair of seamless invisible shear tights, there zero remanufacturing. Additionally, and even though all three factories vary considerably in their contributions for the production/remanufacturing of both final products, it can be stated that Gissi represents the smaller overall contributor, leaving the remaining with the highest impacts. In regards to the inventory data provided by Figure 30, the overall highest storage levels are of product 2, strongly due to Vallese Di Oppeano warehouse's efforts, while product 1 is stored fairly evenly across all three opened warehouses. Similarly to case A, and according to Figure 31, in case D, trucks of a smaller size are preferred over the ones of a larger size, being the biggest difference in the amount purchased: case D requires seven additional smaller trucks, and six larger ones. It should also be noted that in case D airplane connections are made between Italy and both Portugal and Poland. Finally, and as depicted in Figure 32, the economic sustainability pillars sees a positive increase of 28.42%, which may be due rely, not only on the amount of product sold, but also to the fact that no remanufacturing technology investment has been made for one type of product, thus lowering both investment and labour costs. Following the same rationale, this increase in the Net Present Value might also be due to the exclusion of one facility, the Poland warehouse, in regards to the deterministic case, hence leading to fewer construction and labour costs. On another note, there has also been a positive decrease of 48.49% in environmental concerns, which, even though is not being supported by the remanufacturing of product 2, nor on the fact that airplane connections are being considered, may be explained by the fewer number of established facilities, as well as possible higher rates of end-of-life products returns. Lastly, in regards to the social assessment, there has been a nearly insignificant decrease in its total score, possibly due to the economic development that has been unconsidered with the exclusion of one facility when compared to the deterministic case.

Bearing in the mind the information above, and as depicted in Figures Figure 27Figure 32, the final two cases in the tactical analysis, cases E and F, represent the combination of more than one of the above discussed uncertain parameters, so that further and more reliable conclusions may be made in the selection of the more critical parameters. Hence, and in regards to the entities considerations for both networks (E and F) represented in Figure 27, it becomes clear that these are aligned with the network of case B, where demand was said to be uncertain, only varying in some of the entities installation areas, which in general, are higher in case F. Moreover, no changes have been made in the suppliers allocation since Italy continues to be the only supplier in the equation, as provided in Figure 28. Now considering the production and remanufacturing of products depicted in Figure 29, it is clear that, in case E, the Croatian factory has a critical role in the network, whereas the remaining have cases where little to no contributions are made. In case F, however, the overall contributions are more dispersed, having, nonetheless, cases where the Avio factory is the highest or even the only entity considered, greatly differing from cases A and B. Figure 30 considers the final products' inventory levels, where can state that one major difference between cases E and F is the product with the overall higher level of inventory, where case E is aligned with case A's main findings, whereas case F follows the same pattern as in situations where only demand is said to be uncertain. Additionally, the warehouses that mostly contribute for the inventory levels in case E are the same as in case B, that is, Spain, Portugal, and Poland, whereas in case F, Varazdin and Castagnaro also play key roles in this matter. Transportation heavily relies on trucks for both cases E and F, where no air or sea transportations are considered, as seen in Figure 31. Furthermore, the total amount of trucks in both cases is smaller than the values for both cases A and B. Finally, in the economic assessment, depicted in Figure 32, case E registers a total decrease of 61.39%, leading to a slightly higher total NPV than in case B. This may be explained by, among other aspects, the following considerations: (i) smaller investment in trucks; and, (ii) no air transportation considerations. Now considering the environmental assessment of case E, it is clear that there has been a positive increase of 17.02%, is lower than the one observed in case B, and possibly aligned with the fact that the entities installation areas are greater in case E. As of case F, and firstly considering the economic assessment, a total decrease in the NPV of 68% is observed, leading to higher negative contributions than case E. This may be explained by the fact that, not only are the facilities installed considering higher construction areas, but also due to the larger investment in trucks, especially in the large-sized ones. Lastly, and in regards to social considerations, both cases E and F represent the same residual increase of 0.0024%, possibly due to the increase in the economic development.

1. Entities & Capacities

Entities & Capacities		A. Deterministic		B. Uncertain Demand		C. Uncertain Supply		D. Uncertain Products Rate of Return		E. Uncertain Demand & Supply		F. Uncertain Demand, Supply & Rate of Return	
Suppliers	Italy	✓	NA	✓	NA	✓		✓	NA	✓	NA	✓	NA
	China	✗	-	✗	-	✗		✗	-	✗	-	✗	-
Factories	Avio (Italy)	✓	100%	✓	24.44%	✓	23.52%	✓	30.36%	✓	23.52%	✓	23.52%
	Gissi (Italy)	✓	100%	✓	26.34%	✓	23.52%	✓	29.15%	✓	23.82%	✓	23.52%
	Croatia	✓	100%	✓	100%	✓	100%	✓	35.92%	✓	100%	✓	100%
Warehouses	Vallese di Oppeano (Italy)	✓	100%	✓	7.76%	✓	7.22%	✓	100%	✓	3.66%	✓	14.69%
	Castagnaro (Italy)	✓	100%	✓	5.37%	✓	8.07%	✓	36.72%	✓	3.94%	✓	86.80%
	Varazdin (Croatia)	✓	100%	✓	100%	✓	100%	✓	100%	✓	100%	✓	100%
	Spain	✗	-	✓	100%	✗	-	✗	-	✓	100%	✓	100%
	France	✗	-	✓	100%	✗	-	✗	-	✓	100%	✓	100%
	Germany	✗	-	✓	100%	✗	-	✗	-	✓	100%	✓	100%
	Portugal	✗	-	✓	100%	✓	100%	✗	-	✓	100%	✓	100%
	Poland	✓	100%	✓	100%	✗	-	✗	-	✓	100%	✓	100%

✓ Entity is considered in the network ✗ Entity is not considered in the network

Figure 27 - Tactical uncertainty results analysis - entities

2. Suppliers Selection & Allocation

Suppliers & Supply Allocation		A. Deterministic	B. Uncertain Demand	C. Uncertain Supply	D. Uncertain Products Rate of Return	E. Uncertain Demand & Supply	F. Uncertain Demand, Supply & Rate of Return
Suppliers	Italy	Supplies all factories at 100%	Supplies all factories at 100%	Supplies all factories at 100%	Supplies all factories at 100%	Supplies all factories at 100%	Supplies all factories at 100%
	China	✗	✗	✗	✗	✗	✗

Figure 28 - Tactical uncertainty results analysis - suppliers

3. Production & Remanufacturing Technologies

Technologies & Factories		A. Deterministic	B. Uncertain Demand	C. Uncertain Supply	D. Uncertain Products Rate of Return	E. Uncertain Demand & Supply	F. Uncertain Demand, Supply & Rate of Return
Production Technology	Pair of cotton mid-calf socks	Produced in Avio (34.5%), Gissi (34.5%), & Croatia (30%)	Produced in Avio (29 - 40%), Gissi (34 - 41%), & Croatia (22 - 33%)	Produced in Avio (29 - 38%), Gissi (28 - 40%), & Croatia (29 - 39%)	Produced in Avio (31 - 39%), Gissi (29 - 35%), & Croatia (29 - 38%)	Produced in Avio (33 - 35%), Gissi (31 - 35%), & Croatia (30 - 35%)	Produced in Avio (30 - 43%), Gissi (29 - 39%), & Croatia (15 - 35%)
	Pair of seamless invisible shear tights	Produced in Avio (27.3%), Gissi (71%), & Croatia (1.7%)	Produced in Avio (1 - 14%), Gissi (36 - 55%), & Croatia (38 - 56%)	Produced in Avio (0 - 5%), Gissi (47 - 76%), & Croatia (24 - 53%)	Produced in Avio (24 - 70%), Gissi (0 - 9.5%), & Croatia (30 - 70%)	Produced in Avio (0 - 0.000006%) & Croatia (99.999 - 100%)	Produced in Avio (92 - 100%), Gissi (0 - 8%), & Croatia (0 - 8%)
Remanufacturing Technology	Pair of cotton mid-calf socks	Remanufactured in Avio (58%), Gissi (33%), & Croatia (9%)	Remanufactured in Avio (7 - 22%), Gissi (0 - 20%), & Croatia (68 - 85%)	Remanufactured in Gissi (0 - 19%) & Croatia (81 - 100%)	Remanufactured in Avio (28 - 70%), Gissi (0 - 27%), & Croatia (18 - 54%)	Remanufactured in Gissi (0 - 0.000025%) & Croatia (99.999 - 100%)	Remanufactured in Avio (0 - 39%), Gissi (3 - 44%) & Croatia (26 - 68%)
	Pair of seamless invisible shear tights	Remanufactured in Gissi (96.4%) & Croatia (3.6%)	Remanufactured in Avio (0 - 12%), Gissi (25 - 65%), & Croatia (33 - 75%)	Remanufactured in Avio (3 - 10%), Gissi (0 - 16%), & Croatia (74 - 97%)	Not considered	Remanufactured in Avio (0 - 0.00001%), Gissi (0 - 1.46%), & Croatia (98.54 - 100%)	Remanufactured in Avio (100%)

Figure 29 - Tactical uncertainty results analysis - technologies

4. Inventory per Product

Products in Inventory	A. Deterministic	B. Uncertain Demand	C. Uncertain Supply	D. Uncertain Products Rate of Return	E. Uncertain Demand & Supply	F. Uncertain Demand, Supply & Rate of Return
Overall Configuration	Pair of cotton mid-calf socks with overall higher inventory	Pair of seamless invisible shear tights with overall higher inventory	Pair of seamless invisible shear tights with overall higher inventory	Pair of seamless invisible shear tights with overall higher inventory	Pair of cotton mid-calf socks with overall higher inventory	Pair of seamless invisible shear tights with overall higher inventory
Pair of cotton mid-calf socks	Mostly stored in Poland's warehouse (51%)	Mostly stored in Spain (18 - 47%) & Portugal's (19 - 33%) warehouses	Mostly stored in Portugal's warehouse (42 - 64.3%)	Stored fairly evenly throughout Vallese Di Oppeano (20 - 44%), Castagnaro (22 - 46%), & Varazdin's (24 - 45%) warehouses	Mostly stored in Spain (10 - 29%), Portugal (31 - 61%) & Poland's (10 - 36%) warehouses	Mostly stored in Varazdin (6 - 24%), Spain (8 - 31%), Portugal (11 - 22%) & Poland's (4 - 24%) warehouses
Pair of seamless invisible shear tights	Mostly stored in Poland's warehouse (65%)	Mostly stored in Spain (8 - 33%), Portugal (17 - 39%), & Poland's (3 - 43%) warehouses	Mostly stored in Portugal's warehouse (68 - 80%)	Mostly stored in Vallese Di Oppeano's warehouse (54 - 86%)	Mostly stored in Spain's warehouse (36 - 58%)	Mostly stored in Castagnaro (6 - 71%) & Portugal's (4 - 47%) warehouses

Figure 30 - Tactical uncertainty results analysis - inventory

5. Transportation Modes

Transportation Modes	A. Deterministic	B. Uncertain Demand	C. Uncertain Supply	D. Uncertain Products Rate of Return	E. Uncertain Demand & Supply	F. Uncertain Demand, Supply & Rate of Return
Road Transportation	Trucks of a smaller size are preferred over trucks of a larger size (28 vs 13)	Trucks of a smaller size are preferred over trucks of a larger size (26 vs 21)	Trucks of a smaller size are preferred over trucks of a larger size (24 vs 13)	Trucks of a smaller size are preferred over trucks of a larger size (35 vs 19)	Trucks of a smaller size are preferred over trucks of a larger size (22 vs 14)	Same amount of trucks of both a smaller and a larger size (19 vs 19)
Air Transportation	Not considered	1 intracontinental connection between Italy & Portugal	Not considered	2 intracontinental connections between Italy and both Portugal & Poland	Not considered	Not considered
Sea Transportation	Not considered	Not considered	Not considered	Not considered	Not considered	Not considered

Figure 31 - Tactical uncertainty results analysis - transportation modes

6. Sustainable Indicators

Sustainabale Indicators	A. Deterministic	B. Uncertain Demand	C. Uncertain Supply	D. Uncertain Products Rate of Return	E. Uncertain Demand & Supply	F. Uncertain Demand, Supply & Rate of Return
Economic	152219400	52664490 (-65.40%)	18600000 (-87.80%)	195486300 (+28.42%)	58766710 (-61.39%)	48068810 (-68%)
Environmental	1007686.439	797559.874 (-20.85%)	562333.218 (-44.20%)	519010.829 (-48.49%)	836181.363 (-17.02%)	744688.684 (-24%)
Social	873436.219	873456.979 (+0.000024%)	786091.873 (-10%)	873429.902 (-0.000723%)	873456.979 (+0.00238%)	873456.979 (+0.0024%)

Figure 32 - Tactical uncertainty results analysis - sustainable indicators

Finally, and considering the analysis above, it becomes clear that, when accounting for each uncertain parameter on its own, demand represents the highest contributor to the overall changes in a sustainable supply chain network. This remark is further supported by cases E and F, where demand has been combined with other uncertain parameters, and where one can state that the obtained networks follow the same pattern as if demand was the only uncertain aspect. Hence, and even though these additional parameters did not portray major changes on the network on their own, when combined with the uncertain demand, greater impacts have been registered, thus validating the significant relevance of having uncertain demand on a sustainable supply chain.

