



Supply Chain Resilience: Tactical-Operational Quantitative Models

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Abstract

The complex structure of modern supply chains (SC) and their tendency towards globalization, have increased their exposure to unpredictable events. In order for companies to sustain their competitive advantage, establishing resilient SCs has become a concern over the years, and now with the current pandemic, a priority. Nonetheless, despite the increasing awareness on the importance of resilience enhancing actions, it still presents a growing body of literature scarce on quantitative tools to aid decision-makers (DM), particularly, at the tactical-operational decision level. To understand the current state of the art on this subject, this work performs a systematic literature review. Focus is given on the SC activity that is addressed and which operations research methods are used. It is also highlighted how the analysed publications model risk and uncertainty, as well as which resilience metrics have been used, culminating in the identification of paths for future research. Towards reducing the identified gaps, a multi-objective mixed integer linear programming (MILP) model is developed in this present dissertation with a novel stochastic approach to deal with uncertain parameters. Further uncertainties are explored regarding the disruptions time frame and source of occurrence. Focus is also given in understanding the weight of timely responses. The model is then applied to a case study, where insights on operational decisions taken under disruptive events are discussed and final conclusions are withdrawn.

Keywords: Supply chain resilience; tactical-operational; quantitative models; operations research methods; metrics; uncertainty.

Resumo

A complexidade das cadeias de abastecimento modernas e a sua tendência para a globalização tem aumentado a sua exposição a eventos imprevisíveis. Com o propósito das empresas sustentarem a sua vantagem competitiva, estabelecer cadeias de abastecimento resilientes tem se tornado uma preocupação ao longo dos anos e com a presente pandemia, uma prioridade. Contudo, apesar da crescente consciencialização da importância de ações que reforçam a resiliência, esta continua a apresentar um crescente desenvolvimento de literatura escasso de ferramentas quantitativas que auxiliem decisores, particularmente, na tomada de decisões ao nível tático-operacional. De modo a compreender o presente estado da arte nesta área, este trabalho desenvolve uma revisão sistemática da literatura. Atenção é dada à atividade da cadeia de abastecimento que é abordada e ao método de investigação operacional que é utilizado. Também é realçado como as publicações analisadas modelam risco e incerteza, assim como quais métricas de resiliência têm sido usadas, culminando na identificação de direções para investigações futura. De modo a reduzir as lacunas identificadas, um modelo multiobjectivo MILP é desenvolvido nesta presente dissertação com uma nova abordagem estocástica para considerar parâmetros incertos. Outras incertezas também são exploradas relativamente ao intervalo temporal das disrupções e a sua fonte de ocorrência. Também é dada atenção à importância na rapidez de resposta. O modelo é aplicado a um caso de estudo, onde decisões operacionais face a eventos disruptivos são discutidas e conclusões finais são retiradas.

Palavras-chave: Resiliência em cadeias de abastecimento, tático-operacional; modelos quantitativos, métodos de investigação operacional; métricas; incerteza.

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List of Acronyms

CLSC	Closed Loop Supply Chain
DM	Decision Maker
MILP	Mixed Integer Linear Programming
OF	Objective Function
OR	Operations Research
SC	Supply Chain
SCR	Supply Chain Resilience
SCRM	Supply Chain Risk Management

1 Introduction

This chapter aims to introduce the present dissertation. Therefore, in section 1.1, the subject to be addressed is contextualized along with the motivation for its study. The dissertation's objectives are clarified in section 1.2, followed by the methodology adopted to tackle the subject at hand in section 1.3. Lastly, in section 1.4, the dissertation's structure is outlined.

1.1 Problem contextualization

Recent past has experienced several unpredictable catastrophic events, from natural disasters to terrorist attacks and now the current pandemic. While supply chain risk management (SCRM) has been able to deal, in part, with predictable and well-known events that might disturb operations, to deal with these unpredictable events it is crucial to complement such measures with resilience management for companies to successfully respond (Fiksel, 2015). Being able to respond and recover quickly to disruptions is a key factor for companies to survive by maintaining their competitive advantage (Munoz & Dunbar, 2015).

Modern supply chains (SC) are becoming ever more exposed to these unpredictable events due to its increasing complexity and globalization (Christopher & Peck, 2004; Kamalahmadi & Parast, 2016). In fact, daily operations require the normal functioning of several interlinked entities that are geographically dispersed. Therefore, local disturbances in one node can cause severe consequences that can quickly ripple throughout the whole network. Due to this, and coupled with the current pandemic conditions, interest on supply chain resilience (SCR) is significantly increasing for companies worldwide, as they are forced to cope with a "new normal", as well for the academic community.

The present crisis sets apart from previous disruptions by its global reach and the severe impact to both supply and demand simultaneously. As pointed out recently by Sodhi & Tang, (2021), there is an urgency in further researching SCM for these "extreme" conditions. By witnessing current challenges the importance of SCR has become more visible, but also exposed new paths to be considered in future works, such as the study of the shift towards automation, governmental interventions and the struggle of small businesses with e-commerce competition (Sodhi & Tang, 2021).

In recent years, resilience in the context of supply chain management has gained more attention by the academic community, thus developing significant work to establish a sound definition by consolidating knowledge of other areas where it has been more thoroughly researched (Ponomarov & Holcomb, 2009). Although no consensus has been achieved on a single SCR definition, in this present work, the following definition proposed by Ribeiro & Barbosa-Povoa, (2018) will be considered: *"A resilient supply chain should be able to prepare, respond and recover from disturbances and afterwards maintain a positive steady-state operation in an acceptable cost and time."*

Regarding the literature on SCR, much of what has been published revolves heavily on qualitative insights. Quantitative approaches on SCR remain scarce and directed to the strategic and tactical level, while being relatively unexplored on the operational decision level (Ribeiro & Barbosa-Povoa, 2018). Reducing this gap is fundamental, given that these quantitative models are of most value,

aiding decisions makers to evaluate and adopt strategies towards resiliency. Additionally, models tackling resilience alongside sustainability factors are relatively limited.

1.2 Dissertation objectives

The objective of this work intends to contribute to the literature by further developing the knowledge on quantitative SCR models at the tactical-operational decision level. Towards that end, firstly, this dissertation aims to establish a well-founded understanding of the subject from the importance of the industry's point of view, and on how the academic community has tackled it. To achieve the latter, a systematic literature review was elaborated, focused on quantitative models addressing SCR at the tactical-operational decision level. The review additionally focused on the modelling approaches adopted to integrate uncertainty, risk, and which metrics have been used to quantify SCR. With this assessment, directions for future research are identified and motivated the second part of the work.

Secondly, a quantitative model is developed to further enlighten the tactical-operational decisions taken under disruptive events. Particularly, attention is given in addressing the importance of timely decisions, by incorporating in the model outsourcing options and alternative products. In this line, it is also explored the time frame of the disruptive events, which is taken as uncertain. The results of the model applied to a case study will serve to provide insights, and outline future work to be developed in this field.

1.3 Methodology

The methodology applied throughout this work is presented in figure 1, which is constituted by five steps, joined by two phases.

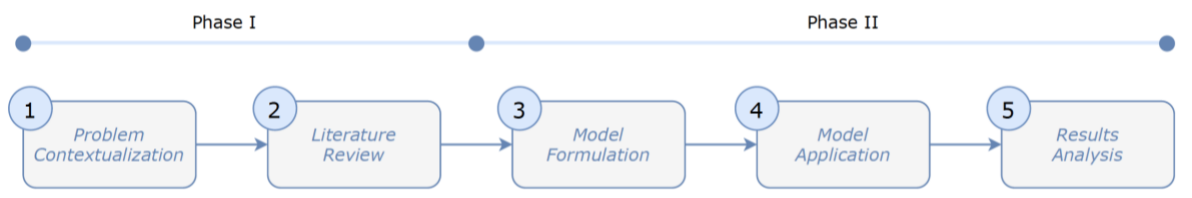


Figure 1: Work methodology

The first phase corresponds to the assessment of the literature and identification of any gaps. The second phase regards the succeeding work that is elaborated with a sound understanding on the subject, established by the reviewed literature, aiming to provide novel developments to the field. Each phase follows two and three stages, respectively, as follows:

1. Problem contextualization

The goal of the first stage is to provide sufficient information on the subject of study to clarify its scope and importance.

2. Literature review

The second stage executes a systematic literature review with the aim to establish a sound knowledge on SCR quantitative models addressing the tactical-operational decision level to sustain the following stages of this work.

3. Model formulation

The third stage aims to construct a quantitative model based on extant literature, applying the necessary modifications in order to fit the study of SCR. Upon this, aspects identified for future research in the second stage are considered, as well as the modelling of uncertain parameters and disruptive scenarios.

4. Model application

In this step the formulated model is applied to a case study, retrieving results of the behaviour of said model under varying disruptive events.

5. Results analysis

Lastly, the results from the previous stage are critically analysed, providing insights on decisions regarding SCR at the tactical and operational level.

1.4 Dissertation outline

This dissertation is composed by six chapters. This first chapter aims to introduce the theme and the motivation of its study along with the objectives, methodology and the final structure of the document. The remainder of this dissertation is composed five chapters as follows:

– Chapter 2: Industry view on resilience

The aim of this chapter is to understand companies' outlook on SCR and how it is changing due to the COVID-19 outbreak. The effects of the pandemic on particular SCs are discussed, which leads to the discussion on major actions and trends to achieve tactical-operational resilience. Other forthcoming strategies and considerations, in particular, for digital adaptations and sustainability concerns are also explored.

– Chapter 3: Systematic literature review

This chapter aims to construct a reliable assessment on the state of the art of SCR quantitative models with a focus on the tactical-operational decision level through a systematic literature review methodology. Relevant content is retrieved, reflecting the established research questions, which is then thoroughly analysed. The problems addressed in the literature are reviewed, focusing on the operations research method used. How aspects such as risk and uncertainty are considered and modelled are analysed. Additionally, it is reviewed which

resilience metrics could be identified and whether sustainability metrics have been considered. Then, these results are discussed, and guidelines for future research are proposed.

– **Chapter 4: Model formulation**

This chapter presents the formulated model to tackle the subject of SCR at a tactical-operational decision level based on the work of Liu & Papageorgiou (2013), with some additions based on Cardoso, Barbosa-Póvoa, & Relvas (2013) to extend it to become applicable to closed loop supply chains (CLSC). A general overview of the goals of the model is provided followed by in depth details of its components, namely, sets, parameters, objective functions (OF) and constrains. Further adaptations of the model are clarified in order to consider uncertain parameters and disruptive scenarios. Lastly, the solution approach adopted to solve the model is described.

– **Chapter 5: Case study, discussion and results**

This chapter introduces the case study to be applied to the developed model and the analyses to be performed alongside their goal. The results of the outlined analyses are presented and critically discussed.

– **Chapter 6: Conclusions**

The conclusions of the dissertation are presented in this final chapter, as well as future research paths in the field.

2 Industry view on resilience

Over the years, most companies have adopted a more reactive approach in face of disruptions, still allocating more importance into maximising efficiency rather than building up resilience (Alicke & Strigel, 2020; Christopher & Peck, 2004). Increases in overall consumer consumption have made just-in-time and lean practices appealing for optimizing SCs despite leaving them vulnerable to unpredictable events. According to a Gartner survey on May 2020 (Gartner Inc., 2020a), one of the first reports on the consequences of the COVID-19 pandemic, only 21% of the SC leaders that were inquired (33% for high-tech and CPG's) considered their SC, up-to-date, as being highly resilient.

Nonetheless, despite not achieving a high level of resiliency, over the years, companies have been found to adopt some strategies against disruptive events such as diversifying operations and establishing multi-sourcing options whenever feasible (Alicke & Strigel, 2020). Lacking, however, in establishing SCRM teams and processes, which aim to increase organisations' preparedness by monitoring trends, taking measures to increase transparency and developing scenario analyses (Alicke, Barriball, et al., 2020; Alicke & Strigel, 2020). Without this practice, organisations are more susceptible to lose valuable time in circumstances where quick responses are fundamental. On the other hand, such permanent response teams can be found midst advanced companies which usually present more complex and global SCs (e.g. leading automotive OEM's, chemicals and electronics generally belong to this group), and, consequently, are more exposed to risk (Lund et al., 2020).

Still, it is acknowledged that it would be financially unfeasible for a single organization to be fully prepared for every possible disruption. Companies need to find the right balance between costs and their willingness to risk exposure. And so, strategies to achieve resilience will vary between different industries, being necessary to account for their current exposure to risks derived from their geographic footprint and factors of production. For instance, market position; nature of the product; profitability; and market regulations influence companies' ability to invest in capacity buffers (Gartner Inc., 2020a). Therefore, despite existing well-known strategies towards establishing a more resilient SC, these need to be implemented reflecting each organisation's unique characteristics that shape their interest and operations more adequately. It has been observed that taking active procedures in establishing a resilient SC is highly beneficial, aiding companies to obtain competitive advantage (Ribeiro & Barbosa-Povoa, 2018). In fact, it has been reported that after the 2008 financial crisis resilient companies not only managed to return to its previous state but thrived in the following years, taking advantage of opportunities and even exhibit growth when less advanced companies still struggled (S. Arora et al., 2020), and all indicates the same regarding SCs.

Presently, the COVID-19 outbreak has disrupted operations worldwide and continues to do so in unpredictable patterns. The inability to foresee when and where restricted governmental measures might occur, or mass infections may surge, has created an unstable environment for businesses.

Thus, having briefly described how companies have been viewing resilience over the past few years, it can be assessed that the current pandemic is changing companies' perspective, which are now placing more value into resilience and planning to improve their SCs in the next two to three years towards that

end (Gartner Inc., 2020a). Hence, this chapter aims to understand how companies' present outlook on resilience is changing, how they envision to acquire long-term SCR and what means/trends can be beneficial to achieve that end.

Foremost, it is necessary to understand how COVID-19 effectively is changing our day-to-day environment, what implications it presents for industries and how it will influence long-term consumer behaviour. To enlighten the effect of these changes, five leading SCs will be individually analysed on how they responded to the disturbances caused by the pandemic, and identify which capabilities were crucial to assure business continuity. For these immediate actions, general actions to guarantee tactical-operational resilience are discussed. Also, digital adaptations to SCs are explored and how these contribute to obtain resiliency. This links to the next section where major forthcoming strategies towards resiliency are presented, highlighting which actions industries are planning to prioritize in the near future. Lastly, some final remarks are given regarding sustainability and its importance to maintaining future stability by taking advantage of current conditions.

2.1 COVID-19 reshaping business

The current pandemic has caused disturbances in a magnitude far greater than any other catastrophic event from the recent past. Not only due to its global reach but also by the uncertainty of when the disruption will end. For instance, after the attacks on 9/11 it took passengers about three years to return to its previous flying pattern (Panetta, 2020). Thus, bearing this in mind, it can be safely assumed that depending on the economic sector, some activities will endure these effects for a longer period of time, unknowingly when it will be possible to return to its prior state. Due to this inability to foresee the returning to normal conditions, worldwide populations were forced to adapt to a "new normal" and adopting behaviours that will undoubtedly have a long-lasting effect in society.

To contain the spread of the virus, strict measures were adopted. Organisations globally were forced to close offices or temporarily shut down operations and send workers home. This halt in operations, added to travel restrictions, impacted SCs worldwide causing organisations to experience raw material shortages and constrained production and distribution capacities (Alicke, Gupta, et al., 2020). The implementation of enhanced hygiene measures, social distancing and limited social gatherings created an atmosphere of insecurity in frequenting public spaces, reducing overall consumption. The alteration of the work environment and the change in consumer behaviour represent strong forces that reshape people's lives and immediately impact SCs to incorporate these changes.

According to a recent study on consumer sentiment, significant changes in demand are verified and in the means used to satisfy it (N. Arora et al., 2020). Consumers' pessimistic outlook on economic recovery led them to reevaluate their purchases. By adopting a mindful approach, shoppers redirect their spending towards more essential products (e.g. grocery and household products) and trading down to cut costs. Consequently, companies' production will need to be readjusted to reflect its clients' needs and provide the right products. Also, with the closing of physical stores, consumers turned heavily to online channels. It is reported that 86% of new users are satisfied with the provided online service and that about 75% of consumers intend to continue using digital services even with the cease of this pandemic (McKinsey, 2020). This change propels companies to consider alterations needed in their

SCs to implement or further enhance their online channel or omnichannel. Additionally, being this crisis a humanitarian challenge, consumers value brands that actively guarantee hygienic packaging and employees' well-being. Another finding is that consumers are more open to trying new brands if their preferred one suffered supply disruptions or does not transmit a safe image (N. Arora et al., 2020).

Regarding the altered workforce and much of it being reallocated to their homes (e.g. between April and May, remote work increased about 50%), manufacturing plants and warehouses still require on-site employees to execute operations. Companies share three main areas of focus for on-site work: protect the workforce; manage risk to ensure business continuity and drive productivity at a distance (Furtado et al., 2020).

As expected, managers acknowledge the importance of establishing a safe work environment as a top priority. Organisations now need to provide protective equipment and reinforce workstations' cleaning as measures to ensure workers health. Also, communication has been highlighted as a mean to keep workers motivated. By providing information on current conditions and how the company intends to tackle the pandemic, gives its employees a sense of stability. Additionally, due to the need of social distancing, operations need to be reshaped to ensure business continuity. Alterations to shift schedules and even plant layouts will have to be considered. With this changing environment, it is acknowledged that planning models that have guided operational decisions will necessarily need to be rebuilt, by incorporating these economic and structural shifts. Scenario planning has been frequently referred to as a means to that end.

This crisis's impact presents a long and uncertain duration, with disturbances being faced on both the demand and supply side. From what has been here presented, it is clear that demand forecasting can no longer be guided by historical data, implying changes in production scheduling, and possibly the introduction of new products, for companies to promptly respond to its customers' updated needs and maintain their competitive advantage. Similar consequences are witnessed on the supply side, were transportation restrictions and changes in the workspace constrain business continuity. Thus, understanding the current volatile environment is essential not only to meet immediate challenges but also to comprehend how to tackle future endeavours. Presently, companies need to sense these changes and adapt their SC accordingly to recover from the disturbances they face in a timely manner. Also, to build long-term resilient SCs, it is necessary to keep in mind the long-lasting effect of these forces and how they will influence strategies towards resiliency.

To fully grasp the impact of the COVID-19 outbreak and how it is increasing awareness into building more resilient SCs, specific companies can be explored to illustrate how these above-mentioned changes have impacted their business and how they have responded.

2.2 Master SCs' response to COVID-19 outbreak

In order to retain valuable insights from responses to this pandemic, focus will be given to renowned SCs and what measures they considered as essential to cope with the disruption. To that end, the five companies here considered are those that acquired the status of master SCs for the year of 2020, according to the recently released report by Gartner (Gartner Inc., 2020b). Amazon, Apple, McDonald's,

Procter & Gamble and Unilever received this distinction for being long time leaders, attaining top-five composite scores of Gartner's ranking for at least seven out of the last ten years. These SCs distinguished themselves by excelling in business performance, exhibiting remarkable financial returns combined with environmental, social and governance initiatives, and were recognised by their peers. Following, each of these companies will be individually analysed focusing on how the current pandemic affected their well-established SCs and how resilience capabilities stood out to assure business continuity.

Amazon

As mentioned beforehand, in the rise of COVID-19, consumers turned heavily to online shopping during the imposed lockdowns. Consequently, Amazon, being a leader in online selling, experienced a noteworthy rise in demand. In order to guarantee operations and satisfy their clients, besides expanding services and launching new features, Amazon hired about 175 000 additional workers during the initial peak to integrate the fulfilment and delivery network for their U.S operations (Day One Staff, 2020).

More particularly, grocery delivery is amongst Amazon's services that considerably increased in demand. By punctually sensing these changes, in order to successfully serve customers, the company converted five Amazon Fresh grocery stores to temporarily solely fulfil delivery orders. This measure helped the company increase its overall grocery delivery capacity by more than 160% (Amazon, 2020b), which relied on the flexibility of these stores and the workers to perform activities outside of their usual responsibility. Also, Whole Foods market pickup locations tripled in number.

Nevertheless, in light of the "new normal", alterations to the work environment became necessary. To that end, Amazon updated about 150 processes of its regular operations, being workers safety the top concern (Amazon, 2020c). Personal protective equipment needed to be provided, such as masks, gloves and hand sanitiser. Also, janitorial staffers were increased to reinforce enhanced cleaning of the facilities and some team members were reallocated outside their usual work to perform safety-related tasks (e.g. temperature checks).

Regarding social distancing, and to guarantee its compliance, adjustment to the way teams clock in and out were made, thus avoiding congestions. A more innovative approach towards the same end is the use of machine learning. Amazon introduced "Distance Assistant" to provide employees with real-time feedback on social distancing (Amazon, 2020a). Essentially, monitors display individuals highlighted with green or red circles if they are at least 1,8 meters apart or if they are less, respectively. Also, it provides site leaders with a mean to assess which areas have higher traffic.

Apple

For years, Apple has relied on factories located in China to produce its products, especially iPhones. Therefore, its SC was affected early on with the surge of the virus. Facilities were forced to halt operations and even after reopening production occurred at a slower pace than expected. That led the company to announce in February that worldwide iPhone supply would be temporarily constrained and that it would be likely for the company not to meet its revenue guidance for the March Quarter (Apple Inc., 2020).

This dependability on China to concentrate a substantial portion of Apple's manufacturing capacity has been a concern even before the outbreak due to the US-China trade war. However, due to the well-established electronic industry in China, no major structural change has been pronounced.

McDonald's

Unlike Amazon, McDonald's experienced a severe decline in sales and demand, due to imposed lockdowns and clients' reluctance to frequent restaurants. Such negative impact on the business led the company to reduce the opening of new restaurants that were scheduled in order to ensure its overall financial flexibility.

During the initial peak of COVID-19, McDonald's temporarily closed most of its physical stores to indoors serving worldwide. Nonetheless, to continue serving their clients, the company kept approximately 75% of its restaurants operational (McDonald's, 2020a), operating exclusively through McDelivery, take-out service and Drive-Thru (McDonald's, 2020b). To feasibly provide these services employees were redeployed from their usual work. Up-to-date, McDonald's has changed up to 50 processes to provide a work environment in accordance with the "new normal" as explored previously. Nevertheless, even with the reopening of stores to on-site servings, McDonald's continues to experience a reduced demand level reflecting consumers' apprehension in frequenting restaurants. Regarding disruptions experienced in other SC activities, no relevant public information was found.

Procter & Gamble

One of P&G's SC characteristics that lets them stand out from competitors is its highly optimized supply planning, being awarded FICO Decision Award in 2019 in the Decision Management Innovation category (FICO, 2020). Its innovation allowed P&G to enhance analytic efficiency by 90%, reducing weekly analysis time to less than five minutes, increasing the SC's overall responsiveness, which is of most value when confronted with unplanned events. Additionally, data analytics are also used to precisely locate stores and along with machine learning the company is more capable of understanding its customers' needs and setting up shelf sets, placements, sampling and marketing strategies accordingly (P&G, 2020a).

In response to the pandemic, the company relied on the flexibility of its facilities and workers. Since January, P&G mobilized teams to produce and deliver hand sanitiser as well as nonmedical face masks and face shields. In just two weeks, plant operators managed to operationalize idle equipment to meet the surge in demand for essential hygiene products (P&G, 2020b). The company also highlighted the importance that its robust and diverse supplier network played in order to achieve its goals (P&G, 2020c).

Unilever

Unilever's SC has distinguished itself for being highly innovative and agile. By strongly investing in digital capabilities, the organisation has been able to increase the transparency of the whole SC and shorten its planning cycles.

The company's fast-responding SC allowed, during the COVID-19 outbreak, for one of its deodorant production lines to be adapted to produce hand sanitiser, taking the process only four days from laboratory trials to production (Unilever, 2020). To achieve this, the fast response of suppliers and workers were key enablers. While one of the raw materials for hand sanitiser was already being used on-site, others were quickly sourced from other facilities or outsourcing partners.

On more recent announcements of the company, since January, production capacity has been drastically increased. Intending to satisfy the increasing demand for essential products, Unilever repurposed its production lines for beauty products and personal care, which decreased in demand. Demonstrating not only the flexibility of Unilever's existing production lines but also their responsiveness to market demand.

Regarding technological capabilities, Unilever, through the use of crawlers and AI has been capable of detecting early on signs of potential risks or shortages (Raghu, 2020). By analysing data of its suppliers and delivery patterns, warning signs can be detected such as suppliers struggling to meet demand or if they are experiencing financial difficulties, thus allowing Unilever to react quickly and search for alternative sources.

Overall, these leading companies have demonstrated the importance of quickly sensing disturbances to their business, whether of clients' demand or overall environmental necessity, and their rapid responsiveness. Surges in demand for specific products were quickly identified and resources/capacity were reallocated accordingly, highlighting, now more than ever, the importance of agility and flexibility of their SCs. These transformative capabilities were crucial in quickly understanding and responding to consumers' needs and ensuring the delivery of value. These short/medium term actions illustrate tactical-operational resilient actions, where responsive measures are restricted to existing capabilities.

2.3 Actions towards tactical-operational resilience

From the former section, the main actions to ensure tactical-operational resilience can be identified (Table 1), which aid in creating adaptive SCs. The added responsiveness comes through enhanced flexibility as well as the increase of digital adaptations to improve the speed in which the SC can acknowledge and start responding to disruptions.

Table 1: The five master SCs identified strategies

Strategy	Company
Flexibility of facilities	Amazon P&G Unilever
Flexibility of employees	Amazon McDonald's P&G Unilever
Technological investment	Amazon P&G Unilever
Collaboration with suppliers	P&G Unilever

SCs that are capable of adapting their business when faced with a disruption according to the nature of the event and resume their activities are considered as flexible. Therefore, flexibility enhances resilience and benefits day-to-day operations where changes may become necessary due to other minor disturbances. There are multiple options in order to develop flexible SCs, some related to the establishment of redundancy (Tukamuhabwa et al., 2015). For example, maintaining unutilised production capacity that can be resorted to in circumstances where other nodes of the chain are unable to operate or insufficient. The benefit of this measure was identified in the previously discussed case of P&G.

Nonetheless, flexibility can also be achieved by altering products characteristics and/or processes. Regarding products, reduction of their complexity can increase resilience by eliminating possible bottlenecks of customized single-source components (Alicke, Barriball, et al., 2020). By standardizing SKU components, production can shift more seamlessly towards higher demand products and inventory can be more easily shared between facilities (Hippold, 2020). The same advantages can be obtained by postponing the product's point of differentiation (Tang & Tomlin, 2008). Moreover, establishing flexible processes enables different plants to produce the same products, thus avoiding a product to be manufactured in a single location (Tang & Tomlin, 2008). Rather than creating economies of scale, streamlined processes are performed in parallel instead of in series, which are engineered to reduce the overall number of stages involved (Christopher & Peck, 2004). For example, Intel recurs to similar layouts across plants to facilitate production shifts (Sheffi, 2005).

On another note, tactical-operational responsive actions can be implemented more easily if each individual can contribute to the development of solutions and are prepared for such necessity (Kamalahmadi & Parast, 2016). By empowering workers to take the initiative when problems arise, even for lower hierarchical positions, negative impacts can be controlled more swiftly (Sheffi, 2005). Indeed, human resource management can positively influence SCR, through education and training programs to improve employees' skill sets and understanding of the SC (Hohenstein et al., 2015). With these measures, workers' flexibility is increased and cross-functional teams can be established (Sawyer & Harrison, 2020). The importance of the capability to redeploy human resources during a crisis was also illustrated in the previous section, and the most resorted to (table 1).

Recurrently, digital adaptations have been mentioned in responsive actions and as future investments to achieve resilience. In fact, they have been vastly acknowledged as key drivers in executing changes towards resilience without compromising overall efficiency.

2.4 Digital adaptations

Undoubtedly, we are witnessing an unprecedented move towards digital solutions. Over the years, the shift has been occurring gradually, but now, its speed has magnified manifold in response to the pandemic. In fact, it is reported that consumer and business adaptation to digital solutions managed to increase in a span of mere eight weeks to a point that was only expected to occur within the next five years (Baig et al., 2020).

Digitalisation is on the rise and transforming several aspects of typical businesses. With the increased ease in obtaining valuable data, advanced analytics and big data are the most commonly adopted technologies. Nonetheless, others such as robotic process automation, artificial intelligence, machine learning and internet of things applications are also gaining adherence. To deal with the aforementioned change in consumer behaviour and alterations to the work environment, digital solutions can increase the SCs' responsiveness by providing methods that predict the ever-changing clients' demand and speed up decision making.

Being able to sense and, to some degree, predict customer demand is essential for organizations to retain their customer base. Not only that but also to manage inventory of the right products and coordinate production and distribution accordingly. Time-series that have been used in forecasting tools until now have been disrupted with new trends emerging in uncertain patterns. Historical sales data are no longer sufficient to obtain reliable forecasts on its own, it should also be taken into consideration current macroeconomic aspects. Through the use of analytics, most up-to-date information can be incorporated aiding to distinguish what are short term surges of demand to others that are more long-lasting (Fabius et al., 2020). Ultimately, advanced analytics are an efficient method to obtain more reliable forecasts that quickly update on relevant current conditions more accurately.

Due to the unpredictable behaviour of the virus's spread, a range of scenarios can be explored by using data and analytics to easily adapt operations as events occur. For instance, by simulating digital twins, organizations can analyse different staffing and production levels and ultimately optimise operations planning (Park et al., 2020). Given the nature of this disruption, routine activities, when possible and feasible, have been automated allowing resources to be redeployed to more complex or value-adding functions. Once again, this approach to automation is likely to have a long-lasting effect in operations as companies view productivity increases.

However, many companies were not technologically prepared when this crisis hit. In fact, on a survey performed on 60 senior SC executives, it was observed that about 85% struggled with insufficient digital capabilities (Alicke, Gupta, et al., 2020). On the other hand, technologically advanced companies have been able to respond faster to this changing environment. Digitalizing SCs has been recognized as an efficient mean to increase agility and visibility of the entire network (e.g. cluster maps can be developed to reveal alternative sourcing options). Thus, organisations are investing in acquiring and enhancing digital capabilities to achieve long-term resilience efficiently.

