Modelling Uncertainty in the Design and Planning of Sustainable Supply Chains

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Abstract The present work focuses on the design and planning of sustainable supply chains under uncertainty. Thus, a stochastic dynamic mathematical model formulation is proposed, which accounts for several uncertain parameters, namely: demand, supply, products' rate of return, and construction and transportation costs. Moreover, sustainability concerns are acknowledged through the multi-objective nature of the model, where three distinctive objective functions are considered as follows: economic, through Net Present Value; environmental, assessed using the Lice Cycle Assessment approach; and social, through the incorporation of key insights on the fairly recent social methodology, Social Life Cycle Assessment. The formulated model is then applied to a representative case-study of Calzedonia Group, an Italian group established in the garment industry. This work contributes to the literature by building on several identified research gaps such as: the need to incorporate uncertainty concerns into the sustainable supply chain management studies; the need for an integrated approach that accounts for uncertainty in several distinctive parameters and throughout a larger time horizon; and the increasingly need to account for an integrated approach for the social assessment of any supply chain.

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

1. Introduction

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 [1]. Over the years, there has been a growing concern in environmental issues, leading to the incorporation of reverse logistics in SC's activities, and thus, the introduction of the term closed-loop supply chain [1]–[3]. More recently, and apart from economic and environmental concerns, social issues, namely job creation, 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 as the "*development that meets the needs of the present without compromising the ability of future generations to meet their own needs*" [4]. 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 [5]. Accordingly, sustainable supply chain 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 [1], [6].

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 [7]–[9]. 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). Additionally, the participants of a supply chain often face various uncertainties, which may consider several parameters, namely, raw material supplies, products demands, and commodity prices and costs, and highly impact the overall structure and network of a supply chain [10]. Hence, tackling and modelling the inherent uncertainty in sustainable supply chain systems is vital so that the decision-maker may act with more knowledge and confidence.

To answer this challenge, the use of operational research methods is a path to explore [1]. Deterministic optimization is not best-suited 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 have been acknowledged, such as: 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, where the worst-case scenario is taken into consideration [11].

The remainder of this paper is organized as follows. Section 2 identifies several optimization methods suitable for modelling uncertainty. Section 3 presents a literature review on the advances made in the field. Section 4 focuses on the problem statement and mathematical formulation. al model Section 5 represents the model validation through its application into a representative case-study of Calzedonia Group. Finally, in section 6, final remarks of the work developed are stated.

2. Modelling Uncertainty Methods

Stochastic Programming

Stochastic mathematical programming considers that certain data are unknown, and hence follows a discrete or continuous probability distribution, which is either based on historical data, or estimated [11], [12]. Considering this, two types of stochastic programming may be acknowledged: (i) the recourse-based stochastic programming approach, which deals with decision variables organized into two sets, and whose goal is to minimize the expected recourse costs; and, (ii) the probabilistic or chance-constraint stochastic programming method, whose focus is on the system's ability to meet feasibility in an uncertain environment, where the constraints to be optimized depend on certain probabilities. Considering the latter, and 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 may be reached. Therefore, the most commonly cited stochastic method is the standard two-stage/recourse-based approach, where decision variables of an optimization problem under uncertainty are partitioned into two sets [11]. Thus, the *first-stage* variables (*"here and now"* decisions) must be decided before the actual realization of the uncertain parameters, and once the decision-maker takes some action upon the first-stage, random events occur, affecting the outcome of these. Subsequently, further design/operational policy improvements can be made by selecting, at a given cost, the values of the *second-stage*/*recourse*, variables (*"wait and see"* decisions), being these interpreted as corrective measures against any infeasibilities arising due to a particular realization of uncertainty. Hence, the goal is to choose the first-stage variables 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 feasible for all realizations of the uncertain parameters [11], [13].

Considering the above, the key aspect of stochastic programming is that it is mainly based on commonly known and applied probabilistic terms. Moreover, this approach allows decision-makers to have a complete view of the effects of uncertainties and the relationships between uncertain inputs and resulting solutions. Nonetheless, in real-case scenarios 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. Additionally, the further incompleteness/impreciseness of observed information (due to market turbulence, for instance) may lead to dual uncertainties of randomness, as decision-makers express different subjective judgements upon a same problem [14]. Finally, and as recent works model uncertainty through the scenario-based approach, the great number of scenarios may lead to large-sized, computationally challenging problems [15], [16].