On another note, it becomes clear that case D, where the end-of-life products rate of return is uncertain, represents the scenario where a higher Net Present Value is obtained. The best possible score for the environmental assessment is also considered in this case, where extra contributions may be due to possibly higher amounts of returned products and consequently higher remanufacturing processes. Lastly, cases B, E and F represent the overall best social assessment, which may heavily rely on the increased economic development created with the establishment of additional entities.

6.2.2. Economic Objective Function Uncertainty

Following the analysis performed above, in the economic objective function uncertainty assessment, that is, for the consideration of uncertainty in both construction and (variable) transportation costs that affect the economic objective function, a result analysis on the network changes is performed. In this analysis, a total of three cases is considered, namely: (G) uncertain construction costs; (H) uncertain (variable) transportation costs; and (I) combination of construction and variable transportation costs. Likewise, these cases are to be compared with the initial network of the deterministic case, that is, case A, in the six identified key points for this analysis. The uncertainty variation of each parameter and case in analysis is provided in Figure 33, which follows the same pattern as seen above, where, for each case, five scenarios are considered with the respective probabilities of occurrence. Finally, the obtained results for this analysis are depicted in Figures Figure 34 Figure 39.

	G. Uncertain Construction Costs	H. Uncertain Tranportation Costs	I. Uncertain Construction & Transportation Costs
Scenario 1	Construction Costs Variation = 0% Scenario Probability = 20%	Fuel / Variable Plane / Variable Ship Costs Variation = 0% / 0% / 0% Scenario Probability = 25%	Construction Costs Variation = 0% Fuel / Variable Plane / Variable Ship Costs Variation = 0% / 0% / 0% Scenario Probability = 22.5%
Scenario 2	Construction Costs Variation = -10% Scenario Probability = 5%	Fuel / Variable Plane / Variable Ship Costs Variation = -10% / -10% / -10% Scenario Probability = 10%	Construction Costs Variation = -10% Fuel / Variable Plane / Variable Ship Costs Variation = -10% / -10% / -10% Scenario Probability = 7.5%
Scenario 3	Construction Costs Variation = +10% Scenario Probability = 25%	Fuel / Variable Plane / Variable Ship Costs Variation = +10% / -15% / -15% Scenario Probability = 35%	Construction Costs Variation = +10% Fuel / Variable Plane / Variable Ship Costs Variation = +10% / -15% / -15% Scenario Probability = 30%
Scenario 4	Demand Variation = +30% Scenario Probability = 30%	Fuel / Variable Plane / Variable Ship Costs Variation = +15% / +5% / +5% Scenario Probability = 15%	Construction Costs Variation = +30% Fuel / Variable Plane / Variable Ship Costs Variation = +15% / +5% / +5% Scenario Probability = 22.5%
Scenario 5	Construction Costs Variation = +45% Scenario Probability = 20%	Fuel / Variable Plane / Variable Ship Costs Variation = +20% / +10% / +10% Scenario Probability = 15%	Construction Costs Variation = +45% Fuel / Variable Plane / Variable Ship Costs Variation = +20% / +10% / +10% Scenario Probability = 17.5%

Figure 33 - Economic objective function uncertainty results analysis - scenario probability per case G – I

Accordingly, all three cases under analysis, G – I, are represented along with case A, so as to properly compare them with the deterministic version of the network's case-study. Therefore, and firstly considering the case where the entities' construction costs are uncertain (case G), as depicted in Figure 34, one can state that all opened facilities in this scenario are aligned with the ones considered in the deterministic one. The main difference, however, is the installation area per entity, which, in case G, is very limited considering the maximum permitted, whereas in the deterministic version, all entities are installed to the maximum allowed. Moreover, and given that only one supplier is considered in the network in case G, Italy is in charge of supplying all factories at 100% (see Figure 35). On another note, and when accounting for the final products' production and remanufacturing per factory represented in Figure 36, the Gissi facility is a key contributor in the production process. Nonetheless, when considering the remanufacturing of products, this key role shifts towards the Croatian factory, in charge of all the remanufacturing processes in case G, leading to a major difference from the baseline case A, where most of the remanufacturing contributions come from the factory established in Gissi. As of the amount of inventory per product, depicted in Figure 37, both cases (A and G) give preference to the overall storage of product 1 (pair of mid-calf socks). Nonetheless, and while in case A the warehouse from Poland represents higher inventory products levels, in case G, this facility is combined with the contributions also made from Vallese Di Oppeano and Varazdin warehouses. Regarding the transportation modes selection, case G follows the same rationale as case A by only accounting for road transportation, and by giving preference to smaller-sized trucks, with a total of less four than in case A (see Figure 38). Finally, sustainability indicators from Figure 39 show that the NPV has an increase of 33.85% when compared to the initial deterministic value, which, at first glance may be unexpected, since there is high uncertainty regarding construction costs. Nonetheless, one should note that, even though construction costs may be higher, the installed area in some entities has greatly decreased, whereas in the deterministic version, they are at their fullest. Other key factors may rely on the fact that very little remanufacturing has been made in the Croatian warehouse in case A, which may lead to higher and possibly unnecessary investment and labour costs. Finally, in case G there has been a smaller investment in transportation modes, which positively impacts the Net Present Value of this scenario. Additionally, environmental concerns register a positive decrease of 39.31%. This decrease heavily relies on the less impacts created by the entities total capacities, but also on the usage of less road transportation trips than in case A. Finally, the social impact assessment only registers a positive residual increase, possibly due to a slight positive difference in the economic development.

Now considering case H, where variable transportation costs, that is variable truck (namely, fuel price), plane, and ship costs, are uncertain, it is possible to observe the resemblances between its network and the one created in case A, depicted in Figure 34. Thus, all suppliers, factories, and warehouses accounted for in the deterministic case are also being considered in the case where transportation costs are uncertain, with the same installed capacities (100%). Supplier selection remains unaltered since no other supplier than the Italian one are considered in neither network (see Figure 35). In regards to the production and remanufacturing of final products in factories, depicted in Figure 36, significant changes should be noted, namely: in case H, the production of product 2 is only considered in two facilities, with higher contributions from the Avio factory; the remanufacturing of product 1 is only held in Avio and Gissi, being the former responsible for almost the entire process; and, case H considers the remanufacturing of product 2 in all factories, with special emphasis on the Avio factory, while this is not at all included in this process in case A. Additionally, and now considering the inventory levels per product, provided in Figure 37, both cases acknowledge that product 1, that is, the pair of mid-calf socks, is the one with the highest overall storage in the facilities. Nonetheless, and while case A clearly defines a key warehouse in the inventory levels per product, case H identifies all warehouses to be fairly equal in its inventory relevance. As of transportation modes selection, represented in Figure 38, one significant difference to the baseline scenario is the consideration of one airplane connection, held between Italy and Portugal, followed by the smaller investment in the overall number of trucks. Finally, when acknowledging the economic assessment of case H given in Figure 39, one is faced with a high negative decrease of the NPV in 77.61%, which may be due on several aspects, such as: (i) establishment of remanufacturing technologies that are idle, leading to higher investment and labour costs; (ii) higher investment in total amount of large-sized trucks; and, (iii) investment of a air connection between Italy and Portugal, leading to several costs, such as fixed transportation costs, fixed hub terminal costs, handling costs per unit at hub terminals, and, variable air transportation costs, here in analysis. Regarding the environmental assessment, this has suffered a positive decrease of 12.32%, which may rely on the usage of fewer trucks. Lastly, the social assessment as provided no changes since the economic development, the number of accidents, and the wage gender ratio is similar in both cases.

Case I represents the final scenario under analysis, where both construction and variable transportation costs, analysed above individually, are combined and considered to be uncertain. Hence, and firstly accounting for the overall network structure obtained, and as depicted in Figure 34, one can state that all entities present in case I are aligned with the ones established in both case A, that is, the deterministic scenario, and cases G and H. Additionally, and regarding the installation areas considered, all opened facilities in case I are at their maximum capacity, similarly to both cases A and H. As of suppliers selection and allocation, case I follows the same pattern as all cases previously discussed, where only the Italian supplier is acknowledged (see Figure 35). On another note, and similarly to case H, the production of final products is assured by all three established factories, being Avio the key contributor for this process (depicted in Figure 36). Moreover, the remanufacturing process of product 1, that is, the pair of mid-calf socks, is mainly held in the Avio factory, followed by small contributions of both Croatia and Gissi warehouses; product 2, on the other hand, is only remanufactured in the Avio factory, thus strengthening the cruciality of this facility in case I. When accounting for product inventory, provided in Figure 37, case I follows the same pattern as case A, where product 2 (pair of seamless invisible shear tights) is the one with the overall largest amount stored in all available warehouses. Looking further into this subject, one can state that Varazdin warehouse plays a crucial role in the storage of product 1, whereas for product 2, this facility is combined with the efforts made from the Vallese Di Oppeano warehouse. As of transportations modes selection, represented in Figure 38, case I differs from both cases A and G, by accounting for, not only road, but also for air transportation. Thus, and considering the former, this is supported by a total of 27 trucks, where most are of a smaller size. Regarding the latter, air transportation is performed by accounting for two distinctive connections, from Italy to both Portugal and Poland. Finally, and according to Figure 39, the economic sustainability indicator represents an overall decrease of the NPV of 85.17%, which may be explained by, among others, the following aspects: (i) establishment of production/remanufacturing technologies that are idle, leading to higher investment and labour costs (ii) incorporation of two air connections, often used in the network and hence increasing the fixed transportation costs, fixed hub terminal costs, handling costs per unit at hub terminals, and, variable air transportation costs; and, (iii) potentially higher construction and transportation costs, here considered to be uncertain. Furthermore, and as of the total score of the environmental considerations, case I portrays a total positive decrease of 11.82%, which is intrinsically connected with the smaller amount of trucks purchased. Nonetheless, and when compared with case G, this decrease is smaller, which may be explained by the usage of air transportation, hence greatly impacting the environment. Finally, social considerations are in line with the remaining cases.