2.5 Forthcoming strategies towards resilience

It can be assessed that companies are adopting a long-term view on the actions taken to mitigate the impact of this crisis on SCs, aiming to acquire resilience for future disruptive events. On May 2020, McKinsey's survey reported that 93% of the leading global companies that were inquired are planning to increase resilience in the near future (Lund et al., 2020). Amongst the planned actions to build resilience, dual sourcing of raw materials is the most mentioned strategy by the respondents followed by increases in inventory of critical products and nearshoring and expanding supplier base. However, it is relevant to keep in mind that the importance of these strategies can vary by industry. For instance,

for automotive companies, nearshoring is the most cited option to improve SCR, and only secondly would be dual sourcing of raw materials.

As aforementioned, companies still largely operate on just-in-time and lean production systems. These policies have allowed them to improve efficiency and consequently increase profits at the cost of reduced inventory levels. Nonetheless, the importance of holding not only buffer inventory but also overall capacity has been gaining more awareness. With travel restrictions to quarantined zones, this strategy aids in mitigating the impact of supply shortages. As we have seen, some industries can experience significant surges in demand depending on the nature of the crisis, which can be somewhat met with back-up inventory or increased production of other facilities.

Some companies currently rely on a single source for critical components, while some that do take advantage of multiple sources, these alternatives may be geographically concentrated, which is not ideal (Tukamuhabwa et al., 2015). Once again, companies have operated in these conditions mainly to reduce costs, although leaving them more exposed to disruptive events risking ceasing general operations due to impacts on one single entity or region (Christopher & Peck, 2004). Therefore, establishing alternative sources of raw materials has been considered as a priority. It also reflects the increasing concern of companies on the current geographic footprint exhibited by their SCs, keeping in mind that weakening international relationships will continue even with the cease of the pandemic.

In this line, it has also been observed that increased globalisation accentuated companies' lack of visibility beyond tier-1 suppliers, whose consequences became evident by the current pandemic as disruptions rippled throughout the chain (KPMG, 2020). Hence the renewed consideration in establishing more regional suppliers. Therefore, by actively identifying and investing in backup sourcing and nearshoring when possible, businesses are less exposed to shocks and can respond and recover more quickly.

On the other hand, collaboration among entities has been recognized to augment SCs' visibility. By actively sharing information between partners, disruptions can be identified and dealt with more quickly (Kamalahmadi & Parast, 2016). Indeed, synchronization of schedules can reduce uncertainty and even allow suppliers to decrease their reliance on inventory buffers without compromising resilience (Christopher & Peck, 2004). This crisis has demonstrated the importance of strengthening relationships, given that SC partners can become vital in these circumstances by rerouting and expediting critical shipments (Lund et al., 2020).

2.6 Sustainability

Last but not least, it is important to stress that sustainability goals should not be overshadowed by economic recovery actions but rather complement them. The reduction of economic activities, and consequently reduced wealth, may lead companies to take advantage of lower oil prices or delay capital allocation towards lower-carbon solution investments. However, contrary to most disruptions that present immediate consequences, climate change effects are more gradual and cumulative. Therefore, disregarding climate action altogether would only result in another global challenge in the years to come with more profound effects than this pandemic.

In recent years, the circular economy concept has attained more attention in the rise of organisations' determination to operate more sustainably. Indeed, before this crisis, sustainability was gaining significant awareness and was being integrated on the agenda of several leading companies (Pinner et al., 2020). For instances, all five leading companies explored previously (section 2.2) adopt sustainable measures into their operations and set goals for the near future to reduce their environmental impact, being the shift towards renewable energy and reduction of carbon emission the most frequently cited approaches (Gartner Inc., 2020b). Even with the hit of the pandemic, some of the strategies and forces shaping the “new normal” mentioned beforehand are easily aligned with sustainable practices. From consumers mindful approach towards consumption to increases in remote working, these promote lower carbon emissions. In fact, some temporary environmental benefits were witnessed as lockdowns took place and overall travels reduced (e.g. satellite images of China demonstrated a severe reduction in pollution during the initial outbreak). Thus, it is important to reinforce this trend and acknowledge the opportunities present in current conditions to take further actions to reduce climate change.

2.7 Chapter conclusions

Companies longstanding concern in operating efficiently is now giving place to actions on establishing more resilient SCs. Over the years, SCs have been designed to operate under a narrow range of conditions that were taken for granted which ultimately left them vulnerable for unpredictable events. The current pandemic has turned evident the need for resiliency as companies are presently re-evaluating their operations and identifying weaknesses that would otherwise remain unnoticed. Tremendous efforts have been observed in attenuating disturbances which consequently placed more awareness on resilience than any other past event has.

Therefore, in this chapter, to fully grasp these changes, an initial overview of how SCR has been viewed over the years is presented, followed by identifying strong forces that are shaping a new business environment due to the COVID-19 outbreak and how it has affected SCs worldwide. To exemplify these effects, the operations of five master SCs during the outbreak were analysed, where it was found that SC flexibility and agility were essential to cope with the disruption. In this line, general actions on achieving tactical-operational resilience are presented. Additionally, digital adaptations are analysed since these have been recognised, along the chapter, as being beneficial not only for short-term actions but also for long-term ones to enhance SCR without compromising companies longstanding concern in operating efficiently. General strategies to achieve SCR are explored, highlighting dual sourcing and increased inventory levels as a current priority for companies. Lastly, the importance in acknowledging sustainable measures for the inevitable economic recovery actions is pointed out. Overall, despite all the difficulties that are being faced, organisations can take current conditions as an opportunity to innovate and balance back more agile than before.

3 Systematic literature review

This chapter aims to construct a reliable assessment on the state of the art on SCR quantitative models with a focus on the tactical-operational level, through a systematic literature review. The methodology adopted is clarified in the first section, which ultimately introduces this chapter's subsequent sections. Previous literature reviews on the matter are explored, after setting the research questions, allowing to position and distinguish the present review among extant ones. The meticulous procedure of the material collection is described along with a descriptive analysis of the constituted sample, as well as the establishment of structural dimensions used to categorize the papers.

The content of the sample is then thoroughly evaluated to answer the research questions adequately. Namely, insights that can be withdrawn from recent research on the effects of the pandemic are discussed. Next, the focus is directed to quantitative approaches, where the identified models are divided into four general categories (distribution, inventory, production and SC). Attention is given to the OR method used, how risk and uncertainty are considered and modelled, and, finally, what metrics have been used. The results are then discussed, and directions for future research are proposed.

3.1 Methodology

The methodology adopted in this work follows an adapted form of the one presented by Ribeiro & Barbosa-Povoa, (2018), consisting in six main steps, which will constitute the subsequent sections of this chapter in the following order:

1. Research questions: establishment of pertinent questions to guide the work to be developed;
2. Previous literature reviews: analysis of extant literature reviews on SCR with the goal to position the present paper and its contribution;
3. Material collection: procedure to collect and select relevant literature to be analysed;
4. Descriptive analysis: analysis on the characteristics of the constituted sample;
5. Category selection: creation of structural dimensions to categorize the collected material and aid the subsequent process of evaluation;
6. Material evaluation: evaluation of the papers' content by answering the research questions established in step 1.

3.2 Research questions

In order to assess the current quantitative developments that can be found in the SCR literature, with a focus on tactical-operational decisions, seven research questions were established, which will serve as a guide throughout this work, as follows:

1. What insight can be withdrawn on SCR from the COVID-19 pandemic responses?
2. How has tactical and operational resilience been tackled in SC?
3. How have OR methods been used to support tactical and operational decisions?
4. How has uncertainty and risk been modelled in tactical and operational problems?
5. What sustainability metrics have been considered within SCR?
6. Which resilience quantitative metrics have been used?

3.3 Previous literature reviews

In order to identify relevant reviews existent on the subject, a search on the Web of Science core collection database was performed for the terms “*supply chain*” and “*resilience*” and “*review*” published in English from 2010 up to November 2020, categorized as either review or article in a peer-reviewed journal. An initial data set of 160 results was obtained, which was then refined to 124 by excluding results where the term “*resilience*” solely appeared as a Keyword Plus. As a selection criteria of these results, those that did not specifically address SCR were excluded, as well as those that were not considered as a literature review, resulting in a final set of 17 reviews. These papers were classified according to their main focus, the research methodology that was adopted, the number of papers analysed and their timespan, approach, and, finally, whether a definition of SCR is proposed, as presented in table 2.

From these results, it is notable a significant rise in literature reviews over time, being 2020 the year with most published works. Such reflects the increased awareness of the academic community on further developing the subject (A. Ali et al., 2017; Shashi et al., 2020; Shekarian & Parast, 2020). In fact, all authors have recognized that research on SCR has been steadily increasing over the past few years, identifying the early 2000's as a starting point, and highlighting 2003 as a particular turning point, given that more work was developed in the aftermath of highly disruptive events, such as the 9/11 attacks (Hohenstein et al., 2015; Ribeiro & Barbosa-Povoa, 2018).

All the reviews analysed adopted a systematic literature review methodology, with distinctions verified in the work of Kochan & Nowicki (2018) that implemented a CIMO logic (context, intervention, mechanisms and outcomes) to their findings, and I. Ali & Gölgeci (2019) complemented the SLR with a VOSviewer co-occurrence analysis (VCA) to identify trends in the evolutionary trajectory of the SCR research.

The papers here reviewed have all recognized that a sound definition of SCR still lacks in the literature and that the root for such problem may rely on the inherent multidisciplinary nature of the term resilience. Additionally, the ambiguity revolving SCR elements and how they are interdependent, has lead them to be used interchangeably. This problem has also been referred to as a source that hinders the development of a single definition of SCR, given that no consensus has currently been achieved (Hosseini et al., 2019). Hence, earlier reviews have focused on developing and clarifying conceptual terms such as SCR principles, elements and strategies, with the goal to propose well-founded definitions of SCR and establish the groundwork for future investigation.

The earliest reviews identified were in 2015 with the works of Hohenstein et al. (2015) and Tukamuhabwa, Stevenson, Busby, & Zorzini (2015), where both proposed a solid definition for SCR. Towards that end, the former performed an analysis of 67 papers with the focus to identify SCR phases (readiness, response, recovery and growth), elements and metrics, while the latter relied on 91 papers to assess the most cited strategies. Additional to these reviews, Kamalahmadi & Parast (2016) has also been vastly referred to on succeeding works. The authors reviewed 100 papers with a focus on SCR principles, proposing a framework that incorporates major components of a resilient SC, strategies and measurement.

Table 2: Previous literature reviews on SCR

Paper	Focus	Research Methodology	Number of Papers	Timespan	Approach	Propose SCR Definition
Hohenstein et al., (2015)	SCR phases, elements and metrics	Systematic Review	67	2003-2013	Qualitative and Quantitative	Yes
Tukamuhabwa et al., (2015)	SCR definitions, strategies and proposal of a theoretical lens	Systematic Review	91	up to 2014	Qualitative	Yes
Kamalahmadi & Parast, (2016)	Organisational and SC resiliency principles, strategies and measurement	Systematic Review	100	2000-2014	Qualitative and Quantitative	Yes
Wang et al., (2016)	SCN concept and resilient SC systems	Systematic Review	48	up to 2009	Qualitative	Yes
A. Ali et al., (2017)	SCR phases, strategies and capabilities to develop concept mapping framework	Systematic Review	103	2000-2015	Qualitative	No
Datta, (2017)	SC practices to enhance resilience in a given SC context	Systematic Review	84	1996-2016	Qualitative	Yes
Ribeiro & Barbosa-Povoa, (2018)	SCR quantitative models and metrics	Systematic Review	39	2009-2016	Qualitative and Quantitative	Yes
Stone & Rahimifard, (2018)	Review SCR definitions, elements and strategies and how they apply to AFSCs	Systematic Review	137	up to 2016	Qualitative	Specific for AFSC
Kochan & Nowicki, (2018)	Development of a typological SCR framework	Systematic Review	228	2000-2017	Qualitative and Quantitative	No
Hosseini et al., (2019)	SCR quantitative models and resilience capacity of SCs	Systematic Review	168	2002-2017	Qualitative and Quantitative	Yes
I. Ali & Gölgeci, (2019)	Identify recent trends and trajectory of SCR literature	Systematic Review + VCA	155	2003-2018	Qualitative	No
Shashi et al., (2020)	Propose a framework for SCR assessment, research on SCR barriers, metrics and strategies	Systematic Review	125	2003-2018	Qualitative and Quantitative	No

Table 2 (continued)

Paper	Focus	Research Methodology	Number of Papers	Timespan	Approach	Propose SCR Definition
Sawyers & Harrison, (2020)	SCR elements and high-reliability organisations characteristics	Systematic Review	107+18	1997-2017	Qualitative	No
Gkanatsas & Krikke, (2020)	Quantitative modelling of 3PL SC network design for resiliency	Systematic Review	138	2008-2019	Qualitative and Quantitative	Specific for 3PL SCNs
Shekarian & Parast, (2020)	SCR enhancers on mitigation of various SC sources of disruption	Systematic Review	98	2000-2017	Qualitative	No
Zavala-Alcívar et al., (2020)	Propose a framework to integrate SC resilience management to increase sustainability	Systematic Review	232	2000-2020	Qualitative and Quantitative	No
Han et al., (2020)	SCR capabilities and metrics	Systematic Review	153	2003-2019	Qualitative and Quantitative	No

Later on, surged works that did not propose a SCR definition, but still pursued other qualitative objectives. A. Ali et al. (2017) took the constructs of the existing SCR definitions to develop a concept mapping framework to provide clarity on the subject of SCR for both managerial implications as well as research implications. Through the analysis of 103 articles, three essential constructs of SCR were identified: phases (pre-disruption, during disruption and post-disruption), strategies and capabilities. These constructs represent the core of their proposed mapping framework. Posteriorly, Zavala-Alcívar, Verdecho, & Alfaro-Saiz (2020) extended on the previously mentioned work, and of others, by adding elements to their resilience principles. These principles then constituted one of the three building blocks of their proposed framework, whose goal is to integrate key components for analysis, measurement and management of resilience to enhance sustainable SCs.

It can also be verified the appearance of more context-specific reviews, with two of the works here analysed proposing particular SCR definitions, one regarding third-party logistics providers (Gkanatsas & Krikke, 2020), and another that takes into consideration the unique characteristics of agri-food supply chains (AFSC) (Stone & Rahimifard, 2018).

Overall, despite some papers addressing quantitative approaches, as indicated in table 2, much of it is executed briefly and without much depth (Hohenstein et al., 2015; Kamalahmadi & Parast, 2016; Kochan & Nowicki, 2018; Shashi et al., 2020; Zavala-Alcívar et al., 2020). Indeed, it has been acknowledged that the literature on SCR quantitative models and metrics is scarce (A. Ali et al., 2017; Hosseini et al., 2019; Kamalahmadi & Parast, 2016; Ribeiro & Barbosa-Povoa, 2018). Further development on this subject has been recognized as necessary, and of most importance given its' usefulness in aiding decision-makers (DM) to adopt adequate strategies and to assess their performance (Gkanatsas & Krikke, 2020; Han et al., 2020; Ribeiro & Barbosa-Povoa, 2018).

Out of the 17 reviews, only three were found to execute an in-depth review on SCR quantitative models and/or metrics.

The first paper to actively focus their review on a quantitative approach to address SCR is Ribeiro & Barbosa-Povoa (2018). Through a content analysis of 39 papers, the authors explored not only OR methods and metrics used in modelling SCR but also at what SCM decision level such has been researched. Subsequently, it was found that quantitative models are scarce, not representative of any industry and mostly focused on the strategic level.

Later on, Hosseini et al. (2019) explored the advances of analytical approaches on SCR by reviewing 168 papers, guided by the concept of resilience capacity. The authors clarify the significance of the three distinctive capacities (absorptive, adaptive and restorative) and present an analysis of the key drivers of each capacity, with a focus on important factors for quantitative models. The findings of the examined analytical papers are then classified into those capacities, thus categorizing the identified SCR models. The restorative capacity was the one that presented the least dedicated quantitative literature. Additionally, modelling approaches, metrics and key objectives in SCR models are summarized.

Most recently, the goal of the review of Han et al. (2020) is to connect SCR capabilities to performance metrics through a single conceptual framework. Towards that end, 153 papers were analysed of which only 36 discussed SCR performance metrics, and the remainder discussed SCR

capabilities qualitatively. Once again, this disproportion shows the lack of research on SCR metrics relative to conceptual work. In total, 11 capabilities were identified and associated with three dimensions of SCR (readiness, response and recovery). However, only for 8 of these capabilities was it possible to associate performance metrics, lacking literature for the remaining 3 (security, leadership and knowledge management). Overall, the authors highlighted the importance to further develop research on SCR measurement, emphasizing the benefit brought to research and practice. In fact, a clearer understanding on what capabilities are in need to be developed can be achieved by using performance metrics.

In this present work, the goal is to further research quantitative approaches on SCR, distinguishing from former reviews by focusing on tactical and operational decisions, as reflected in the previously established research questions. In line with answering these questions, an assessment on recent literature regarding companies' response to COVID-19 outbreak and what insight can be retrieved from it will be performed. Following, the core body of the paper will then focus on how tactical and operational decisions have been treated in the SCR literature and its analytical developments.

3.4 Material collection

With the goal of retrieving significant articles, a set of keywords was established to conduct a search on the Web of Science collection database. The keywords considered were “*supply chain*” and “*resilience*” with the combination of each of the following terms: “*tactical*”; “*operational*”; “*quantitative*”; “*optimization*”; “*simulation*”; “*heuristics*”; “*metrics*”; “*routing*”; “*scheduling*”; “*statistics*” and “*COVID-19*”. All consultations were restricted to publications in peer-reviewed journals, written in English, and published between 2010 and December 2020. The results obtained from each individual consultation can be seen in figure 2, along with further refinements that were applied. After removing the duplicates from the executed searches, a set of 385 papers was obtained, which was reduced to 256 papers that present the term *resilience* in the abstract to assure that these actively address resiliency. Then, to guarantee the relevance of these results for the present work, the following selection criteria were considered:

- Articles must have SCR as the main focus;
- Purely qualitative approaches were excluded;
- Articles that focus on a strategic level problem were excluded.

The final sample obtained comprises a total of 42 articles. However, an exception was made to publications addressing the current pandemic, not taking into consideration the last two selection criteria, which was considered necessary in order to respond more aptly to the first research question, thus retaining six papers for that sole purpose.

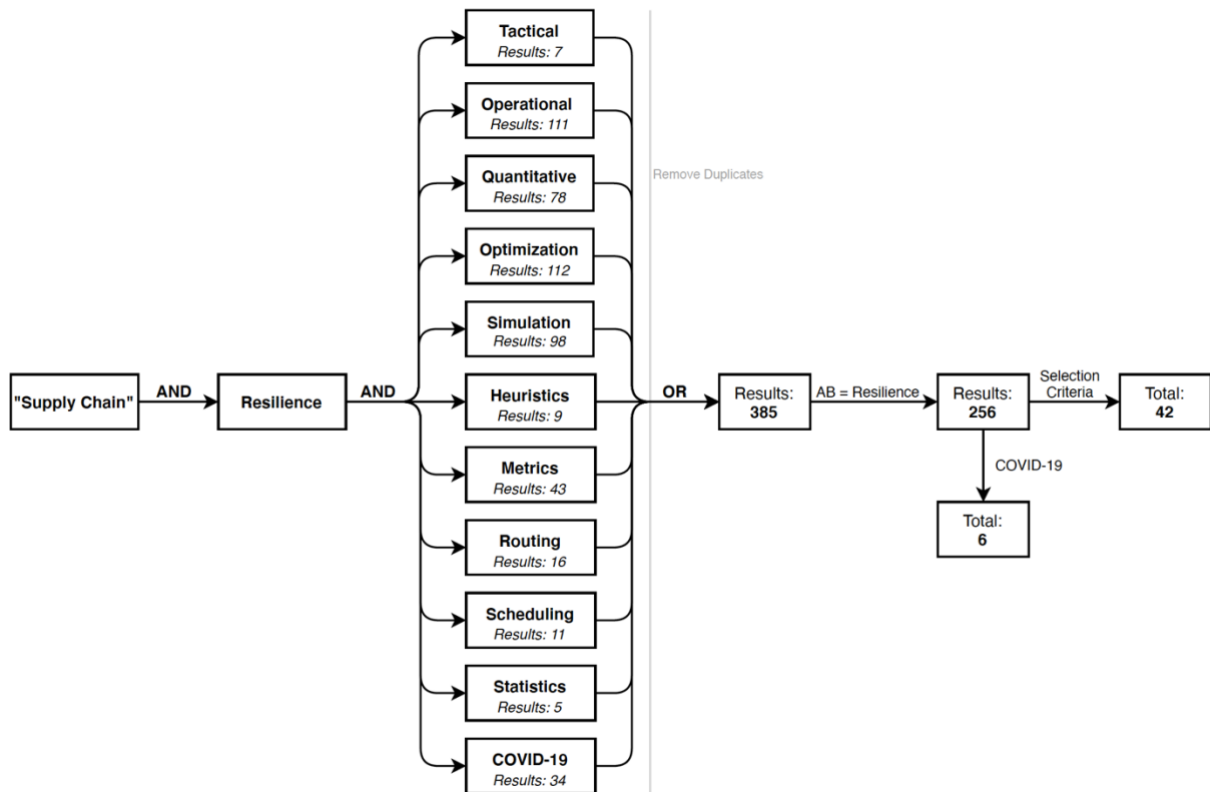


Figure 2: Overview of the material collection process

3.5 Descriptive analysis

Preceding the content analysis of the collected material, relevant characteristics of the articles that compose this sample can be studied to enlighten primary elements of the literature on the subject, such as its temporal evolution, geographical distribution and the source of the publication. Given the exception applied to the six papers addressing the current pandemic, these will not be included in the analysis. Thus the final sample of 42 papers will be used. The reasoning for this exclusion relies on the fact that these six results are not representative of the literature on SCR with a quantitative approach. Therefore, omitting these results safeguards the accuracy of the conclusions that will be withdrawn.

Figure 3 illustrates the increase in the research developed on quantitative models over the years, with a slight decline observed in 2018, while 2020 clearly stands out with an elevated number of publications. Nonetheless, when observing the average number of citations, the papers that compose the sample receive throughout the years (figure 4), a smooth increase is visible. Comparing this last graph with the former one might assume that SCR literature, in general, is increasing steadily, while the more restricted sample, with attention on tactical-operational quantitative models, presents more volatility, but still exhibiting recent noteworthy developments.

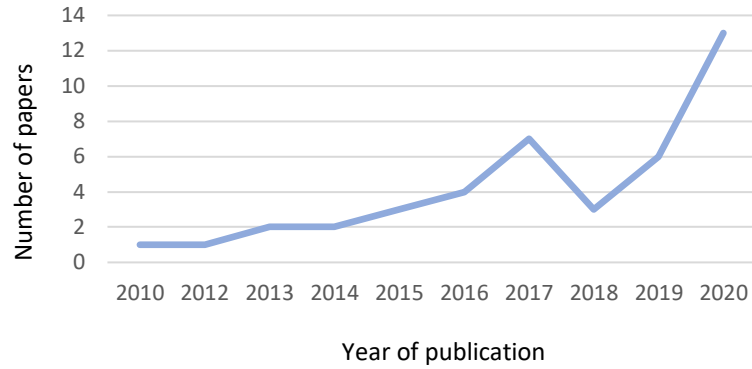


Figure 3: Number of articles published per year

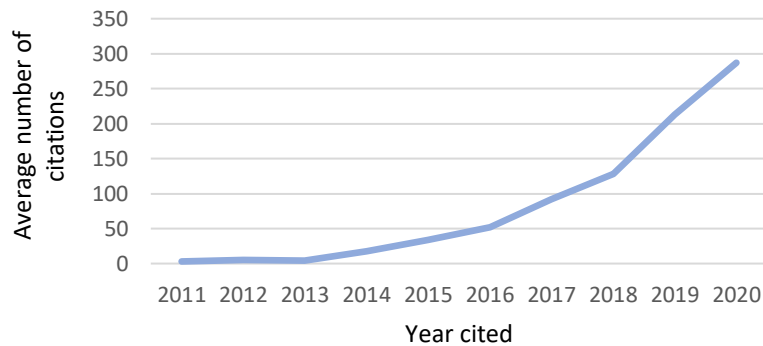


Figure 4: Average number of citations per year of the sample

Regarding the country of the institution of the authors (figure 5), USA is clearly visible as the predominant origin of the developed research followed by Germany, China, Canada, India, and Iran with similar values.

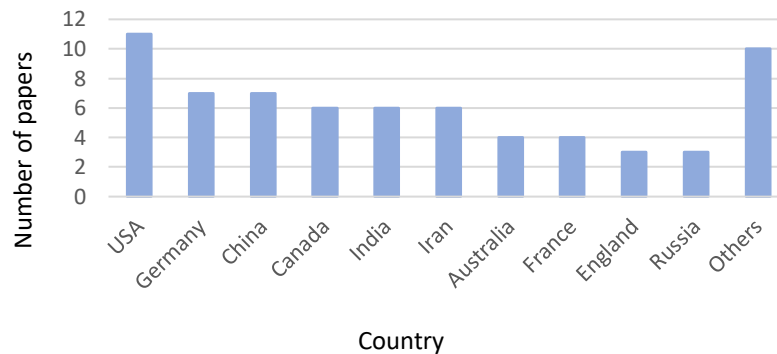


Figure 5: Number of papers from the country of the corresponding author

Considering the source in which the articles of this sample are published in, 29 journals were identified, presenting in table 3 the top five with most occurrences, demonstrating a prevalence in the field of engineering and management. To be noted that the remaining 24 journals, not included in the table, presented a single record within the sample, which indicates the multidisciplinary nature of the subject.

Table 3: Top five journals present in the sample

Source Title	Records	Frequency (% of 42)
International Journal of Production Research	9	21,43%
International Journal of Production Economics	3	7,14%
Computers Industrial Engineering	2	4,76%
OMEGA International Journal of Management Science	2	4,76%
Reliability Engineering System Safety	2	4,76%

3.6 Category selection

Considering the span of the collected material, it is pertinent to define structural dimensions in order to guide the following material evaluation and appropriately answer the established research questions. Hence, the papers are categorized following the logic depicted in figure 6, accounting for three main dimensions:

- COVID-19 outbreak: How does the paper approach SCR in the context of the COVID-19 outbreak (quantitative, qualitative and case study);
- Decision level: What decision level is addressed, and for those that tackle the tactical-operational level consider the following:
 - What problem main area is addressed: distribution, inventory, production or SC;
 - What kind of risk is considered (operational and/or disruptive) and how it is modelled;
 - How is uncertainty considered and modelled (stochastic approach, robust approach, fuzzy approach or sensitivity analysis).
- OR approach: What OR method is adopted and what resilience and sustainability metrics are used.

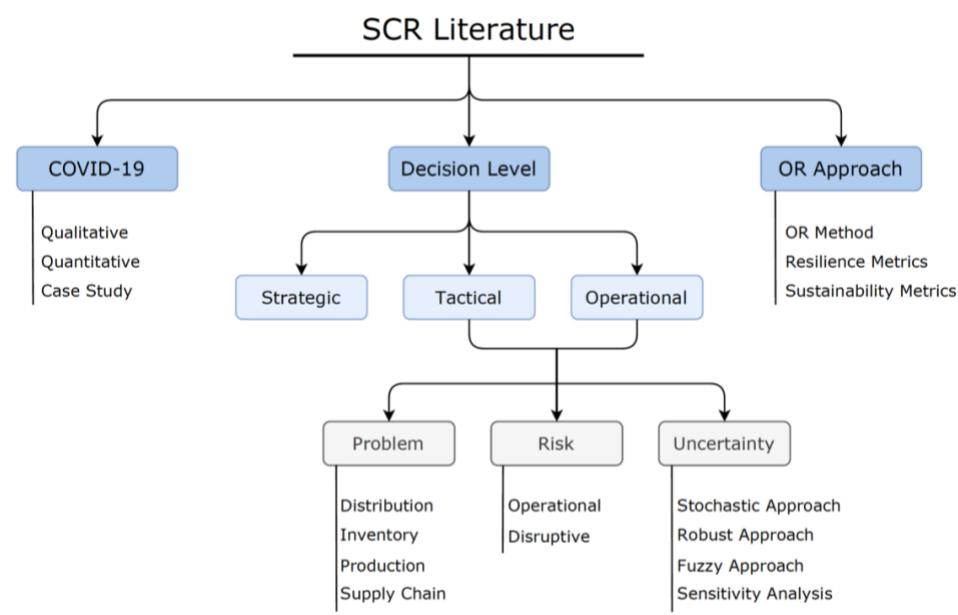


Figure 6: Mind-map for category selection

3.7 Material evaluation

3.7.1 Insights on SCR from COVID-19 outbreak responses

(Research Question 1)

At the time of writing, the global pandemic declared by the World Health Organisation (WHO) on March 11th of 2020 is still an ongoing worldwide disruption. While initial vaccination procedures are starting to take place, further evolution and impacts of this crisis remain highly uncertain globally.

Although some literature addressing the impacts of the outbreak on SCs, with resilient considerations, has been published, an important point to keep in mind is the time frame of their elaboration. The works available on December 2020 that are here considered, are mostly early assessments developed between March and May of the same year. Thus, most articles have a strong speculative approach on the matter due to the lack of information, the volatility of current conditions and the rush to publish. Nonetheless, despite not providing definitive conclusions and exploring mainly impacts, some valuable insights can still be withdrawn by understanding the disruption's effect and responses.

The severity of this crisis on SCs mostly derives from the simultaneous impact on both supply and demand, due to forces that are reshaping the business environment, as explored in the previous chapter. Despite verifying many communalities across sectors on the caused effects, overall disruptions are essentially industry-specific (Marzantowicz et al., 2020). Hobbs (2020) and Zhu, Chou, & Tsai (2020) address food and medical SC, respectively, where a Just-In-Time (JIT) philosophy is adopted and concluded that these were not able to fully withstand unpredictable spikes in demand, be it from panic buying of groceries or increased necessity for high volumes of personal protective equipment, which led to short-run stockouts.