Fuzzy Programming
The fuzzy programming approach may be applied when situations are not clearly defined, or an exact value is not critical to the problem. Hence, fuzzy programming does not require an event to either be black or white (crisp set), 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 numbers and constraints are treated as fuzzy sets. Moreover, some constraint violation is allowed and the degree of satisfaction of a given constraint is defined as the membership function of the constraint [11].
Furthermore, two main types of fuzzy programming may be acknowledged: flexible, and possibilistic programming, where the former deals with right-hand side uncertainties and can be applied when there is uncertainty regarding the exact values of the coefficients, and some constraints violation is acceptable within a certain range. As for the possibilistic programming, it recognizes uncertainties in both the objective function and constraint coefficients [11], [14]. Finally, 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 [11].
On another note, and 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. Hence, the first step is to model the fuzzy system only using easily achieved information. The decision-maker must then decide which additional information has to be collected and processed, based on the fuzzy model solution. The data representation and the solution may be improved stepwise by gathering objective-oriented additional information, and since the collection of input data is cut back, its incurring costs can be considerably reduced [17]. Another key aspect of the fuzzy sets' theory is that it offers a practical way to model vague and qualitative data. Hence, and instead of replacing vague data by "average data", these are modelled by fuzzy numbers and fuzzy intervals, as precisely as a decision-maker will be able describe them [17]. Besides, fuzzy models allow for the mixed integer 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 fuzzy models, the right-hand sides are not crisp boundaries, and the decision-maker can thus choose one of the neighbour solutions [17]. Considering this, the key aspect of this method is its capability to estimate trough possibility rather than probability, key in situations with information ambiguity [18]. Likewise, the fuzzy approach does not allow the final deterministic equivalent formulation of the uncertain model to blow up in size with the increased number of uncertain parameters [13]. Moreover, the fuzzy logic application can provide significant advantages for sustainable supply chains, as it allows the construction of compromises between conflicting objectives, by considering an overall satisfaction degree as trade-off between several objectives and constraints. Additionally, intersection of fuzzy constraints and overall objectives can be smoother, increasing the chance to get a better solution within the overlapping areas of constraints and objectives. Nonetheless, the fuzzy method still lacks in its inability to represent the exact uncertainty nature, leading to results that could depend on the fuzzification approach [13].

Robust Optimization
Robust optimization provides a framework capable of handling the parameters uncertainty in 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 needs a priori knowledge, it does not require the actual distribution, but only the relevant distribution, leading to a much easier process [15]. The main purpose of the model is thus to find a solution which is feasible and optimal, that is, to always satisfy the constraints despite parametric uncertainties.
Furthermore, 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 allocation, project management, supply chain planning, and capacity expansion [16]. 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 [19]. Moreover, this method also leads to a reduction in computational costs and combines computational tractability with the structural properties of the optimal policy [16], [27]. 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 [20].
The adaptive robust optimization approach, on the other hand, has been proposed so as to mitigate the conservatism present in the traditional version of static robust optimization. Hence, instead of optimizing all decision variables solely as *here-and-now*, this approach incorporates two stages of decision (*wait-and-see*), with the intent of reaching the desirable goal, while anticipating the worst-case materialization of the uncertain parameters within an uncertainty set [21]–[23]. Moreover, the adaptive robust optimization model may be more practical than the conventional stochastic programming one, given that it only requires a deterministic uncertainty set, rather than a hard-to-obtain probability distribution on the uncertain data [24]. Additionally, 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" [23]. Lastly, this method has been applied to decision-making problems under uncertainty in areas, such as: unit commitment for power systems; network flow optimization; and, robust transportation problems and production scheduling problems for batch manufacturing processes [23].