1. Entities & Capacities

Entities & Capacities		A. Deterministic		G. Uncertain Construction Costs		H. Uncertain Transportation Costs		I. Uncertain Construction & Transportation Costs	
Suppliers	Italy	✓	NA	✓	NA	✓	NA	✓	NA
	China	✗	-	✗	-	✗	-	✗	-
Factories	Avio (Italy)	✓	100%	✓	23.52%	✓	100%	✓	100%
	Gissi (Italy)	✓	100%	✓	23.52%	✓	100%	✓	100%
	Croatia	✓	100%	✓	100%	✓	100%	✓	100%
Warehouses	Vallese di Oppeano (Italy)	✓	100%	✓	15.35%	✓	100%	✓	100%
	Castagnaro (Italy)	✓	100%	✓	4.16%	✓	100%	✓	100%
	Varazdin (Croatia)	✓	100%	✓	100%	✓	100%	✓	100%
	Spain	✗	-	✗	-	✗	-	✗	-
	France	✗	-	✗	-	✗	-	✗	-
	Germany	✗	-	✗	-	✗	-	✗	-
	Portugal	✗	-	✗	-	✗	-	✗	-
	Poland	✓	100%	✓	100%	✓	100%	✓	100%

✓ Entity is considered in the network ✗ Entity is not considered in the network

Figure 34 - Economic objective function uncertainty results analysis - entities

2. Suppliers Selection & Allocation

Suppliers & Supply Allocation		A. Deterministic	G. Uncertain Construction Costs	H. Uncertain Transportation Costs	I. Uncertain Construction & Transportation Costs
Suppliers	Italy	Supplies all factories at 100%	Supplies all factories at 100%	Supplies all factories at 100%	Supplies all factories at 100%
	China	✗	✗	✗	✗

Figure 35 - Economic objective function uncertainty results analysis - suppliers

3. Production & Remanufacturing Technologies

Technologies & Factories		A. Deterministic	G. Uncertain Construction Costs	H. Uncertain Transportation Costs	I. Uncertain Construction & Transportation Costs
Production Technology	Pair of cotton mid-calf socks	Produced in Avio (34.5%), Gissi (34.5%), & Croatia (30%)	Produced in Avio (26 - 35%), Gissi (30 - 37%), & Croatia (34 - 37%)	Produced in Avio (37.5 - 39%), Gissi (37 - 39%), & Croatia (21 - 26%)	Produced in Avio (34 - 40%), Gissi (35 - 38%), & Croatia (23 - 29%)
	Pair of seamless invisible shear tights	Produced in Avio (27.3%), Gissi (71%), & Croatia (1.7%)	Produced in Gissi (80 - 99.64%) & Croatia (0.36 - 20%)	Produced in Avio (92 - 95%) & Croatia (5 - 8%)	Produced in Avio (90.95 - 96.15%), Gissi (0.00002 - 2.4%), & Croatia (3.67 - 6.6%)
Remanufacturing Technology	Pair of cotton mid-calf socks	Remanufactured in Avio (58%), Gissi (33%), & Croatia (9%)	Remanufactured in Croatia (100%)	Remanufactured in Avio (78 - 99.999993%) & Gissi (0.000007% - 22%)	Remanufactured in Avio (87 - 97.3%), Gissi (0.32% - 3%), & Croatia (0.5 - 12%)
	Pair of seamless invisible shear tights	Remanufactured in Gissi (96.4%) & Croatia (3.6%)	Remanufactured in Croatia (100%)	Remanufactured in Avio (90 - 96%), Gissi (0 - 0.0002%), & Croatia (4 - 10%)	Remanufactured in Avio (100%)

Figure 36 - Economic objective function uncertainty results analysis - technologies

4. Inventory per Product

Products in Inventory	A. Deterministic	G. Uncertain Construction Costs	H. Uncertain Transportation Costs	I. Uncertain Construction & Transportation Costs
Overall Configuration	Pair of cotton mid-calf socks with overall higher inventory	Pair of cotton mid-calf socks with overall higher inventory	Pair of cotton mid-calf socks with overall higher inventory	Pair of seamless invisible shear tights with overall higher inventory
Pair of cotton mid-calf socks	Mostly stored in Poland's warehouse (51%)	Mostly stored in Varazdin (6 - 24%) & Poland's (4 - 24%) warehouses	Stored fairly evenly throughout Vallese Di Oppeano (27 - 33%), Castagnaro (25 - 27%), Varazdin (21 - 23%), & Poland's (21 - 23%) warehouses	Mostly stored in Varazdin's warehouse (22 - 60%)
Pair of seamless invisible shear tights	Mostly stored in Poland's warehouse (65%)	Mostly stored in Vallese Di Oppeano (9 - 47%), Varazdin (10 - 59%), & Poland's (23 - 62%) warehouses	Stored fairly evenly throughout Vallese Di Oppeano (26 - 27%), Castagnaro (26 - 27%), Varazdin (21 - 23%), & Poland's (23 - 28%) warehouses	Mostly stored in Vallese Di Oppeano (19 - 68%) & Varazdin's (12 - 38%) warehouses

Figure 37 - Economic objective function uncertainty results analysis - inventory

5. Transportation Modes

Transportation Modes	A. Deterministic	G. Uncertain Construction Costs	H. Uncertain Transportation Costs	I. Uncertain Construction & Transportation Costs
Road Transportation	Trucks of a smaller size are preferred over trucks of a larger size (28 vs 13)	Trucks of a smaller size are preferred over trucks of a larger size (24 vs 11)	Similar amount of trucks of both a smaller and a larger size (17 vs 16)	Similar amount of trucks of both a smaller and a larger size (17 vs 10)
Air Transportation	Not considered	Not considered	1 Intracontinental connections between Italy & Portugal	2 Intracontinental connections between Italy and both Portugal & Poland
Sea Transportation	Not considered	Not considered	Not considered	Not considered

Figure 38 - Economic objective function uncertainty results analysis - transportation modes

6. Sustainable Indicators

Sustainabale Indicators	A. Deterministic	G. Uncertain Construction Costs	H. Uncertain Transportation Costs	I. Uncertain Construction & Transportation Costs
Economic	152219400	203741700 (+33.85%)	34084310 (-77.61%)	22580490 (-85.17%)
Environmental	1007686.439	611619.461 (- 39.31%)	883551.812 (-12.32%)	888553.356 (-11.82%)
Social	873436.219	873436.819 (+0.00007%)	873436.219 (0%)	873436.725 (+0.000000579%)

Figure 39 - Economic objective function uncertainty results analysis - sustainable indicators

Considering this analysis, it becomes clear that, when accounting for each uncertain parameter on its own, neither portrays major changes in the overall network structure. Moreover, when combined, this network remains unaltered, thus leading to believe that, even though both parameters lead to changes in several aspects, neither is seen as critical when uncertain. Nonetheless, both uncertainties should always be acknowledged when present, since these may affect several characteristics, such as production, remanufacturing, inventory, and transportation options.

Finally, and when considering the sustainability indicators, it becomes clear that case G, where construction costs are uncertain, represents the scenario where a higher Net Present Value is obtained. The best possible score for the environmental assessment is also considered in this case. Finally, all three cases under analysis, G, H and I, represent similarities in the overall best social assessment.

6.2.3. Dynamic Optimization Assessment

Given the result analysis presented above, where one may conclude the influence of each uncertain parameter on a sustainable supply chain network, it becomes clear that demand portrays the most significant changes in the network. Considering this, this parameter has been further analysed and here studied in a dynamic environment, where its uncertainty is dependent on time periods/stages. Hence, and as depicted in Figure 40 , the stochastic dynamic approach follows a scenario tree formulation, where demand is considered to be uncertain for a time period of five years. Therefore, all nodes have been assigned a probability of occurrence, while each branch an associated demand variation (either +10% or –10%). Finally, and according to subchapter 5.2 main findings, a total of 16 scenarios have been originated. From this, results for this analysis have been obtained, leading to a new case under analysis, case J, whose results are compared with cases A (deterministic) and B (uncertain demand), as depicted in Figure 41Figure 46.

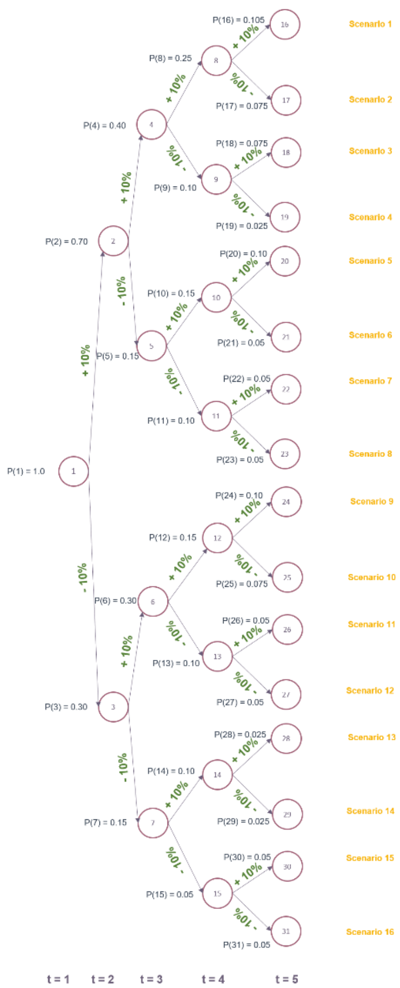

Figure 40 – Stochastic dynamic results analysis for uncertain demand - scenario tree representation

Accordingly, and as depicted in Figure 41, case J network greatly differs from case B, where demand was studied as an uncertain parameter, by only opening 7 out of 13 possible facilities. Moreover, and even though it is relatively similar to the baseline case, that is case A, none of the considered entities in case J have reached the maximum permitted capacity installation area, leading to believe that, when accounting for uncertainty considerations throughout time, major changes are obtained in the overall network structure of the sustainable supply chain. As of the suppliers selection and allocation, represented in Figure 42, this remains unchanged, since only the supplier from Italy is acknowledged in any of the cases here considered, which may be explained by high transportation costs from other valid suppliers (namely in China), to the factories established in Europe. Moreover, and as seen in Figure 43, case J's production of final product 1 is fairly distributed across all three factories, with slightly higher contributions from the Croatian factory. As of final product 2, its production heavily relies on the facility established in Gissi, followed by contributions made by the Avio and Croatia factories. Nonetheless, and when considering the remanufacturing of both products 1 and 2, the Croatian factory holds full responsibility, with no contributions from the remaining. These aspects, when compared to both cases A and B, lead to significant changes in the overall production and remanufacturing of both final products, especially when accounting for the remanufacturing process. As of the amount of inventory per facility, represented in Figure 44, and even though only three warehouses have been considered in case J, all three are seen as key contributors. Accordingly, Vallese Di Oppeano represents the facility with the highest overall inventory level of product 1, followed by Castagnaro and Varazdin; as of product 2, it is mainly stored in Varazdin, followed by Vallese Di Oppeano and Castagnaro warehouses. Thus, and when accounting for the obtained results in both cases A and B, one can state the obvious differences, as in these cases preferences are given to facilities that are not considered in case J. One final aspect to consider in the inventory analysis is the resemblance of case J to case B in the final product with the overall highest inventory, where product 2 has been preferred. On another note, and now accounting for the main findings portrayed in Figure 45, only one transportation mode has been considered in case J, leaving all product flows being taken care by road transportation. Hence, and even though these remarks lead to similarities to case A, differences from case B are acknowledged by having case J not accounting for air transportation options. Furthermore, and despite being the only transportation option for products flows in case J, the total amount of trucks invested in case J is less than case A and B by 6 and 22, respectively. Finally, and considering Figure 46, one may state the great differences from both the economic and environmental objective functions obtained in case J for either case A or B. Thus, and even though some aspects may be due to several topics mentioned in the above analysis, special remarks should be given to the following points: (i) possible higher economic and environmental negative impacts as a consequence of higher demand values from the ones obtained in cases A and B, as a result of the uncertain variations throughout time; and, (ii) possible higher economic and environmental costs as a result of recourse actions taken between time periods, seen as corrective measures once the outcome of a given time period/stage is presented.

1. Entities & Capacities

Entities & Capacities		A. Deterministic		B. Uncertain Demand		J. Uncertain Demand - Dynamic Optimization	
Suppliers	Italy	✓	NA	✓	NA	✓	NA
	China	✗	-	✗		✗	-
Factories	Avio (Italy)	✓	100%	✓	24.44%	✓	23.52%
	Gissi (Italy)	✓	100%	✓	26.34%	✓	23.52%
	Croatia	✓	100%	✓	100%	✓	34%
Warehouses	Vallese di Oppeano (Italy)	✓	100%	✓	7.76%	✓	54.92%
	Castagnaro (Italy)	✓	100%	✓	5.37%	✓	58.25%
	Varazdin (Croatia)	✓	100%	✓	100%	✓	94%
	Spain	✗	-	✓	100%	✗	-
	France	✗	-	✓	100%	✗	-
	Germany	✗	-	✓	100%	✗	-
	Portugal	✗	-	✓	100%	✗	-
	Poland	✓	100%	✓	100%	✗	-

✓ Entity is considered in the network ✗ Entity is not considered in the network

Figure 41 – Stochastic dynamic results analysis for uncertain demand - entities

2. Suppliers Selection & Allocation

Suppliers & Supply Allocation		A. Deterministic	B. Uncertain Demand	J. Uncertain Demand - Dynamic Optimization
Suppliers	Italy	Supplies all factories at 100%	Supplies all factories at 100%	Supplies all factories at 100%
	China	✗	✗	✗

Figure 42 - Stochastic dynamic results analysis for uncertain demand - suppliers

3. Production & Remanufacturing Technologies

Technologies & Factories		A. Deterministic	B. Uncertain Demand	J. Uncertain Demand - Dynamic Optimization
Production Technology	Pair of cotton mid-calf socks	Produced in Avio (34.5%), Gissi (34.5%), & Croatia (30%)	Produced in Avio (29 - 40%), Gissi (34 - 41%), & Croatia (22 - 33%)	Produced in Avio (15 - 43%), Gissi (20 - 47%), & Croatia (19 - 53%)
	Pair of seamless invisible shear tights	Produced in Avio (27.3%), Gissi (71%), & Croatia (1.7%)	Produced in Avio (1 - 14%), Gissi (36 - 55%), & Croatia (38 - 56%)	Produced in Avio (3 - 55%), Gissi (17 - 96%), & Croatia (1 - 44%)
Remanufacturing Technology	Pair of cotton mid-calf socks	Remanufactured in Avio (58%), Gissi (33%), & Croatia (9%)	Remanufactured in Avio (7 - 22%), Gissi (0 - 20%), & Croatia (68 - 85%)	Remanufactured in Croatia (100%)
	Pair of seamless invisible shear tights	Remanufactured in Gissi (96.4%) & Croatia (3.6%)	Remanufactured in Avio (0 - 12%), Gissi (25 - 65%), & Croatia (33 - 75%)	Remanufactured in Croatia (100%)