Marzantowicz et al. (2020) performed in-depth individual interviews among SC operations managers of Polish companies. Most of the respondents experienced disturbances to their operations due to imposed restrictions in order to comply with protective regulation, witnessed a reduction in orders quantity and also extended transportation times, stating that most managers had to delay deliveries due to the problem of filling and ensuring transportation. The latter consequence was also identified as a primary disturbance by Rapaccini, Saccani, Kowalkowski, Paiola, & Adrodegari (2020), that studied the impact on northern Italian manufacturing companies, the first ones to be affected in the European territory, as a result of travel restrictions employed in the region.

Hoek (2020) by interviewing SC executives, recognized that actions are being taken to reduce single-sourcing dependence and increase the pursuit of local and nearshoring options (for suppliers and plants). In fact, De Assunção, Medeiros, Moreira, Paiva, & Paes (2020), on a research done on Brazilian SCs, concluded that shorter SCs were less impacted by having closer proximity to regional suppliers, opposed to longer ones that were more affected due to transport modes restrictions.

One measure that has been vastly referred to for future improvements on SCR are technological investments towards digitizing end-to-end operations (Hoek, 2020; Marzantowicz et al., 2020; Zhu et al., 2020), which has been discussed more in-depth in the previous chapter. Cooperation between SC entities has also been identified as crucial (Hoek, 2020; Marzantowicz et al., 2020; Rapaccini, Saccani, Kowalkowski, Paiola, & Adrodegari, 2020), recognizing the importance in

strengthening relationships in order to attenuate the negative impacts of the disruption, along with changes to inventory management policies, allowing levels to be increased (Hobbs, 2020; Zhu et al., 2020).

Overall, up-to-date, the insights that can be withdrawn are still very limited, given that more data is required in order to conduct further studies at the tactical and operational level (Zhu et al., 2020). Nonetheless, richer literature, such as empirical exploration on current events, can be expected in the near future.

3.7.2 SCR quantitative models on the tactical and operational level

(Research Question 2 and 3)

In this section, firstly, quantitative studies that validate strategies present in qualitative works in the extant literature, whose conclusion can benefit tactical-operational decisions, are reviewed. Secondly, papers addressing tactical-operational problems and developing OR models to facilitate decision making are analysed.

As it was concluded in the previous section, the collaboration between entities can be critical during a disruptive event, aiding to increase SC's responsiveness as a whole. In the work of Lohmer, Bugert, & Lasch, (2020), the goal is to study the effect of the implementation of blockchain technology (BCT) on traditional SCR strategies, concluding from a qualitative analysis that SC collaboration and agility are the strategies that are most positively impacted by the technology. To quantify the effect of the former strategy, an agent-based simulation is performed. It was found that the application BCT favours simulation output values that measure the disruption cost, the number of affected entities and the recovery time. Nonetheless, to fully benefit from the technology, the authors advert that suitable expertise should be present at each SC partner and that the advantages also depend on the length of the disruption. Moreover, to study how to build collaborative resilient SCs, Aggarwal & Srivastava, (2019) resort to a grey-based Decision Making Trial and Evaluation Laboratory (DEMATEL) approach, finding the commitment of top management as the most prominent factor. Nonetheless, collaboration culture and design resilience in operations were identified to have a strong influence in the remaining success factors.

In the work of Azadeh, Atrchin, Salehi, & Shojaei, (2014), redundancy, considered as the augmentation of the number of resources, was one of the strategies, along with visibility, to provide the best results. The goal of the paper is to test the importance of four resilience factors (visibility, velocity, redundancy, and flexibility) on a transportation system of a 3-echelon SC, through simulation and Fuzzy Data Envelopment Analysis (FDEA) ranking of the results. Salehi, Salehi, Mirzayi, & Akhavizadegan, (2020) evaluate the same factors, with the addition of adaptability, on a pharmaceutical SC. A FDEA approach is also adopted, however, such is employed on the results of a questionnaire, arriving to a similar conclusion where redundancy, e.g. redundancy in the form of additional storage capacity, presented the most positive results.

More concerned with the cascading effect of a disruption Zhao, Zuo, & Blackhurst, (2019) study the effect of reactive and proactive strategies of a SC viewed as a complex adaptive system (CAS).

Agent-based simulations are performed to test the effect of the strategies by removing a node from the chain and assess the ability of the chain to seek alternative suppliers (reactive) or recur to pre-established alternatives (proactive) by reconfiguring connections. It is concluded that reactive strategies are able to reduce significantly the number of nodes impacted, however, proactive strategies are validated as being an overall superior option. More generally, Chowdhury & Quaddus, (2015) through a multi-objective optimisation model based on Quality Function Deployment (QFD) methodology, found in three main areas, namely, procurement, processing, and distribution, eight strategies that promote SCR (backup capacity; building relations with buyers and suppliers; quality control; skill and efficiency development; ICT adoption; demand forecasting; responsiveness to customers, and security system improvements).

Models that tackle SCR problems and support decisions at the tactical-operational level, are now separated into four general categories:

- Distribution problems: regard the coordination of product flows, through optimization of supply lead time and routing assignments;
- Inventory problems: solutions for inventory management decisions;
- Production problems: planning and scheduling considerations for production;
- Supply Chain problems: models that tackle the implementation of recovery policies and timely allocation of resources in more than one SC activity.

Of the collected papers, it was found that production problem are the least addressed in the quantitative SCR literature, and distribution, inventory and SC integrated activities in the recovery process problems are equally prevalent. Such is visible in the graph presented in figure 7 (yellow bars), along with the most used OR method for the corresponding problem. Optimization and simulation are the clear preferred method adopted across problems, with residual occurrences that use meta-heuristics, heuristics and decision analysis methods.

The succeeding subsections are now separated into these four categories, analysing extant quantitative models.

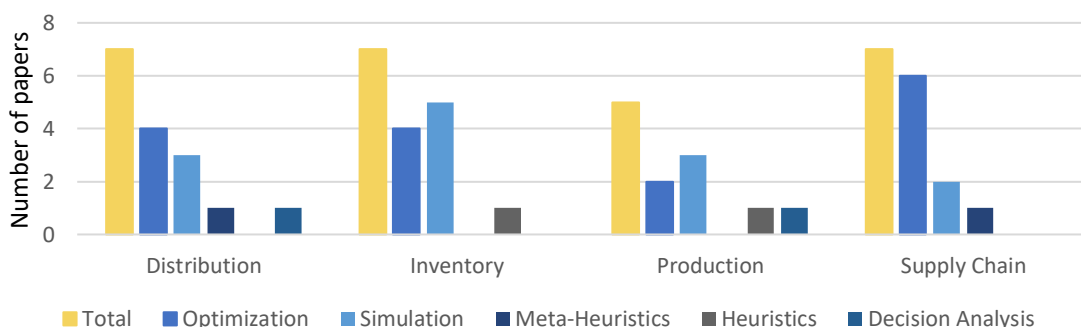


Figure 7: OR methods employed in tactical-operational problems

Distribution Problems

Considering the geographic reach of modern SCs and their complexity, disruptions to one node of the network can result in significant alterations of overall product flow. This problem is addressed by

Harrison et al., (2016), that takes into consideration disruptions on a SC node, flow or activity by iteratively deleting that component from the network and inserting mitigation strategies, which is the essence of the READI (Resiliency Enhancement Analysis via Deletion and Insertion) optimization model they propose. As one of the mitigation strategies, rerouting of product flow is adopted for short-term resilience. On the other hand, Wang, Herty, & Zhao, (2016) focus on disruptions occurred specifically on supplier nodes. Due to such disturbances, the authors investigate how changes in DMs' preference for suppliers implies changes to the coordination of product flows. The updated preferences are modelled based on a product allocation model considering three decision criteria (production capacity, product quality and production costs), which then feed a non-linear programming model to reroute product flow accordingly, and maximize service level, which is used as a measure of performance of resilience. Contemplating sustainability concerns, Ayoughi, Dehghani, Raad, & Talebi, (2020) propose a four objective model where three of the OFs account for each sustainability pillar, and the fourth for risk minimization. This model tackles a location-inventory-routing problem of a Closed-Loop Supply Chain (CLSC) for which the authors rely on two meta-heuristic algorithms for the solution approach, the Whale Optimization Algorithm and NSGA-II.

Studies on specific SCs focusing on this problem can be found for the New York motor-fuel SC and the New Zealand's forestry SC. The first one is researched by Beheshtian, Donaghy, Geddes, & Rouhani, (2017), that tackle distribution routing on the second stage of the bi-stage integer non-linear stochastic model they propose, which serves as a planning tool for DMs to address the resilience of SCs' vulnerability to natural hazards. Childerhouse, Al Aqqad, Zhou, & Bezuidenhout, (2020) explore the second case, which they evaluate through a 2-tier modelling approach. Firstly, a macro LP optimization is executed that serves as an input for the following microanalysis performed by a discrete event simulation, modelling operational activities for port closure scenarios.

When optimizing product flow, one major concern is the lead time and how it can disturb SCs operations. Therefore, in the work of Colicchia, Dallari, & Melacini, (2010), the variability of supplier lead time (SLT) is used as a proxy for SCR, where the goal is to study inbound flows and how it impacts global sourcing processes. A simulation-based framework is developed using a Monte Carlo method, where four contingency plans (alternative transportation solutions) and three mitigation strategies are tested on a home appliance retailer case study, where the EXW (ex-works) Incoterm is assumed so that the sourcing company takes full responsibility of supply-related risks. In line with this work, Chang & Lin, (2019) investigate the same problem of SLT, recurring to a discrete event system dynamics model that follows an Automatic Pipeline, Inventory, and Order Based Production Control System (ABIOBPCS) with an order-up-to inventory policy, where four different lead times (two short and four long with different periods) are simulated.

Inventory Problems

As addressed in the previous section, unexpected surges in demand can lead companies to fail to meet customer requirements, a concern that is reflected in the work of Schmitt & Singh, (2012) that use the percentage of immediately satisfied customers as a performance metric in the developed discrete-event simulation. However, their ultimate goal is to analyse inventory placement and back-up capabilities to

improve system resilience. Thus, optimizing inventory levels with resilience considerations are of most value in diminishing the negative impact of SC disturbances. In this line, Wu, Huang, Blackhurst, Zhang, & Wang, (2013) study the impact before, during and after the occurrence of stockouts through agent-based simulation with experiments to assess impacts on consumer response, initial store market share and stockout duration. However, Lücker & Seifert, (2017) resort directly to stockout quantity and stockout time as resilience metrics to develop their mathematical model that aims to determine optimal risk mitigation inventory (RMI) level.

Indeed, optimizing inventory levels enables DMs to avoid risks of mismatching supply and demand. To evade such risks, Spiegler, Potter, Naim, & Towill, (2016) use non-linear control theory combined with a simulation model to assess the resilience of a DC replenishment system of a grocery SC, allowing the identification of changes needed in stock and shipment responses. Addressing a (s,S) inventory policy, Gholami-Zanjani, Jabalameli, Klibi, & Pishvaei, (2020) study a Robust Location-Inventory Problem (RLIP) as a 2-stage scenario-based MILP, that unlike the other papers here mentioned, takes into consideration DMs' level of risk aversion.

Nonetheless, some novel approaches can be found on this subject, such as the work of Yang, Pan, & Ballot, (2017), being the first study to develop a simulation-based optimization model to determine inventory decisions and cost reductions when faced with a disruption of an interconnected network applying Physical Internet (PI) to enhance SCR. With the same end goal, Gružasuskas, Gimžauskienė, & Navickas, (2019) explore how information sharing (collaboration) can improve forecasting accuracy, along with other considerations (market size and type, and consumer integration). The authors use an agent-based simulation with machine learning algorithms which offer adaptation opportunities to enhance the system's resilience.

Production Problems

Additionally to inventory management, decision-making systems capable of dictating production decisions in order to fulfil customers' demand in response to unexpected events, are deemed necessary to enhance SCR. Towards that end, Singh, Ghosh, Jayaram, & Tiwari, (2019) recur to a hybrid of 2 heuristics, the Particle Swarm Optimization (PSO) and the Differential evolution (DE), while in the work of Das & Lashkari, (2017) a bi-objective non-linear model is proposed.

For more context-specific operating conditions, Ehlen, Sun, Pepple, Eidson, & Jones, (2014) use the impact of a hurricane on a butanediol SC to develop a large scale agent-based simulation and address problems verified in production scheduling, chemical buying, selling and shipping, obtaining ideal production levels by solving a collection of LP constrained problems.

Nonetheless, it is necessary to bear in mind that production systems can operate under different strategies which influence how such systems need to be modelled. In the papers here analysed, models contemplating Make-to-Stock and Make-to-Order environments can be found. For the former, Thomas & Mahanty, (2019) developed a two part model, were firstly an analytical investigation based on control engineering techniques and system dynamics is conducted, followed by a simulation as an Inventory and Order-Base Production Control System (IOBPCS) in order to study control structures and production paradigm where production lead time, inventory control and demand smoothing are set as

control parameters. While for the latter, which accounts for personalised production, Park, Son, & Noh, (2020) present a novel approach for applying Cyber-Physical Structure (CPS) and Digital Twins (DT) to SCs. The method proposed recurs to DT simulation to predict and coordinate production of various agents and achieve resilient planning in operation stages in SC production, able to deal with the bullwhip effect and the ripple effect caused by disruptions.

Supply Chain Problems

Resilient SCs need to react quickly in order for a timely recovery of the network as a mean to maintain/acquire a competitive advantage, coordinating available resources efficiently. For that end, Mao, Lou, Yuan, & Zhou, (2020) propose a model to optimize restoration schedules of the SC towards resiliency, which includes the sequencing of restoration activities and work crews' jobs. Such is performed by a bi-objective non-linear programming model which the authors solve by a simulated annealing algorithm. Addressing similar concerns, Ivanov, Sokolov, Solovyeva, Dolgui, & Jie, (2016) develop a dynamic model recurring to optimal program control theory, implemented then through simulation as a tool to aid operations and SC planners in the adoption of reactive recovery policies when faced with the ripple effect caused by a disruption. Alternatively, instead of simulation, Ivanov, Dolgui, & Sokolov, (2018) recur to attainable sets and optimal control theory. In this paper, two scheduling models are developed, the first one regards the execution of material flow, where the found control variables serve then as constraints for the second model that schedules recovery actions of SC resources capacity (e.g. job assignments).

Also addressing recovery strategies, the tool developed by Goldbeck, Angeloudis, & Ochieng, (2020) takes into consideration multiple operational adjustments (production rate, inventory levels, link flows and repair rates), taking the form of a multi-stage stochastic programming model. A more unifying framework is proposed by Ivanov & Sokolov, (2019), accounting for both structural and operational dynamics, that is, functional level recovery control of individual firms are integrated with structural recovery control. The authors acknowledged that SCR can be modelled as a trajectory of several degradation and recovery states, thus developing their model as a feedback-driven framework. The model provides an optimal program control able to re-allocate supply and demand, to analyse disruptions and their recovery dynamically, and improve recovery plans.

Rather than proposing a tool, Ivanov, (2020) develop a discrete-event simulation to investigate timely and efficient recovery policies and redundancy (re)allocation by considering the novel concept of SC overlays of disruptions that are separated into two types, reciprocal (single supplier disruption in times of low demand) and aggravated (disruptions in multiple suppliers in times of high demand).

On a more tactical level, Khalili, Jolai, & Torabi, (2017) tackle a production-distribution planning problem for the introduction of the manufacture of new product sets. The authors develop a two-stage scenario-based mixed stochastic-possibilistic programming model with resilience enhancing options (additional production capacity, backup transportation links and prepositioning of emergency inventory in DCs) for parts in the SC considered as vulnerable to disruptions.

3.7.3 Risk and uncertainty in tactical and operational models

(Research Question 4)

When addressing SCR problems, these inevitably consider risk events, whether operational and/or disruptive, as can be deduced from the previous section. These type of risks are essentially distinguished by the level of their impact and frequency, being the former descriptive of low impact and high-frequency events (LIHF), and the latter for high impact and low-frequency ones (HILF) (Khalili et al., 2017; Namdar et al., 2018).

In figure 8, the type of risks that are modelled in the previously analysed papers are indicated. As could be expected, being resilience of great value for dealing HILF events, disruptive risks are the most considered. Nonetheless, given that these works tackle the tactical-operational level, eight papers were identified to address resilience in face of LIHF events while five addressed both risks simultaneously.

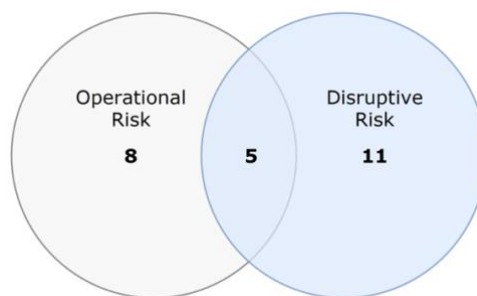


Figure 8: Type of risk modelled

However, regarding how these risks are modelled, in the vast majority, simple approaches are adopted. For instance, some works that address the occurrence of severe disruptions, model such events in a pre-specified time frame. Ehlen et al., (2014), Chang & Lin, (2019) and Mao et al., (2020) specify the instance for the event to take place and Wang et al., (2016) consider that suppliers are disrupted from the beginning, while Lücker & Seifert, (2017), Harrison et al., (2016), Childerhouse et al., (2020) and Ivanov, (2020) select which node of the network to be disrupted with a given time length.

Another approach is the setting of different risk profiles that may arise. Such is adopted by Wu et al., (2013), Beheshtian et al., (2017), Ivanov et al., (2016) and Singh et al., (2019) as well as Schmitt & Singh, (2012) which base the risk profiles on interviews on operational personnel and literature, Das & Lashkari, (2017) recur to historical data and Yang et al., (2017) use a model defined in the extant literature.

Nevertheless, a few works can be found to actively develop formulations to account for risk events in their models. Ivanov et al., (2018) develop a perturbation function to assess its impact, and Thomas & Mahanty, (2019) use unit step impulse for customer demand disturbances.

Relative to uncertainty, a few papers have been identified to integrate such condition into their model. In the stochastic model proposed by Khalili et al., (2017), production and distribution of new products are taken as imprecise parameters and are formulated in the form of triangular fuzzy numbers. This approach is also adopted by Ayoughi et al., (2020) to deal with demand, facility costs and inventory costs parameter, which are taken as uncertain. Also adopting a stochastic approach, Goldbeck et al., (2020), in order to deal with uncertainty present in asset failure, generate a scenario tree with an input-

output method that accounts for the propagation risk to its initial impact, as well as the interdependency between assets. Lastly, through a robust approach, Gholami-Zanjani et al., (2020) also address uncertainty in selected parameters recurring to a Monte Carlo method to generate plausible scenarios.

3.7.4 SCR metrics

(Research Question 5 and 6)

Relative to resilience metrics that are applied in the context of SCR, it can be said that these are greatly influenced by the end goal of the paper in which they are proposed and/or used, presenting diverse forms. Table 4 confirms this affirmation, where it is possible to verify the affinity between the nature of the tackled problem and the indicators used. This table was constructed based on the findings detailed beforehand, hence they regard the tactical-operational decision level problems.

Khalili et al., (2017) present three indicators relevant for each activity of the SC considered, which are all computed in terms of product/period unit, and whose weighted sum provide the resilience of the chain as a whole. PR is obtained by the sum of the initial production capacity (K_j) and the difference between the decision variables of the additional initial production capacity (w_j) and production capacity that is available in t for scenario s (up_{jt}^s). Regarding transportation, DR is calculated considering the difference between the transmission capacity of the transportation mode (K_m^l), in case that mode is available at a given link (regulated by the binary variable z_{jc}^{ml}), with the transportation capacity that is available under scenario s (ut_{jct}^s). Following a similar reasoning, IR is computed through the difference between the additional capacity of a DC for a given product (w_{kc}) and the emergency inventory level available for scenario s (ub_{kct}^s).

Table 4: Resilience indicators in tactical-operational models

Paper	Problem addressed	Resilience indicators	Formula
Khalili et al., (2017)	Supply Chain	Availability of production capacity (PR)	$PR_s = \sum_j \sum_t (K_j + w_j - up_{jt}^s)$
		Availability of transportation capacity (DR)	$DR_s = \sum_j \sum_c \sum_m \sum_l \sum_t (z_{jc}^{ml} K_m^l - ut_{jct}^s)$
		Availability of emergency inventory (IR)	$IR_s = \sum_k \sum_c \sum_t (w_{kc} - ub_{kct}^s)$
Lücker & Seifert, (2017)	Inventory	Stockout surface	$S = - \int_{t_1}^{t_2} I(t) dt$
		Mitigation surface	$M = \int_0^{t_2} I(t) dt + \int_{t_D}^{\tau} (td) dt + \int_{\tau}^{t_2} t(d+p) dt$
Chang & Lin, (2019)	Distribution	Stability of the net inventory Impact propagation	n.a.
Mao et al., (2020)	Supply Chain	Cumulative loss	$R_u = 1 - \frac{\int_{t_e}^{t_e+M} [\varphi(t_0) - \varphi(t)] dt}{M_{max} \times \varphi(t_0)}$
		Restoration rapidity	$R_m = 1 - \frac{M}{M_{max}}$

The indicators proposed by Mao et al., (2020) are normalized in terms of resilience, where the range of its' value are between 0 and 1, and are positively correlated with the effectiveness of the restoration strategy, given that both subtract terms that are desired to have a low value to 1. Therefore, the main term of the resilience of cumulative loss is calculated by the ratio of the area measured between the performance of the SC ($\varphi(t)$) between the instant the disruption occurs and the end of the restoration activities ($t_e + M$), with the product of the maximum makespan value of the restoration strategy (M_{max}) and the performance in the initial state. More simply, the main term of the resilience of the restoration rapidity is obtained by the ratio of the observed makespan of the restoration strategy (M) and its maximum value.

Lücker & Seifert, (2017) constructed a resilience metric ($\rho = \frac{M}{M+s}$) based on a hybrid approach of considering both the stockout quantity and time. The indicator of the stockout surface (S) is measured by the negative integral of the RMI level ($I(t)$) between the time the stockout occurs (t_1) and the time backlog ends (t_2). Also, as a component of the resilience metric, the successfully mitigated area (M) is used, which is obtained by the sum of three integrals that measure stock quantities at different instances. Up until the backlog ends it is calculated by the RMI level, between the time delay of the dual-source (t_D) and the disruption length (τ), the production rate of the dual-source (d) is considered, and after the disruption until t_2 , the production rate at the primary site (p) added to d is used.

In the work of Chang & Lin, (2019) a mathematical formulation of the indicators used is not presented, but rather described. The stability of the net inventory level is assessed by observing the variation of the time between critical inventory points, and the impact propagation is defined as the ratio between the stockout duration with the duration of the initial disruptive event.

Regarding indicators used in papers that do not tackle a specific problem but rather set out to measure the resilience of SCs on a more holistic approach, are presented in table 5. To note that due to the established selection criteria in the material selection phase, these are mainly operational indicators.

Ahmadian, Lim, Cho, & Bora, (2020) developed a general quantitative model to assess the resilience of various physical networks, with the goal to easily identify components of the SC that require improvements, evaluate its cost given budget constraints and provide a mean for comparison with other networks. Measuring the resilience of individual components, in this paper, is key since it is considered that the resilience of the whole SC is determined by the lowest performing node, resulting in a max-min optimization problem. Of the four considered indicators, criticality is introduced by the authors to measure the ability of the network to perform in case of component failure, while the remaining indicators are more prevalent in the literature given that they derive from the resilience triangle principles (readiness, response and recovery). Indeed, for instance, recovery was also identified in the work of Munoz & Dunbar, (2015) and Y. Li & Zobel, (2020). In the first paper, a simulation model is run for a specified disruption profile, and multidimensional metrics are analysed that set out to explain the impact of disruptions on transient responses, while the latter publication complements a simulation model with a regression analysis where the aim is to research the measurement of both short and long term impact of disruptions. Likewise, Raj et al., (2015) construct a regression model for the measurement of

resilience through the recovery time (output of the model) based on cox-proportional hazard survival model, where sources of disruption are used as input variables.

Table 5: Resilience indicators

Paper	Resilience indicators
Munoz & Dunbar, (2015)	Recovery Performance loss Impact Profile Length
Dixit et al., (2016)	Percentage of unfulfilled demand Total transportation cost post-disaster
R. Li et al., (2017)	Amount of product delivered Average delivery distance
Sprecher et al., (2017)	Time lag Response speed Maximum magnitude
Sharma & George, (2018)	<u>Dimensions of resistive capacity:</u> Maintenance Fuel price variability hedging Skilled labour and management Communication and coordination Security Insurance Mode flexibility <u>Dimensions of restorative capacity:</u> Risk assessment Budget availability
Ramezankhani et al., (2018)	Average inventory <u>Economic:</u> Cost Part unit profit <u>Social:</u> Number of employees Employee satisfaction <u>Environmental:</u> Waste Recyclable waste
Chen et al., (2020)	Cost of order loss Cost of order backlog Sales revenue Cost of resilience ability
Ahmadian et al., (2020)	Probability of disruption Impact of the disruption Recovery to normal state Criticality
Y. Li & Zobel, (2020)	Robustness at initial impact Robustness at full impact Recovery time Average performance retained over time

R. Li, Dong, Jin, & Kang, (2017) considered that SCR measures should reflect key performance indexes (KPIs) of the system, hence, two metrics that are of most importance to guarantee end-customers' satisfaction are proposed, which are able to measure whether products are delivered as required (amount of product delivered and average delivery distance). These are then tested with a case study, using Monte Carlo simulation combined with graph theory to estimate resilience. Similar concerns can be identified in the work of Dixit, Seshadrinath, & Tiwari, (2016) with communalities between the metrics they propose with those of the former paper, one related to order fulfilment and the other to transportation costs. These metrics are implemented in the two minimization OFs of a multi-objective stochastic mixed-integer problem. While for Chen, Dui, & Zhang, (2020) the indicators revolve more on economic interests, three measuring costs (order loss, order backlog and resilience ability) and one for sales revenue.

On the other hand, concerns can be directed more to the nature of the handled product. Such is the case for the work of Sprecher et al., (2017), which establish resilience indicators for SCs of critical materials. Here it is possible to conclude that time measures are of the essence. Sharma & George, (2018) direct their attention to the characteristics of trucking companies SC, highlighting two main dimensions of resilience, namely, resistive capacity and restorative capacity, developing a Bayesian network analysis of the considered resilience factors.

Relative to sustainability metrics, only one paper has been identified to consider resilience and sustainability factors concurrently. Ramezankhani, Torabi, & Vahidi, (2018) recur to a hybrid method using QFD methodology along with DEMATEL to determine the most influential resilience and sustainable factors.

3.8 Discussion and future research directions

SCR presents a fast-growing body of literature that is expected to continue to grow, with current conditions inciting a possible stream of case studies to be explored. Regarding extant decision-supporting tools, these present a variety of applications, while some challenges still need to be addressed (figure 9).

The models developed thus far, dealing with tactical and operational decisions, present a clear preference for optimization and simulation techniques. Only selected few works can be found to use heuristics and decision analysis methods. Consequently, the benefits that these two OR methods may provide remain relatively unexplored and future efforts should be made in exploring both. Heuristics could be of value, especially regarding tactical and operational decisions, due to its capability in delivering rapid results. While decision analysis is an interesting option, especially considering the inherent subjective behaviour of DMs towards risk.

The inclusion of risk events within the models is a common practice. However, it was found that a vast majority is modelled deterministically. In fact, uncertainty, considering as well other parameters of the model, has also been scarcely addressed. In order to reflect more accurately the dynamics and randomness of real-world events, which are particularly frequent in day-to-day operations, future research should consider the adoption of stochastic approaches.

Nevertheless, resilience performance metrics need to be carefully selected to guarantee that they truthfully reflect the objectives of the developed model. Choosing inadequate metrics to be optimized can lead to drastically different results. Thus, despite existing in the literature some indicators that are more vastly cited, these are still majorly context-driven. On this subject, a gap has been identified regarding sustainability metrics, given that only one paper was found addressing resilience and sustainability concerns concurrently. Research to bridge this gap needs to be developed, which could be executed by studying the adaptation of what has been developed in research addressing the strategic level to the tactical and operational level.

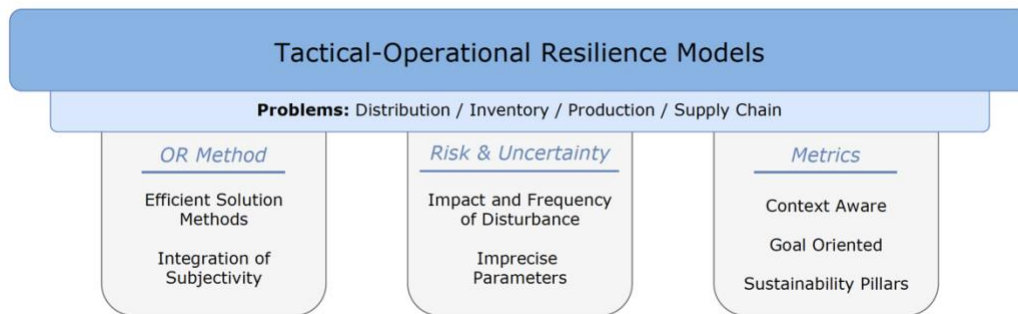


Figure 9: Research framework on tactical-operational SCR model

3.9 Chapter conclusions

With the goal to review the current state of the art on SCR quantitative models, with a focus on the tactical-operational decision level, a systematic literature review is here presented. Through a solid methodology, key research questions were defined which shaped the outcome of this chapter.

By analysing previous literature reviews, it was found that SCR is a fairly recent research field, exhibiting rapid growth in recent years. Of these reviews, it was found that quantitative approaches on the subject are scarce, thus positioning the present work to reduce this gap, and distinguishing from others by focusing on the tactical and operational decision level.

However, motivated by the conditions experienced at the time of writing, an overview on the literature developed addressing the COVID-19 pandemic was executed, and some insights were withdrawn, acknowledging that these are still very limited to early assessments.

To better understand the focus of the developed models, these were divided into four general categories (distribution, inventory, production and SC), as well as the OR method used within each category. Production was identified as the category with the least dedicated research. Regarding the OR methods, it was found that optimization and simulation are the most commonly adopted, while others such as heuristics and decision analysis lack dedicated research, which could be explored as possible efficient and more customizable alternatives, respectively. Succeeding, it was analysed how risk and uncertainty have been modelled, concluding that it is necessary to invest future investigation on how to model risk and uncertainty beyond deterministic approaches, for a more accurate representation of disturbances.