Dynamic Optimization
In dynamic approaches, optimization is performed over time, with focus its on maximizing or minimizing the costs/benefits of a given objective function over a period of time, and where the decision-maker is responsible of making multiple decisions over time. 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. [25]. Objective functions show a sequential structure, and decisions are made in stages where each, besides providing an immediate reward, affects the future rewards and hence the context of future decisions [26].
Considering the above, stochastic dynamic programming focuses on solving multi-stage optimization problems, where one or several parameters in the problem are modelled as stochastic variables/processes [27]. The principle of the stochastic dynamic programming approach is based on a recursive decomposition of a multi-stage problem into simpler sub-problems that, once solved, are assembled to provide an overall solution [28].
In robust dynamic programming, however, information is revealed in subsequent stages, and "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" [29]. Few advances have been made in this field, however, the worst-case formulations can be expressed as semi-infinite programs [30]. A probabilistic framework may also 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 [31].
Given its structure, applying dynamic optimization to real-world situations may encounter several difficulties, such as the large computational burden 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 [26], [32]. Finally, several authors have explored the possibility of combining at least two methods and hence produce a hybrid approach. As a result more robust techniques are applied, and drawbacks mitigated , by combining the best characteristics of each approach.

3. Literature Review
In order to provide a thorough analysis and review on the advances made in the field, a literature review has been performed on the optimization methods that have been developed for designing supply chain networks under

uncertainty. Hence, key research questions 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, and in order to provide proper answers to the questions above, this analysis focuses, not only on bringing new relevant data to the main findings of the work developed in [33] 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, a sample of 72 key articles has been selected and added to the research already conducted in [33], where a total of 170 have been considered. Moreover, this literature review accounts for both sustainable and non-sustainable supply chains under uncertainty so as to provide proper awareness on the work being developed on the subject.

Therefore, a literature review has been conducted, 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 [33] 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 this work. Finally, all papers concerning only one sustainability pillar have been excluded, leaving only papers where at least two sustainability pillars have been accounted for.

Accordingly, several aspects have been considered so as to characterize the sample of papers analysed. Thus, and in light of the main findings of [33], 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 work has been developed in the field of sustainable supply chain network design (SSCND). Hence, 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. Further aspects reveal that a larger quantity of contributions on SCND under uncertainty have been provided by the European Journal of Operational Research, whereas the Journal of Cleaner Production represents the higher contribution in the modelling of uncertainty in supply chains with a sustainability focus. Finally, the sample of 72 papers has also showed that a large contribution has been provided by authors from China, Canada, and the USA. Other relevant contributors are European countries, such as France, Germany, Norway, and Italy.

Sample Categorization

A sample categorization has been conducted so as to provide crucial information on the studied sample of papers, while answering questions Q1 – Q5 presented above. Considering this, question Q1's purpose is to understand the parameters that are most often considered to be uncertain. Thus, and in light of both this research and the work developed in [33], it becomes clear that the parameters with the highest frequency of being uncertain, in both SCND and SSCND are, respectively: demand; supply; environmental and/or social impacts (only considered in the latter scenario); supply; costs (namely, transportation, and production); capacities; and, rates of products' returns.

On another note, question Q2 aims at understanding the distribution of papers among the discussed methods used to model uncertainty in supply chains, as discussed in Section 2. Accordingly, and aligned with the work developed in [33], papers that account for uncertainty concerns most often considered the stochastic programming approach as the best-suited approach, for both SCND, and SSCND. Following this is robust programming, and fuzzy programming. Additionally, special considerations should also be made for the application of more sophisticated and robust approaches, such as stochastic dynamic programming, hybrid programming, and robust adaptive programming.

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. Accordingly, demand uncertainty as showed to be mainly modelled through the usage of stochastic programming, followed by robust programming and fuzzy programming. Moreover, environmental impacts uncertainties are mainly modelled through stochastic 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.

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. Accordingly, one can conclude that these papers have been mainly focused on both strategic and tactical aspects. Considering the former, most decisions relate to the supply chain network design of any kind, forward, reverse, or 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. Furthermore, it is also possible to state that several papers considered strategic and tactical aspects, while only a few looked at both strategic and operational levels. As of tactical and operational aspects, these have been rarely combined, while no paper has considered all three decision levels.

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. Therefore, 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 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.