Figure 43 - Stochastic dynamic results analysis for uncertain demand - technologies

4. Inventory per Product

Products in Inventory	A. Deterministic	B. Uncertain Demand	J. Uncertain Demand - Dynamic Optimization
Overall Configuration	Pair of cotton mid-calf socks with overall higher inventory	Pair of seamless invisible shear tights with overall higher inventory	Pair of seamless invisible shear tights with overall higher inventory
Pair of cotton mid-calf socks	Mostly stored in Poland's warehouse (51%)	Mostly stored in Spain (18 - 47%) & Portugal's (19 - 33%) warehouses	Mostly stored in Valesse Di Oppeano warehouse (17 - 62%), followed by Castagnaro (14 - 49%), and Varazdin (21 - 42%) warehouses
Pair of seamless invisible shear tights	Mostly stored in Poland's warehouse (65%)	Mostly stored in Spain (8 - 33%), Portugal (17 - 39%), & Poland's (3 - 43%) warehouses	Mostly stored in Varazdin warehouse (8 - 80%), followed by Valesse Di Oppeano (7 - 79%), and Castagnaro (8 - 64%) warehouses

Figure 44 - Stochastic dynamic results analysis for uncertain demand - inventory

5. Transportation Modes

Transportation Modes	A. Deterministic	B. Uncertain Demand	J. Uncertain Demand - Dynamic Optimization
Road Transportation	Trucks of a smaller size are preferred over trucks of a larger size (28 vs 13)	Trucks of a smaller size are preferred over trucks of a larger size (26 vs 21)	Trucks of a smaller size are preferred over trucks of a larger size (17 vs 8)
Air Transportation	Not considered	1 intracontinental connection between Italy & Portugal	Not considered
Sea Transportation	Not considered	Not considered	Not considered

Figure 45 - Stochastic dynamic results analysis for uncertain demand - transportation modes

6. Sustainable Indicators

Sustainabale Indicators	A. Deterministic	B. Uncertain Demand	J. Uncertain Demand - Dynamic Optimization
Economic	152219400	52664490 (-65.40%)	942504.082 (-99.4%)
Environmental	1007686.439	797559.874 (-20.85%)	1908430.826 (+89.4%)
Social	873436.219	873456.979 (+0.000024%)	873429.9 (-0.00072%)

Figure 46 - Stochastic dynamic results analysis for uncertain demand - sustainable indicators

Henceforth, and when comparing both types of analysis here performed, one may conclude that, when uncertain considerations throughout time are acknowledged, the impact on the overall network structure is highly influenced. This, along with the fact that decision-makers more than ever need a holistic view of the consequences of a given uncertain parameter while accounting for a given time horizon, lead to conclude that dynamic approaches, namely, stochastic dynamic programming, are a necessary tool for the design and planning of a sustainable supply chain.

6.3. Chapter Final Remarks

The present chapter focuses on the validation of the stochastic dynamic model for sustainable supply chains under uncertainty through its application into a representative case-study of Calzedonia Group, an Italian company established in the garment industry, and with a strong focus on the European market.

Considering the large problem complexity and subsequent computational burden in analysing several uncertain parameters in a dynamic environment (see Appendix E), the present study has been divided into three main parts, being the first two relative to a two-stage stochastic programming model, while the third one focused in a stochastic dynamic approach. Hence, these parts are defined as: (i) tactical uncertainties results analysis, where five distinctive cases have been accounted for, namely demand uncertainty, supply uncertainty, products' rate of return uncertainty, demand and supply uncertainties, and, demand, supply, and products' rate of return uncertainties; (ii) economic objective functions results analysis, which acknowledged three situations, such as construction costs uncertainty, variable transportation costs uncertainty, and, construction and variable transportation uncertainties; and, (iii) dynamic uncertainty results analysis, where the parameter(s) with the highest influence on the overall model network, in this case, the final products' demand, have been considered in a stochastic dynamic approach.

Henceforth, all cases B - J have been compared with a baseline case (case A), that is, the deterministic version of the Calzedonia Group network. Moreover, these have been evaluated considering six distinctive aspects, such as: (1) entities and corresponding capacities; (2) suppliers selection and allocation; (3) production and remanufacturing technologies; (4) inventory per product; (5) transportation modes; and, (6) sustainable indicators.

Considering the above, main findings conclude that uncertain demand has led to more significant changes in the network, both on its own, but also when combined with other uncertain parameters. From this, one may conclude that this parameter represents a critical point in any (sustainable) supply chain, and should thus be properly accounted for so that its uncertainties do not negatively affect both the network and the decision-makers' actions. Moreover, and even though other uncertain parameters have not lead to great impacts in the network, relevant obtained changes should also be considered since these represent key points that highly affect any network economically, environmentally, and socially. Examples of these relate to transportation modes selection, inventory management, and even production and remanufacturing processes of final products.

Additionally, and once demand as considered to be uncertain in a dynamic environment, major changes in both the network and in tactical aspects have been acknowledged. This, along with the increasing necessity of decision-makers to properly forecast parameters variations across time, lead to validate the great necessity and importance of more robust and sophisticated methods for the uncertain parameters assessment, such as stochastic dynamic programming. Finally, and from these results, it is also possible to state great negative impacts in both the economic and environmental assessments, which may be in line with possible higher impacts due to higher demand variations throughout time, as well as possible recourse actions taken as corrective measures once the outcome of a given stage is known.

On that note, and considering the work presented, final considerations should be given. Hence, and regardless of analysing a sustainable supply chain network academically or professionally, one should always account for the inherent demand uncertainty faced. Nonetheless, other key parameters should not be unacknowledged, since these may lead to significant changes in the overall network, depending on its characteristics. Moreover, and in order to properly account for all possible origins of uncertainty, the first step of the design and planning of any (sustainable) supply chain should focus on the identification of all possible sources of uncertainty in the network. From there, these should be properly studied and accounted for, so as to not negatively influence the decisions to be made in the network. Another key aspect to be considered by any decision-maker is the possibility of having great improvements in the sustainability indicators, despite facing uncertain parameters, leading to believe that this is not necessarily a negative aspect of the network, but instead, an opportunity for improvement sustainably. Finally, one should note the great importance of the usage of more sophisticated methods for the uncertainty assessment, such as stochastic dynamic programming, as this has showed to greatly impact the overall network structure, thus leading to more reliable and complete results.

7. FINAL CONCLUSION & FUTURE WORK

The closing chapter of the present work focuses on both the final conclusion of the developed work, and on providing relevant aspects to be considered in the future with a further analysis on the topic. Hence, relevant findings are highlighted in section 7.1, and limitations to be tackled in the future identified in Section 7.2.

7.1. Final Conclusion

The present dissertation focuses on a commonly faced challenge to any decision-maker when designing and planning a sustainable supply chain, that is, the inherent and inevitable uncertainty faced in several parameters. Thus, and so as to provide sufficient knowledge on the topic, some of the frequently applied optimization methods to model uncertainty have been identified and described, where special considerations are given to more rigorous and sophisticated methods, namely dynamic and hybrid optimization.

A comprehensive literature review has been provided so as to identify the main contributions to the literature and potentially identify research gaps that need to be acknowledged and tackled. Thus, this review firstly concluded that, even though several articles explore supply chain networks under uncertainty, little has been done so as to incorporate sustainability concerns as well, where special emphasis should be given to the lack of articles exploring all three pillars of sustainability. Moreover, it has also been concluded that a large percentage of the work developed only considers static optimization, leaving the dynamic optimization advantages highly unutilized.

Considering the above, and in order to provide relevant advances to this topic, a decision-support tool has been developed with the purpose of properly modelling uncertainty in sustainable supply chains. This tool is developed following the work developed by (Mota et al. 2018), which has been adapted so as to model uncertainty in several parameters (demand, supply, products' rate of return, and construction and transportation costs) while using stochastic dynamic optimization. Moreover, the economic assessment has been performed through the Net Present Value, and with special considerations to the risk often faced when having large investment decisions. In regards to the environmental impact assessment, this has followed a holistic approach, though the Life Cycle Assessment. Lastly, social concerns have been tackled by providing a relevant review on S-LCA, and applying its key points, while following the same rationale as the LCA.

Finally, the model validation has considered a representative case-study of Calzedonia Group, an Italian company settled in the garment industry, often dealing with complex and extensive networks. Hence, this analysis has been divided into three main parts: tactical, with regards to the objective function, and with dynamic considerations. Thus, and while the first two have been studied in a two-stage stochastic environment, the latter has focused on the impact of an uncertain parameter in a sustainable supply chain throughout time, that is, while accounting for a dynamic analysis. From these, several conclusions have been made, namely the great impact obtained from having demand as an uncertain parameter, and the need to always account for all possible uncertain parameters of a sustainable supply chain network since the beginning of its design and planning process, which does not necessarily negatively impacts the overall obtained sustainable indicators. Another key consideration is the great added value obtained from the incorporation of a more sophisticated method, such as, the stochastic dynamic programming, which has led to significant changes in the network structure and functioning.

Considering the above, it is foreseen that the research and work developed in this dissertation serve as a proper guideline to model uncertainty in sustainable supply chains. Hence, it is expected that contributions are to be made for both academically, but also professionally, as a supporting tool for decision-makers aiming for a sustainable supply chain without suffering from uncertainty.

7.2. Future Work

Future research on this subject is foreseen so as to continue the work developed in this dissertation. Thus, one aspect to be considered is the further investment in the optimization tools available, and hence dive deeper on the advantages of, both the dynamic method, and the hybrid programming, with a hybrid dynamic optimization approach. Moreover, additional uncertain parameters should be explored, namely entities varying capacities, environmental and social considerations, among others relevant depending on the type of network and case under analysis. Nonetheless, with the improved robustness and sophistication of the optimization methods used, comes computational burdens, which may lead to a higher level of complexity in obtaining valid solutions. Therefore, and in order to tackle such issue, one should further explore efficient solution techniques, which may rely on the problem's decomposition, or even in the utilization of metaheuristics to properly reach the desirable outcome.

Another aspect that should be considered in the future relies on the social assessment. Even though the present dissertation provides relevant research on the S-LCA, further development should be made, where, for instance, additional social indicators should be considered. Furthermore, this assessment should also follow on the continuous advances being made in the S-LCA methodology, as it is proving to be a great holistic tool for social considerations.

On another note, and following the work here developed, the epsilon constraint method is another aspect interesting to be explored. Thus, it is expected that from this, one can further understand the impact of uncertainty in a sustainable supply chain, by analysing the different outcomes and impacts of having the three objective functions varying in emphasis on one (or more) over other(s), hence, avoiding having to assign specific weights to each objective function.

Finally, further applications of the work developed in real case-studies represent an interesting topic to explore, where the results obtained from to model would be compared to a deterministic baseline held by a company. Interesting industries to explore are those that, not only suffer from high uncertainties, but also represent a great case to further explore social concerns, thus involving entities from distinctive countries and hence different regional developments and living conditions.

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Bibliography

Akbari, Kaveh, Mohammad Mahdi Nasiri, Fariborz Jolai, and Seyed Farid Ghaderi. 2014. "Optimal Investment and Unit Sizing of Distributed Energy Systems under Uncertainty: A Robust Optimization Approach." *Energy and Buildings* 85:275–86.

Aliev, R. A., B. Fazlollahi, B. G. Guirimov, and R. R. Aliev. 2007. "Fuzzy-Genetic Approach to Aggregate Production-Distribution Planning in Supply Chain Management." *Information Sciences* 177(20):4241–55.

Barbosa-Póvoa, Ana Paula. 2014. "Process Supply Chains Management - Where Are We? Where to Go Next?" *Frontiers in Energy Research* 2(JUN).

Barbosa-Póvoa, Ana Paula, Cátia da Silva, and Ana Carvalho. 2018. "Opportunities and Challenges in Sustainable Supply Chain: An Operations Research Perspective." *European Journal of Operational Research* 268(2):399–431.