Ultimately, notable work has been developed in constructing decision-supporting tools, however, several aspects still require further investigation to enrich the applicability and efficiency of these tools.

4 Model formulation

This chapter aims to present the formulated model to tackle the subject of SCR at the tactical-operational decision level. A general overview of the goals of the model is provided followed by in-depth details of its components. Namely, the used sets and parameters are presented with a brief description followed by a more detailed clarification of the OFs and constrains. The adaptation of the model with a stochastic approach is explained in section 4.9, and the modelling of disruptions in section 4.10. Lastly, the solution approach to solve the model is described in section 4.11.

4.1 Model overview

The model here presented considers a four-echelon closed-loop supply chain (CLSC), composed by suppliers, factories, retailers, and markets. Figure 10 illustrates this structure along with the allowed flows among the entities. For the formulation of this model, the production, distribution and capacity planning model developed by Liu & Papageorgiou (2013) was used as a basis, upon which considerable alterations were made. Namely, SC echelons were added (supplier and retailer), as well as further node links such as the direct flow from the factories to the markets and all the reverse flows and activities. It was also introduced the transformation of raw materials into final products with the consideration of the time required for the process, and also the possibility of having alternative products. The proposed model also explores different planning goals. This is a multi-objective model with the goal to maximize a resilience metric, minimize the total flow time, and maximize the total profit. The second objective intends to optimize the SC's responsiveness, hence considering the transportation time between entities as well as the production time of the products to minimize the lead time.

Being this a planning-operational model, relative to production, the model determines which product should be produced, given that demand can be satisfied by alternative products; where they should be produced, considering the restricted set of products that the factories are capable of manufacturing; and whether it is necessary to extend the original production capacity. The expansion can occur either by increasing the capacity of owned factories (activation of redundant capacity) or through outsourcing. Additionally, the products are also restricted to markets in which they can be sold.

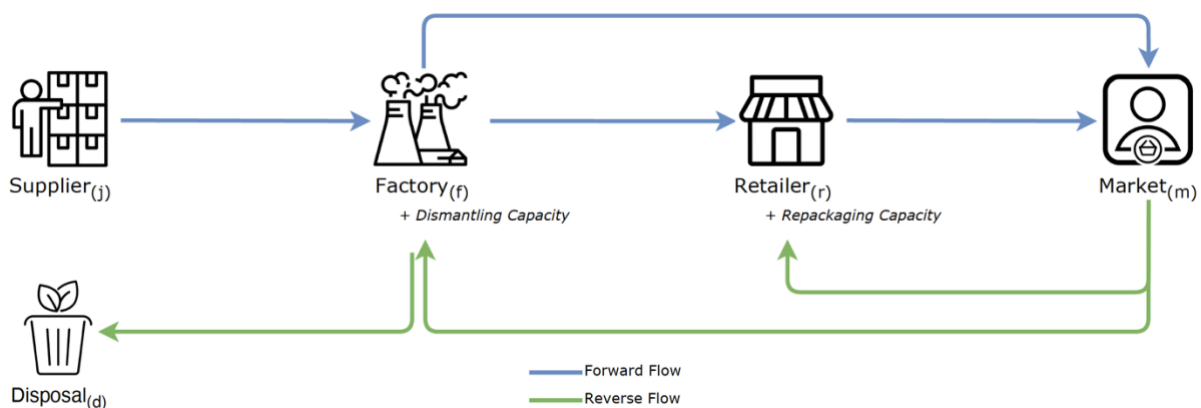


Figure 10: Supply chain structure

Following a similar approach as the one in the work of Cardoso, Barbosa-Póvoa, & Relvas (2013), the reverse flow can occur for non-conforming products as well as for end-of-life products, where they are returned to the retailer to be repacked or to the factory to be disassembled, respectively, and reintegrate the forward flow. It is also taken into account that some end of life products are too damaged to be repurposed and are therefore disposed of. For this end, it is assumed that the factories and retailers possess the necessary capabilities to dismantle and recondition products, respectively.

4.2 Set and indices

The sets of the model and its corresponding index are presented in table 6 along with their description.

Table 6: Model's sets and indices

Sets	Indices	Description
I	i	Raw materials
P	p, pp	Products
J	j	Suppliers
F		Factories
<u>Subsets:</u>		
F _{own}	f	Owned factories
F _{out}		Outsourcing factories
R	r	Retailers
M	m	Markets
D	d	Disposal entities
T	t, tt	Time periods
K	k	Objective functions
PF	(p,f)	Product p that can be produced at factory f
PM	(p,m)	Product p that can be sold in market m
ALT	(p,pp)	Alternative product pp for a given product p

4.3 Parameters

4.3.1 Costs

- $mc_{i,j}$ material cost of raw material i at supplier j (€/unit)
- $vpc_{p,f}$ variable production cost of product p at factory f (€/unit)
- $fpc_{p,f}$ fixed production cost of product p at factory f (€)
- $vcec_f$ variable capacity expansion cost of factory f (€/unit)
- $fcec_f$ fixed capacity expansion cost of factory f (€)
- $vtcs_{i,j,f}$ variable transportation cost of raw material i between supplier j and factory f (€/unit)
- $vtcr_{p,f,r}$ variable transportation cost of product p between factory f and retailer r (€/unit)
- $vtcd_{p,f,m}$ variable transportation cost of product p between factory f and market m (€/unit)

$vtcm_{p,r,m}$	variable transportation cost of product p between retailer r and market m (€/unit)
$vtcdd_{p,d,f}$	variable transportation cost of product p between factory f and disposal site d (€/unit)
$ftcs_{j,f}$	fixed transportation cost between supplier j and factory f (€/unit)
$ftcr_{f,r}$	fixed transportation cost between factory f and retailer r (€/unit)
$ftcd_{f,m}$	fixed transportation cost between factory f and market m (€/unit)
$ftcm_{r,m}$	fixed transportation cost between retailer r and market m (€/unit)
$invcfi_{i,f}$	inventory cost of raw material i at factory f (€/unit)
$invcfp_{p,f}$	inventory cost of product p at factory f (€/unit)
$invcr_{p,r}$	inventory cost of product p at retailer r (€/unit)
$\beta_{p,p}$	coefficient for variable production cost for product p in the duty function (%)
$\gamma_{p,p}$	coefficient for variable transportation cost for product p in the duty function (%)
$drm_{f,m}$	duty rate from factory f to market m in each time period (%)
$drr_{f,r}$	duty rate from factory f to retailer r in each time period (%)
$dcm_{p,f,m}$	duties cost of product p from factory f to market m (€/unit)
$dcr_{p,f,r}$	duties cost of product p from factory f to retailer r (€/unit)

4.3.2 Time measures

$pt_{p,f}$	production time of product p at factory f (weeks)
lt_p	life time of product p (weeks)
$stime_f$	set up time required to activate additional production capacity at factory f (weeks)
$tts_{j,f}$	transportation time between supplier j and factory f (weeks)
$ttr_{f,r}$	transportation time between factory f and retailer r (weeks)
$ttd_{f,m}$	transportation time between factory f and market m (weeks)
$ttm_{r,m}$	transportation time between retailer r and market m (weeks)

4.3.3 Production

$icap_f$	initial production capacity of factory f (units)
$pmax_{p,f}/pmin_{p,f}$	maximum/minimum production of product p at factory f (units)
$ireq_{p,i}$	quantity of raw material i required to produce product p (units)
$liunit_i$	logistics unit of raw material i
$lunit_p$	logistics unit of product p
$ivol_i$	volume of raw material i
vol_p	volume of product p

4.3.4 Inventory

$invinr_{p,r}$	initial inventory of product p at retailer r (unit)
$invinfi_{i,f}$	initial inventory of raw material i at factory f (unit)
$invinfp_{p,f}$	initial inventory of product p at factory f (unit)
$invminfi_{i,f}/invminfp_{p,f}$	minimum inventory of raw material i /product p at factory f (unit)
$invminr_{p,r}$	minimum inventory of product p at retailer r (unit)

$invmax_f/invmax_r$ maximum inventory at factory f /retailer r (unit)

4.3.5 Demand

$dem_{p,m,t}$ demand of product p in market m in time period t (units)

$sellprice_p$ sell price of product p (€)

4.4 Scalars

$turn$ inventory turnover ratio

$pcemin/pcemax$ minimum/maximum proportional capacity expansion rate (%)

$ocemin/ocemax$ minimum/maximum expansion for outsourcing factory (units)

$scosti$ spoilage cost of raw material i (€/unit)

$scostp$ spoilage cost of product p (€/unit)

ds acceptable percentage of lost sales (%)

$pmarginu$ profit margin (%)

$pmarginl$ profit margin for alternative products (%)

$fmin/fmax$ minimum/maximum flow of product (units)

$tnum$ number of time periods

dis fraction of products that are too damaged to be repurposed (%)

$nconf$ fraction of products that are non-conforming (%)

$mincol$ minimum fraction of product collection in the reverse flow (%)

$profitREF$ profit reference value without a disruption

4.5 Decision variables

4.5.1 Continuous variables

$CAP_{f,t}$ production capacity of factory f in time period t

$CAPInc_{f,t}$ production capacity increment of factory f in time period t

$FSF_{i,j,f,t}$ flow of raw material i from supplier j to factory f in time period t

$FFR_{p,f,r,t}$ flow of product p from factory f to retailer r in time period t

$FFM_{p,f,m,t}$ flow of product p from factory f to market m in time period t

$FRM_{p,r,m,t}$ flow of product p from retailer r to market m in time period t

$RMR_{p,m,r,t}$ reverse flow of product p from market m to retailer r in time period t

$RMF_{p,m,f,t}$ reverse flow of product p from market m to factory f in time period t

$RFD_{p,f,d,t}$ reverse flow of product p from factory f to disposal site d in time period t

$INVfi_{i,f,t}$ inventory of raw material i at factory f in time period t

$INVfp_{p,f,t}$ inventory of product p at factory f in time period t

$INVR_{p,r,t}$ inventory of product p at retailer r in time period t

$CON_{i,f,t}$ amount of raw material i consumed at factory f in time period t

$SPOi_{i,f,t}$ amount of raw material i spoiled at factory f in time period t

$SPOp_{p,f,t}$ amount of product p spoiled at factory f in time period t

- $PRO_{p,f,t}$ amount of product p ordered to produce at factory f in time period t
- $ONG_{p,f,t,t}$ ongoing production of product p at factory f
- $SA_{p,pp,m,t}$ sales of product pp at market m in time period t
- $LS_{p,m,t}$ lost sales of product p at market m in time period t

4.5.2 Binary variables

- $E_{p,f}$ if product p is produced at factory f
- $W_{p,f,t}$ if product p production is assigned to factory f in time period t
- $Ys_{j,f,t}$ if link between supplier j and factory f is established in time period t
- $Yr_{f,r,t}$ if link between factory f and retailer r is established in time period t
- $Yd_{f,m,t}$ if link between factory f and market m is established in time period t
- $Ym_{r,m,t}$ if link between retailer r and market m is established in time period t
- $Ync_{m,r,t}$ if link between market m and retailer r in the reverse flow is established in time t
- $Yel_{m,f,t}$ if link between market m and factory f in the reverse flow is established in time t
- $Xs_{j,f}$ if link between supplier j and factory f is established
- $Xr_{f,r}$ if link between factory f and retailer r is established
- $Xd_{f,m}$ if link between factory f and market m is established
- $Xm_{r,m}$ if link between retailer r and market m is established
- $Xnc_{m,r}$ if link between market m and retailer r in the reverse flow is established
- $Xel_{m,f}$ if link between market m and factory f in the reverse flow is established
- XE_f if production capacity of factory f is expanded

4.6 Objective function auxiliary terms

- TMC total manufacturing costs
- TTC total transportation costs
- TDC total duties costs
- TIC total inventory costs
- TEC total capacity expansion costs
- $profit$ auxiliary variable to determine profit
- $sales$ auxiliary variable to determine the revenue from sales

4.7 Objective functions

The following sub-sections present the three OFs considered in this present model. The first metric intends to balance the economic performance of the SC with the delivered service level, whose benefit is further explained next (Pires Ribeiro & Barbosa-Póvoa, n.d.). Secondly, the flow time OF's goal is to optimize the SC's responsiveness by guaranteeing the minimum lead time possible, which has been shown in the literature to boost SCR. Lastly, to reinforce the importance to maintain appealing economic returns and sustain financial viability, a typical profit maximization is considered.

4.7.1 Objective function 1: Resilience metric

The first OF involves both economic goals and customer satisfaction to guarantee SC resilience (equation 1). In the first term a reference value (profitREF) is used, which represents the optimal profit level within normal operating conditions. Hence, the first term favours profit levels that approximate to the reference value. This term is then balanced out with a measure of service level. The second term will deteriorate the overall function with increased lost sales (LS_{p,m,t}), thus taking into account the concern to meet customers' demand. Since both terms are valued equally, customers' satisfaction are not disregarded in pursuit of economic returns.

$$Max Z_1 = \frac{profit}{profitREF} - \frac{\sum_p \sum_{m \in PM} \sum_t LS_{p,m,t}}{\sum_p \sum_{m \in PM} \sum_t dem_{p,m,t}} \quad (1)$$

$$profit = sales - (TMC + TTC + TIC + TDC + TEC) \quad (1.1)$$

Equation 1.1 determines the profit value. For simplicity, auxiliary variables are used to measure sales and costs in individual terms, divided in the following categories:

- Sales

The total revenues are obtained by the amount of products sold (SA_{p,pp,m,t}) at price sellprice_{pp}, by equation 1.2.

$$sales = \sum_p \sum_{pp \in ALT} \sum_{m \in PM} \sum_t sellprice_{pp} \times SA_{p,pp,m,t} \quad (1.2)$$

- Total Manufacturing Cost

Equation 1.3 measures the costs incurred during production. It includes the costs of raw materials (mc_{i,j}) that are supplied for production (FSF_{i,j,f,t}), the fixed cost of opting to operate facility f to produce product p (fpc_{p,f}) as well as the variable cost (vpc_{p,f}) per unit produced at each factory (PRO_{p,f,t}). Also, it is accounted the possibility of raw materials or product to be spoiled (SPO_{i,f,t}, SPO_{p,f,t}), incurring in a unitary cost (scosti, scostp).

$$TMC = \sum_i \sum_j \sum_f \sum_t mc_{i,j} \times FSF_{i,j,f,t} + \sum_{p \in PF} \sum_f \sum_t vpc_{p,f} \times PRO_{p,f,t} + \sum_{p \in PF} \sum_f fpc_{p,f} \times E_{p,f} \\ + \sum_i \sum_f \sum_t scosti \times SPO_{i,f,t} + \sum_{p \in PF} \sum_f \sum_t scostp \times SPO_{p,f,t} \quad (1.3)$$

- Total Transportation Cost

The TTC is calculated by equation 1.4, where the unitary transportation cost of product p between two entities (vtcs_{i,j,f}, vtrc_{p,m,r}, vtcd_{p,f,m}, vtcm_{p,r,m}, vtcd_{p,d,f}) is multiplied by the quantity of its' flow in all time periods. Here it is assumed that the cost between two entities is equal whether it is a forward or reverse flow (RMF_{p,m,f}, RMR_{p,m,r}), as is the case between markets and factories or retailers. The remaining terms add a fixed cost (ftcs_{j,f}, ftrc_{r,r}, ftcd_{f,m}, ftrm_{r,m}) whether a transportation link is established throughout the planning horizon (Xs_{j,f}, Xr_{r,r}, Xd_{f,m}, Xm_{r,m}).

$$\begin{aligned}
TTC = & \sum_i \sum_j \sum_f \sum_t vtc_{i,j,f} \times FSF_{i,j,f,t} + \sum_{p \in PF} \sum_f \sum_r \sum_t vtc_{p,f,r} \times FFR_{p,f,r,t} \\
& + \sum_{p \in PF} \sum_f \sum_{m \in PM} \sum_t vtc_{p,f,m} \times (FFM_{p,f,m,t} + RMF_{p,m,f,t}) \\
& + \sum_p \sum_r \sum_{m \in PM} \sum_t vtc_{p,r,m} \times (FRM_{p,r,m,t} + RMR_{p,m,r,t}) \\
& + \sum_{p \in PF} \sum_f \sum_d \sum_t vtc_{d,p,d,f} \times RFD_{p,d,f,t} + \sum_j \sum_f ftc_{j,f} \times XS_{j,f} + \sum_f \sum_r ftc_{f,r} \times Xr_{f,r} \\
& + \sum_f \sum_m ftc_{f,m} \times Xd_{f,m} + \sum_r \sum_m ftc_{r,m} \times Xm_{r,m}
\end{aligned} \tag{1.4}$$

– Total Inventory Cost

Equation 1.5 calculates the inventory cost by multiplying the unitary holding cost ($invcf_{i,f}$, $invcp_{p,f}$, $invcr_{p,r}$) by the amount of inventory that is held in each time period ($INVf_{i,f,t}$, $INVfp_{p,f,t}$, $INVR_{p,r,t}$). The first term is for the inventory of raw materials and the second term for final products, both held at the factories, while the last term serves for the final products held at the retailers.

$$TIC = \sum_i \sum_f \sum_t invcf_{i,f} \times INVf_{i,f,t} + \sum_{p \in PF} \sum_f \sum_t invcp_{p,f} \times INVfp_{p,f,t} + \sum_p \sum_r \sum_t invcr_{p,r} \times INVR_{p,r,t} \tag{1.5}$$

– Total Duties Cost

The total duties cost are assumed to occur when final products leave the factories, either directly to the market ($FFM_{p,f,m,t}$) or to a retailer ($FFR_{p,f,r,t}$) where a duty cost is applied ($dcm_{i,s,p,f,m}$ and $dcr_{i,s,p,f,r}$, respectively). The referred duty costs depended on the products' characteristics and the duty rate applied between the two locations ($drm_{p,f,m}$, $drr_{p,f,r}$), and are therefore calculated beforehand by equation 1.6.1 and 1.6.2.

$$TDC = \sum_{p \in PF} \sum_f \sum_{m \in PM} \sum_t dcm_{p,f,m} \times FFM_{p,f,m,t} + \sum_{p \in PF} \sum_f \sum_r \sum_t dcr_{p,f,r} \times FFR_{p,f,r,t} \tag{1.6}$$

$$dcm_{p,f,m} = drm_{p,f,m} \times (\beta_p \times vpc_{p,f} + \gamma_p \times vtc_{p,f,m}) \tag{1.6.1}$$

$$dcr_{p,f,r} = drr_{p,f,r} \times (\beta_p \times vpc_{p,f} + \gamma_p \times vtc_{p,f,r}) \tag{1.6.2}$$

– Total Expansion Cost

For recurring to a production capacity expansion, the total cost is calculated by equation 1.7 depending on the expanded amount ($CAPInc_{f,t}$), applying a unitary variable cost ($vcec_f$) additional to the head cost ($fcec_f$) for selecting said option (XE_f).

$$TEC = \sum_f fcec_f \times XE_f + \sum_f \sum_t vcec_f \times CAPInc_{f,t} \tag{1.7}$$

4.7.2 Objective function 2: Flow time

The second OF has the function to minimize the total flow time, optimizing the SC's responsiveness. The goal of this metric is to increase the SC's capability to react rapidly to customers demand. Such is of most importance to the modern fast-changing markets, and in particular to this case since response time is a critical component of SCR. Thus, equation 2 measures the transportation time between two entities ($tts_{j,f}$, $ttr_{f,r}$, $ttd_{f,m}$, $ttm_{r,m}$) with an importance proportional to amount sent ($FSF_{i,j,f,t}$, $FFR_{p,f,r,t}$, $FFM_{p,f,m,t}$, $FRM_{p,r,m,t}$), adjusted according to the products' volume within a container ($lunit_p$). This unit is obtained by equation 2.1, which is based on the twenty-foot equivalent unit (TEU), according to each products' individual volume (vol_p). Additionally, it is also included the necessary production time of the item ($pt_{p,f}$).

$$\begin{aligned}
 Min Z_2 = & \sum_i \sum_j \sum_f \sum_t (tts_{j,f} \times lunit_i \times FSF_{i,j,f,t}) \\
 & + \sum_{p \in PF} \sum_f \sum_t pt_{p,f} \times PRO_{p,f,t} + \sum_{p \in PF} \sum_f \sum_r \sum_t (ttr_{f,r} \times lunit_p \times FFR_{p,f,r,t}) \\
 & + \sum_{p \in PF} \sum_f \sum_{m \in PM} \sum_t (ttd_{f,m} \times lunit_p \times FFM_{p,f,m,t}) \\
 & + \sum_p \sum_r \sum_{m \in PM} \sum_t (ttm_{r,m} \times lunit_p \times FRM_{p,r,m,t})
 \end{aligned} \tag{2}$$

$$lunit = \frac{vol_p}{teu} \tag{2.1}$$

4.7.3 Objective function 3: Profit

Lastly, the third OF is a straightforward profit maximisation, where total costs are subtracted to the revenue obtained by the sold products ($SA_{p,pp,m,t}$), as seen in equation 1.1.

4.8 Constraints

4.8.1 Production constraints

This section presents the equations which define and constrain production at the factories. Equation 3 defines the upper and lower limit ($pmin_{p,f}$ and $pmax_{p,f}$) for initiating production of product p at factory f in each time period ($PRO_{p,f,t}$). The binary variable $W_{p,f,t}$ imposes this limits if the product is assigned to be produced at the designated factory and time period, otherwise it takes the value of 0.

To obtain final products it is necessary the consumption of raw materials ($CON_{i,f,t}$) in a given quantity according to each product's requirements ($ireq_{p,i}$), which is accounted for in equation 4. Equation 5 guarantees that total production does not surpass the production capacity of the factory ($CAP_{f,t}$). For this limit, the production initiated at instant t is considered as well as any ongoing operations. Such is necessary given that the production time ($pt_{p,f}$) varies by product and factory. The first term accounts for products with immediate production ($pt_{p,f} = 0$), while for higher production durations it is measured by variable $ONG_{p,f,t,tt}$, as defined by equation 6, which takes the value of the initiated production ($PRO_{p,f,t}$) at time t until the end of production at $t+pt_{p,f}$.

$$pmin_{p,f} \times W_{p,f,t} \leq PRO_{p,f,t} \leq pmax_{p,f} \times W_{p,f,t} \quad \forall (p,f) \in PF, t \quad (3)$$

$$\sum_{p \in PF} (PRO_{p,f,t} \times ireq_{p,i}) = CON_{i,f,t} \quad \forall i, f, t \quad (4)$$

$$\sum_{p: pt=0} PRO_{p,f,tt} + \sum_t \sum_{p \in PF} ONG_{p,f,t,tt} \leq CAP_{f,tt} \quad \forall f, tt \quad (5)$$

$$ONG_{p,f,t,tt} = PRO_{p,f,t} \quad \forall (p,f) \in PF, t \leq tt < t + pt_{p,f} \quad (6)$$

As aforementioned, if needed, equation 7 allows the factories' production capacity to be increased in $CAPInc_{i,t-stime}$ units, where $stime_i$ stands for the necessary set up time for the capacity to become available. This increase is added to the capacity at the previous instant ($CAP_{i,t-1}$), with the exception for the first instant where the initial production capacity ($icap_f$) is considered (equation 8). However, this increase can be executed in different manners; either by activating redundant capacity present at the owned factories, or through outsourcing. The former option is represented by equation 9, here the increase allowed is proportional to the original capacity of the factory, having a minimum and maximum percentage ($pcemin_f$ and $pcemax_f$), while for the latter option, since these do not belong to the original SC, do not have an initial capacity, still, appropriate bounds are established by equation 10.

$$CAP_{f,t} = CAP_{f,t-1} + CAPInc_{f,t-stime_f} \quad \forall f, t > 1 \quad (7)$$

$$CAP_{f,t} = icap_f + CAPInc_{f,t-stime_f} \quad \forall f, t = 1 \quad (8)$$

$$pcemin \times icap_f \times XE_f \leq \sum_t CAPInc_{f,t} \leq pcemax \times icap_f \times XE_f \quad \forall f \in F_{own} \quad (9)$$

$$ocemin \times XE_f \leq \sum_t CAPInc_{f,t} \leq ocemax \times XE_f \quad \forall f \in F_{out} \quad (10)$$

4.8.2 Mass balance constraints

A most important aspect to consider is the assurance of flow continuity along the SC. Since both factories and retailers are allowed to hold inventory, the mass balances presented in this section (equation 11-16), equal the inventory at time t to the inventory at the previous time period, plus any inbound flows and minus any outbound flows.

Equation 11 models the flow of raw material i at the factories, where the inbound flows derive from a supplier ($FSF_{i,j,f,t-tts}$) or through the reverse flow of end-of-life products ($RMF_{p,m,f,t-ttd}$), both considering the required transportation time from the origin entity, tts and ttd , respectively. From the reverse flow the products that arrive are disassembled into its' components ($ireq_{p,i}$). Here it is considered that factories capable of dismantling a given product are equal to those that are capable of producing it. However, since not all end-of-life products are fit to be repurposed, $(1-dis)$ adjusts to the returned amount that is not disposed of. $CON_{i,f,t}$ accounts for the amount of raw materials that are consumed at instant t , and $SPO_{i,f,t}$ measures the spoiled amount. Equation 12 takes into consideration the initial

inventory ($invinfi_{i,t}$) for the first instant. Equation 14 and 16 serve the same purpose for their respective mass balance.

$$\begin{aligned}
INVfi_{i,f,t} &= INVfi_{i,f,t-1} - CON_{i,f,t} - SPOi_{i,f,t} + \sum_j FFS_{i,j,f,t-tts_{s,f}} \\
&+ (1 - dis) \times \sum_{p \in PF \wedge F_{own}} \sum_{m \in PM} (RMF_{p,m,f,t-ttd_{f,m}} \times ireq_{p,i}) \quad \forall i, f, t > 1
\end{aligned} \tag{11}$$

$$\begin{aligned}
INVfi_{i,f,t} &= invinfi_{i,f} - CON_{i,f,t} - SPOi_{i,f,t} + \sum_j FFS_{i,j,f,t-tts_{s,f}} \\
&+ (1 - dis) \times \sum_{p \in PF \wedge F_{own}} \sum_{m \in PM} (RMF_{p,m,f,t-ttd_{f,m}} \times ireq_{p,i}) \quad \forall i, f, t = 1
\end{aligned} \tag{12}$$

Equation 13 establishes the flow of final products at the factories. Here final products arrive once their production is complete ($PRO_{p,f,t-pt}$) and leave either to a retailer ($FFR_{p,f,r,t}$) or directly to the markets ($FFM_{p,f,m,t}$) in which they can be sold, or even due to spoilage ($SPO_{p,f,t}$).

$$INVfp_{p,f,t} = INVfp_{p,f,t-1} + PRO_{p,f,t-pt} - SPO_{p,f,t} - \sum_r FFR_{p,f,r,t} - \sum_{m \in PM} FFM_{p,f,m,t} \quad \forall (p, f) \in PF, t > 1 \tag{13}$$

$$INVfp_{p,f,t} = invinfp_{p,f} + PRO_{p,f,t-pt} - SPO_{p,f,t} - \sum_r FFR_{p,f,r,t} - \sum_{m \in PM} FFM_{p,f,m,t} \quad \forall (p, f) \in PF, t = 1 \tag{14}$$

Equation 15 concerns the mass balance at the retailers. Here products arrive from the previously mentioned flow from the factories, after their transportation time ($ttr_{f,r}$), or from the reverse flow in the form of non-conforming products returned from the market ($RMR_{p,m,r,t-ttm_{r,m}}$). There is only one outbound flow to the markets ($FRM_{p,r,m,t}$).

$$INVr_{p,r,t} = INVr_{p,r,t-1} + \sum_{f \in PF} FFR_{p,f,r,t-ttr_{f,r}} + \sum_{m \in PM} RMR_{p,m,r,t-ttm_{r,m}} - \sum_{m \in PM} FRM_{p,r,m,t} \quad \forall p, r, t > 1 \tag{15}$$

$$INVr_{p,r,t} = invinr_{p,r} + \sum_{f \in PF} FFR_{p,f,r,t-ttr_{f,r}} + \sum_{m \in PM} RMR_{p,m,r,t-ttm_{r,m}} - \sum_{m \in PM} FRM_{p,r,m,t} \quad \forall p, r, t = 1 \tag{16}$$

4.8.3 Reverse flow constraints

Regarding the reverse flows, these can occur for two kinds of products: non-conforming and end-of-life products. The first are regular returns from the market to the retailer due to minor defects, defined by equation 17, which can occur up to a fraction ($nconf$) of the total sales ($SA_{p,pp,m,t}$) and higher than a minimum collection percentage ($mincol$). These products are then repacked and reintegrated in the forward flow (as seen in equation 15). The second type takes into account the life span of the product itself (lt_p), after which they are returned to the factories ($RMF_{p,m,f,t}$). Similarly, as the previous case, these returns are bounded by the total sales of the product and a minimum percentage of collection through equation 18. The items are disassembled, and its individual parts integrate the factories source of raw materials to be repurposed in the production of new products (as seen in equation 11). Nonetheless, once at the factories, a fraction of products are considered as unsalvageable (dis) and are disposed of, which is considered in equation 19 that defines the amount sent to disposal ($RFD_{p,f,d,t}$).

$$mincol \times nconf \times \sum_{p \in ALT \wedge PM} SA_{p,pp,m,t} \leq \sum_r RMR_{pp,m,r,t} \leq nconf \times \sum_{p \in ALT \wedge PM} SA_{p,pp,m,t} \quad \forall (pp, m) \in PM, t \quad (17)$$

$$mincol \times \sum_{p \in ALT \wedge PM} SA_{p,pp,m,t-lt_p} \leq \sum_{f \in PF \wedge F_{own}} RMF_{pp,m,f,t} \leq \sum_{p \in ALT \wedge PM} SA_{p,pp,m,t-lt_p} \quad \forall (pp, m) \in PM, t \quad (18)$$

$$\sum_d RFD_{p,f,d,t} = dis \times \sum_{m \in PM} RMF_{p,m,f,t-ttd_{f,m}} \quad \forall (p, f) \in PF \wedge F_{own}, t \quad (19)$$