Bearing this in mind, one can further detail the information provided and present the major aspects considered in each sustainability pillar. Thus, and as of the economic pillar, research shows that cost reduction has been the main economic objective function. The Net Present Value (NPV), an indicator suitable for investment situations with high risk levels, however, is only considered in a small percentage of the papers. Moreover, when considering the environmental pillar assessment, it is clear that the majority of papers cover the global warming factor, represented by aspects related to carbon dioxide emissions and greenhouse gases. Hence, it is possible to state that the environmental studies have been exploring a narrow perspective, where only aspects related with the carbon footprint have been measured. Additionally, utilities consumption is also considered, followed by waste reduction, even if the latter does not represent an environmental impact category, but instead a flow. Following these are biodiversity, products recovery, and fuel and energy consumption. Finally, the use of the Life-Cycle Assessment (LCA) approach is verified in a small sample of papers. This approach, described as the most scientifically reliable method currently available for studying and evaluating the impacts of a certain product or process, as had little attention, despite being more complete methodology to assess environmental impacts. Lastly, and regarding the social pillar, it is possible to verify that job creation has been the most common indicator, followed by aspects related to regional, safety and health of workers, and overall satisfaction of consumers. Considering this, 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.

Sample Assessment – Conceptual Map

A sample assessment has been performed through a conceptual map so as to graphically portray the literature focus and the interest devoted to the research community to each one of the sustainable supply chain dimensions analysed. Thus, and according to Figure 1, sustainable supply chain (SSC) under uncertainty is represented as the central point in this map, which then ramifies into three main research streams representing the decision levels: strategic; tactical; and operational. In turn, the sample of papers concerning specifically SSCND 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. Hence, and considering the decision levels dimension, the strategic level has been the most studied one. 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% 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. 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.

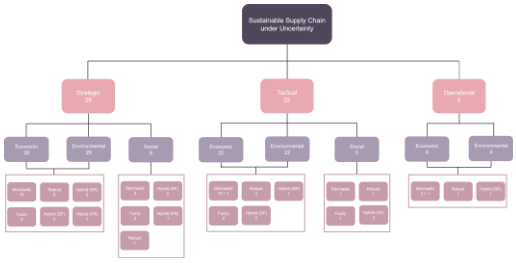

Figure 1 - Conceptual Map on modelling uncertainty in sustainable supply chains

Current Challenges

Considering this, one may characterize the current challenges faced when modelling uncertainty in sustainable supply chains. Accordingly, and considering Figure 2, 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., transportation); and numerous capacities (e.g., facilities, transportation). Thus, 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. Hence, 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 easily obtained, optimization approaches dealing with more exact values and results should be investigated. Moreover, multi-stage 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 contemplating sustainability issues in a comprehensive manner, while fostering a supply chain holistic view.

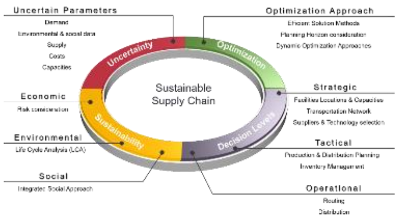

Figure 2 - Research Framework on sustainable supply chain under uncertainty

4. Problem Statement & Mathematical Model Definition

he 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 in [7], 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. Hence, the present work models the same generic supply chain representation, following a four-echelon structure, whose goals are to maximize the Net Present Value, minimize the environmental impact of a supply chain network, and maximize the social benefits inherent to such structure. Accordingly, this model formulation mainly varies from the one presented in [7] in the following topics: (i) uncertainty acknowledgement 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; (ii) risk consideration in the economic objective function; (iii) environmental assessment based on the ReCiPe 2016 LCA methodology; and, (iv) social assessment though the incorporation of social indicators related to the contribution to economic development, equal opportunities/discrimination, and health and safety of workers.

Considering this, and so as to properly model the uncertainty considerations of the model, a dynamic approach has been selected, since it brings robustness and generalization when compared to static optimization methods, while innovation as it has not been widely explored in the modelling of sustainable supply chains under uncertainty yet. 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 taking into consideration the relevant literature's contributions and insights on the subject, the stochastic dynamic optimization approach has been applied through the scenario-based technique, applicable when a continuous range of future outcomes is not available. In this 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 [34]. 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 [35].

As of the environmental assessment, LCA has been selected as the most appropriate tool, since it is described to be 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 [36]. Accordingly, LCA is a 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 Thus, 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.
Within the LCA approach, there are several distinctive methods available and developed, which may use different models in the characterization step, different normalization assumptions and/or different weighting factors [37]. The ReCiPe methodology, however, is considered to be a proper one since, not only portrays a follow up of the Eco-Indicator 99 method, but also combines the CML 2002, while following the typical LCA structure, leading to confirm this to be a proper tool to apply in this paper.