Benoit-Norris, Catherine. 2013. "T He M Ethodological S Heets for S Ub - Categories in S Ocial L Ife C Ycle a Ssessment (S-Lca)." *Pre Publication- Version. The Methodological Sheets for Subcategories in Social Life Cicle Assessment (S-LCA).*

Benoît, Catherine., Bernard. Mazijn, United Nations Environment Programme., CIRAIG., Processes and Services. Interuniversity Research Centre for the Life Cycle of Producs, and Canadian Electronic Library. 2013. *Guidelines for Social Life Cycle Assessment of Products*.

Bertsimas, Dimitris, Eugene Litvinov, Xu Andy Sun, Jinye Zhao, and Tongxin Zheng. 2013. "Adaptive Robust Optimization for the Security Constrained Unit Commitment Problem." *IEEE Transactions on Power Systems* 28(1):52–63.

Bertsimas, Dimitris and Aurelie Thiele. 2019. "Operations Research Inf7TSIiTT3 _ A Robust Optimization Approac Inventory Theory." 54(1):150–68.

Bozorgi-Amiri, Ali, M. S. Jabalameli, and S. M. J. Mirzapour Al-e-Hashem. 2013. "A Multi-Objective Robust Stochastic Programming Model for Disaster Relief Logistics under Uncertainty." *OR Spectrum* 35(4):905–33.

Brandenburg, Marcus, Kannan Govindan, Joseph Sarkis, and Stefan Seuring. 2014. "Quantitative Models for Sustainable Supply Chain Management: Developments and Directions." *European Journal of Operational Research* 233(2):299–312.

Cardoso, Sónia R., Ana Paula F. D. Barbosa-Póvoa, and Susana Relvas. 2013. "Design and Planning of Supply Chains with Integration of Reverse Logistics Activities under Demand Uncertainty." *European Journal of Operational Research* 226(3):436–51.

Carvalho, Ana, Ana Filipa Mimoso, Acácio Nobre Mendes, and Henrique A. Matos. 2014. "From a Literature Review to a Framework for Environmental Process Impact Assessment Index." *Journal of Cleaner Production* 64:36–62.

Chen, Cheng Liang and Wen Cheng Lee. 2004. "Multi-Objective Optimization of Multi-Echelon Supply Chain Networks with Uncertain Product Demands and Prices." *Computers and Chemical Engineering* 28(6–7):1131–44.

Chen, Cheng Liang, Bin Wei Wang, and Wen Cheng Lee. 2003. "Multiobjective Optimization for a

Multienterprise Supply Chain Network.” *Industrial and Engineering Chemistry Research* 42(9):1879–89.

Chen, Cheng Liang, Tzu Wei Yuan, and Wen Cheng Lee. 2007. “Multi-Criteria Fuzzy Optimization for Locating Warehouses and Distribution Centers in a Supply Chain Network.” *Journal of the Chinese Institute of Chemical Engineers* 38(5–6):393–407.

Consigli, G. and M. A. H. Dempster. 1998. “Dynamic Stochastic Programming for Asset-Liability Management.” *Annals of Operations Research* 81:131–61.

Development, World Commission on Environment and. 1987. “The Brundtland Report: ‘Our Common Future.’” *Medicine and War* 4(1):17–25.

Drahansky, Martin, M. .. Paridah, Amin Moradbak, A. .. Mohamed, Folahan abdulwahab taiwo Owolabi, Mustapha Asniza, and Shawkataly H. .. Abdul Khalid. 2016. “We Are IntechOpen , the World ’ s Leading Publisher of Open Access Books Built by Scientists , for Scientists TOP 1 %.” *Intech* i(tourism):13.

Elkington, John. 1997. *91. John Elkington*. Oxford: Capstone Publishing Limited.

European Commission, Institute for Environment and Sustainability. 2010. *International Reference Life Cycle Data System (ILCD) Handbook - General Guide for Life Cycle Assessment - Detailed Guidance*. Publications Office of the European Union.

Farrokh, Mojtaba, Adel Azar, Gholamreza Jandaghi, and Ehsan Ahmadi. 2018. “A Novel Robust Fuzzy Stochastic Programming for Closed Loop Supply Chain Network Design under Hybrid Uncertainty.” *Fuzzy Sets and Systems* 341:69–91.

Feitó-Cespón, Michael, William Sarache, Frank Piedra-Jimenez, and Roberto Cespón-Castro. 2017. “Redesign of a Sustainable Reverse Supply Chain under UncertaintyA Case Study.” *Journal of Cleaner Production* 151:206–17.

Fleischmann, Moritz, Jacqueline M. Bloemhof-Ruwaard, Rommert Dekker, Erwin Van Der Laan, Jo A. E. E. Van Nunen, and Luk N. Van Wassenhove. 1997. “Quantitative Models for Reverse Logistics: A Review.” *European Journal of Operational Research* 103(1):1–17.

Fu, Haobo, Peter R. Lewis, Bernhard Sendhoff, Ke Tang, and Xin Yao. 2014. “What Are Dynamic Optimization Problems?” *Proceedings of the 2014 IEEE Congress on Evolutionary Computation, CEC 2014* 1550–57.

Gabrel, V., M. Lacroix, C. Murat, and N. Remli. 2014. “Robust Location Transportation Problems under Uncertain Demands.” *Discrete Applied Mathematics* 164:100–111.

Ghaderi, Hamid, Alireza Moini, and Mir Saman Pishvaee. 2018. “A Multi-Objective Robust Possibilistic Programming Approach to Sustainable Switchgrass-Based Bioethanol Supply Chain Network Design.” *Journal of Cleaner Production* 179:368–406.

Giannoccaro, Ilaria, Pierpaolo Pontrandolfo, and Barbara Scozzi. 2003. “A Fuzzy Echelon Approach for Inventory Management in Supply Chains.” *European Journal of Operational Research* 149(1):185–96.

Gorissen, Bram L., Ihsan Yanikoğlu, and Dick den Hertog. 2015. “A Practical Guide to Robust Optimization.” *Omega (United Kingdom)* 53:124–37.

Govindan, Kannan, Mohammad Fattahi, and Esmaeil Keyvanshokooh. 2017. “Supply Chain Network

Design under Uncertainty: A Comprehensive Review and Future Research Directions." *European Journal of Operational Research* 263(1):108–41.

Govindan, Kannan, Hamed Soleimani, and Devika Kannan. 2015. "Reverse Logistics and Closed-Loop Supply Chain: A Comprehensive Review to Explore the Future." *European Journal of Operational Research* 240(3):603–26.

Group, Calzedonia. 2019. "Calzedonia Sustainability Report." 1–64.

Gupta, Anshuman and Costas D. Maranas. 2003. "Managing Demand Uncertainty in Supply Chain Planning." *Computers and Chemical Engineering* 27(8–9):1219–27.

Haugen, Kjetil K. 2016. *Stochastic Dynamic Programming*. 1st ed. The University Press.

Hinderer, Karl, Ulrich Rieder, and Michael Stieglitz. 2016. *Dynamic Optimization - Deterministic and Stochastic Models*. Vol. 120. Springler.

Iyengar, Garud N. 2005. "Robust Dynamic Programming." *Mathematics of Operations Research* 30(2):257–80.

Janak, Stacy L., Xiaoxia Lin, and Christodoulos A. Floudas. 2007. "A New Robust Optimization Approach for Scheduling under Uncertainty. II. Uncertainty with Known Probability Distribution." *Computers and Chemical Engineering* 31(3):171–95.

Li, Congbo, Fei Liu, Huajun Cao, and Qiulian Wang. 2009. "A Stochastic Dynamic Programming Based Model for Uncertain Production Planning of Re-Manufacturing System." *International Journal of Production Research* 47(13):3657–68.

Li, Y. P., J. Liu, and G. H. Huang. 2014. "A Hybrid Fuzzy-Stochastic Programming Method for Water Trading within an Agricultural System." *Agricultural Systems* 123:71–83.

Li, Yongping, Guo H. Huang, Amornvadee Veawab, Xianghui Nie, and Lei Liu. 2006. "Two-Stage Fuzzy-Stochastic Robust Programming: A Hybrid Model for Regional Air Quality Management." *Journal of the Air and Waste Management Association* 56(8):1070–82.

Liang, Tien Fu. 2006. "Distribution Planning Decisions Using Interactive Fuzzy Multi-Objective Linear Programming." *Fuzzy Sets and Systems* 157(10):1303–16.

Lin, Xiaoxia, Stacy L. Janak, and Christodoulos A. Floudas. 2004. "A New Robust Optimization Approach for Scheduling under Uncertainty: I. Bounded Uncertainty." *Computers and Chemical Engineering* 28(6–7):1069–85.

Linton, Jonathan D., Robert Klassen, and Vaidyanathan Jayaraman. 2007. "Sustainable Supply Chains: An Introduction." *Journal of Operations Management* 25(6):1075–82.

Liu, Ming Long and Nikolaos V. Sahinidis. 1996. "Optimization in Process Planning under Uncertainty." *Industrial and Engineering Chemistry Research* 35(11):4154–65.

Marques, Inês and M. Eugénia Captivo. 2017. "Different Stakeholders' Perspectives for a Surgical Case Assignment Problem: Deterministic and Robust Approaches." *European Journal of Operational Research* 261(1):260–78.

Martinez-Mares, Alberto and Claudio R. Fuerte-Esquivel. 2013. "A Robust Optimization Approach for the Interdependency Analysis of Integrated Energy Systems Considering Wind Power Uncertainty." *IEEE Transactions on Power Systems* 28(4):3964–76.

Messmann, Lukas, Victoria Zender, Andrea Thorenz, and Axel Tuma. 2020. "How to Quantify Social

Impacts in Strategic Supply Chain Optimization: State of the Art." *Journal of Cleaner Production* 257:120459.

Miodrag Belosevic, Mohamed Gamal El Din Zengquan Shu James R. Bolton. 2014. "Decomposition Analysis on Influence Factors of Direct Household." *Environmental Science & Technology* 33(2):482–89.

Mitra, Kishalay, Ravindra D. Gudi, Sachin C. Patwardhan, and Gautam Sardar. 2009. "Towards Resilient Supply Chains: Uncertainty Analysis Using Fuzzy Mathematical Programming." *Chemical Engineering Research and Design* 87(7):967–81.

Ben Mohamed, Imen, Walid Klibi, and François Vanderbeck. 2020. "Designing a Two-Echelon Distribution Network under Demand Uncertainty." *European Journal of Operational Research* 280(1):102–23.

Mota, Bruna, Maria Isabel Gomes, Ana Carvalho, and Ana Paula Barbosa-Povoa. 2015. "Towards Supply Chain Sustainability: Economic, Environmental and Social Design and Planning." *Journal of Cleaner Production* 105:14–27.

Mota, Bruna, Maria Isabel Gomes, Ana Carvalho, and Ana Paula Barbosa-Povoa. 2018. "Sustainable Supply Chains: An Integrated Modeling Approach under Uncertainty." *Omega (United Kingdom)* 77:32–57.

Mota, Bruna, Maria Isabel, Ana Carvalho, and Ana Paula Barbosa-povoa. 2015. "Towards Supply Chain Sustainability : Economic , Environmental and Social Design and Planning." *Journal of Cleaner Production* 105:14–27.

Mulvey, John M. and Robert J. Vanderbei. 1995. "89. Robust Optimization of Large-Scale Systems.Pdf." 264–81.

Ness, Barry, Evelin Urbel-Piirsalu, Stefan Anderberg, and Lennart Olsson. 2007. "Categorising Tools for Sustainability Assessment." *Ecological Economics* 60(3):498–508.

Nie, X. H., G. H. Huang, Y. P. Li, and L. Liu. 2007. "IFRP: A Hybrid Interval-Parameter Fuzzy Robust Programming Approach for Waste Management Planning under Uncertainty." *Journal of Environmental Management* 84(1):1–11.

Petrovic, Dobrila, Rajat Roy, and Radivoj Petrovic. 1998. "Modelling and Simulation of a Supply Chain in an Uncertain Environment." *European Journal of Operational Research* 109(2):299–309.

Pishvaee, M. S., J. Razmi, and S. A. Torabi. 2012. "Robust Possibilistic Programming for Socially Responsible Supply Chain Network Design: A New Approach." *Fuzzy Sets and Systems* 206:1–20.

Pishvaee, M. S., J. Razmi, and S. A. Torabi. 2014. "An Accelerated Benders Decomposition Algorithm for Sustainable Supply Chain Network Design under Uncertainty: A Case Study of Medical Needle and Syringe Supply Chain." *Transportation Research Part E: Logistics and Transportation Review* 67:14–38.