4.8.4 Flow constraints

These aforementioned flows between entities are constrained by the following equations 20-25 which establish a lower and upper bound for the permitted amount to be sent, in case the link is established which is controlled by a binary variable.

$$fmin \times Ys_{j,f,t} \leq \sum_i FSF_{i,j,f,t} \leq fmax \times Ys_{j,f,t} \quad \forall j, f, t \quad (20)$$

$$fmin \times Yr_{f,r,t} \leq \sum_{p \in PF} FFR_{p,f,r,t} \leq fmax \times Yr_{f,r,t} \quad \forall f, r, t \quad (21)$$

$$fmin \times Yd_{f,m,t} \leq \sum_{p \in PF \wedge PM} FFM_{p,f,m,t} \leq fmax \times Yd_{f,m,t} \quad \forall f, m, t \quad (22)$$

$$fmin \times Ym_{r,m,t} \leq \sum_{p \in PM} FRM_{p,r,m,t} \leq fmax \times Ym_{r,m,t} \quad \forall r, m, t \quad (23)$$

$$fmin \times Ync_{m,r,t} \leq \sum_{p \in PM} RMR_{p,m,r,t} \leq fmax \times Ync_{m,r,t} \quad \forall r, m, t \quad (24)$$

$$fmin \times Yel_{m,f,t} \leq \sum_{p \in PF \wedge PM} RMF_{p,m,f,t} \leq fmax \times Yel_{m,f,t} \quad \forall f, m, t \quad (25)$$

4.8.5 Inventory constraints

The next equations 26-30 define the minimum and maximum limits of the inventory level at the factories and retailers. Minimum values are established depending on the item ($invminfi_{i,t}$, $invminfp_{p,f}$, $invminr_{p,r}$) while the maximum values depend on the storage capacity of the entity ($invmaxf_i$, $invmaxr_r$). Equation 31 enforces the inventory kept at the retailers to present a reasonable level on average by imposing an inventory turnover ratio (turn) to be satisfied.

$$invminfi_{i,f} \leq INVfi_{i,f,t} \quad \forall i, f, t \quad (26)$$

$$invminfp_{p,f} \leq INVfp_{p,f,t} \quad \forall (p, f) \in PF, t \quad (27)$$

$$\sum_{p \in PF} INVfp_{p,f,t} + \sum_i INVfi_{i,f,t} \leq invmaxf_f \quad \forall f, t \quad (28)$$

$$invminr_{p,r} \leq INVR_{p,r,t} \quad \forall p, r, t \quad (29)$$

$$\sum_p INV_{p,r,t} \leq invmaxr_r \quad \forall r, t \quad (30)$$

$$\frac{\sum_p \sum_t INV_{p,r,t}}{tnum} \leq \frac{\sum_p \sum_{m \in PM} \sum_t FRM_{p,r,m,t}}{turn} \quad \forall r \quad (31)$$

4.8.6 Demand constraints

The following equations address demand satisfaction. Equation 32 allows the demand for product p ($dem_{p,m,t}$) to be met by the sale of that product or an alternative one pp ($SA_{p,pp,m,t}$) which are defined in set ALT. Equation 33 establishes these sales to occur from products arriving directly from the factories or from retailers ($FFM_{pp,f,m,t-ttd}$ and $FRM_{pp,r,m,t-ttm}$, respectively). Lastly, any demand not satisfied at the specified time period is considered as lost ($LS_{p,m,t}$) by equation 34. However, to ensure a target service level, the lost sales need to be lower than an acceptable amount of the total demand (ds) that needs to be satisfied (equation 35).

$$\sum_{pp:(pp,m) \in PM \wedge (p,pp) \in ALT} SA_{p,pp,m,t} \leq dem_{p,m,t} \quad \forall (p,m) \in PM, t \quad (32)$$

$$\sum_{p:(p,m) \in PM \wedge (p,pp) \in ALT} SA_{p,pp,m,t} = \sum_{f \in PF} FFM_{pp,f,m,t-ttd_{f,m}} + \sum_r FRM_{pp,r,m,t-ttm_{r,m}} \quad \forall (pp,m) \in PM, t \quad (33)$$

$$dem_{p,m,t} - \sum_{pp:(pp,m) \in PM \wedge (p,pp) \in ALT} SA_{p,pp,m,t} = LS_{p,m,t} \quad \forall (p,m) \in PM, t \quad (34)$$

$$\sum_p \sum_{m \in PM} \sum_t LS_{p,m,t} \leq ds \times \sum_p \sum_{m \in PM} \sum_t dem_{p,m,t} \quad (35)$$

4.8.7 Logical constraints

Lastly, some logical constraints are considered. Equation 36 defines that if production of product p is not assigned to factory f ($E_{p,f}$), then production at that factory cannot occur in any time period. The same logic is applied for the remaining equations 37-40, however in these cases it is related to whether a transportation link between two entities is established.

$$\sum_t W_{p,f,t} \leq tnum \times E_{p,f} \quad \forall (p,f) \in PF \quad (36)$$

$$\sum_t YS_{j,f,t} \leq tnum \times XS_{j,f} \quad \forall j, f \quad (37)$$

$$\sum_t Yd_{f,m,t} \leq tnum \times Xd_{f,m} \quad \forall f, m \quad (38)$$

$$\sum_t Yr_{f,r,t} \leq tnum \times Xr_{f,r} \quad \forall f, r \quad (39)$$

$$\sum_t Ym_{r,m,t} \leq tnum \times Xm_{r,m} \quad \forall r, m \quad (40)$$

4.9 Uncertainty modelling

With the goal to adapt the presented deterministic model to a stochastic model where demand and product return rates are uncertain, a scenario tree approach is adopted. The scenario tree is composed by nodes and arcs at each stage. The former represent scenarios of a possible state of the uncertain parameter, while each arc of the tree has a probability associated to the occurrence of the scenario it leads to. Therefore, the probability of each node is computed by the product of the probabilities of the arcs that constitute the path from the root node to said node. It is also guaranteed that the sum of the nodes' probabilities at each stage add up to one.

Since we are dealing with a tactical-operational model, considering each time period of the planning horizon as a stage would result in an excessive amount of scenarios. Additionally, given the relatively reduced time frame between decisions (weekly or daily basis), it would not be realistic for the parameters' values to present a noteworthy level of uncertainty with such frequency. To overcome these limitations, and to the best of the authors' knowledge, a novel approach is developed. In this case, a different time description is presented solely when new information becomes available, being that subsequent time periods where no alterations are expected are clustered within the same time description. This novel approach, allows the construction of a scenario tree with fewer ramifications and, consequently, with reduced number of scenarios to reflect more realistically when new information should be taken into consideration, thus being more adaptable for cases with different characteristics. Figure 11 illustrates a scenario tree following the described approach.

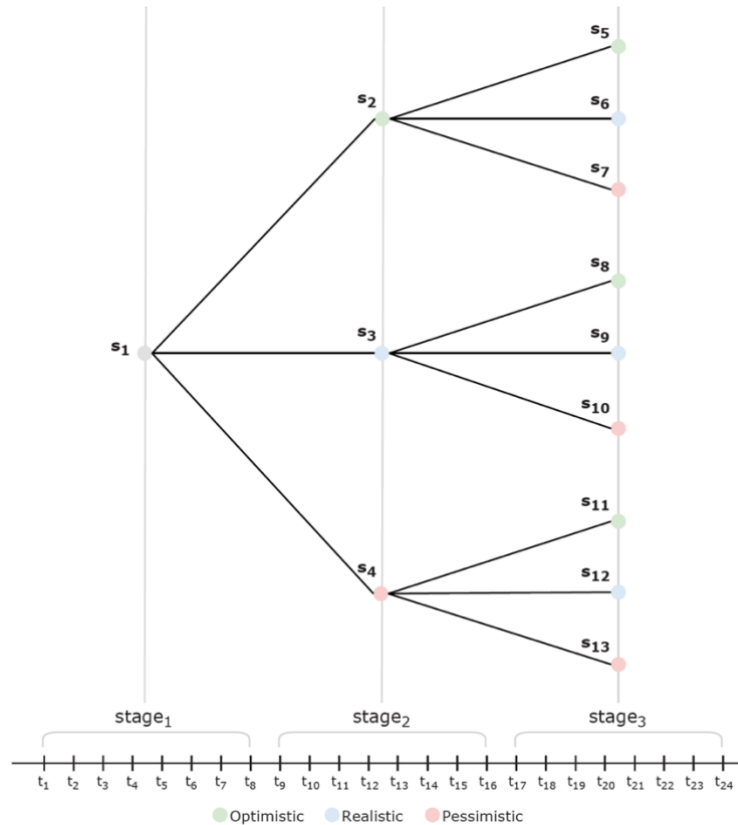


Figure 11: Scenario tree for uncertain parameters

To implement this approach it was necessary to add the sets presented in table 7 to the deterministic model, mainly to integrate the possible scenarios and suitable sets to associate said scenarios to the corresponding time periods.

Table 7: Additional sets for the stochastic model

Sets	Indices	Description
S	s, ss	Scenario nodes
ST	(s,t)	Time periods belonging to a scenario node
DT	dt	Number of time periods
preS	(ss,s,dt,t)	Predecessor ss of scenario s at a distance dt from period t
fwS	(ss,s,dt,t)	Successor ss of scenario s at distance dt from period t

The OFs were updated accounting with the probability of the scenarios (pb_s), resulting in equation 41 for the resilience metric, equation 42 for the profit, and equation 43 for the flow time.

$$Max Z_1 = \frac{profit}{profitREF} - \frac{\sum_p \sum_{m \in PM} \sum_{t \in ST} \sum_s pb_s \times LS_{p,m,s,t}}{\sum_p \sum_{m \in PM} \sum_{t \in ST} \sum_s pb_s \times demand_{p,m,s,t}} \quad (41)$$

$$profit = \sum_s pb_s \times (sales_s - (TMC_s + TTC_s + TIC_s + TDC_s)) - \sum_{p \in PF} \sum_f fpc_{p,f} \times E_{p,f} + \sum_f fcec_f \times XE_f \\ + \sum_f \sum_t vcec_f \times CAPInc_{f,t} + \sum_j \sum_f ftcs_{j,f} \times Xs_{j,f} + \sum_f \sum_r ftr_{f,r} \times Xr_{f,r} \\ + \sum_f \sum_m ftcd_{f,m} \times Xd_{f,m} + \sum_r \sum_m ftr_{r,m} \times Xm_{r,m} \quad (42)$$

$$Min Z_2 = \sum_s pb_s \times \left(\sum_i \sum_j \sum_f \sum_{t \in ST} (tts_{j,f} \times liunit_i \times FSF_{i,j,f,s,t}) \right. \\ + \sum_{p \in PF} \sum_f \sum_{t \in ST} pt_{p,f} \times PRO_{p,f,s,t} + \sum_{p \in PF} \sum_f \sum_r \sum_{t \in ST} (ttr_{f,r} \times lunit_p \times FFR_{p,f,r,s,t}) \\ + \sum_{p \in PF} \sum_f \sum_{m \in PM} \sum_{t \in ST} (ttd_{f,m} \times lunit_p \times FFM_{p,f,m,s,t}) \\ \left. + \sum_p \sum_r \sum_{m \in PM} \sum_{t \in ST} (ttm_{r,m} \times lunit_p \times FRM_{p,r,m,s,t}) \right) \quad (43)$$

Another aspect important to highlight is the modelling of the node's precedence under an approach to time periods in the scenario tree. Due to the clustering of time periods into stages, when recalling previous instant variables' values, these may or may not belong to a different stage and, consequently, to a different scenario. For example, by observing the blue arrows in figure 12, at t_{11} observing the previous instant would still belong to the same scenario in stage 2, but at t_9 the predecessor would belong to stage 1. On the other hand, this is also influenced by the temporal distance from the present node. Observing now the red arrows from figure 12, which require values three time periods away, for this case, t_{11} would already call a predecessor belonging to stage 1. Hence, the set that links scenarios to their predecessors needs to take into account the current time period as well as the temporal distance to the predecessor.

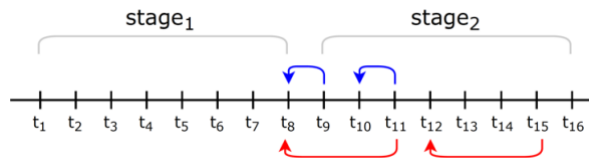


Figure 12: Scenario node precedence illustration
Blue for distance=1t; Red for distance=3t

Lastly, the set fwS was created to deal with a single variable present in the model, specifically, variable $ONG_{p,f,t,tt}$, which requires two indexes of time periods to measure any ongoing production at time tt having started at time t . Consequently, this variable in the stochastic model also requires two scenario indexes to link to each time index ($ONG_{p,f,s,ss,t,tt}$). Hence, set fwS has the function of providing the succeeding scenario ss that should be linked to time tt for non-null production times.

The remaining constraints of the model were all updated to integrate the scenario index in the necessary variables, resorting to the appropriate sets presented to link the time periods with the correct scenario. The full formulation of this approach is present in annex A.

4.10 Disruption modelling

Regarding the disruption modelling here it is certain that a disruption will take place, however, the means by which it occurs will be considered as uncertain. For a disruption type, possible scenarios are constructed which can disturb the SC activity at hand as illustrated by figure 13. These scenarios are then associated to a probability which reflects the likelihood of its incidence compared to those within the same disruption type. Under resilience setting here the probabilities do not intend to reflect the likelihood of occurrence of a particular event, under the unpredictability, that separates risk management with scenario case. For example, for a production type disruption, if a factory is located in a region prone to natural disasters, the probability of the scenario where this facility becomes inoperable will be higher than for the other facilities that operate in more stable conditions. Hence, within each disruption type, the sum of the probabilities of the possible scenarios is equal to 1.

To implement this approach in the model an additional index was added to the variables (ds) to register the disruptive scenario at hand.

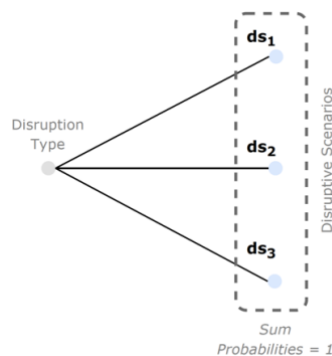


Figure 13: Generic event tree for disruptive scenarios modelling

4.11 Solution approach

Given the OFs presented previously, a suitable multi-objective optimization method is deemed necessary to appropriately solve the model. For this end, the augmented ε -constraint method with lexicographic optimization (AUGMECON2) developed by Mavrotas & Florios, (2013) will be used. This method is an improvement from a former algorithm proposed by the same author (Mavrotas, 2009), improving the efficiency particularly for mixed integer problems, and for problems with more than two OFs, as is the present case. The algorithm can be briefly summarized in the following steps:

- **Step 1: Construct payoff table**

Every OF is lexicographically optimized to construct the payoff table with only efficient solutions. Such is performed sequentially according to the preference established among the objectives. For each row, after the optimization of the OF at hand, its' value will be set as a constraint and the remaining functions will be optimized sequentially in the established priority. This approach enhances the conventional ε -constraint method by guaranteeing the pareto optimality of the obtained solutions.

- **Step 2: Generate grid**

From the payoff table, the functions' lower and upper bound are obtained, which allows to calculate their range. This range is then divided into q_k equally distanced points, measured by $step_k$, resulting in q_k+1 grid points, represented by e_{kt} .

- **Step 3: ε -constraint resolution**

Finally, the problem is solved considering the equations presented below. The values of e_k are those obtained in step 2, drawn from the grid point of the respective function, S_k represents a slack variable, and $eps \in [10^{-6}, 10^{-3}]$. As it can be observed, this OF also performs a kind of lexicographic optimization where the optimal solution will be found valuing the numeric order of the OFs.

$$\max (Z_1(x) + eps \times (\frac{S_2}{r_2} + 10^{-1} \times \frac{S_3}{r_3} + \dots + 10^{-(p-2)} \times \frac{S_p}{r_p}))$$

subject to:

$$Z_2(x) - S_2 = e_2$$

$$Z_3(x) - S_3 = e_3$$

$$x \in S \text{ and } S_i \in \mathbb{R}^+$$

The algorithm also takes advantage of a bypass value in order to produce the exact Pareto front in a reasonable computation time. When the slack value is higher than the step unit, it is implied that the next iteration will return the same solution, hence it is possible to jump redundant iterations.

$$b = \text{int}(\frac{S_2}{step_2})$$

5 Case study, results and discussion

This chapter will apply the model presented in the previous chapter to a case-study in order to study SCR for decision taken at the tactical and operational level. The case study is presented in terms of its' characteristics as well as any additional assumptions that were made. The desired analyses to be performed are explained in section 5.2. The final results are then presented, thoroughly analysed and discussed.

5.1 Case overview

The case study here presented consists of a CLSC, with a configuration as illustrated in figure 14, that produces 3 different products (p_1 - p_3) to serve 6 markets dispersed in the European region. In this SC there are 3 suppliers, 4 factories (f_1 - f_4), and 2 retailers.

As mentioned, the production capacity expansion can be achieved by increasing the capacity of the owned factories or by resorting to outsourcing. For the former strategy it is assumed that the factories possess idle redundant capacity that can be activated when necessary. In this case, it is considered that these factories can increase up to 25% of their current capacity. For the outsourcing factories four options were designed to understand the trade-off between offshore and nearshoring decisions. These options are summarized in table 8, noting that the production costs are presented relative to the difference of the average values verified at owned factories. It is assumed that the products at outsourcing factories have no production time, simulating the condition that the product is already in stock and ready to be purchased.



Figure 14: SC representation

Table 8: Outsourcing options design

Factory	Location	Time to markets	Production Cost
f ₅	Offshore	Further away than f ₆	x 2,00
f ₆	Offshore	Slower to markets	x 2,30
f ₇	Nearshore	Faster to all markets	x 4,30
f ₈	Nearshore	Faster to most markets	x 4,00

The outsourcing facilities are considered to be capable of producing any product, which deviates from the owned factories, which may only be qualified to manufacture some products. Table 9 presents this relation, along with the initial capacity of each facility.

Table 9: Owned factories characteristics

Factory	Products	Initial Capacity (units)
f ₁	all	700
f ₂	p ₁ , p ₁₁ , p ₁₂ , p ₁₃	300
f ₃	p ₂ , p ₁₃	150
f ₄	p ₃ , p ₁₃	150

The products stated in table 9 beyond p₁-p₃ represent the alternative products for product p₁. The study of the benefits of alternative products is conducted by allowing p₁, the product with the highest demand, to have three additional options to satisfy its demand. These items are supposed to be sold at a lower price, forfeiting 5% of the profit margin, but offering appealing features which ease their production process to compensate the loss they provide in revenue as follows:

- **Option 1:** Lower production time;
- **Option 2:** Fewer raw material requirements;
- **Option 3:** Possible to produce at more factories.

This SC experiences weekly demands in the horizon of 24 time periods, which are considered constant for the deterministic model (figure 15). However, these values will be taken as uncertain for the stochastic model. All initial inventories and ongoing production are set to zero, therefore, to integrate a warm-up period, the demand is to be initiated only at t₈.

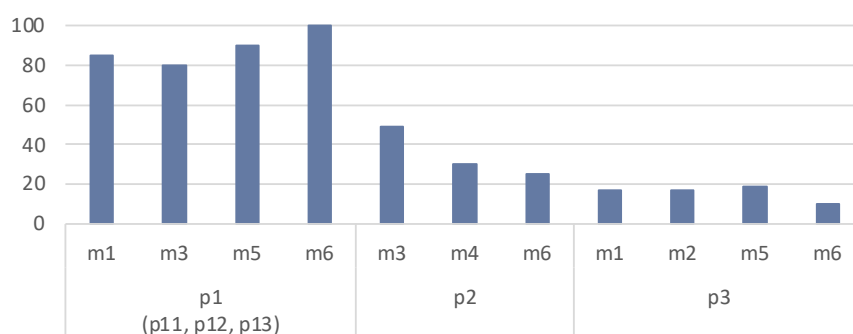


Figure 15: Deterministic demand volume

Regarding the reverse flows, it is set that 20% of the products sold are non-conforming, and that 20% of the end-of-life products are too damaged to be repurposed after their 10 week life-span. Both types of reverse flow need to meet a minimum of 10% of product collection. The uncertainty of these values will also be considered in the stochastic model.

5.2 Discussion outline

The remaining sections of this chapter will now focus on analysing the results obtained by applying the model presented in the previous chapter to the present case study. The analyses are divided for the deterministic model and, subsequently, compared with the stochastic model, where demand and product return rates will be considered as uncertain parameters. Adopting a multistage approach, it will be studied different prioritization of the OFs prior to the occurrence of a disruption and how this preference influences the corrective measures taken to sustain operations for both models. Consequently, it will demonstrate which indicator leaves the SC more resilient to the disruptions that will be tested. Three types of point of the pareto front will be used for this end as representative of the value attributed to the OFs, being characterised as follows:

- **Point A:** The point that values most the resilience metric.
- **Point B:** The point that values most the flow time.
- **Point C:** An in-between solution, representing a configuration which balances more equally the three OFs.
- **Point D:** The point that values most the profit.

Nonetheless, the response to a crisis can take different forms, being possible to alternate the DM's priority in regards to which is the most relevant indicator to optimise promptly. An analysis of response strategies will be conducted to clarify the effects of exchanging the OFs' preference when faced with a disruption.

5.3 Deterministic model results

The following sub-sections present the results of the deterministic model for the previously outlined analyses. These results are obtained using GAMS software running the CPLEX solver with a gap of 0%. The number of grid-points for the multi-objective resolution was set to 5.

5.3.1 Reference case analysis

Foremost, the model is run for normal operating conditions where no disruption takes place as well as no uncertainty is included. Being this a multi-objective problem, a priority of the OFs needs to be accounted for, which ultimately should reflect the interest of the DM.

Here two possible priorities are tested to understand the impact of the optimizations' sequencing on the subsequent results:

- **Priority 1:** Resilience Metric; Flow time; Profit.
- **Priority 2:** Resilience Metric; Profit; Flow time.

Table 10 presents the payoff table obtained by setting priority 1 and executing step 1 of the solution approach explained in section 4.11. The objective of this table is to know the optimal value that each

OF is capable of achieving. For that end three cases are run where each OF takes place at being the firstly optimized function and establishing their value as a constraint for the optimization of the remaining OFs, sequentially. Each of these cases correspond to a row of the table. Here it is also important to highlight that the optimization order loops.

However, solely running priority 1 lacks the possibility of the profit being optimized following the resilience metric or of the latter being optimized following the flow time, given that the priority fixes the successor of a given OF. To view if such condition significantly influences the results, the sequence was rearranged to priority 2, obtaining the payoff table present in table 11.

It can be concluded that when the profit is maximised firstly, the order of the other two OFs has no influence. For the remaining cases slight differences can be observed, however not very substantial.

Table 10: Payoff table of the deterministic model for priority 1

	Res Metric (RM)	Flow Time (FT)	Profit (PF)
max RM→FT→PF	1,000	50 733,88	396 305,37
min FT→PF→RM	0,146	7 986,60	97 665,91
max PF→RM→FT	1,000	51 124,26	396 403,47

Table 11: Payoff table of the deterministic model for priority 2

	Res Metric (RM)	Profit (PF)	Flow Time (FT)
max RM→PF→FT	1,000	396 364,04	51 119,00
max PF→FT→RM	1,000	396 403,47	51 124,26
min FT→RM→PF	0,146	97 654,45	7 986,60

Adopting priority 1 results in the solution set plotted in figure 16. To ease its interpretation a two-dimensional representation is given in figure 17 where the extreme points of the front are signalled as well as an in-between point. Point A represents the solution that delivers the maximum resilience metric and profit value, contrasting to point B for the lowest flow time possible, and C as a trade-off point between the extremes. Point D is not represented since it closely coincides with point A, and will be excluded from the succeeding analyses due to its similar behaviour to point A the conclusions would be redundant. Observing figure 17, the solutions are spaced by intervals of approximate sizes of flow time increases, improving the resilience metric by varying degrees. Point C provides the best resilience metric improvement for similar a degradation of the flow time function compared to the other solutions. This point is also of interest to analyse since it maintains a low flow time value but fully meets customers' demand, as well as balances outsourcing needs between nearshore and offshore solutions.

From the payoff table (table 10) it can be concluded that maximising initially the resilience metric or the profit will result in approximate solutions. However, comparing this solution to the one that favours firstly the flow time, the differences are significant, as it is visible in figure 17.

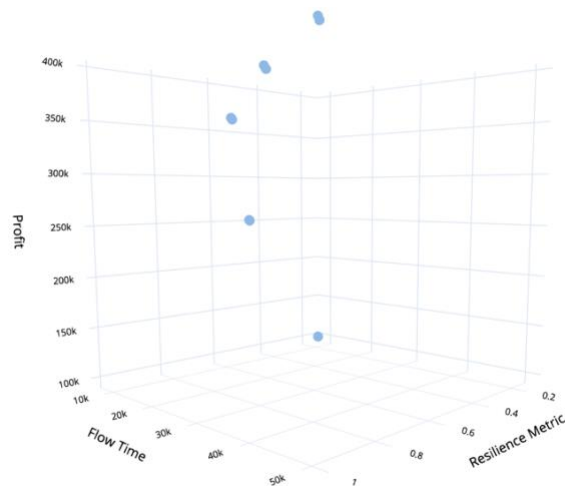


Figure 16: Three-dimensional representation of the deterministic model multi-objective solution

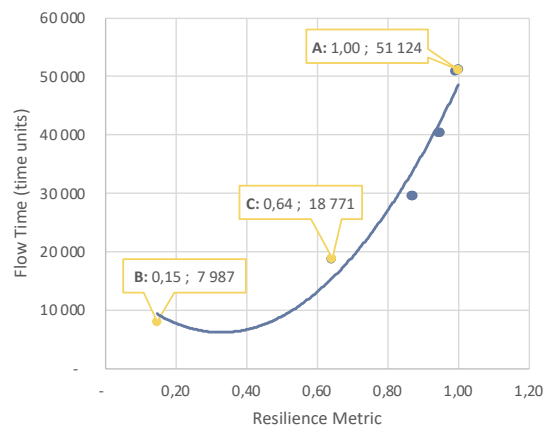


Figure 17: Two-dimensional representation of the deterministic model multi-objective solution

Table 12 presents the values of performance indicators of the selected solutions to further comprehend their difference. Multiple conditions aggravate the disparity between point A and point B. Firstly, the flow time OF does not include any concern regarding the service level, limiting the solution to fulfil the minimum acceptable amount of demand that is pre-established, in this case, of 90%. This accounts directly for 0,10 difference in the resilience metric, being the remaining $\approx 0,75$ decrease due to the deviation of the profit from its reference value. The amount of lost sales directly impacts the revenues obtained throughout the planning horizon, but does not singly justify the profit decrease. The selection of outsourcing options weight significantly in clarifying this difference.

Regarding the production capacity expansion, point B demonstrates an elevated increase of both nearshoring alternatives (f_7 and f_8). This selection benefits the flow time indicator two-fold, given that outsourcing facilities do not impose any production time, as well as the proximity to the final markets delivers reduced transportation times. Nonetheless, these are the most costly options available, translating in the elevated manufacturing costs by comparison to point A that does not recur to outsourcing. Point C also significantly resorts to outsourcing, taking advantage of both offshore and nearshore options (f_6 and f_8) but valuing more the former, thus exhibiting lower manufacturing costs than point B, however, producing more elevated duties cost.

Table 12: Deterministic model performance indicators of selected solutions

Point	SL	Revenue	Costs					Outsourcing capacity expansion (units)			
			TMC	TTC	TDC	TIC	TEC	f ₅	f ₆	f ₇	f ₈
A	1,00	632 683	175 121	54 260	4 323	326	2 250	-	-	-	-
B	0,90	561 713	428 093	10 466	7 034	335	18 118	-	-	54	239
C	1,00	628 612	324 923	21 116	13 194	263	14 473	-	204	-	119

SL: Service Level; TMC: Manufacturing Cost; TTC: Transportation Cost; TDC: Duties Cost; TIC: Inventory Cost; TEC: Capacity Expansion Cost

Overall, the distinction of the three SC configurations that the points represent is mostly driven from production related decisions. Point A concentrates production internally, even increasing the capacity of f_2 by 75 units while point B only operates with outsourcing production facilities leaving the owned factories idle. Point C only scarcely selects f_1 for production, receiving most products from outsourcing options.

Some general recommendations can be provided depending on a final DM's preference. Foremost, it is important to have a clear understanding of financing targets that may be required to achieve. Point B stands out in this regard by exhibiting a far lower profit value as compared to the other solutions. Such low income may not be appealing to achieve even if the flow time is a high priority. To overcome such concern, it would be recommended to study the implementation of an additional restriction that would guarantee the delivery of a profit level more in line with the DM's goals. Such can be performed by understanding the maximum profit achievable (profitREF) to aid the assessment of the DM's willingness in forfeiting profit in order to prioritize the flow time firstly.

Similarly, point A may lead the SC to operate under a total flow time which could not be of interest. The elevated time consumed from supply to delivery to the final consumer may hinder the business to react swiftly to demand spikes or other sudden events. Once again, this concern would depend on the DM and whether such concern presents a significant weight.

Lastly, point C delivers a solution that mitigates these former two concerns. As showcased by the value of the resilience metric, this configuration would not completely disregard economic returns as point B, and would guarantee a higher customer satisfaction. Such is achieved at a cost of a reasonable increase of the flow time. Nevertheless, such as point B, these solutions present a high reliance on third parties for production necessities. The loss of control provoked by the selection of outsourcing should be taken into consideration, developing an assessment on the resilience of said entities which directly impacts the performance of the SC that heavily depends on their operations.

5.3.2 Disruptions analysis

As mentioned, to analyse the impact of disruptive events on SC' configuration from different OFs, a two stage approach is followed where the three previously analysed points will be used as first stage decisions. For the second stage optimization the OFs take the same preference order as the one to

obtain the point at hand, that is, for point A and C maximizing firstly the resilience metric while for point B minimizing firstly the flow time.