Finally, and regarding the social pillar of sustainability, it has been concluded 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, it is thus crucial to account for this issue and hence propose a possible method to be followed. Hence, and according to [38], the Social Life Cycle Assessment (SLCA) is presented as the most effective technique, within the Life Cycle Sustainability Assessment (LCSA), 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 [38], [39]. Lastly, and taking into consideration the work developed by [39], the SLCA follows a similar framework as the (environmental) LCA, and is thus organized in four steps as: (i) goal and scope definition; (ii) Social Life Cycle Inventory analysis; (iii) Social Life Cycle Impact assessment; and, (iv) Social Life Cycle Interpretation.

Part of the mathematical model formulated is here presented, where the objective functions are identified and defined. Thus, it should be noted that additional parameters, variables, and constraints are not here identified.

Mathematical Formulation

<u>Indices and related sets</u>

i, j Entities or locations $I = I_{sup} \cup I_f \cup I_w \cup I_c \cup I_{air} \cup I_{port} = I_{loc1} \cup I_{loc2} \ldots$
- I_{sup} Suppliers
- I_f Factories
- I_w Warehouses
- I_c Markets/Clients
- I_{air} Airports
- I_{port} Seaports
- I_{loc1} , II_{oc2} 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 $G = G_{prod} \cup G_{rem}$
- 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 materials flows between entities $F = \{(m, i, j): (m, i) \in V \wedge (i, j) \in U\}$
- The description of each subset considers the given examples:
- FINFFP –final product (FP) that enters(IN) factories(F) and comes from entity i
- FOUTFFP –final product(FP) that leaves(OUT) factories(F) and goes to entity i
- FOUTW – allowed flows of products leaving (OUT) warehouses (W)

Net Allowed transport modes between entities $Net = \{(a, i, j): a \in A \wedge (i, j) \in U\}$

NetP All allowed network $NetP = \{(a, m, i, j): (a, i, j) \in Net \wedge (m, i, j) \in F\}$

<u>Parameters</u>

Entity related parameters

w_i Workers needed when opening entity i

lc_i Labour cost at location i

$wpsq_i$ Necessary number of workers per sqm for entity i

Product related parameters

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

opc_g Operational costs of technology g

w_g Fixed workers per technology g

tec_g Installation cost of technology g

Transportation related parameters

mhw Maximum driving hours per week

ftc_a Fixed transportation cost for transportation mode a

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

Environmental related parameters

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 (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

Social related parameters

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

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

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

Others

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

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

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

Several constraints have been developed in the model so as to properly represent a sustainable supply chain. Thus, these may be grouped into five categories, namely: material balances; entity capacity; transportation; technology; and, non-anticipatively. As of the latter, these are necessary when modelling a sustainable supply chain under uncertainty in a dynamic environmental, and are represented as follows.

Non-anticipatively constraints:

$$S_{mits} = S_{mits'}, P_{mgits} = P_{mgits'}, R_{mgits} = R_{mgits'}, X_{maijts} = X_{maijts'}, YCT_{its} = YCT_{its'}, \quad K_{aits} = K_{aits'}, Q_{aijts} = Q_{aijts'},$$
$$, m \in M,\ i,j \in I,\ g \in G,\ a \in A,\ t \in T \quad \wedge \quad s,s' \in S\, x\, (s \neq s') \tag{1}$$

Objective Functions

Economic Objective Function

$$max\, rNPV = \sum_s \rho_s \left(\sum_{t \in T} \frac{CF_{ts}.\partial}{(1+ir)^t} - \sum_\gamma FCI_\gamma \right) \tag{2}$$

$$CF_{ts} = \begin{cases} NE_{ts}, & t = 1,\dots,NT-1 \wedge s \in S \\ NE_{ts} + \sum_\gamma \left(sv_\gamma FCI_\gamma \right), & t = NT \wedge s \in S \end{cases} \tag{3}$$