Pishvaee, M. S., S. A. Torabi, and J. Razmi. 2012. "Credibility-Based Fuzzy Mathematical Programming Model for Green Logistics Design under Uncertainty." *Computers and Industrial Engineering* 62(2):624–32.

Pishvaee, Mir Saman, Masoud Rabbani, and Seyed Ali Torabi. 2011. "A Robust Optimization Approach to Closed-Loop Supply Chain Network Design under Uncertainty." *Applied Mathematical Modelling* 35(2):637–49.

Popovic, Tamara, Ana Barbosa-Póvoa, Andrzej Kraslawski, and Ana Carvalho. 2018. "Quantitative Indicators for Social Sustainability Assessment of Supply Chains." *Journal of Cleaner Production* 180:748–68.

Purohit, Arun Kr, Ravi Shankar, Prasanta Kumar Dey, and Alok Choudhary. 2016. "Non-Stationary Stochastic Inventory Lot-Sizing with Emission and Service Level Constraints in a Carbon Cap-and-Trade System." *Journal of Cleaner Production* 113:654–61.

Puschke, Jennifer, Hatim Djelassi, Johanna Kleinekorte, Ralf Hannemann-Tamás, and Alexander Mitsos. 2018. "Robust Dynamic Optimization of Batch Processes under Parametric Uncertainty: Utilizing Approaches from Semi-Infinite Programs." *Computers and Chemical Engineering* 116:253–67.

Ramos Huarachi, Diego Alexis, Cassiano Moro Piekarski, Fabio Neves Puglieri, and Antonio Carlos de Francisco. 2020. "Past and Future of Social Life Cycle Assessment: Historical Evolution and Research Trends." *Journal of Cleaner Production* 264:121506.

Rommelfanger, Heinrich J. 2004. "The Advantages of Fuzzy Optimization Models in Practical Use." *Fuzzy Optimization and Decision Making* 3(4):295–309.

Saffar, Mohammad Mahdi, G. Hamed Shakouri, and Jafar Razmi. 2015. "A New Multi Objective Optimization Model for Designing a Green Supply Chain Network under Uncertainty." *International Journal of Industrial Engineering Computations* 6(1):15–32.

Sahinidis, Nikolaos V. 2004. "Optimization under Uncertainty: State-of-the-Art and Opportunities." *Computers and Chemical Engineering* 28(6–7):971–83.

Sazvar, Z., S. M. J. Mirzapour Al-E-Hashem, A. Baboli, and M. R. Akbari Jokar. 2014. "A Bi-Objective Stochastic Programming Model for a Centralized Green Supply Chain with Deteriorating Products." *International Journal of Production Economics* 150:140–54.

Schöggl, Josef Peter, Morgane M. C. Fritz, and Rupert J. Baumgartner. 2016. "Toward Supply Chain-Wide Sustainability Assessment: A Conceptual Framework and an Aggregation Method to Assess Supply Chain Performance." *Journal of Cleaner Production* 131:822–35.

Schön, Cornelia and Eva König. 2018. "A Stochastic Dynamic Programming Approach for Delay Management of a Single Train Line." 271:501–18.

Seuring, Stefan and Martin Müller. 2008. "From a Literature Review to a Conceptual Framework for Sustainable Supply Chain Management." *Journal of Cleaner Production* 16(15):1699–1710.

Shabani, Nazanin and Taraneh Sowlati. 2016. "A Hybrid Multi-Stage Stochastic Programming-Robust Optimization Model for Maximizing the Supply Chain of a Forest-Based Biomass Power Plant Considering Uncertainties." *Journal of Cleaner Production* 112:3285–93.

Shang, Chao and Fengqi You. 2018. "Distributionally Robust Optimization for Planning and Scheduling under Uncertainty." *Computers and Chemical Engineering* 110:53–68.

Shi, Hanyu and Fengqi You. 2015. "Pyrolysis of Heavy Oil in the Presence of Supercritical Water: The Reaction Kinetics in Different Phases." *AICHE Journal* 61(3):857–66.

Stewart, Jeffrey J., Peter N. Allison, and Ronald S. Johnson. 2001. "Putting a Price on Biotechnology

Many Bioentrepreneurs Incorrectly Estimate the Value of Their Technology by Failing to Account." 813–17.

Sungur, Ilgaz, Fernando Ordóñez, and Maged Dessouky. 2008. "A Robust Optimization Approach for the Capacitated Vehicle Routing Problem with Demand Uncertainty." *IIE Transactions (Institute of Industrial Engineers)* 40(5):509–23.

Tajik, N., R. Tavakkoli-Moghaddam, Behnam Vahdani, and S. Meysam Mousavi. 2014. "A Robust Optimization Approach for Pollution Routing Problem with Pickup and Delivery under Uncertainty." *Journal of Manufacturing Systems* 33(2):277–86.

Topaloglou, Nikolas, Hercules Vladimirou, and Stavros A. Zenios. 2008. "A Dynamic Stochastic Programming Model for International Portfolio Management." *European Journal of Operational Research* 185(3):1501–24.

Tranfield, David, David Denyer, Palminder Smart, Dale L. Goodhue, and Ronald L. Thompson. 2003. "Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review." *British Journal of Management* 14(2):207–22.

Tsao, Yu Chung, Vo Van Thanh, Jye Chyi Lu, and Vincent Yu. 2018. "Designing Sustainable Supply Chain Networks under Uncertain Environments: Fuzzy Multi-Objective Programming." *Journal of Cleaner Production* 174:1550–65.

United Nations Developments Report. 2018. "Gender Inequality Index." 156–59.

Vallerio, Mattia, Dries Telen, Lorenzo Cabianca, Flavio Manenti, Jan Van Impe, and Filip Logist. 2016. "Robust Multi-Objective Dynamic Optimization of Chemical Processes Using the Sigma Point Method." *Chemical Engineering Science* 140:201–16.

Weinmann, Alexander. 1991. *Uncertain Models and Robust Control*. 1st ed. Springer-Verlag Wien GmbH.

Xie, Shiwei, Zhijian Hu, and Jueying Wang. 2020. "Two-Stage Robust Optimization for Expansion Planning of Active Distribution Systems Coupled with Urban Transportation Networks." *Applied Energy* 261(January):114412.

Zahiri, Behzad, Nallan C. Suresh, and Jurriaan de Jong. 2020. "Resilient Hazardous-Materials Network Design under Uncertainty and Perishability." *Computers & Industrial Engineering* 143(March):106401.

Zhang, Xiaodong, Guo H. Huang, and Xianghui Nie. 2009. "Robust Stochastic Fuzzy Possibilistic Programming for Environmental Decision Making under Uncertainty." *Science of the Total Environment* 408(2):192–201.

Zhao, Liang, Chao Ning, and Fengqi You. 2019. "Operational Optimization of Industrial Steam Systems under Uncertainty Using Data-Driven Adaptive Robust Optimization." *AIChE Journal* 65(7):21–24.

APPENDIX A

Table A.1 - Sample of 72 papers analysed

Articles	Decision Levels	Optimization Approach	Uncertainty Parameters	Sustainability Considerations
Ahn and Han (2018)	Strategic & Tactical	Stochastic Programming	Demand	Economic & Environmental
Alem, Clark, and Moreno (2016)	Tactical	Stochastic Programming	Demand, nature and magnitude of disaster, supply, transportation links & resources availability	N/A
Alizadeh, Amiri-Aref, et al. (2019)	Strategic & Operational	Stochastic Programming & Robust Optimization	Demand & Transportation capacity	N/A
Alizadeh, Ma, et al. (2019)	Strategic & Operational	Stochastic Programming & Robust Optimization	Carbon tax rate/price	Economic & Environmental
Alvarez et al. (2020)	Tactical & Operational	Robust Optimization	Yield	N/A
Ameknassi, Aït-Kadi, and Rezg (2016)	Strategic & Tactical	Stochastic Programming	Demand, facilities capacities, variable costs & returned products quality	Economic & Environmental
Amiri-Aref, Klibi, and Babai (2018)	Strategic & Tactical	Stochastic Programming	Demand	N/A
Balcik and Yanıkoğlu (2020)	Operational	Robust Optimization	Travel times	N/A
Banasik et al. (2019)	Tactical	Stochastic Programming	Demand & Yield	Economic & Environmental
Ben Mohamed, Klibi, and Vanderbeck (2020)	Strategic	Stochastic Dynamic Optimization	Demand	N/A

Bertazzi and Maggioni (2018)	Tactical	Stochastic Dynamic Optimization	Demand	N/A
Buergin et al. (2019)	Tactical	Stochastic Programming & Robust Optimization	Location & production periods	N/A
Chen and Monahan (2010)	Tactical	Stochastic Programming	Demand & environmental waste limit	Economic & Environmental
Cunha, Raupp, and Oliveira (2017)	Strategic	Stochastic Programming	Demand	N/A
Dai et al. (2018)	Tactical	Fuzzy Programming	Capacity & carbon emissions	Economic & Environmental
Diehlmann et al. (2019)	Strategic & Operational	Stochastic Programming	Demand, supply & product prices	Economic & Environmental
Feitó-Cespón et al. (2017)	Strategic	Stochastic Programming	Demand & supply	Economic, Environmental & Social
Felfel, Ayadi, and Masmoudi (2016)	Tactical	Stochastic Programming	Demand	N/A
Gambella, Maggioni, and Vigo (2019)	Tactical	Stochastic Programming	Waste Generation	N/A
Gao and You (2017)	Strategic & Operational	Stochastic Programming	Demand, supply product productivity, economic cost & life cycle inventories	Economic & Environmental
Gilani Larimi and Yaghoubi (2019)	Tactical	Stochastic Programming & Robust Optimization	Demand	N/A
Golsefidi, Reza, and Jokar (2020)	Strategic	Robust Optimization	Demand, number of defective products collected from each retailer & reproduction cost of each product	N/A

Govindan et al. (2020)	Strategic	Fuzzy Programming	Demand	Economic & Environmental
Haddadsisakht and Ryan (2018)	Strategic & Tactical	Stochastic Programming & Robust Optimization	Demand, returned products supply & carbon tax rate	Economic & Environmental
Hong et al. (2018)	Strategic & Tactical	Stochastic Programming	Demand	Economic & Environmental
Hu and Hu (2020)	Tactical	Stochastic Programming & Robust Optimization	Demand & overtime processing costs	N/A
Isuru et al. (2020)	Tactical	Robust Adaptive Optimization	Supply	N/A
Jabbarzadeh, Haughton, and Pourmehdi (2019)	Tactical	Robust Optimization	Demand	Economic & Environmental
Jeihoonian, Kazemi Zanjani, and Gendreau (2017)	Strategic	Stochastic Programming	Returned products quality	Economic & Environmental
Jiang et al. (2020)	Strategic	Robust Optimization	Demand	Economic & Environmental
Jiao et al. (2018)	Strategic & Tactical	Robust Optimization	Demand, waste ratio & buyers' expectations	Economic & Environmental
Kuşakcı et al. (2019)	Strategic & Tactical	Fuzzy Programming	Amount of End-of-life vehicles generated	N/A
Li and Hu (2017)	Tactical	Stochastic Programming	Demand & workforce uncertainty	N/A
Li, Yang, and Hu (2018)	Tactical	Stochastic Programming	Demand & supply	Economic & Environmental
Liao and Deng (2018)	Tactical	Stochastic Programming	Demand	Economic & Environmental

Liu et al. (2020)	Tactical	Robust Optimization	Demand	N/A
Lu et al. (2020)	Strategic	Fuzzy Programming	Transportation costs, return rates & waste ratios	N/A
Martí, Tancrez, and Seifert (2015)	Strategic & Tactical	Stochastic Programming	Demand	Economic & Environmental
Mirmajlesi and Shafaei (2016)	Strategic & Tactical	Robust Optimization	Demand	N/A
Modarres and Izadpanahi (2016)	Tactical	Robust Optimization	Demand & production capacity	Economic & Environmental
Mohammad Hasany and Shafahi (2017)	Tactical	Stochastic Programming	Demand & supply	N/A
Mota et al. (2018)	Strategic & Tactical	Stochastic Programming	Demand	Economic, Environmental & Social
Ouhimmou et al. (2019)	Strategic	Robust Optimization	Demand	N/A
Paul and Zhang (2019)	Strategic	Stochastic Programming	Location, supply amount & shipping capacity	N/A
Pishvaee, Razmi, and Torabi (2014)	Strategic & Tactical	Fuzzy Programming	Demand, returned products, capacities, costs, environmental impacts, number of days lost, job opportunities, potential hazardous products, economic value & social impacts	Economic, Environmental & Social