The disruptions to be modelled are separated into three types according to the SC activity they affect, and are run independently. Each disruption type include different disruptive scenarios as explained in section 4.10. The three types here considered are adapted from Rice & Caniato, (2003) as follows:

- **Supply:** For a supply type disruption the scenarios cover each supply node present in the SC. That is, three scenarios will be considered taking each of the three suppliers of this case study to become incapable of providing raw materials. The probabilities of these scenarios are of 30%, 40% and 30% to disturb j_1 , j_2 and j_3 , respectively. To deal with this type of disruption the literature most commonly refers to the establishment of multiple sources of supply or local sources, modification to inventory levels, and even the standardization of parts among products. Having this in mind, the present model does not restrict the solution to a single source of supply and provides the option to produce alternative products with lower raw material requirements.
- **Production:** The production disruption will prohibit factories to initiate any new production. Similarly to the supply disruption, unless stated otherwise, this type will consider four scenarios to cover the four production entities of this case study with equal probabilities of occurrence. To attune the effects of this kind of event it is advised the use of multiple sites each capable of producing multiple products, modification to inventory levels and/or shift to a standardized production process, as well as the establishment of backup facilities. For this end, the model designed alternative products with lower production times, and the possibility to be produced at a wider range of facilities. Also, the modelling of capacity expansion strategies will allow to recur to backup capacities.
- **Transportation:** Disruptions occurring at transportation links, due to the diverse possibilities, only the four most important connections between factories and markets will be considered, with equal probabilities. However, the links to be disrupted also vary according to the analysis being performed. Given the distinctive behaviour of the solutions to be studied, the transportation links considered as the most critical depend on such decisions. Therefore, for each selected pareto point, the four links directed to the final markets with the highest flow at t_{10} and t_{11} are selected to become unavailable. It is expected that the complexity of the SC structure here modelled to enhance rerouting strategies.

For a more in depth discussion of the strategies mentioned above see section 2.3.

Additional uncertainty will be explored regarding the length of the disruption as well as the time necessary to sense a disruption took place. Firstly, the previously described disruptions will be modelled to take place at t_{10} for the duration of two and four weeks. This allows to understand the impact of each disruption type on the SC and the necessary corrective measures taken, and if such conclusions remain unaltered for longer disruptions by comparing both cases with varying lengths of the event. However, as past experiences have shown, identifying disturbances in the SC may not occur immediately, which

is represented by the red lines in figure 18. It will be considered a case in which a four week long disruption takes place, but only after two weeks such event is recognized and dealt with.

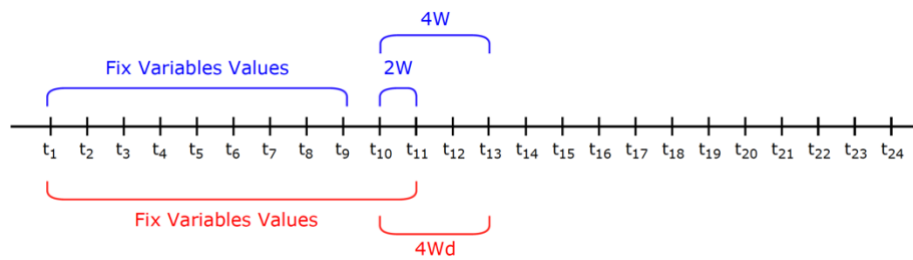


Figure 18: Disruption modelling. Blue: Immediate Response; Red: Delayed Response

In order to prevent the model to anticipate the occurrence of the disruptive event, and thus more realistically react to it, a 2-stage approach is adopted. Foremost, the variables' value obtained by the selected point in analysis are fixed for all instants previous to the disruption, as illustrated in figure 18. The model is then run for each disruption type presented above, individually, and corrective actions are taken.

Point A

Table 13 presents the results obtained taking point A as the decisions taken prior to any disruption, separated by the varying disruptions' length. As to be expected, the scenarios with a four weeks long disruption with delayed sensing present the most damaging results to the resilience metric and profit. The source of lower profits can be traced, with a significant impact, to the selection of outsourcing in order to sustain operations continuity, but also to other cost increases resulted from spoilages and decreases of revenue.

Figure 19 exhibits the capacity expansions experienced in the cases here considered. Indeed, the delayed sensing cases present the most elevated need for production capacity expansions, as well as the only situation where a nearshoring option is resorted to, in particular for production and transportation type disruptions. Such demonstrates the necessity of rapid solutions for when a disruption has already been ongoing.

Furthermore, figure 19 allows to visualise which capacity expansion strategy is more appropriate to tackle each case studied. It is visible that the transportation disruptions do not resort to offshore facilities. Such can be justified given that the links disrupted connect to the final markets. Therefore, opting for solutions more distant than the current operation may not be appealing if the delivery of products were to take longer than the disruptions' length. However, if the loss in revenue becomes too significant, and to further avoid service level declines, nearshoring solutions become necessary, as mentioned.

Table 13: Deterministic model results considering disruptive events, fixing decisions of point A

Case	Res Metric	Flow Time	Profit	SL	Revenue	TMC	TTC	TDC	TIC	TEC
Ref	1,000	51 124	396 403	1,000	632 683	175 121	54 260	4 323	326	2 250
<i>2 Weeks Disruption</i>										
Supply	0,993	50 052	393 485	1,000	630 791	175 928	53 588	4 351	370	3 068
Prod	0,986	50 236	390 670	1,000	630 807	177 993	54 280	4 236	379	3 249
Transp	0,994	50 329	394 617	0,999	630 129	174 765	54 069	4 045	383	2 250
<i>4 Weeks Disruption</i>										
Supply	0,988	49 710	391 678	1,000	631 414	177 379	53 353	4 717	404	3 883
Prod	0,981	49 798	389 044	1,000	631 407	179 639	53 599	4 709	473	3 942
Transp	0,994	50 392	394 533	0,999	630 060	174 724	54 114	4 055	384	2 250
<i>4 Weeks Disruption with Delay</i>										
Supply	0,983	49 438	389 643	1,000	631 609	178 876	52 714	4 893	336	5 148
Prod	0,951	48 301	377 706	0,998	627 541	185 546	53 108	4 765	409	6 008
Transp	0,973	50 065	389 571	0,990	625 687	174 516	53 498	4 200	596	3 305

SL: Service Level; TMC: Manufacturing Cost; TTC: Transportation Cost; TDC: Duties Cost; TIC: Inventory Cost; TEC: Capacity Expansion Cost

The other two types of disruptions recur to outsourcing for all the cases run. The supply disruptions favour most the expansion of f_5 , and also of f_6 for the delayed response case, being the only disruption type to disregard the need for nearshoring. The difference between the two offshore facilities lies on their cost and distance to the markets. Facility f_5 represents the lower cost solution at the expense of increased distance to the markets when compared to f_6 . This concludes that opposed to the transportation disruption, the supply disturbance can take the liberty to reach for solutions with longer implementation time without compromising service level. On the other hand, the production disruption favours more f_6 , which demonstrates the need for faster solutions.

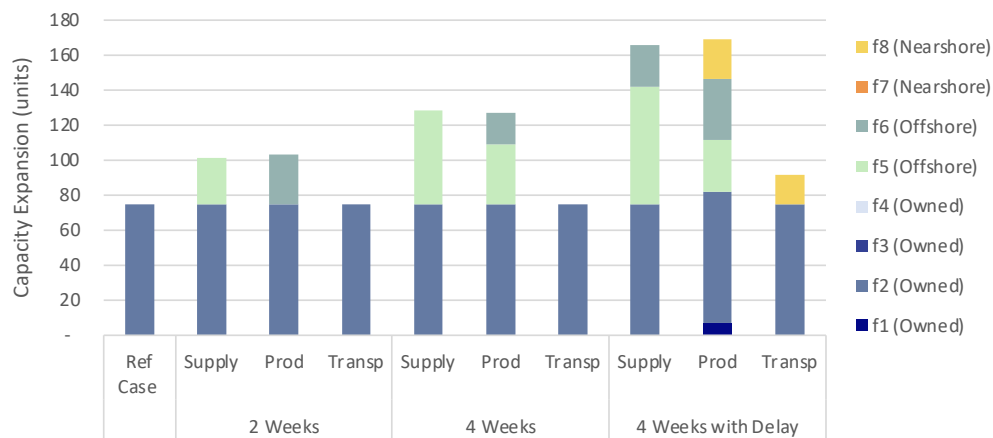


Figure 19: Capacity expansions of the deterministic model under disruptions, fixing point A

Regarding the type of disruption, it can be viewed that for all scenarios a production related disruption causes the highest impact to the resilience metric. This type of disruption is also the only one to incur in additional costs due to raw material spoilage as presented in table 14. Such is due to the fact that shipments of raw material are already in course at the time of the disruption expecting to be immediately used for production. Once they arrive at a production facility that is incapable to initiate production, all materials that exceed the storage capacity of the factory are considered as spoiled and disposed of. For a two and four weeks long disruption a total of 345,25 units of raw materials are spoiled, increasing to 991 units for the case with a delay in sensing the disruption. This allows to conclude that the length of the disruption should not influence the amount of spoilage only if the disruption is immediately acknowledged.

Table 14: Amount of product sold and spoilages occurred for the deterministic model under disruptions, fixing point A

Case	Products Sold (units)						Spoilage (units)	
	p ₁	p ₂	p ₃	p ₁₁	p ₁₂	p ₁₃	SPO _i	SPO _p
Ref	5 778,13	1 768,00	1 071,00	256,87	-	-	-	-
<i>2 Weeks Disruption</i>								
Supply	5 525,76	1 768,00	1 071,00	509,24	-	-	-	-
Prod	5 531,70	1 768,00	1 070,70	503,30	-	-	345,25	-
Transp	5 530,79	1 764,15	1 071,00	497,21	-	-	-	-
<i>4 Weeks Disruption</i>								
Supply	5 608,88	1 768,00	1 071,00	426,12	-	-	-	-
Prod	5 616,07	1 768,00	1 070,34	418,93	-	-	345,25	-
Transp	5 529,04	1 763,38	1 071,00	498,96	-	-	-	-
<i>4 Weeks Disruption with Delay</i>								
Supply	5 634,86	1 768,00	1 071,00	400,14	-	-	-	-
Prod	5 239,28	1 754,32	1 070,27	795,03	-	-	991,00	-
Transp	5 542,96	1 763,38	1 070,10	411,79	-	-	-	-

p₁₁: Alternative product 1 (lower production time); p₁₂: Alternative product 2 (fewer raw material requirements); p₁₃: alternative product 3 (possible to produce at more factories); SPO_i: Spoilage of raw materials; SPO_p: spoilage of final products

The disruptions tested, in general, also provoked a decrease in revenues even in cases with full met demand. This is justified by the decision to increase the delivery of alternative products with a lower production time across all disruptions, which is also presented in table 14. On the other hand, figure 20 plots the sales over time for the cases where demand was not fully met. The vertical red line was added to signal the instant the disruptions originate. Recalling that to incorporate a warm-up period, demand surges only at t_8 , thus the lack of sales prior to that instant.

From the studied cases, all transportation disruptions incurred in a slight drop in sales. The production disruption with a delayed response also verified a minor decline in sales volume, meeting the demand in its entirety for the remaining instances (figure 20). Within the transportation disruptions it is visible that not only does the four weeks disruption with delay present the highest sales decline, its'

return to regular sales values takes longer than for the case of a disruption with the same duration but that is immediately sensed. This latter case can recover after two weeks and stabilize sales even though the disruption remains ongoing. Furthermore, the lost sales of this kind of disruptions are immediately sensed by the end consumer, whereas for a production type such is experienced further along.

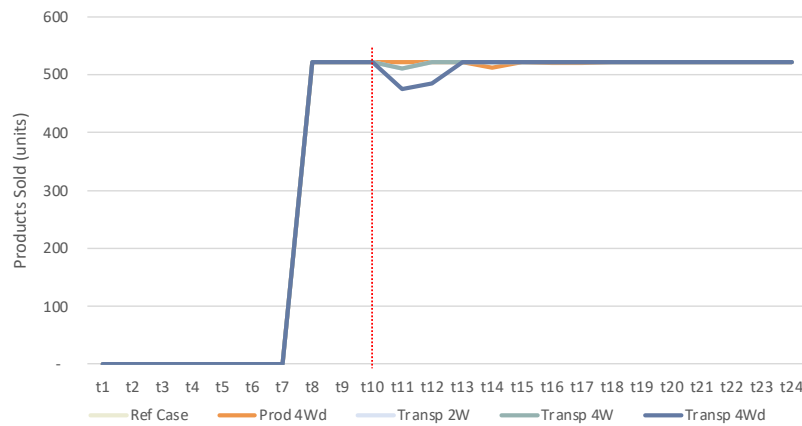


Figure 20: Sales level over time of the deterministic model under disruptions fixing point A

Point B

For the case in which the first stage decisions are fixed to achieve point B, the overall results are presented in table 15. The minimum flow time value from the reference case remains unchanged for all the tested cases. Likewise, the service level also steadies at 90% since it is the minimum percentage of the total demand that needs to be satisfied, however at a cost of the profit level that is achieved. Hence, the decrease of the resilience metric stems only from the profit's further deviation from the reference value.

For this configuration, the supply related disruptions have no influence in the solutions since all products are sourced from external entities, as explained previously, whose raw material supply was assumed to be near unlimited as to mimic the condition of purchasing final products.

Regarding the production and transportation disruption, it was considered pertinent to model them taking into account the outsourcing entities. Therefore, the production disruption was considered to take place at factory f_7 and f_8 , and the transportation type disrupted links f_8-m_5 ; f_8-m_1 ; f_8-m_3 ; f_7-m_4 . The scenarios within both type of disruptions were considered to be equally probable.

Similarly to point A, the production disruptions incurred in higher costs than the transportation disruptions. Figure 21 demonstrates the capacity expansions experienced, noting that f_7 is mostly increased to deal with the production disruptions, further increasing with the length of the disturbance and with the delayed sensing case. Overall, the production decisions across cases shifts only between the two factories that were already in use (f_7 and f_8), thus continuing to deliver a reduced resilience metric value.

Table 15: Deterministic model results considering disruptive events, fixing decisions of point B

Case	Res Metric	Flow Time	Profit	SL	Revenue	TMC	TTC	TDC	TIC	TEC
Ref	0,146	7 987	97 666	0,90	561 713	428 093	10 466	7 034	335	18 118
<i>2 Weeks Disruption</i>										
Supply	0,146	7 987	97 666	0,90	561 706	428 087	10 466	7 034	335	18 118
Prod	0,132	7 987	91 834	0,90	561 846	432 616	10 328	6 917	387	19 765
Transp	0,142	7 987	95 899	0,90	562 529	430 305	10 430	6 975	348	18 572
<i>4 Weeks Disruption</i>										
Supply	0,146	7 987	97 666	0,90	561 706	428 087	10 466	7 034	335	18 118
Prod	0,114	7 987	84 825	0,90	561 707	434 414	10 332	6 620	381	25 135
Transp	0,136	7 987	93 520	0,90	561 757	431 152	10 394	6 898	359	19 436
<i>4 Weeks Disruption with Delay</i>										
Supply	0,146	7 987	97 666	0,90	561 706	428 087	10 466	7 034	335	18 118
Prod	0,098	7 987	78 467	0,90	564 668	439 802	10 277	6 615	405	29 101
Transp	0,134	7 987	92 917	0,90	561 872	432 300	10 354	6 983	378	18 940

SL: Service Level; TMC: Manufacturing Cost; TTC: Transportation Cost; TDC: Duties Cost; TIC: Inventory Cost; TEC: Capacity Expansion Cost

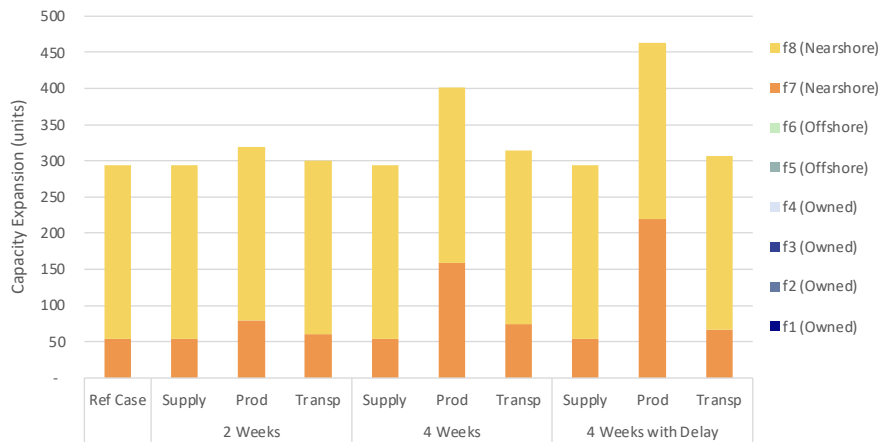


Figure 21: Capacity expansions of the deterministic model under disruptions, fixing point B

Point C

Taking now the trade-off point as the first stage decision, the results of table 16 are obtained. Due to the higher computational effort these results were, exceptionally, attained running with a 1% gap.

As with the previously analysed point B, it is worth mentioning that for this case the production and transportation disruptions were applied including outsourcing entities. As it is visible in figure 22, which presents the amount produced by each factory, the reference case concentrated its production in f_6 followed by f_8 and f_1 . Hence, the production disruption scenarios were modelled for these entities with a probability of 30%, 40%, and 30%, respectively. The disrupted transportation links were f_6 - m_5 , f_8 - m_5 , f_8 - m_1 , and f_8 - m_3 , with equally distributed probabilities.

Table 16: Deterministic model results considering disruptive events, fixing decisions of point C

Case	Res Metric	Flow Time	Profit	SL	Revenue	TMC	TTC	TDC	TIC	TEC
Ref	0,642	18 771	254 643	1,000	628 612	324 923	21 116	13 194	263	14 473
<i>2 Weeks Disruption</i>										
Supply	0,776	29 368	307 547	1,000	630 984	264 294	32 393	10 868	287	15 595
Prod	0,763	31 374	306 923	0,989	624 961	258 290	34 585	9 829	242	15 092
Transp	0,778	31 837	311 407	0,993	627 620	256 556	34 985	9 930	268	14 473
<i>4 Weeks Disruption</i>										
Supply	0,777	30 342	307 939	1,000	631 690	263 486	33 485	10 933	252	15 595
Prod	0,753	30 531	303 174	0,988	624 320	260 515	33 680	10 299	243	16 409
Transp	0,778	31 796	311 476	0,993	627 409	256 402	34 894	9 903	262	14 473
<i>4 Weeks Disruption with Delay</i>										
Supply	0,742	27 214	294 224	1,000	631 672	277 431	30 011	11 862	249	17 895
Prod	0,698	27 376	283 434	0,983	620 418	274 918	30 322	10 890	235	20 619
Transp	0,735	28 587	295 188	0,990	625 289	271 365	31 472	10 949	223	16 092

SL: Service Level; TMC: Manufacturing Cost; TTC: Transportation Cost; TDC: Duties Cost; TIC: Inventory Cost; TEC: Capacity Expansion Cost

It is visible in figure 22 that production at owned factories for the disruptive cases increased from the reference case as a mean to reduce costs, also reducing production of the nearshore alternative across all cases. Nonetheless, it can also be observed that outsourcing production is higher for the cases of delayed responses, meaning that owned factories lacked the capacity of rapid responses when needed.

Once again the production type disruptions proved to degrade the resilience metric the most, however, for this configuration no spoilage of raw materials was verified. Regarding the length of the disruptions low declines are verified by increasing the disruptions' length from two to four weeks, being far more impactful the delay in responsive actions.

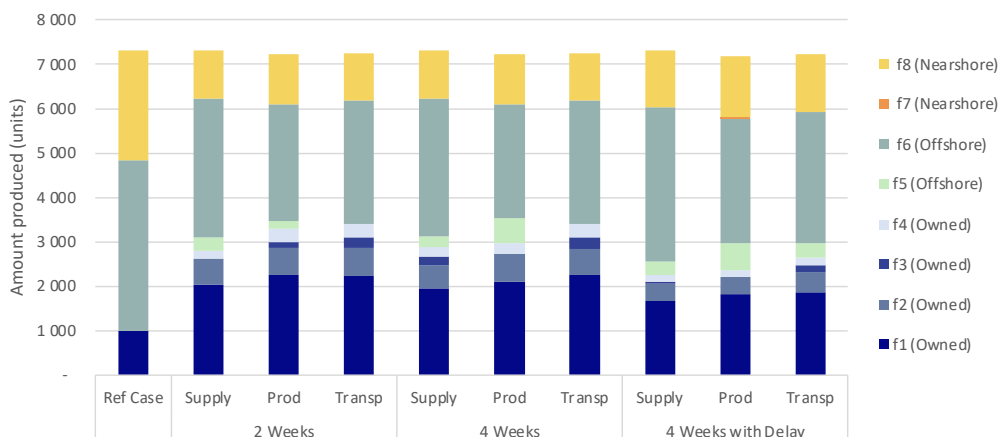


Figure 22: Amount produced by each factory for the deterministic model under disruptions, fixing point C

Concerning the service level, only the supply disruption was capable to maintain full satisfaction of customers' demand. Regarding the remaining disruptions, figure 23 and figure 24 present the sales level over time for the production and transportation type disruptions, respectively. For both cases the drop in sales for a 2 week disruption is barely noticeable. It is also visible that delaying the responsive actions will also increase the time it takes to resume regular sales levels. Due to the characteristics of point C, favouring somewhat a reduced lead time as first stage decisions, the effects of the production disruptions were felt immediately as opposed to the above results for point A.

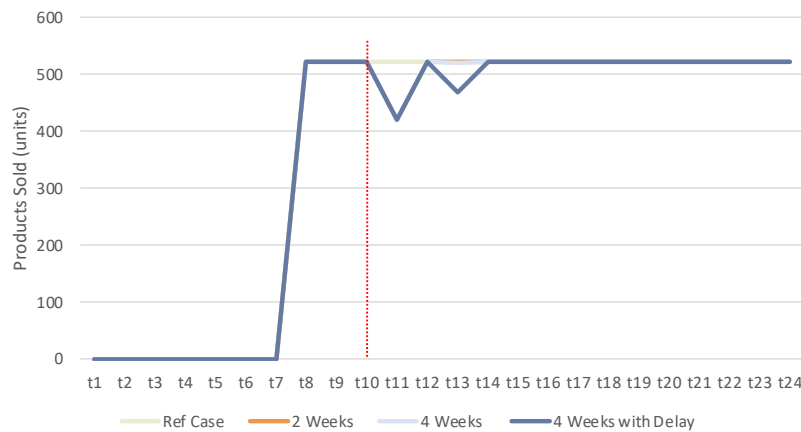


Figure 23: Sales level of the deterministic model, fixing point C under a production disruption

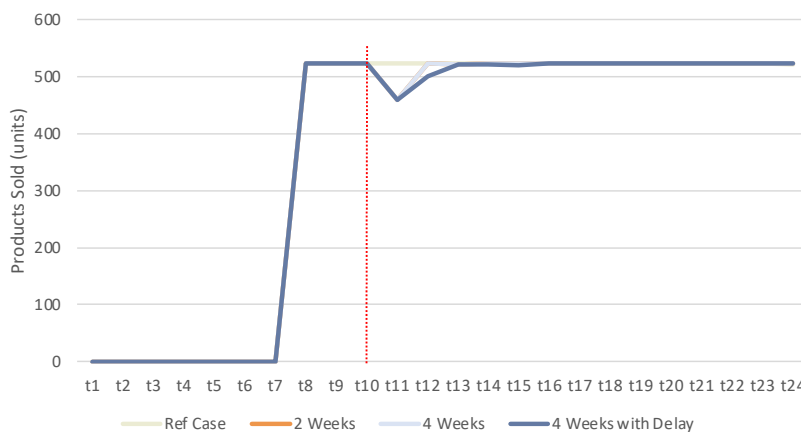


Figure 24: Sales level of the deterministic model, fixing point C under a transportation disruption

Overall, the three configurations here presented represent the behaviour of SCs with contrasting end goals. While for point A and C priority is given to maintain an elevated resilience metric, for point B the main concern lies on the flow time exhibited by the SC. The latter point succeeded at delivering a flow time with no degradation to the value incurred in the reference case. Nonetheless, such achievement required inevitably higher costs. This consequence is valid for the three points, varying however on the means the additional costs are applied to. The cost indicator that experienced highest increases to deal with the circumstances was related to manufacturing operations, which is also closely related to the

selection of production capacity expansions. Point A invested, when possible, in low cost alternatives provided by offshore facilities while point B maintained nearshore sourcing and even increasing in volume. On the other hand, point C boosted its own production.

Like point B, point C concentrates production at outsourcing entities prior to any disruption which allowed to avoid spoilages of raw materials. On the other hand, point C experienced higher loss in sales for production cases than point A.

To sum up, the three analysed points, despite their diverging behaviours, still present some communalities in terms of the results. In short, the following conclusions can be withdrawn:

- A production type disruption with delayed responses affects most negatively the resilience metric;
- Transport related disruptions are more likely to produce lost sales;
- Delayed responses also delay the returning to a steady-state of operation even compared to a disruption with the same length.

5.3.3 Response strategy analysis

In this section it is studied the effects of adjusting the indicators' preference in the presence of a disruptive event, meaning that the DM may consider appropriate to tackle the situation by alternating the OFs priority as opposed to the priority employed preceding said event as depicted in figure 25. The full results are present in annex B, adopting this form of second stage optimisation to point A, B and C, while table 16 provides a summarized view of the results. Here point A', B' and C' deviate from the previous analyses throughout section 5.3.2, by adopting an opposite preference of the OFs at the second stage yet maintaining the decisions taken for the first nine time periods of the reference case points analysed in section 5.3.1 of point A, B and C, respectively. These results allowed a 1% gap.

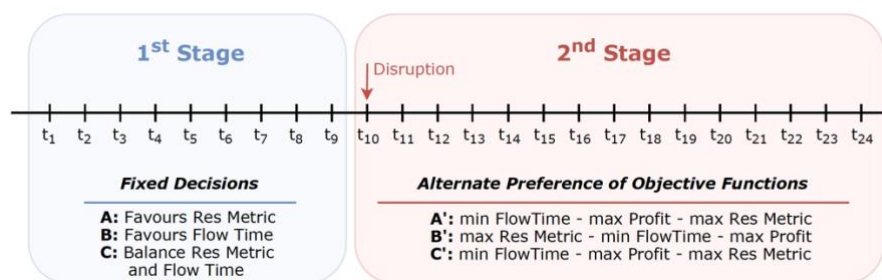


Figure 25: Response strategy analysis schema

For both point A' and C' the OF with the highest priority was updated to the flow time indicator. For these cases the value of the indicator is decreased notably to a stable value, independent of the disruption type and length (table 17). However, this value experiences increases for the case of a delayed sensing of the disruption. Contrasting to former results of the point B analysis, which through economical resources was capable of maintaining the minimum flow time value, in these cases where the priority of the flow time is only considered after the occurrence of the disturbance, delayed responses will ultimately damage its value. The highest increase is verified for a transportation type

disruption. For this type, production schedules will remain unaltered for two weeks before noticing a disruption took place to key transportation links, which has a significant weight in the OF, deteriorating with elevated production times. To remark that the continued production at owned factories justifies the increase of the resilience and profit metric as opposed to the immediately sensed disruption of the transportation type. Given that point C is a trade-off point, and already submitted to outsourcing facilities that benefit the OF by not requiring production times, the degradation of the flow time value is less notable as to point A, and inconsequential for a supply disruption in terms of the flow time value.

Table 17: Results of the deterministic model changing OF priority at the 2nd stage

Solution	Point A'			Point B'			Point C'		
	Res Metric	Flow Time	Profit	Res Metric	Flow Time	Profit	Res Metric	Flow Time	Profit
Ref	1,000	51 124	396 403	0,146	7 987	97 666	0,642	18 771	254 643
<i>2 Weeks Disruption</i>									
Supply	0,288	27 971	153 676	0,597	27 754	240 907	0,186	10 880	113 246
Prod	0,288	27 971	153 823	0,588	27 785	240 576	0,180	10 880	111 012
Transp	0,288	27 971	153 587	0,597	28 349	241 957	0,184	10 880	112 363
<i>4 Weeks Disruption</i>									
Supply	0,287	27 971	153 304	0,591	26 320	238 484	0,185	10 880	112 948
Prod	0,288	27 971	153 788	0,577	28 976	239 557	0,175	10 880	108 944
Transp	0,287	27 971	153 304	0,596	28 183	241 703	0,180	10 880	110 978
<i>4 Weeks Disruption with Delay</i>									
Supply	0,255	28 862	140 805	0,540	22 955	218 095	0,180	10 880	111 134
Prod	0,273	31 350	147 656	0,505	23 962	211 473	0,139	10 895	94 877
Transp	0,321	32 572	166 896	0,528	23 869	217 660	0,128	10 883	90 380

Regarding the shift between privileging the flow time to the resilience metric, the case of point B', the best performing solutions will deliver a resilience metric close to 0.60, being the two weeks supply disruption the case to provide the best result. Comparing to the case where the resilience metric is already optimised firstly for the first stage decisions, here the service level experiences higher fluctuations (table 26, annex B).

Figure 26 presents the capacity expansions incurred for this analysis of point B'. Relative to the selection of outsourcing, similar increases are observed for preferring offshore alternatives (both f_5 and f_6), whereas the production disruption with a delayed response remains the sole solution that requires further increases through nearshoring. Since the first stage production was concentrated at outsourcing factories, no spoilage of raw materials are incurred to with any disruption.

In sum, altering the OFs priority in face of a disruption will aid in improving the updated preferred indicator. For the switch to prioritizing firstly the flow time, point A' and C', these cases validate the feasibility of improving said indicator regardless of the disruptions length. However, while point A'

achieves this with minor degradations to the resilience metric, point C' experiences higher declines with lengthier disruption, namely of the production and transportation type.

On the other hand, point B' is also capable of increasing notably the new preferred indicator (resilience metric), nonetheless, displaying far lower performing results for the delayed cases.