$$NE_{ts} = (1-tr) \Bigg[\sum_{\substack{(m,i,j) \in F_{INCFP} \\ (a,m,i,j) \in NetP}} psu_m X_{maijts} - \Bigg(\sum_{\substack{(m,i,j) \in F_{OUTSUPRM} \\ (a,m,i,j) \in NetP}} rmc_{mi} X_{maijts} +$$

$$\sum_{\substack{(m,g) \in H_{prod} \\ i \in I_f}} opc_g P_{mgits} + \sum_{\substack{(m,i,j) \in F_{OUTCRP} \\ (a,m,i,j) \in NetP}} rpc_m X_{maijts} + \sum_{\substack{(m,g) \in H_{rem} \\ i \in I_f}} opc_g R_{mgits} +$$

$$\sum_{\substack{(a,m,i,j) \in NetP \\ a \in A_{truck}}} \left(\frac{avc_a}{100} fp + vcm \right). 2 d_{ij} Q_{aijts} + \sum_{\substack{(a,m,i,j) \in NetP \\ a \in (A_{plane} \cup A_{boat})}} tc_{as}. pw_m. d_{ij}. X_{maijts} +$$

$$\sum_{\substack{(a,m,i,j) \in NetP \\ (j \in I_{air} \wedge i \notin I_{air}) \cup (j \in I_{port} \wedge i \notin I_{port})}} hhc_j. X_{maijts} + \sum_{i \in I_{air} \cup I_{boat}} cfp_i. Y_i + \sum_{(m,i) \in V} sc_m S_{mits} +$$

$$\sum_{i \in I_f \cup I_w} w_i. lc_i. wwh. wpt. Y_i + \sum_{i \in I_f \cup I_w} wpsq. lc_i. wwh. wpt. YC_i +$$

$$\sum_{\substack{(m,g) \in H \\ i \in I_f}} w_g. lc_i. wwh. wpt. Z_{mgi} + \sum_{\substack{i \in I \\ a \in A_{truck}}} w_a. lc_i. wwh. wpt. K_{ai} \Bigg) \Bigg] + tr. DP_t \tag{4}$$

$$DP_t = \sum_\gamma DP_{\gamma t} FCI_\gamma \tag{5}$$

$$FCI_{\gamma} = \begin{cases} \sum_{i \in I_f \cup I_w} sqmc_{is}.YC_i \ , \ \gamma = 1 \\ \sum_{\substack{(m,g)\in H \\ i \in I_f}} tec_g Z_{gmi} \ , \ \gamma = 2 \\ \sum_{\substack{(a,i,j)\in Net \\ a \in A_{truck}}} ftca_a.K_{ai} \ , \ \gamma = 3 \end{cases} \quad (6)$$

Environmental Objective Function

$$min\ EnvImpact = \sum_s \rho_s \left(\sum_c \eta_c \left(\sum_{\substack{t \in T, i \in I_f \\ (m,g) \in H}} ei_{mgc}.pw_m.(R_{mgits} + R_{mgits}) + \sum_{\substack{t \in T \\ (a,m,i,j) \in NetP}} ei_{ac}.pw_m.d_{ij}.X_{maijts} + \sum_{i \in I_f \cup I_w} ei_{ic}.YC_i \right) \right) \quad (7)$$

Social Objective Function

$$max\ SocBenefit = \sum_s \rho_s \left(wed\,.si^{ed}_{nor} + \mathrm{wgr}\,.si^{gr}_{nor} - wacc\,.si^{acc}_{nor} \right) =$$

$$\sum_s \rho_s \left(wed\,.\ \frac{\sum_{i \in I_f \cup I_w} \frac{fsc_i}{tfv_i} ev_i(1-rd_i).Y_i - si^{ed}_{min}}{si^{ed}_{max} - si^{ed}_{min}} + wgr\,.\ \frac{\sum_{i \in I_f \cup I_w} ce_i.\frac{faw_i}{maw_i}.Y_i - si^{gr}_{min}}{si^{gr}_{max} - si^{gr}_{min}} + wacc\,.\frac{si^{acc}_{max} - \sum_{i \in I_f \cup I_w} \frac{fsc_i}{tfv_i} ra_i.Y_i}{si^{acc}_{max} - si^{acc}_{min}} \right) \quad (8)$$