Pourjavad and Mayorga (2019)	Strategic	Fuzzy Programming	Demand, products returned rates & facilities capacities	Economic, Environmental & Social
Purohit et al. (2016)	Tactical	Stochastic Dynamic Optimization	Demand	Economic & Environmental
Rahmani and Mahoodian (2017)	Strategic & Operational	Robust Optimization	Demand	Economic & Environmental
Rajendran and Ravi Ravindran (2019)	Tactical	Stochastic Programming	Demand	N/A
Ren et al. (2019)	Strategic	Stochastic Programming	Carbon tax rate/price	Economic & Environmental
Sahling and Kayser (2016)	Strategic	Stochastic Programming	Demand	N/A
Samuel et al. (2020)	Strategic	Robust Optimization	Returned products quality	Economic & Environmental
Sazvar et al. (2014)	Tactical & Operational	Stochastic Dynamic Optimization	Demand	Economic & Environmental
Schildbach and Morari (2016)	Strategic	Stochastic Programming	Demand	N/A
Schön and König (2018)	Tactical	Stochastic Dynamic Optimization	Future delays	N/A
Shabani and Sowlati (2016)	Tactical	Robust & Stochastic Dynamic Optimization	Product supply quality	N/A
Shang and You (2018)	Tactical	Robust Dynamic Optimization	Demand	N/A
Sherafati et al. (2019)	Strategic & Tactical	Robust Optimization	Costs	Economic, Environmental & Social
Shi et al. (2019)	Strategic	Robust Optimization	Waste generation	Economic & Environmental

Song et al. (2017)	Strategic & Tactical	Stochastic Programming	Demand & carbon tax rate/price	Economic & Environmental
Stefansdottir and Grunow (2018)	Tactical	Stochastic Programming	Demand	N/A
Trochu, Chaabane, and Ouhimmou (2020)	Strategic	Stochastic Programming	Recycling rates & Returned products supply	Economic & Environmental
Tsao and Thanh (2019)	Strategic	Fuzzy Programming & Robust Optimization	Demand, CO_2 emissions & social costs related to traffic congestion, unemployment & immigration	Economic, Environmental & Social
Tsao et al. (2018)	Strategic & Tactical	Stochastic & Fuzzy Programming	Demand, cost, capacity, CO_2 emissions, number of job opportunities, generation of hazardous products & average number of workdays lost due to implementation of new technologies	Economic, Environmental & Social
Xie et al. (2020)	Strategic & Tactical	Robust Adaptive Optimization	Demand & load power	N/A
Yu and Solvang (2017)	Strategic	Stochastic Programming	Generation of different types of end-of-use and end-of-life products, price of recycled products & recovered energy	Economic & Environmental
Yu and Solvang (2018)	Strategic & Tactical	Stochastic Programming	Amount of used products, price of recovered products or energy & quality	Economic & Environmental

			level of used products	
Zahiri and Pishvaee (2017)	Strategic	Fuzzy Programming & Robust Optimization	Demand, supply, travel time & costs	N/A
Zahiri et al. (2018)	Strategic & Tactical	Stochastic Dynamic Optimization	Demand & Supply	N/A
Zahiri et al. (2020)	Strategic	Stochastic Dynamic Optimization	Demand	N/A
Zhalechian et al. (2016)	Strategic & Tactical	Stochastic & Fuzzy Programming	Distance travelled & transportation time, costs, lead time, number of created job opportunities, economic value, regional development, environmental impact of CO_2 emissions & fuel consumption, average acceleration of vehicle, front space of vehicle, coefficient of air friction, capacity of vehicles used	Economic, Environmental & Social
Zhen, Huang, and Wang (2019)	Strategic	Stochastic Programming	Demand	Economic & Environmental

Appendix B

Table B.1 - Social subcategories of social lifecycle assessment (adapted from Benoit-Norris (2013))

Stakeholder Categories	Subcategories (i.e., social indicators)
Workers	Freedom of Association and Collective Bargaining
	Child Labour
	Fair Salary
	Hours of Work
	Forced Labour
	Equal Opportunities / Discrimination
	Health and Safety
	Social Benefit / Social Security
Local Community	Delocalization and Migration
	Community Engagement
	Cultural Heritage
	Respect of Indigenous Rights
	Local Employment
	Access to Immaterial Resources
	Access to Material Resources
	Safe and Healthy Living Conditions
	Secure Living Conditions
Society	Public Commitment to Sustainability Issues
	Prevention and mitigation of Conflicts
	Contribution to Economic Development
	Corruption
	Technology Development
Consumers	Health and Safety
	Feedback Mechanism
	Privacy
	Transparency
	End-of-Life Responsibility
Value Chain Actors	Fair Competition
	Respect of Intellectual Property Rights
	Supplier Relationships
	Promoting Social Responsibility

APPENDIX C

Figure C.2 - Calzedonia Group case-study - network elementsFigure C.2 depicts the general considerations on the network elements considered on the Calzedonia Group case-study.

CALZEDONIA GROUP - Overall General Considerations

Fabric Suppliers	Factories	Warehouses	Markets - Top European Countries	
Italy	Avio (Italy)	Vallese Di Oppeano (Italy)	Italy	934
China	Gissi (Italy)	Castagnaro (Italy)	Spain	401
	Croatia	Varazdin (Croatia)	France	154
		Spain	Germany	125
		France	Portugal	124
		Germany	Poland	99
		Portugal		
		Poland		

Figure C.2 - Calzedonia Group case-study - network elements

Figure C.3 represents all entities accounted for in the Calzedonia Group case-study, namely, the entities, the technologies, the materials, and the transportation modes.

Entities Names & Definitions - Superstructure

Suppliers	Factories	Warehouses	Markets	Airports	Seaports	Technologies
sItaly (l_{sup})	fAvio (l_f)	wValleseDiOppeano (l_w)	cItaly (l_c)	airItaly (l_{air})	portItaly (l_{port})	Production (gp)
sChina (l_{sup})	fGissi (l_f)	wCastagnaro (l_w)	cSpain (l_c)	airPortugal (l_{air})	portChina (l_{port})	Remanufacturing (gr)
	fCroatia (l_f)	wVarazdin (l_w)	cFrance (l_c)	airPoland (l_{air})		
		wSpain (l_w)	cGermany (l_c)			
		wFrance (l_w)	cPortugal (l_c)			
		wGermany (l_w)	cPoland (l_c)			
		wPortugal (l_w)				
		wPoland (l_w)				

Entities Names & Definitions - Materials

Raw Materials		Final Products		Recovered Products	
rm1 (M_{rm})	10g Cotton	fp1 (M_{fp})	1 pair cotton socks (100g)	rp1 (M_{rp})	1 pair cotton socks (100g)
rm2 (M_{rm})	10g Polyamide (nylon)	fp2 (M_{fp})	1 pair sheer tights (60g)	rp2 (M_{rp})	1 pair sheer tights (60g)
rm3 (M_{rm})	10g Elastane (lycra)				

Entities Names & Definitions - Transportation Modes

Land Transportation		Air Transportation		Air Transportation	
atruck1 (A_{truck})	Smaller Truck	aplane (A_{plane})	Airplane	aplane (A_{plane})	Airplane
atruck2 (A_{truck})	Bigger Truck				

Figure C.3 - Calzedonia Group case-study - entities names and definitions

Figure C.4 depicts all parameters and respective assigned values related to the entities considered in the Calzedonia Group case-study, namely: maximum and minimum supply capacities; raw materials unit costs; maximum and minimum installation areas; hourly labour costs per entity; construction costs per entity; number of necessary workers per entity; maximum flow considered in the network; maximum and minimum allowed inventory levels per entity; and initial stock per entity.

Entity related Parameters Definitions & Values

Suppliers Capacities & Raw Materials Costs

Maximum supply capacity, sc_{ml}^{max}	sItaly	sChina	
rm1	100,000,000	600,000,000	
rm2	8,000,000	17,000,000	
rm3	3,000,000	55,000,000	
			(per 10g per year)

Minimum order quantity, sc_{ml}^{min}	sItaly	sChina	
rm1	0	0	
rm2	0	0	
rm3	0	0	(per 10g per year)

Raw Material Unit Cost (€), rmc_{ml}	sItaly	sChina
rm1	0.0323	0.0248
rm2	0.0269	0.0207
rm3	0.0309	0.0238

Installation Areas per Entity

	Maximum Installation Area (m^2), ea_l^{max}	Minimum Installation Area (m^2), ea_l^{min}
sItaly	-	-
sChina	-	-
fAvio	12,000	-
fGissi	12,000	-
fCroatia	10,000	-
wVallesseDiOppeano	8,000	-
wCastagnaro	8,000	-
wVarazdin	5,000	-
wSpain	5,000	50
wFrance	5,000	50
wGermany	5,000	50
wPortugal	5,000	50
wPoland	5,000	50
cItaly	-	-
cSpain	-	-
cFrance	-	-
cGermany	-	-
cPortugal	-	-
cPoland	-	-
airItaly	-	-
airPortugal	-	-
airPoland	-	-
portItaly	-	-
portChina	-	-

Variable Costs per Entity

	Hourly Labour Costs (€), lc_l	Construction Costs (€/m^2), $sqmc_l$
sItaly	28.8	-
sChina	5.6	-
fAvio	28.8	-
fGissi	28.8	-
fCroatia	11.1	-
wVallesseDiOppeano	28.8	-
wCastagnaro	28.8	-
wVarazdin	11.1	-
wSpain	21.0	460.0
wFrance	36.6	732.0
wGermany	35.6	677.0
wPortugal	14.6	459.0
wPoland	10.7	456.0
cItaly	28.8	-
cSpain	21.0	-
cFrance	36.6	-
cGermany	35.6	-
cPortugal	14.6	-
cPoland	10.7	-
airItaly	28.8	-
airPortugal	14.6	-
airPoland	10.7	-
portItaly	28.8	-
portChina	5.6	-
		-

Workers per Entity

	Fixed number of workers, w_l	Number of workers per square meter, $wpsq_l$
Factories	8	0.01
Warehouses	7	0.01

Maximum Flow

Maximum Flow, ec_l^{max}	7,000,000,000

Final Products Inventory Management								
Maximum Inventory Capacity per Entity, ic_{mi}^{max}	wValleseDiOppeano	wCastagnaro	wVarazdin	wSpain	wFrance	wGermany	wPortugal	wPoland
fp1	12,000,000	12,000,000	10,000,000	10,000,000	10,000,000	10,000,000	10,000,000	10,000,000
fp2	12,000,000	12,000,000	10,000,000	10,000,000	10,000,000	10,000,000	10,000,000	10,000,000
Minimum Inventory Level per Entity, ic_{mi}^{min}	wValleseDiOppeano	wCastagnaro	wVarazdin	wSpain	wFrance	wGermany	wPortugal	wPoland
fp1	120,000	120,000	100,000	100,000	100,000	100,000	100,000	100,000
fp2	120,000	120,000	100,000	100,000	100,000	100,000	100,000	100,000
Stock Level in stage 1, ins_{mi}	wValleseDiOppeano	wCastagnaro	wVarazdin	wSpain	wFrance	wGermany	wPortugal	wPoland
fp1	2,000	1,500	500	-	-	-	-	-
fp2	800	1,000	800	-	-	-	-	-

Figure C.4 - Calzedonia Group case-study - entities parameters and values

Figure C.5 represents the product characterization parameters, namely: product weight; price per unit sold; inventory cost per unit; necessary area per unit of product; recovered product costs. Besides, the products bill of materials (BOM) is also depicted, as well as the recovered products return fraction.

Products Characterization

Products Characterization - General Information

	Product Weight (Kg), pw_m	Price per Unit sold (€), psu_m	Inventory Cost per unit (€), sc_m	Necessary Area per Unit of Product (m^2), apu_m	Recovered Product Cost (€), rpc_m
rm1	0.01	-	-	0.001	-
rm2	0.01	-	-	0.001	-
rm3	0.01	-	-	0.001	-
fp1	0.1	6	0.01	0.001	-
fp2	0.06	15	0.01	0.001	-
rp1	0.1	-	-	0.001	0.15
rp2	0.06	-	-	0.001	0.15

Products Bill of Material (BOM)

Manufacturing relation between Raw Materials & Final Products at Factories	fp1	fp2
rm1	8.8	-
rm2	0.9	4.5
rm3	0.3	1.5

Remanufacturing relation between Recovered Products & Final Porducts at Factories	fp1	fp2
rp1	4	-
rp2	-	5

Final Products relation at Factories (in and out)	fp1	fp2
fp1	1	-
fp2	-	1

Final Products & Recovered Products relations at Warehouses & Airports (in and out)	fp1	fp2	rp1	rp2
fp1	1	-	-	-
fp2	-	1	-	-
rp1	-	-	1	-
rp2	-	-	-	1

Final Products & Recovered Products relations at Markets (in and out)	fp1	fp2
rp1	1	-
rp2	-	1

Recovered Products Return Fraction after 12 months (1 stage)	
rp1	0.1
rp2	0.05

Figure C.5 - Calzedonia Group case-study - products characterization

Figure C.6 depicts the technologies characterization, where values have been assigned to the following parameters: maximum and minimum production capacities; installation costs; operational costs per unit produced; and the fixed number of workers per technologies.