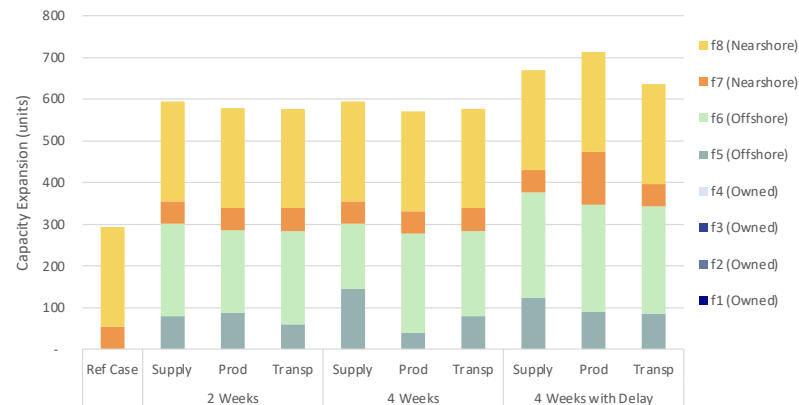


Figure 26: Capacity expansions of the deterministic model response strategy, point B'

5.4 Stochastic model results

The following sub-sections present the results of the stochastic model also obtained using the GAMS software running the CPLEX solver, however, given the higher complexity, a gap of 1% is set.

For this model the customer demand and the products' return rate will be modelled as uncertain parameters following the approach described in section 4.9. In this case study, for the planning horizon of 24 weeks (6 months), information regarding the uncertain parameters is updated every two months with a optimistic, realistic and pessimistic variation, which means that each stage of the scenario tree is composed by eight time periods. The variation is applied at the first time period of each stage, remaining constant for the succeeding periods. This results in a three stages scenario tree with nine leaf nodes. Table 18 summarizes the aggregation of time periods for each scenario, the corresponding probability and the variation that is applied to the uncertain parameters.

5.4.1 Reference case analysis

Table 19 presents the payoff table considering priority 1 (Resilience Metric; Flow time; Profit), as previously presented. Once again optimizing the resilience metric or the profit firstly will result in approximate solutions. Nonetheless, it is worth highlighting that a gap of 1% from the optimal solution is being allowed for these results due to the impossibility of retrieving the results in a reasonable computational time with 0% gap. This limitation justifies the higher profit value present in the first row as opposed to when the profit is optimized firstly. Such would not to be expected were the model run with a 0% gap, as for the deterministic model.

Table 18: Characterisation of the scenarios considered in the stochastic model

Node	Associated time periods	Probability (%)	Demand variation (%)	Return rate variation (%)
S1	t ₁ , t ₂ , t ₃ , t ₄ , t ₅ , t ₆ , t ₇ , t ₈	100	0	0
S2	t ₉ , t ₁₀ , t ₁₁ , t ₁₂ , t ₁₃ , t ₁₄ , t ₁₅ , t ₁₆	25	10	10
S3	t ₉ , t ₁₀ , t ₁₁ , t ₁₂ , t ₁₃ , t ₁₄ , t ₁₅ , t ₁₆	50	5	5
S4	t ₉ , t ₁₀ , t ₁₁ , t ₁₂ , t ₁₃ , t ₁₄ , t ₁₅ , t ₁₆	25	-10	0
S5	t ₁₇ , t ₁₈ , t ₁₉ , t ₂₀ , t ₂₁ , t ₂₂ , t ₂₃ , t ₂₄	6,25	10	10
S6	t ₁₇ , t ₁₈ , t ₁₉ , t ₂₀ , t ₂₁ , t ₂₂ , t ₂₃ , t ₂₄	12,50	5	5
S7	t ₁₇ , t ₁₈ , t ₁₉ , t ₂₀ , t ₂₁ , t ₂₂ , t ₂₃ , t ₂₄	6,25	-10	0
S8	t ₁₇ , t ₁₈ , t ₁₉ , t ₂₀ , t ₂₁ , t ₂₂ , t ₂₃ , t ₂₄	12,5	10	10
S9	t ₁₇ , t ₁₈ , t ₁₉ , t ₂₀ , t ₂₁ , t ₂₂ , t ₂₃ , t ₂₄	25	5	5
S10	t ₁₇ , t ₁₈ , t ₁₉ , t ₂₀ , t ₂₁ , t ₂₂ , t ₂₃ , t ₂₄	12,50	-10	0
S11	t ₁₇ , t ₁₈ , t ₁₉ , t ₂₀ , t ₂₁ , t ₂₂ , t ₂₃ , t ₂₄	6,25	10	10
S12	t ₁₇ , t ₁₈ , t ₁₉ , t ₂₀ , t ₂₁ , t ₂₂ , t ₂₃ , t ₂₄	12,50	5	5
S13	t ₁₇ , t ₁₈ , t ₁₉ , t ₂₀ , t ₂₁ , t ₂₂ , t ₂₃ , t ₂₄	6,25	-10	0

Due to the higher complexity of this model, for the epsilon constraint resolution the three OFs proved to require an excessive computational effort. Therefore, to understand the scope of the pareto efficient solutions the model was run for two bi-objective scenarios obtaining the pareto fronts in figure 27 and 28 for the optimization of the flow time function alternating with the resilience metric and profit, respectively. The number of grid-points was set to 5.

Table 19: Payoff table of the stochastic model for priority 1

	Res Metric	Flow Time	Profit
max Res Metric	0,984	48 673,84	414 607,81
min Flow Time	0,200	8 270,83	124 640,27
max Profit	0,979	46 872,99	412 693,28

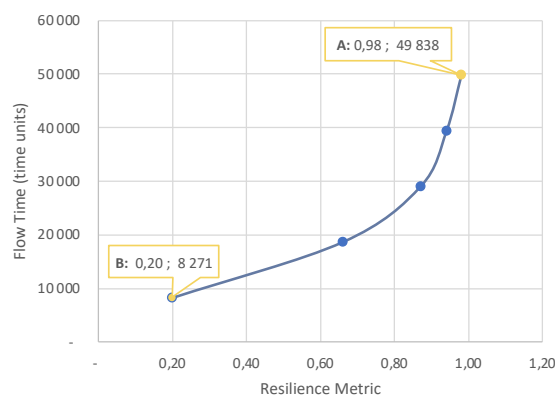


Figure 27: Pareto front of the stochastic model with the resilience metric and flow time as OFs

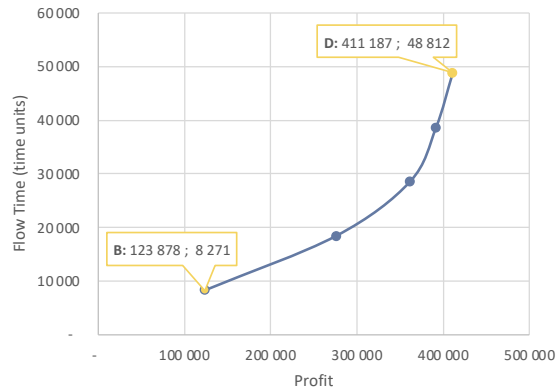


Figure 28: Pareto front of the stochastic model with the profit and flow time as OFs

As it is visible both cases present very similar behaviours, with solutions concentrated to achieve above 0,60 resilience metric value. By observing the curve, moving from the minimum flow time value towards improving either of the two remaining OFs, for instance, a notable increase of 0,40 of the resilience metric can be achieved at a cost of approximately 10 000 time units. However, this improvement reduces its magnitude along the curve for similar flow time increases.

For the analysis of the present model point D was disregarded for the same reasoning of providing redundant results as those of point A. Additionally, no in-between solution was analysed (point C) due to the higher computational effort.

Henceforth, two solutions will be considered, retrieved from the payoff table (table 19) representative of the extreme points A and B, which are also visible in figure 27. Table 20 showcases the selected solutions' performance indicators. In this case point A nearly meets the profit reference value, falling short on the maximum value of the resilience metric mostly due to the service level of 98,6%. Point B only meets 90% of the total demand, for the same reasoning as argued beforehand, and experiences elevated manufacturing cost by heavily resorting to outsourcing alternatives, expanding f_7 by 76,91 units and f_8 by 252,79 units.

Table 20: Stochastic model performance indicators of selected solutions

Point	Res Metric	Flow Time	Profit	SL	Revenue	Costs				
						TMC	TTC	TDC	TIC	TEC
A	0,984	48 674	414 620	0,986	643 841	171 061	53 452	3 895	639	174
B	0,200	8 271	124 653	0,900	584 403	421 932	11 952	7 154	245	18 466

SL: Service Level; TMC: Manufacturing Cost; TTC: Transportation Cost; TDC: Duties Cost; TIC: Inventory Cost; TEC: Capacity Expansion Cost

Comparing these values to the ones obtained for the deterministic model, it can be viewed that the present model returns a higher level of profit from the former 396 305 and 97 666 for point A and B, respectively. This is due to the variations assumed for the uncertain parameters (table 18). Both optimistic and realistic branches of the scenario tree account for a rise in demand values, thus jointly

enforcing the achievement of higher sales volume, consequently, increasing total revenues. The scenarios that account for a rise in the products' return rate also contribute to reduce manufacturing costs from the previous value of 175 121 and 428 093 also for point A and point B, respectively.

Regarding the flow time OF, the stochastic model achieves a higher value from the previous value of 7 986,60 due to the need of delivering and collecting a more elevated volume of products.

5.4.2 Disruption analysis

To analyse the impact of disruptive events on SCs' configuration that value differently the OFs functions, a two stage approach is followed where the two previously analysed points will be used as first stage decisions. Subsequently, for the second stage decisions the model is solved bi-objectively, in order of the preferred indicator of the point at hand. The disruptions implemented follow the same reasoning presented in section 5.4.3.

Point A

This point values primarily an appealing outcome of the resilience metric, and through the results obtained in table 21 it can be concluded that a four week long disruption at production facilities with a delayed response hinders the most the achievement of such goal. In fact, disruptions tested with the delayed response return notable degradations of the resilience metric as opposed to the results where immediate responses are implemented. Overall, the decline of this indicator stems from profit decreases since the service level maintains approximate values to the reference case. The case with a largest decrease of the service level is for a transportation type disruption with a delayed response.

Table 21: Stochastic model results considering disruptive events, fixing decisions of point A

Case	Res Metric	Flow Time	Profit	SL	Revenue	TMC	TTC	TDC	TIC	TEC
Ref	0,984	48 674	414 620	0,986	643 841	171 061	53 452	3 895	639	174
<i>2 Weeks Disruption</i>										
Supply	0,976	47 834	411 562	0,986	643 771	173 369	52 744	4 164	697	1 235
Prod	0,973	48 612	410 120	0,986	643 807	174 119	53 773	4 020	698	1 077
Transp	0,980	48 656	413 580	0,984	642 639	170 882	53 438	3 900	665	174
<i>4 Weeks Disruption</i>										
Supply	0,972	47 604	409 867	0,985	644 667	174 438	52 995	4 451	698	2 218
Prod	0,966	47 331	407 389	0,986	644 038	176 661	52 549	4 427	780	2 231
Transp	0,979	48 696	413 345	0,984	642 635	170 904	53 509	3 893	662	321
<i>4 Weeks Disruption with Delay</i>										
Supply	0,962	45 824	405 671	0,985	642 888	177 154	50 597	4 896	654	3 916
Prod	0,862	39 991	365 641	0,982	637 678	207 727	45 922	6 600	1 021	10 768
Transp	0,959	48 468	408 561	0,975	637 791	170 370	53 074	3 941	932	913

SL: Service Level; TMC: Manufacturing Cost; TTC: Transportation Cost; TDC: Duties Cost; TIC: Inventory Cost; TEC: Capacity Expansion Cost

The cost indicator with the highest increase for supply and production disruptions is the total manufacturing cost, consequence of the production capacity expansion, as its' indicator also increases. Figure 29 demonstrates the capacity expansions per case. Here it is visible the preference for offshore alternatives to deal with the disruption (f_5 and f_6), since they offer lower costs. Nonetheless, for more extreme conditions, as it is the case for lowest performing solution, nearshore options are selected (f_7 and f_8). Like the results of the deterministic model, such occurs for the production and transportation cases with delay.

Nonetheless, it is worth noting that the capacity expansion strategy behaves differently for the transportation type disruptions. These cases scarcely expand their production capacity, accepting the loss of sales and increasing the sale of alternative products with lower production time, as it can be viewed in the reduction of revenues relative to the other cases.

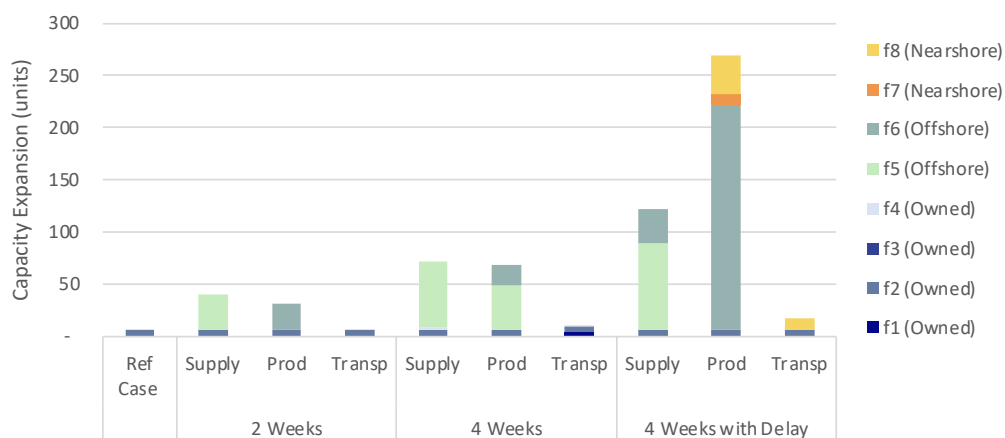


Figure 29: Capacity expansions of the stochastic model under disruptions, fixing point A

Regarding the spoilage of items, such solely occurs for raw materials in case of a production disruption (table 22). For a two weeks long disruption 281,45 units are spoiled, for an increased duration of four weeks the value is of 282,18 units and, lastly, for the delayed response such increases substantially to a total of 1 244,56 units. The same conclusion can be withdrawn as for the deterministic model, where immediate responses, despite still being vulnerable to the possibility of spoilage of raw materials, after acknowledging the occurrence of the event further disposals can be avoided regardless of the disturbance's length. However, lagging in the necessary adjustments to shipments will continuously aggravate the excess of raw materials arriving to production facilities that are unable to be used.

Table 22 further presents the total amount of products sold per case. By comparison to the deterministic model, where the reference case sold 256,87 units of option 1 of the alternative products, for this model the value increases to 511,04 units. It is also visible that this value increases in order to deal with disruptive event, with solely two cases whose value decreases, namely for the four week supply and production disruption. Both these cases opt to not forfeiting revenues in order to cover the increased costs.

Table 22: Amount of product sold and spoilages occurred for the stochastic model under disruptions, fixing point A

Case	Products sold (units)						Spoilage (units)	
	p ₁	p ₂	p ₃	p ₁₁	p ₁₂	p ₁₃	SPOi	SPOp
Ref	5 647,90	1 804,52	1 093,17	511,04	-	-	-	-
<i>2 Weeks Disruption</i>								
Supply	5 632,78	1 804,60	1 093,17	526,79	-	-	-	-
Prod	5 642,78	1 804,60	1 093,10	516,23	-	-	281,45	-
Transp	5 595,91	1 803,34	1 091,62	553,30	-	-	-	-
<i>4 Weeks Disruption</i>								
Supply	5 772,58	1 802,50	1 093,16	386,99	-	-	-	-
Prod	5 668,61	1 804,60	1 093,15	490,96	-	-	282,18	-
Transp	5 603,47	1 802,51	1 091,61	545,74	-	-	-	-
<i>4 Weeks Disruption with Delay</i>								
Supply	5 529,67	1 803,58	1 093,10	629,39	-	-	-	-
Prod	5 116,78	1 797,33	1 093,10	1 014,62	-	-	1 244,56	-
Transp	5 637,50	1 801,38	1 089,95	430,64	-	-	-	-

p₁₁: Alternative product 1 (lower production time); p₁₂: Alternative product 2 (fewer raw material requirements); p₁₃: alternative product 3 (possible to produce at more factories); SPOi: Spoilage of raw materials; SPOp: spoilage of final products

Figure 30 presents the sales level over time for the cases with a transportation type disruption. Here since the demand values are considered as an uncertain parameter, more fluctuations are visible beyond the effects of the disruption. Nonetheless, similar to the results obtained by the deterministic model, it is visible how a delayed response presents to be far more impactful to sales levels as opposed to immediate responses. These latter responses are not only capable to incur in a more reduced value of lost sales, but also to recover faster to a steady-state of operation.

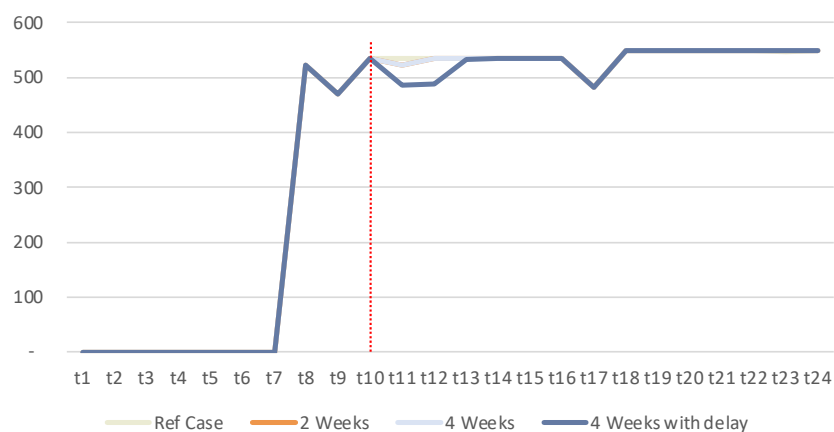


Figure 30: Sales level of the stochastic model, fixing point A under a transportation disruption

Point B

Table 23 presents the results of a SC configuration that prioritizes the minimization of the flow time. It can be seen that the minimum flow time achieved for the reference case is sustained for all type of disruptions. Nonetheless, meeting this value requires the degradation of the profit obtained throughout the planning horizon as well as the resilience metric. Once again it was considered pertinent to model the production and transportation disruptions taking into account the outsourcing entities. Therefore, the production disruption was considered to take place at factory f_7 and f_8 , and the transportation type disrupted links f_8-m_5 ; f_8-m_1 ; f_8-m_3 ; f_7-m_6 . The scenarios within both type of disruptions were considered to be equally probable.

Table 23: Stochastic model results considering disruptive events, fixing decisions of point B

Case	Res Metric	Flow Time	Profit	SL	Revenue	TMC	TTC	TDC	TIC	TEC
Ref	0,200	8 271	124 653	0,90	584 403	421 932	11 952	7 154	245	18 466
<i>2 Weeks Disruption</i>										
Supply	0,199	8 271	124 275	0,90	584 096	421 961	11 910	7 211	272	18 466
Prod	0,183	8 271	117 535	0,90	584 972	428 087	11 602	6 977	265	20 506
Transp	0,194	8 271	122 223	0,90	584 619	424 410	11 766	7 121	349	18 750
<i>4 Weeks Disruption</i>										
Supply	0,199	8 271	124 144	0,90	583 445	421 448	11 876	7 219	292	18 466
Prod	0,183	8 271	117 454	0,90	583 790	425 009	11 818	6 905	270	22 335
Transp	0,186	8 271	118 824	0,90	583 512	424 830	11 789	6 951	279	20 839
<i>4 Weeks Disruption with Delay</i>										
Supply	0,199	8 271	124 023	0,90	584 314	422 425	11 853	7 181	324	18 508
Prod	0,172	8271	113 043	0,90	584 974	427 465	11 749	6 706	266	25 504
Transp	0,183	8 271	117 711	0,90	585 959	429 503	11 683	7 033	252	19 776

SL: Service Level; TMC: Manufacturing Cost; TTC: Transportation Cost; TDC: Duties Cost; TIC: Inventory Cost; TEC: Capacity Expansion Cost

Similar to point A, the disruption to economically strain the results the most is of the production type with a delayed response. On the other hand, all the supply type disruptions present negligible deviations from the reference case due to the same reasoning stated previously for the deterministic model results.

Across the cases tested, a production disruption required higher costs than a transportation related one to maintain a low level of flow time. Once again such can be linked to capacity expansion decisions, which are visible in figure 31. The main increases are verified for f_7 since there exists a higher reliance on f_8 in normal operation conditions.

In sum, this section supports the conclusions stated previously for the deterministic model. The implementation of uncertain parameters lead to different numerical outcomes, however, maintaining coherent the major decisions taken.

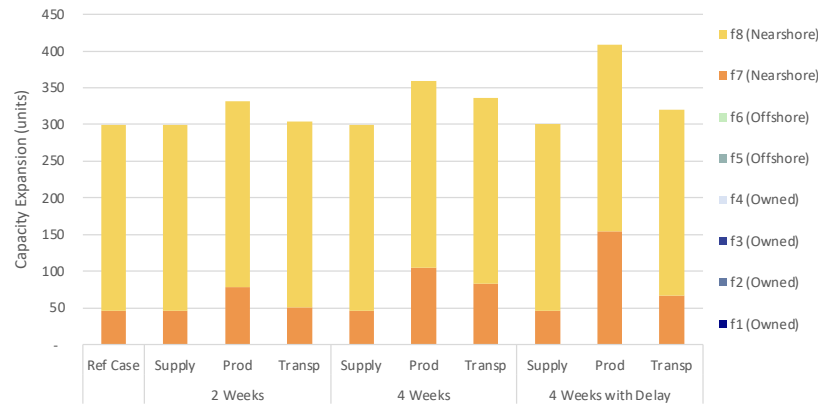


Figure 31: Capacity expansions of the stochastic model under disruptions, fixing point B

5.4.3 Response strategy analysis

The study of adjusting the indicators' preference in the presence of a disruptive event for the present stochastic model did not provide any major differences relative to the conclusions withdrawn for the deterministic model as analysed previously. Nonetheless, the results are present in annex C.

5.5 Discussion

Overall, the cases here studied shed light on the critical role that time plays in SCM when faced with disruptive events. Not only was it possible to witness the clear decline of performance indicators through the modelling of immediate and delayed responses, but also by analysing which operational decisions are taken to mitigate consequences.

To better visualise effect of the different length of a disruption, figure 32 demonstrates the decline of the resilience metric incurred between a two weeks and a four weeks long disruption (blue bars), as well between four weeks and four weeks with a delayed response disruptions (yellow bars). These declines are separated by the SC echelon that is disrupted, as well for each SC configuration analysed in section 5.3. Recalling that point A represents the solution that delivers the maximum resilience metric and, in these particular cases, also the maximum profit value, contrasting to point B for the lowest flow time possible, and point C as a trade-off point between the three OFs. Figure 33 serves the same purpose for the results of the stochastic model.

It is immediately visible that lagging in sensing the presence of a crisis and adopting corrective measures presents in general more deteriorating effects than increases to the disruptions' length. Relative to the deterministic model, the solutions by fixing point C as first stage decision resulted in the highest decline of the resilience metric when considering these delayed responses. Thus, balancing the three OFs did not leave the SC prepared to maintain an elevated level of the resilience metric. Regarding point A and point B, both the results of the deterministic and stochastic model show that the increase in the duration of a disruption is more impactful for point B, which values most a low flow time level, while on the other hand, considering delayed responses, point A verifies higher declines of the resilience metric.

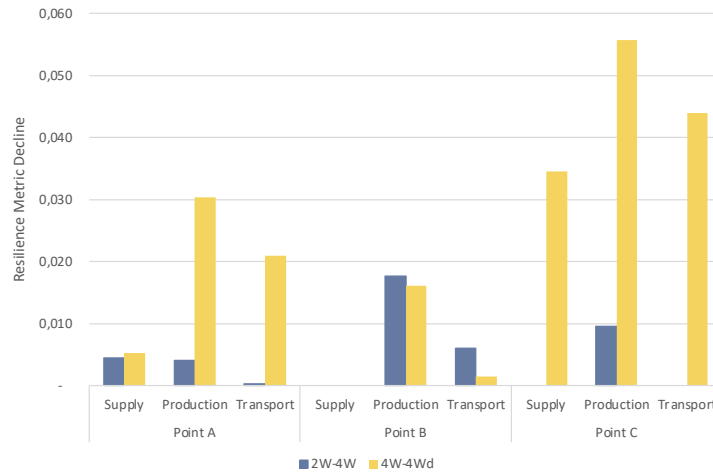


Figure 32: Decline of the resilience metric of the deterministic model results

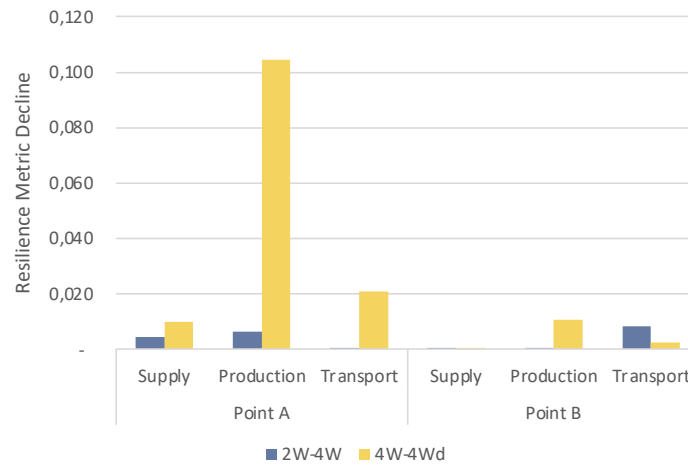


Figure 33: Decline of the resilience metric of the stochastic model results

The differences between the deterministic and stochastic model did not display highly contrasting decisions and conclusions. A more significant deviation between the models is verified in the reference case of the point that optimizes the resilience metric firstly (point A), where for the deterministic case it considers appropriate the expansion of the owned factory f_2 by 75 units while for the stochastic model returned a only mere increase of 5,81 units of the same factory. Deviation between both models is also verified regarding the value of the OFs. Given the assumed variations of the uncertain parameters, the results of the stochastic model returned better outcomes for the resilience metric and profit, and a slight decline for the flow time.

Both models showcased how delayed responses can lead to unnecessary spoilage of raw materials. The results demonstrated that despite spoilage of raw materials being probable to occur when dealing with a production related disruption, their volume is somewhat insensitive to the length of the disruption. If the event is sensed immediately, unnecessary orders are shipped and, consequently, the amount that gets disposed of stabilizes. With delayed responses excesses will continuously be shipped, and depending on the industry such can become even more damageable if we were to consider, for instance, perishable products.

Nonetheless, beyond the modelling of immediate and delayed responses, other operational decisions also highlighted the importance of rapid solutions.

Throughout the analyses, the option to activate redundant capacity at owned factories was not resorted to as a measure to tackle SC disturbances, relying most commonly on outsourcing facilities. The outsourcing solutions in this case study were designed to provide rapid deliveries of the required product by not accounting for any production time, varying mostly on cost and market distance. Therefore, the expansion of the production capacity of owned factories did not prove to be an appealing means to mitigate consequences since any owned facilities would still require regular production times. Additionally, within the outsourcing options it was noted that nearshoring options, despite its elevated costs, were deemed necessary to deal with the most straining conditions to the SC.

In the same line, the selection of alternative products was concentrated to option 1 of the designed solutions which allowed a lower production time. The options that provided flexibility for the products to be produced in a wider range of facilities or to require a reduced amount of raw materials were not selected.

5.6 Academic and managerial insights

Ultimately, supported by the previous discussion of the results of this work, while long lasting disruptions can cause severe damages to the normal operating conditions of a company, lagging in responsive actions not only accentuates such consequences but also may impact their competitive advantage in the long term, as they struggle to return to a steady-state. The results also demonstrated that delayed responses increase the need for rapid solutions and provoke higher spoilage of materials. Both these consequences lead to higher costs that could be avoided were the disruption sensed immediately. Therefore, SCs face a dire need in improving network visibility and enhance communication between entities. As explored in section 2.4, such can be achieved by investing in digital adaptations to SCs. By digitalizing end-to-end operations, disturbances can be more quickly acknowledged and communicated among the connected entities, leaving the SC more resilient in an efficient manner. Also, work culture can aid in this regard as discussed in section 2.3.

Regardless of the time taken to sense the event, swift actions have proven to be of most value to cope with the most straining events to the SC. Alternative products can enhance SCR with changes that ease the production process. In this work it has been concluded that products that imposed reduced production time were most resorted to in the aftermath of a disruption, despite providing a lower profit margin. Thus, it is recommended the assessment of the feasibility of conceiving and manufacturing such products. To this end it can be explored the standardization of processes and/or the reduction of product's complexity.

Also in this line of rapid solutions, nearshoring options have been selected to deliver products amidst the disruptions here tested, even though these have been considered in the case study as high-cost solutions. Having this in mind, it would be of value the establishment of nearby backup facilities with pre-arranged agreements thus to avoid the elevated prices of short notice requirements and assure that such option is effectively available when needed.

It has also been concluded that transport related disruptions are more susceptible to decreases in service levels. It is recommended the study of alternative transportation modes that are available and compatible with the business needs for possible shifts that might arise.

Lastly, the consequences of disruptive events have proven, in general, to be identical between SC configurations that value the OFs differently. Nonetheless, the decisions taken to diminish such impacts differ from one another. This highlights the importance of OR models that are capable to incorporate a multitude of options to deal with disruptions, providing DMs with a range of solutions best suited to their specific capabilities. Due to this, development of future models should have these considerations in mind.

6 Conclusion and future work

The work here developed addressed the need to further extend the extant literature on quantitative approaches in the emerging field of SCR, focusing on the tactical-operational level. Towards that end, a production, distribution and capacity planning model is tailored to retrieve insights on the weight of timely responses in the aftermath of disruptive events, and which decisions are key to sustain operations. A systematic literature review is performed a priori to ground the scope of the subject and assure the relevance of the succeeding work.

SCR has been gaining gradual developments over the years, becoming now with the pandemic a very current subject and a concern for most companies. Such is addressed in chapter 2 where it is highlighted how awareness in planning for unpredictable events is rising, and what strategies are being considered. The relevance of SCR is further sustained by the systematic literature review in chapter 3, however noting the need to enrich the literature on tactical-operational models that incorporate a high level of uncertainties. It was also concluded that it is necessary to invest future investigation on how to model risk and uncertainty beyond deterministic approaches, for a more accurate representation of disturbances.