5. Model Validation – Case-Study Analysis

Case-study Definition & Characterization

The model presented is now applied into a representative case-study concerning the supply chain network of Calzedonia Group, an Italian company focused on the apparel industry. This 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. The focus is on the European region, and particularly in the set of countries where the brand has its strongest presence. The following two brands from Calzedonia Group are considered: Calzedonia and Tezenis Underwear. These represent the vast majority of stores across the European region, while having a fairly compatible array of products. Six of the most influential European markets have been accounted for: Italy, Spain, France, Germany, Portugal, and Poland. Finally, the products considered in the study represent a standard pair of cotton mid-calf socks (product 1), as well as a pair of seamless totally invisible sheer tights (product 2), two widely sold products worldwide under both of these brands.

Additionally, 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 for 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; and, (ii) remanufacturing technology. Considering this, 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.

Results Analysis & Discussion

Given the information presented above, and in order to validate and take relevant remarks of the decision-support tool presented above, 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. It should 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. This decision lies with the belief that the final purpose of any sustainable supply chain should be the equal consideration of each pillar. Hence, the following results analysis is divided into three parts: i) tactical uncertainty; ii) objective function uncertainty; and, iii) dynamic uncertainty. Thus, 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. 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.

<u>Tactical Uncertainty</u>

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 key aspects mentioned above. Hence, a total of five distinctive cases have been considered, 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 (case A), where no uncertainties are considered. The uncertainty variation for each case B to F considers five distinctive scenarios, where, for each parameters variation have been acknowledged. For instance, case B reflects demand variations from -10% to +10%, while case C varies the supply values from -5% to +15%. In uncertain rate of return of final products, however, variations are from -10% to +10%. Finally, both cases E and F see their parameters varying from -10% to +15%.

The obtained results are given in Table 1, where all cases are considered and compared to the deterministic version, for all six relevant aspects mentioned above (1 – 6).

Table 1 - Tactical uncertainties results analysis

Social Indicator	-	Residual increase	Negative decrease of 10%	Residual decrease	Residual increase	Residual increase

Case	Entities	Supplier	Technologies	Inventory	Transportation	Economic Indicator	Environmental Indicator
A	8	Italy	Production process held in all three factories, with little contributions from the Avio facility; remanufacturing process heavily dependent on Gissi factory	Poland warehouse as key contributor; Product 1 with overall highest inventory	Road transportation only, with both small and large-sized trucks (28 vs 13)	-	-
B	12	Italy	Production/Remanufacturing in all 3 factories; Croatia as key contributor	Spain, Portugal, and Poland as key warehouses; Product 2 with overall highest inventory	Airplane links between Italy and Portugal; Higher investment in trucks, both small and large-sized (26 vs 21)	Decrease of 65.40%	Positive decrease of 20.85%
C	8	Italy	Production process held in all three factories, with little contributions from the Avio facility; remanufacturing process heavily dependent on the Croatian factory	Portuguese warehouse as key contributor; Product 2 with overall highest inventory	Road transportation only, with both small and large-sized trucks (24 vs 13)	Decrease of 87.80%	Positive decrease of 44.20%
D	7	Italy	Product 2 without remanufacturing process; Gissi factory with overall smaller contribution in both production and remanufacturing	Vallese Di Oppeano with high contributions; Product 2 with overall highest inventory	Airplane links between Italy and both Portugal and Poland; Higher investment in trucks, both small and large-sized (35 vs 19)	Increase of 28.42%	Positive decrease of 48.49%
E	12	Italy	Croatian factory with a critical role in the network, whereas the remaining have cases where little to no contributions are made	Spain, Portugal, and Poland as key warehouses; Product 1 with overall highest inventory	Road transportation only, with both small and large-sized trucks (22 vs 14)	Decrease of 61.39%	Positive decrease of 17.02%
F	12	Italy	Disperse overall contributions, having cases where the Avio factory is the highest or even the only entity considered	Castagnaro, Varazdin, Spain, Portugal, and Poland as key warehouses; Product 2 with overall highest inventory	Road transportation only, with both small and large-sized trucks (19 vs 19)	Decrease of 68%	Positive decrease of 24%

Hence, when one accounts 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 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. Finally, 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.

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 are considered: (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 for each case G to I considers five distinctive scenarios, where, for each parameters variation have been acknowledged. For instance, case G reflects demand variations from -10% to +45%, while case H varies the supply values from -15% to +20%, and case I from -15% to +45%.