Technologies Characterization

	Maximum Production Capacity (units), pc_g^{max}	Minimum Production Capacity (units), pc_g^{min}	Installation Costs (€), tec_g	Operational Costs per Unit Produced (€), opc_g	Fixed Necessary Workers, w_g
Production (gp)	2,000,000,000	0	150,000	0.12	2
Remanufacturing (gr)	1,700,000,000	0	175,000	0.20	3

Figure C.6 - Calzedonia Group case-study - technologies characterization

Figure C.7 represents the transportation modes characterization, with values assigned to relevant parameters, such as: maximum and minimum transportation capacities; maximum contracted capacities; fixed costs (total investment and monthly payments to carriers); handling costs at hub terminals; variable transportation costs; necessary workers per unit and per transportation mode; and, average vehicle consumption. Furthermore, additional relevant parameters are also accounted for, such as: maximum truck investment; fuel price; vehicle maintenance costs; average speed; maximum driving hours per week; number of weeks per stage; and weekly working hours.

Transportation Modes - Characterization

	Maximum Transportation Capacity (units), ct_a^{max}	Minimum Transportation Capacity (units), ct_a^{min}	Maximum Contracted Capacity per stage (units), cca_a^{max}
Truck 1	50,000	1	-
Truck 2	77,000	1	-
Plane	5,000,000	1	5,000,000
Boat	10,000,000	1	5,000,000

Transportation Modes - Fixed Costs

	Fixed Costs - Total Investment, ftc_a	Fixed Costs - Montly Payment to Carrier	Handling Costs at Hub Terminals per Unit (€)
Truck 1	30,000	-	-
Truck 2	50,000	-	-
airItaly	-	220,000	0.2
airPortugal	-	200,000	0.15
airPoland	-	200,000	0.15
portItaly	-	210,000	0.10
portChina	-	210,000	0.10

Transportation Modes - Variable Costs & Considerations

	Variable Transportation Costs per Kg.km, tc_a	Necessary Workers per Unit (truck), w_a	Necessary Workers per Unit (Kg.km), w_a	Average Vehicle Consumption (L per 100 km), avc_a
Truck 1	0.51	1	-	14
Truck 2	0.57	1	-	18
Plane	0.04	-	2.53E-07	-
Boat	0.01	-	8.63E-11	-

Transportation Modes - Necesary Data

Maximum Truck Investment (€), invt	2,000,000
Fuel Price (€/L), fp	1.5
Vehicle Maintenance Costs (€/km), vmc	0.3
Average Speed (km/h), avs	60
Maximum Driving Hours per Week, mhw	45
Number of Weeks per stage, wpt	52
Weekly Working Hours, wwh	40

Figure C.7 - Calzedonia Group case-study – transportation modes characterization

Figure C.8 depicts other relevant parameters to the Calzedonia Group case-study, namely economic data, such as: interest rate; tax rate; and, salvage value per set considered.

Economic Data

Interest Rate, ir	0.1
Tax Rate, tr	0.3
Salvage Value, $_{sv}$	
Entities	0.5
Technology	0
Trucks	0

Figure C.8 - Calzedonia Group case-study – economic data parameters

Figure C.9 presents the environmental parameters considered for the environmental assessment, obtained trough the methodology ReCiPe 2016, using SimaPro.

Environmental Data

	Entity per m^2	Technology, per kg produced				Transportation Modes			
		gp		gr					
		fp1	fp2	fp1	fp2	truck1	truck2	plane	ship
GW	3.93E+02	4.54E+00	4.03E-01	2.27E+00	1.14E+00	6.13E-08	2.63E-08	5.26E-08	1.09E-09
OD	1.16E-04	1.17E-06	1.42E-07	5.85E-07	2.93E-07	5.63E-09	2.63E-09	1.76E-09	1.06E-10
IR	1.67E+00	3.17E-03	3.58E-03	1.59E-03	7.93E-04	7.19E-09	3.10E-09	6.14E-09	1.18E-10
OHH	1.28E+00	5.30E-03	6.95E-04	2.65E-03	1.33E-03	2.00E-08	9.15E-09	1.00E-07	9.37E-09
FP	7.54E-01	5.38E-03	1.18E-03	2.69E-03	1.35E-03	9.51E-09	4.38E-09	1.53E-08	2.39E-09
OTE	1.32E+00	5.45E-03	7.00E-04	2.73E-03	1.36E-03	2.41E-08	1.10E-08	1.17E-07	1.09E-08
TA	2.40E+00	9.62E-03	1.11E-03	4.81E-03	2.41E-03	1.35E-09	5.90E-09	2.82E-08	4.67E-09
FE	1.06E-02	2.62E-04	3.08E-05	1.31E-04	6.55E-05	1.01E-09	4.35E-10	8.62E-10	1.56E-11
ME	4.51E-03	2.26E-05	7.37E-07	1.13E-05	5.65E-06	2.39E-11	1.13E-11	1.28E-11	1.99E-13
TE	1.77E+03	7.93E+00	1.85E-01	3.97E+00	1.98E+00	5.23E-06	2.86E-06	7.15E-07	1.86E-08
FEC	8.51E-01	3.56E-02	1.36E-04	1.78E-02	8.90E-03	6.96E-07	3.71E-07	1.09E-07	2.00E-09
MEC	2.10E+00	5.12E-02	2.75E-04	2.56E-02	1.28E-02	3.81E-06	2.07E-06	5.47E-07	1.39E-08
HC	1.39E+01	2.67E-02	1.01E-03	1.34E-02	6.68E-03	8.69E-08	3.88E-08	6.34E-08	1.08E-08
HNC	1.44E+02	1.43E+00	4.95E-02	7.15E-01	3.58E-01	5.41E-07	2.89E-07	4.95E-07	2.10E-09
LU	6.31E+01	-9.14E-02	9.20E-03	-4.57E-02	-2.29E-02	1.94E-10	8.34E-11	1.62E-10	4.84E-12
MR	2.76E+01	3.68E-04	6.45E-05	1.84E-04	9.20E-05	3.15E-13	1.36E-13	2.58E-13	9.94E-16
FR	8.50E+01	1.43E+00	1.11E-01	7.15E-01	3.58E-01	1.63E-07	7.01E-08	1.39E-07	2.67E-09
WC	3.26E+00	1.08E-01	1.61E-03	5.40E-02	2.70E-02	6.12E-10	2.64E-10	4.44E-10	4.34E-12

Figure C.9 - Calzedonia Group case-study - environmental data parameters (SimaPro)

Figure C.10 represents the social values assigned to the relevant parameters, obtained through the comprehensive review of the Calzedonia Group Sustainability Report (Group Calzedonia, 2019).

Social Data			
	Wages ratio per entity (female/male)	Number of Accidents per entity	Regional Development of entity
fAvio	10%	1.02	0.70
fGissi	10%	1.02	0.70
fCroatia	10%	1.02	0.50
wVallese	10%	1.02	0.70
wCastagnaro	10%	1.02	0.70
wVarazdin	10%	1.02	0.50
wSpain	10%	1.02	0.65
wFrance	10%	1.02	0.80
wGermany	10%	1.02	0.80
wPortugal	10%	1.02	0.60
wPoland	10%	1.02	0.45

Figure C.10 - Calzedonia Group case-study - social data parameters

APPENDIX D

Figure D.1 depicts all maximization and minimization values obtained for each objective function, as well as the obtained gap percentages in GAMS, in each case considered, from A to J.

1. Deterministic

Maximize			Minimize			Optimal		
Economic	2.28E+08	0.97%	Economic	103882900	0.93%	Economic	152219400	0.70%
Environmental	1069118.275	0.80%	Environmental	340901.045	0.10%	Environmental	1007686.4	0.70%
Social	873436.219	0.00%	Social	873429.902	0.00%	Social	873436.22	0.70%

2. Uncertain Demand

Maximize			Minimize			Optimal		
Economic	1.29E+08	1.80%	Economic	3.33414E-07	0.00%	Economic	52664490	0.00%
Environmental	1217158.145	2.10%	Environmental	229190.726	2.03%	Environmental	797559.87	0.00%
Social	873456.979	0.00%	Social	873429.902	0.00%	Social	873456.98	0.00%

3. Uncertain Supply

Maximize			Minimize			Optimal		
Economic	1.99E+08	4.37%	Economic	138983400	46.10%	Economic	186000000	0.00%
Environmental	967756.415	0.24%	Environmental	306451.681	0.00%	Environmental	562333.22	0.00%
Social	786111.281	0.00%	Social	786086.912	0.00%	Social	786091.87	0.00%

4. Uncertain Rate of Return

Maximize			Minimize			Optimal		
Economic	2.27E+08	4.50%	Economic	155390400	0.00%	Economic	195486300	0.00%
Environmental	1628786.176	0.12%	Environmental	335331.96	0.013%	Environmental	519010.83	0.00%
Social	873456.979	0.00%	Social	873435.518	0.00%	Social	873429.9	0.00%

5. Uncertain Demand + Supply

Maximize			Minimize			Optimal		
Economic	1.25E+08	4.60%	Economic	1.6205E-07	0.00%	Economic	58766710	0.00%
Environmental	1233680.884	0.88%	Environmental	227206.43	0.48%	Environmental	836181.36	0.00%
Social	873456.979	0.00%	Social	873426.585	0.00%	Social	873456.98	0.00%

6. Uncertain Demand + Supply + Rate of Return

Maximize			Minimize			Optimal		
Economic	1.26E+08	1.80%	Economic	0	0.00%	Economic	48068810	4.50%
Environmental	1208263.802	2.60%	Environmental	218815.018	0.0265%	Environmental	744688.68	4.50%
Social	873456.979	0.00%	Social	873434.738	0.00%	Social	873456.98	4.50%

7. Uncertain Construction Costs

Maximize			Minimize			Optimal		
Economic	2.22E+08	3.12%	Economic	153866400	52.1%	Economic	203741700	3.62%
Environmental	1050415.445	2.50%	Environmental	340720.943	0.07%	Environmental	611619.46	3.62%
Social	873435.854	0.00%	Social	873429.902	0.00%	Social	873436.82	3.62%

8. Uncertain Transportation Costs

Maximize			Minimize			Optimal		
Economic	100479600	4.7%	Economic	0	0	Economic	34084310	1.90%
Environmental	931921.169	1.8%	Environmental	340523.84	0.00%	Environmental	883551.81	1.90%
Social	873434.838	0.0%	Social	873429.902	0.00%	Social	873436.22	1.90%

9. Uncertain Construction + Transportation Costs

Maximize			Minimize			Optimal		
Economic	9.61E+07	4.40%	Economic	0	0%	Economic	22580490	
Environmental	726245.519	0.00%	Environmental	340488.453	0.00%	Environmental	888553.36	
Social	873435.47	0.00%	Social	873433.655	0.00%	Social	873436.73	

10. Uncertain Demand - Dynamic Optimization

Maximize			Minimize			Optimal		
Economic	1.29E+06	1.00%	Economic	0	0%	Economic	9.43E+05	0.15%
Environmental	1217158.145	0.80%	Environmental	229190.726	0.10%	Environmental	1908430.8	0.15%
Social	873456.979	0.00%	Social	873429.902	0.00%	Social	4327845.2	0.15%

Figure D.1 - Calzedonia Group case-study - normalization factors per objective function in each case A – J

APPENDIX E

Figure E.1 depicts both the number of restrictions and variables, as well as the execution times for cases A, B F, and J.

A. Deterministic		
Number of restrictions	Number of variables	Execution time (seconds)
9,065	6,066	0.922
B. Uncertain Demand		
Number of restrictions	Number of variables	Execution time (seconds)
44,579	29,908	7.625
F. Uncertain Demand + Supply + Rate of Return		
Number of restrictions	Number of variables	Execution time (seconds)
49,579	29,908	4.281
J. Uncertain Demand - Dynamic Approach		
Number of restrictions	Number of variables	Execution time (seconds)
275,407	184,868	428.719

Figure E.1 - Calzedonia Group case-study - runs specifications for cases A, B, F, and J