The obtained results are given in Table 2, where all cases are considered and compared to the deterministic version, for all six relevant aspects mentioned above (1 – 6).

Table 2 – Economic objective function uncertainties results analysis

Inventory	Transportation	Economic Indicator	Environmental Indicator	Social Indicator
Poland warehouse as key contributor; Product 1 with overall highest inventory	Road transportation only, with both small and large-sized trucks (28 vs 13)	-	-	-
Vallese Di Oppeano, Varazdin and Poland as key contributors; Product 1 with overall highest inventory	Road transportation only, with both small and large-sized trucks (24 vs 21)	Increase of 33.86%	Positive decrease of 39.31%	Residual increase
Stores fairly evenly in all warehouses considered; Product 1 with overall highest inventory	Airplane links between Italy and Portugal; Smaller investment in trucks, both small and large-sized (17 vs 16)	Positive decrease of 12.32%	Positive decrease of 44.20%	No variation
Vallese Di Oppeano and warehouses as key contributors; Product 2 with overall highest inventory	Airplane links between Italy and both Portugal and Poland; Smaller investment in small and large-sized trucks (17 vs 10)	Decrease of 85.17%	Positive decrease of 11.82%	Residual increase

Case	Entities	Supplier	Technologies
A	8	Italy	Production process held in all three factories, with little contributions from the Avio facility; remanufacturing process heavily dependent on Gissi factory
G	8	Italy	Gissi facility as key contributor in production; remanufacturing process entirely done in the Croatian factory
H	8	Italy	Product 2 is only produced in two facilities, with higher contributions from Avio; Remanufacturing of product 1 only held in Avio and Gissi; Avio as key factory in remanufacturing process
I	8	Italy	Production process in all three factories; Avio as key contributor in production; remanufacturing of product 1 mainly held in Avio; Avio as a key facility in remanufacturing process

Considering this, 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.

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 5, 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. Finally, 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 and B.

Accordingly, from the obtained results, it is possible to state that 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. As of the suppliers selection and allocation, 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, to the factories established in Europe. Moreover case J's production of final product 1 is fairly distributed across all three factories, with slightly higher contributions from Croatia. 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. In the remanufacturing of both products 1 and 2, the Croatian factory holds full responsibility. These aspects, when compared to both cases A and B, lead to significant changes in the overall production and remanufacturing of both final products. As of the amount of inventory per facility, all three are seen as key contributors, where 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, only one transportation mode has been considered in case J, leaving all product flows being taken care by road transportation. 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, 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 specific to the six aspects here under discussion, 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.

Henceforth, and when comparing both types of analysis performed, one may conclude that when uncertain considerations throughout time are considered, 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. Conclusion & Future Work

This paper focuses on the design and planning of sustainable supply chains under uncertainty.
Frequently applied optimization methods to model uncertainty are identified and described, and special considerations are given to more rigorous and sophisticated methods. A comprehensive literature review identifies the main contributions and research gaps. It was seen that even though several articles explore supply chain networks under uncertainty, little has been done to incorporate sustainability concerns. Moreover most works only consider static optimization, leaving the dynamic optimization advantages highly unutilized.
A decision-support tool is also developed with the purpose of properly modelling uncertainty in sustainable supply chains. The economic assessment is performed through the Net Present Value, the environmental impact is assessed through LCA, and social concerns are tackled by providing a relevant review on S-LCA, and applying its key points, while following the same rationale as the LCA. This tool is applied to a representative case-study of Calzedonia Group, an Italian company settled in the garment industry, often dealing with complex and extensive networks.
The 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. From these, several conclusions are achieved, 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 sustainability 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.

Future work to be considered includes the further investment in the optimization tools available, exploring the advantages of both the dynamic and hybrid programming, with a hybrid dynamic optimization approach. Moreover, additional uncertain parameters should be explored, namely entities varying capacities, and environmental and social considerations. 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. Following the work here developed, the epsilon constraint method is another tool interesting to be explored so that 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.

The author acknowledges the Portuguese National Science Foundation (FCT) and Portugal 2020 for Project LISBOA-01-0145-FEDER-028071 by UE/FEDER/FNR/OE.

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