In order to meet this need, the model developed in this dissertation accounts for three sources of uncertainties, namely, in selected parameters, the time frame of a disruption, and the source of the disruption. A novel approach was developed to address the first source of uncertainty by adopting a scenario tree approach to cluster time periods into stages. Thus, the ramifications of the scenario tree are more malleable to represent when new information becomes available. Regarding the second source of uncertainty, the disruptions' time frame, more specifically for the study of delayed response cases, it is worth mentioning that fixing decisions following the implementation of the disruption presented some limitations. Decisions taken downstream of the disrupted SC activity could in most cases not be fixed and maintain the model's feasibility. That is, more liberty was given to assure the model's feasibility than what would be a realistic situation where the disruption remains unknown. Future endeavours could explore this matter, possibly by considering alternative OR methods to overcome this limitation.

This work performs a parallel analysis of the results obtained through a deterministic and stochastic model. These did not showcase any major deviation on final conclusions withdrawn, where the primary insights reinforce the need of rapid solutions over cost-efficiency under disruptive events. However, it was experienced a noteworthy increase in computational effort between the deterministic and stochastic model. This latter may present even less appealing computation times were it applied to a more complex case study, being therefore of interest to consider alternative solution approaches for future applications.

Furthermore, it is well acknowledged that responsiveness and cost-efficiency are conflicting measures, thus the present study addressing three OFs, namely, profit and flow time as well as a resilience metric that balances economic returns with service level. It was shown that to achieve the optimal flow time significant financial resources would be required which may not be appealing to a DM,

as well as limiting the service level to achieve only the minimum target. Future efforts should be made to better integrate these concerns in a measure of flow time.

The results proved that delayed responses have in most cases a higher impact on performance indicators than lengthier disruptions. Also, through the implementation of outsourcing and alternative products, the designed options that delivered time efficient solutions prevailed in the decisions taken to overcome impactful disruptions. Nonetheless, it would be of interest to apply a broader selection of these options to cases with different characteristics to corroborate these conclusions. This would also contribute to the limitation of this work being based on an generic case study, whose data are based on a large amount of assumptions, further adding to the results' uncertainty.

6.1 Acknowledgements

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References

- Aggarwal, S., & Srivastava, M. K. (2019). A grey-based DEMATEL model for building collaborative resilience in supply chain. *International Journal of Quality and Reliability Management*, 36(8), 1409–1437. <https://doi.org/10.1108/IJQRM-03-2018-0059>
- Ahmadian, N., Lim, G. J., Cho, J., & Bora, S. (2020). A quantitative approach for assessment and improvement of network resilience. *Reliability Engineering and System Safety*, 200(April), 106977. <https://doi.org/10.1016/j.ress.2020.106977>
- Ali, A., Mahfouz, A., & Arisha, A. (2017). Analysing supply chain resilience: integrating the constructs in a concept mapping framework via a systematic literature review. *Supply Chain Management*, 22(1), 16–39. <https://doi.org/10.1108/SCM-06-2016-0197>
- Ali, I., & Gölgeci, I. (2019). Where is supply chain resilience research heading? A systematic and co-occurrence analysis. *International Journal of Physical Distribution and Logistics Management*, 49(8), 793–815. <https://doi.org/10.1108/IJPDLM-02-2019-0038>
- Alicke, K., Barriball, E., Lund, S., & Swan, D. (2020). Is your supply chain risk blind-or risk resilient? *McKinsey & Company*, May, 6.
- Alicke, K., Gupta, R., & Trautwein, V. (2020). Resetting supply chains for the next normal. *McKinsey & Company Insights*, July, 1–6. <https://www.mckinsey.com/business-functions/operations/our-insights/resetting-supply-chains-for-the-next-normal>
- Alicke, K., & Strigel, A. (2020). Supply chain risk management is back. *McKinsey & Company Insights*, January. <https://www.mckinsey.com/business-functions/operations/our-insights/supply-chain-risk-management-is-back%0D>
- Amazon. (2020a). *Amazon introduces “Distance Assistant.”* <https://blog.aboutamazon.com/operations/amazon-introduces-distance-assistant>
- Amazon. (2020b). *How Amazon is helping customers get groceries.* <https://blog.aboutamazon.com/company-news/how-amazon-is-helping-customers-get-groceries>
- Amazon. (2020c). *How we’re taking care of employees during COVID-19.* <https://blog.aboutamazon.com/company-news/how-amazon-prioritizes-health-and-safety-while-fulfilling-customer-orders>
- Apple Inc. (2020). *Investor update on quarterly guidance.* <https://www.apple.com/newsroom/2020/02/investor-update-on-quarterly-guidance/>
- Arora, N., Charm, T., Grimmelet, A., Ortega, M., Robinson, K., Sexauer, C., Staack, Y., Whitehead, S., & Yamakawa, N. (2020). A global view of how consumer behavior is changing amid COVID-19. *McKinsey & Company*, 1–15. <https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/a-global-view-of-how-consumer-behavior-is-changing-amid-covid-19>
- Arora, S., Böhm, W., Dolan, K., Gould, R., & McConnell, S. (2020). Resilience in transport and logistics. *McKinsey & Company Insights*, February. <https://www.mckinsey.com/business-functions/operations/our-insights/resilience-in-transport-and-logistics>
- Ayoughi, H., Dehghani, H., Raad, A., & Talebi, D. (2020). Providing an Integrated Multi-Objective Model for Closed-Loop Supply Chain under Fuzzy Conditions with Upgral Approach. *INTERNATIONAL JOURNAL OF NONLINEAR ANALYSIS AND APPLICATIONS*, 11(1), 107–136.

- Azadeh, A., Atrchin, N., Salehi, V., & Shojaei, H. (2014). Modelling and improvement of supply chain with imprecise transportation delays and resilience factors. *International Journal of Logistics Research and Applications*, 17(4), 269–282. <https://doi.org/10.1080/13675567.2013.846308>
- Baig, A., Hall, B., Jenkins, P., Lamarre, E., & McCarthy, B. (2020). The COVID-19 recovery will be digital: A plan for the first 90 days. *McKinsey & Company*, May, 1–8. [https://www.mckinsey.com/~media/McKinsey/Business Functions/McKinsey Digital/Our Insights/The COVID 19 recovery will be digital A plan for the first 90 days/The-COVID-19-recovery-will-be-digital-A-plan-for-the-first-90-days-vF.pdf](https://www.mckinsey.com/~media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/The%20COVID%2019%20recovery%20will%20be%20digital%20A%20plan%20for%20the%20first%2090%20days/The-COVID-19-recovery-will-be-digital-A-plan-for-the-first-90-days-vF.pdf)
- Beheshtian, A., Donaghy, K. P., Geddes, R. R., & Rouhani, O. M. (2017). Planning resilient motor-fuel supply chain. *International Journal of Disaster Risk Reduction*, 24(June), 312–325. <https://doi.org/10.1016/j.ijdr.2017.06.021>
- Cardoso, S. R., Barbosa-Póvoa, A. P. F. D., & Relvas, S. (2013). Design and planning of supply chains with integration of reverse logistics activities under demand uncertainty. *European Journal of Operational Research*, 226(3), 436–451. <https://doi.org/10.1016/j.ejor.2012.11.035>
- Chang, W. S., & Lin, Y. T. (2019). The effect of lead-time on supply chain resilience performance. *Asia Pacific Management Review*, 24(4), 298–309. <https://doi.org/10.1016/j.apmr.2018.10.004>
- Chen, L., Dui, H., & Zhang, C. (2020). A resilience measure for supply chain systems considering the interruption with the cyber-physical systems. *Reliability Engineering and System Safety*, 199(July 2019), 106869. <https://doi.org/10.1016/j.ress.2020.106869>
- Childerhouse, P., Al Aqqad, M., Zhou, Q., & Bezuidenhout, C. (2020). Network resilience modelling: a New Zealand forestry supply chain case. *International Journal of Logistics Management*, 31(2), 291–311. <https://doi.org/10.1108/IJLM-12-2018-0316>
- Chowdhury, M. M. H., & Quaddus, M. A. (2015). A multiple objective optimization based QFD approach for efficient resilient strategies to mitigate supply chain vulnerabilities: The case of garment industry of Bangladesh. *Omega (United Kingdom)*, 57, 5–21. <https://doi.org/10.1016/j.omega.2015.05.016>
- Christopher, M., & Peck, H. (2004). Building the Resilient Supply Chain. *The International Journal of Logistics Management*, 15(2), 1–14. <https://doi.org/10.1108/09574090410700275>
- Colicchia, C., Dallari, F., & Melacini, M. (2010). Increasing supply chain resilience in a global sourcing context. *Production Planning and Control*, 21(7), 680–694. <https://doi.org/10.1080/09537280903551969>
- Das, K., & Lashkari, R. S. (2017). Planning Production Systems Resilience by Linking Supply Chain Operational Factors. *Operations and Supply Chain Management: An International Journal*, 10(2), 110–129. <https://doi.org/10.31387/oscm0270184>
- Datta, P. (2017). Supply network resilience: A systematic literature review and future research. *International Journal of Logistics Management*, 28(4), 1387–1424. <https://doi.org/10.1108/IJLM-03-2016-0064>
- Day One Staff. (2020). *Amazon has hired 175,000 additional people*. Day One The Amazon Blog. <https://blog.aboutamazon.com/company-news/amazon-hiring-for-additional-75-000-jobs>
- De Assunção, M. V. D., Medeiros, M., Moreira, L. N. R., Paiva, I. V. L., & Paes, C. A. D. S. (2020).

- RESILIENCE OF THE BRAZILIAN SUPPLY CHAINS DUE TO THE IMPACTS OF COVID- 19. *Holos*, 36(5), 1–20. <https://doi.org/10.15628/holos.2020.10802>
- Dixit, V., Seshadrinath, N., & Tiwari, M. K. (2016). Performance measures based optimization of supply chain network resilience: A NSGA-II + Co-Kriging approach. *Computers and Industrial Engineering*, 93, 205–214. <https://doi.org/10.1016/j.cie.2015.12.029>
- Ehlen, M. A., Sun, A. C., Pepple, M. A., Eidson, E. D., & Jones, B. S. (2014). Chemical supply chain modeling for analysis of homeland security events. *Computers and Chemical Engineering*, 60, 102–111. <https://doi.org/10.1016/j.compchemeng.2013.07.014>
- Fabius, V., Lowrie, J., Magni, M., Murphy, R., & Timelin, B. (2020). How CPG companies can sustain profitable growth in the next normal. *McKinsey & Company Insights*, July.
- FICO. (2020). *Vencedores do FICO Decisions Awards 2019 anunciados! Empresas celebradas por sua excelência analítica*. <https://www.fico.com/br/newsroom/winners-2019-fico-decisions-awards-announced>
- Fiksel, J. (2015). From Risk to Resilience. In *Resilient by Design* (pp. 19–34). https://doi.org/10.5822/978-1-61091-588-5_2
- Furtado, V., Kolaja, T., Mueller, C., & Salguero, J. (2020). Managing a manufacturing plant through the coronavirus crisis. *McKinsey & Company Insights*, April. <https://www.mckinsey.com/business-functions/operations/our-insights/managing-a-manufacturing-plant-through-the-coronavirus-crisis#signin/download/%2F~%2Fmedia%2FMcKinsey%2FBusinessFunctions%2FOperations%2FOur%20Insights%2FManaging%20a%20manufacturing%20plant%20thr>
- Gartner Inc. (2020a). Gartner for Supply Chain Weathering the Storm: Supply Chain Resilience in an Age of Disruption. *Gartner Inc.*, May.
- Gartner Inc. (2020b). The Gartner Supply Chain Top 25 for 2020. In *Gartner Inc.*
- Gholami-Zanjani, S. M., Jabalameli, M. S., Klibi, W., & Pishvae, M. S. (2020). A robust location-inventory model for food supply chains operating under disruptions with ripple effects. *International Journal of Production Research*. <https://doi.org/10.1080/00207543.2020.1834159>
- Gkanatsas, E., & Krikke, H. (2020). Towards a pro-silience framework: A literature review on quantitative modelling of resilient 3PL supply chain network designs. *Sustainability (Switzerland)*, 12(10). <https://doi.org/10.3390/su12104323>
- Goldbeck, N., Angeloudis, P., & Ochieng, W. (2020). Optimal supply chain resilience with consideration of failure propagation and repair logistics. *Transportation Research Part E: Logistics and Transportation Review*, 133(February 2019), 101830. <https://doi.org/10.1016/j.tre.2019.101830>
- Gružauskas, V., Gimžauskienė, E., & Navickas, V. (2019). Forecasting accuracy influence on logistics clusters activities: The case of the food industry. *Journal of Cleaner Production*, 240. <https://doi.org/10.1016/j.jclepro.2019.118225>
- Han, Y., Chong, W. K., & Li, D. (2020). A systematic literature review of the capabilities and performance metrics of supply chain resilience. *International Journal of Production Research*, 58(15), 1–26. <https://doi.org/10.1080/00207543.2020.1785034>
- Harrison, T. P., Houn, P. J., Thomas, D. J., Christopher, W., Journal, S. T., & Spring, N. (2013). Supply Chain Disruptions Are Inevitable — Get READI : Resiliency Enhancement Analysis via Deletion

- and Insertion. *Transportation Journal*, 52(2), 264–276.
- Hippold, S. (2020). 6 Strategies for a More Resilient Supply Chain. Gartner.Com. <https://www.gartner.com/smarterwithgartner/6-strategies-for-a-more-resilient-supply-chain/>
- Hobbs, J. E. (2020). Food supply chains during the COVID-19 pandemic. *Canadian Journal of Agricultural Economics*, 68(2), 171–176. <https://doi.org/10.1111/cjag.12237>
- Hoek, R. van. (2020). Research opportunities for a more resilient post-COVID-19 supply chain – closing the gap between research findings and industry practice. *International Journal of Operations and Production Management*, 40(4), 341–355. <https://doi.org/10.1108/IJOPM-03-2020-0165>
- Hohenstein, N.-O., Feisel, E., Hartmann, E., & Giunipero, L. (2015). Research on the phenomenon of supply chain resilience A systematic review and paths for further. *International Journal of Physical Distribution & Logistics Management*, 45(1/2), 90–117. <https://doi.org/http://dx.doi.org/10.1108/IJPDLM-05-2013-0128>
- Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, 125(December 2018), 285–307. <https://doi.org/10.1016/j.tre.2019.03.001>
- Ivanov, D. (2020). ‘A blessing in disguise’ or ‘as if it wasn’t hard enough already’: reciprocal and aggravate vulnerabilities in the supply chain. *International Journal of Production Research*, 58(11), 3252–3262. <https://doi.org/10.1080/00207543.2019.1634850>
- Ivanov, D., Dolgui, A., & Sokolov, B. (2018). Scheduling of recovery actions in the supply chain with resilience analysis considerations. *International Journal of Production Research*, 56(19), 6473–6490. <https://doi.org/10.1080/00207543.2017.1401747>
- Ivanov, D., & Sokolov, B. (2019). Simultaneous structural–operational control of supply chain dynamics and resilience. *Annals of Operations Research*, 283(1–2), 1191–1210. <https://doi.org/10.1007/s10479-019-03231-0>
- Ivanov, D., Sokolov, B., Solovyeva, I., Dolgui, A., & Jie, F. (2016). Dynamic recovery policies for time-critical supply chains under conditions of ripple effect. *International Journal of Production Research*, 54(23), 7245–7258. <https://doi.org/10.1080/00207543.2016.1161253>
- Kamalahmadi, M., & Parast, M. M. (2016). A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research. *International Journal of Production Economics*, 171, 116–133. <https://doi.org/10.1016/j.ijpe.2015.10.023>
- Khalili, S. M., Jolai, F., & Torabi, S. A. (2017). Integrated production–distribution planning in two-echelon systems: a resilience view. *International Journal of Production Research*, 55(4), 1040–1064. <https://doi.org/10.1080/00207543.2016.1213446>
- Kochan, C. G., & Nowicki, D. R. (2018). Supply chain resilience: a systematic literature review and typological framework. *International Journal of Physical Distribution and Logistics Management*, 48(8), 842–865. <https://doi.org/10.1108/IJPDLM-02-2017-0099>
- KPMG. (2020). *Global Manufacturing Outlook 2020: COVID-19 Special Edition*.
- Li, R., Dong, Q., Jin, C., & Kang, R. (2017). A new resilience measure for supply chain networks. *Sustainability (Switzerland)*, 9(1), 1–19. <https://doi.org/10.3390/su9010144>
- Li, Y., & Zobel, C. W. (2020). Exploring supply chain network resilience in the presence of the ripple

- effect. *International Journal of Production Economics*, 228(June 2019), 107693. <https://doi.org/10.1016/j.ijpe.2020.107693>
- Liu, S., & Papageorgiou, L. G. (2013). Multiobjective optimisation of production, distribution and capacity planning of global supply chains in the process industry. *Omega (United Kingdom)*, 41(2), 369–382. <https://doi.org/10.1016/j.omega.2012.03.007>
- Lohmer, J., Bugert, N., & Lasch, R. (2020). Analysis of resilience strategies and ripple effect in blockchain-coordinated supply chains: An agent-based simulation study. *International Journal of Production Economics*, 228(January). <https://doi.org/10.1016/j.ijpe.2020.107882>
- Lücker, F., & Seifert, R. W. (2017). Building up Resilience in a Pharmaceutical Supply Chain through Inventory, Dual Sourcing and Agility Capacity. *Omega (United Kingdom)*, 73, 114–124. <https://doi.org/10.1016/j.omega.2017.01.001>
- Lund, S., Manyika, J., Woetzel, J., Barriball, E., Krishnan, M., Alicke, K., Brishan, M., George, K., Smit, S., Swan, D., & Hutzler, K. (2020). Risk, resilience, and rebalancing in global value chains. *McKinsey & Company Insights*, August, 112. <https://www.mckinsey.com/business-functions/operations/our-insights/risk-resilience-and-rebalancing-in-global-value-chains?cid=other-eml-nsi-mip-mck&hlkid=adc58eff0fc94b4ab75aaa0b0e82dbec&hctky=11801264&hdpid=c7533413-0bda-4b1d-8c5a-d4d66a414da3>
- Mao, X., Lou, X., Yuan, C., & Zhou, J. (2020). Resilience-based restoration model for supply chain networks. *Mathematics*, 8(2). <https://doi.org/10.3390/math8020163>
- Marzantowicz, Ł., Nowicka, K., & Jedliński, M. (2020). Smart „plan b” – in face with disruption of supply chains in 2020. *Logforum*, 16(4), 487–502. <https://doi.org/10.17270/J.LOG.2020.486>
- Mavrotas, G. (2009). Effective implementation of the ϵ -constraint method in Multi-Objective Mathematical Programming problems. *Applied Mathematics and Computation*, 213(2), 455–465. <https://doi.org/10.1016/j.amc.2009.03.037>
- Mavrotas, G., & Florios, K. (2013). An improved version of the augmented s-constraint method (AUGMECON2) for finding the exact pareto set in multi-objective integer programming problems. *Applied Mathematics and Computation*, 219(18), 9652–9669. <https://doi.org/10.1016/j.amc.2013.03.002>
- McDonalds. (2020a). *McDonald's Provides Update On COVID-19 Impact To The Business And Reports First Quarter 2020 Comparable Sales*. McDonalds. <https://news.mcdonalds.com/news-releases/news-release-details/mcdonalds-provides-update-covid-19-impact-business-and-reports>
- McDonalds. (2020b). *McDonald's USA to Serve Customers through Drive-Thru, Walk-In Take-Out and McDelivery*. <https://news.mcdonalds.com/McDonalds-US-coronavirus-update>
- McKinsey. (2020). Coronavirus' business impact: Evolving perspective | McKinsey. *McKinsey & Company*, 8. <https://www.mckinsey.com/business-functions/risk/our-insights/covid-19-implications-for-business>
- Munoz, A., & Dunbar, M. (2015). On the quantification of operational supply chain resilience. *International Journal of Production Research*, 53(22), 6736–6751.

<https://doi.org/10.1080/00207543.2015.1057296>

- Namdar, J., Li, X., Sawhney, R., & Pradhan, N. (2018). Supply chain resilience for single and multiple sourcing in the presence of disruption risks. *International Journal of Production Research*, 56(6), 2339–2360. <https://doi.org/10.1080/00207543.2017.1370149>
- P&G. (2020a). *CONSTRUCTIVE DISRUPTION ACROSS THE VALUE CHAIN*. <https://us.pg.com/annualreport2020/constructive-disruption-across-the-value-chain/>
- P&G. (2020b). *OUR COVID-19 RESPONSE*. <https://us.pg.com/covid19/>
- P&G. (2020c). *Supporting P&G's Suppliers at A Critical Time*. <https://us.pg.com/blogs/supporting-pg-suppliers-at-critical-time/>
- Panetta, K. (2020). *8 Macro Factors That Will Shape the 2020s*. <https://www.gartner.com/smarterwithgartner/8-macro-factors-that-will-shape-the-2020s/>
- Park, K. T., Son, Y. H., & Noh, S. Do. (2020). The architectural framework of a cyber physical logistics system for digital-twin-based supply chain control. *International Journal of Production Research*, 1–22. <https://doi.org/10.1080/00207543.2020.1788738>
- Pinner, D., Rogers, M., & Samandari, H. (2020). Addressing Climate Change in a Post-Pandemic World. *McKinsey Quarterly*, April, 1–6. <https://www.mckinsey.com/~media/McKinsey/Business Functions/Sustainability/Our Insights/Addressing climate change in a post pandemic world/Addressing-climate-change-in-a-post-pandemic-world-v3.ashx>
- Pires Ribeiro, J., & Barbosa-Póvoa, A. (n.d.). A responsiveness metric for the design and planning of resilient supply chains. *Submitted for Publication*.
- Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. In *The International Journal of Logistics Management* (Vol. 20, Issue 1). <https://doi.org/10.1108/09574090910954873>
- Raghu, A. (2020). *How satellites are helping track food supplies in coronavirus era*. Bloomberg. <https://theprint.in/world/how-satellites-are-helping-track-food-supplies-in-coronavirus-era/400463/>
- Raj, R., Wang, J. W., Nayak, A., Tiwari, M. K., Han, B., Liu, C. L., & Zhang, W. J. (2015). Measuring the resilience of supply chain systems using a survival model. *IEEE Systems Journal*, 9(2), 377–381. <https://doi.org/10.1109/JSYST.2014.2339552>
- Ramezankhani, M. J., Torabi, S. A., & Vahidi, F. (2018). Supply chain performance measurement and evaluation: A mixed sustainability and resilience approach. *Computers and Industrial Engineering*, 126(September), 531–548. <https://doi.org/10.1016/j.cie.2018.09.054>
- Rapaccini, M., Sacconi, N., Kowalkowski, C., Paiola, M., & Adrodegari, F. (2020). Navigating disruptive crises through service-led growth: The impact of COVID-19 on Italian manufacturing firms. *Industrial Marketing Management*, 88(May), 225–237. <https://doi.org/10.1016/j.indmarman.2020.05.017>
- Ribeiro, J. P., & Barbosa-Povoa, A. (2018). Supply Chain Resilience: Definitions and quantitative modelling approaches – A literature review. *Computers and Industrial Engineering*, 115(May 2017), 109–122. <https://doi.org/10.1016/j.cie.2017.11.006>
- Rice, J. B., & Caniato, F. (2003). Building a secure and resilient supply network. *Supply Chain*

- Management Review*, 7(5), 22–30.
- Salehi, V., Salehi, R., Mirzayi, M., & Akhavizadegan, F. (2020). Performance optimization of pharmaceutical supply chain by a unique resilience engineering and fuzzy mathematical framework. *Human Factors and Ergonomics In Manufacturing*, 30(5), 336–348. <https://doi.org/10.1002/hfm.20845>
- Sawyer, E., & Harrison, C. (2020). Developing resilient supply chains: lessons from high-reliability organisations. *Supply Chain Management*, 25(1), 77–100. <https://doi.org/10.1108/SCM-09-2018-0329>
- Schmitt, A. J., & Singh, M. (2012). A quantitative analysis of disruption risk in a multi-echelon supply chain. *International Journal of Production Economics*, 139(1), 22–32. <https://doi.org/10.1016/j.ijpe.2012.01.004>
- Sharma, S. K., & George, S. A. (2018). Modelling resilience of truckload transportation industry. *Benchmarking: An International Journal*, 25(7), 2531–2545. <https://doi.org/10.1108/BIJ-07-2017-0188>
- Shashi, Centobelli, P., Cerchione, R., & Ertz, M. (2020). Managing supply chain resilience to pursue business and environmental strategies. *Business Strategy and the Environment*, 29(3), 1215–1246. <https://doi.org/10.1002/bse.2428>
- Sheffi, Y. (2005). Preparing for the big one. *IEE Manufacturing Engineer*, 84(5), 12–15. <https://doi.org/10.1049/me:20050503>
- Shekarian, M., & Parast, M. M. (2020). An Integrative approach to supply chain disruption risk and resilience management: a literature review. *International Journal of Logistics Research and Applications*, 5567(May). <https://doi.org/10.1080/13675567.2020.1763935>
- Singh, S., Ghosh, S., Jayaram, J., & Tiwari, M. K. (2019). Enhancing supply chain resilience using ontology-based decision support system. *International Journal of Computer Integrated Manufacturing*, 32(7), 642–657. <https://doi.org/10.1080/0951192X.2019.1599443>
- Sodhi, M. S., & Tang, C. S. (2021). Supply Chain Management for Extreme Conditions: Research Opportunities. *Journal of Supply Chain Management*, 57(1), 7–16. <https://doi.org/10.1111/jscm.12255>
- Spiegler, V. L. M., Potter, A. T., Naim, M. M., & Towill, D. R. (2016). The value of nonlinear control theory in investigating the underlying dynamics and resilience of a grocery supply chain. *International Journal of Production Research*, 54(1), 265–286. <https://doi.org/10.1080/00207543.2015.1076945>
- Sprecher, B., Daigo, I., Spekkink, W., Vos, M., Kleijn, R., Murakami, S., & Kramer, G. J. (2017). Novel Indicators for the Quantification of Resilience in Critical Material Supply Chains, with a 2010 Rare Earth Crisis Case Study. *Environmental Science and Technology*, 51(7), 3860–3870. <https://doi.org/10.1021/acs.est.6b05751>
- Stone, J., & Rahimifard, S. (2018). Resilience in agri-food supply chains: a critical analysis of the literature and synthesis of a novel framework. *Supply Chain Management*, 23(3), 207–238. <https://doi.org/10.1108/SCM-06-2017-0201>
- Tang, C., & Tomlin, B. (2008). The power of flexibility for mitigating supply chain risks. *International*

- Journal of Production Economics*, 116(1), 12–27. <https://doi.org/10.1016/j.ijpe.2008.07.008>
- Thomas, A. V., & Mahanty, B. (2019). Interrelationship among resilience, robustness, and bullwhip effect in an inventory and order based production control system. *Kybernetes*, 49(3), 732–752. <https://doi.org/10.1108/K-11-2018-0588>
- Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: Definition, review and theoretical foundations for further study. *International Journal of Production Research*, 53(18), 5592–5623. <https://doi.org/10.1080/00207543.2015.1037934>
- Unilever. (2020). *How we're adopting deodorant production lines to make hand sanitiser*. Unilever. <https://www.unilever.com.my/news/news-and-features/2020/how-were-adapting-deodorant-production-lines-to-make-hand-sanitiser.html>
- Wang, J., Muddada, R. R., Wang, H., Ding, J., Lin, Y., Liu, C., & Zhang, W. (2016). Toward a resilient holistic supply chain network system: Concept, review and future direction. *IEEE Systems Journal*, 10(2), 410–421. <https://doi.org/10.1109/JSYST.2014.2363161>
- Wang, X., Herty, M., & Zhao, L. (2016). Contingent rerouting for enhancing supply chain resilience from supplier behavior perspective. *International Transactions in Operational Research*, 23(4), 775–796. <https://doi.org/10.1111/itor.12151>
- Wu, T., Huang, S., Blackhurst, J., Zhang, X., & Wang, S. (2013). Supply chain risk management: An agent-based simulation to study the impact of retail stockouts. *IEEE Transactions on Engineering Management*, 60(4), 676–686. <https://doi.org/10.1109/TEM.2012.2190986>
- Yang, Y., Pan, S., & Ballot, E. (2017). Mitigating supply chain disruptions through interconnected logistics services in the Physical Internet. *International Journal of Production Research*, 55(14), 3970–3983. <https://doi.org/10.1080/00207543.2016.1223379>
- Zavala-Alcívar, A., Verdecho, M.-J., & Alfaro-Saiz, J.-J. (2020). A conceptual framework to manage resilience and increase sustainability in the supply chain. *Sustainability (Switzerland)*, 12(16), 1–38. <https://doi.org/10.3390/SU12166300>
- Zhao, K., Zuo, Z., & Blackhurst, J. V. (2019). Modelling supply chain adaptation for disruptions: An empirically grounded complex adaptive systems approach. *Journal of Operations Management*, 65(2), 190–212. <https://doi.org/10.1002/joom.1009>
- Zhu, G., Chou, M. C., & Tsai, C. W. (2020). Lessons Learned from the COVID-19 pandemic exposing the shortcomings of current supply chain operations: A long-term prescriptive offering. *Sustainability (Switzerland)*, 12(14), 1–19. <https://doi.org/10.3390/su12145858>

Annex A: Stochastic Model Formulation

Additional sets

Table 24: Additional sets

Sets	Indices	Description
DT	dt	Number of time periods
S	s, ss	Scenario nodes
ST	(s,t)	Time periods belonging to a scenario node
preS	(ss,s,dt,t)	Predecessor ss of scenario s at a distance dt from period t
fwS	(ss,s,dt,t)	Successor ss of scenario s at distance dt from period t

Additional parameters

- $rvar_s$ variation of products' return percentage for scenario s (%)
 $var_{s,t}$ variation of demand for scenario s at time period t (%)
 pb_s probability of node s to occur

Objective functions

$$Max Z_1 = \frac{profit}{profitREF} - \frac{\sum_p \sum_{m \in PM} \sum_{t \in ST} \sum_s pb_s \times LS_{p,m,s,t}}{\sum_p \sum_{m \in PM} \sum_{t \in ST} \sum_s pb_s \times demand_{p,m,s,t}} \quad (A.1)$$

$$profit = \sum_s pb_s \times (sales_s - (TMC_s + TTC_s + TIC_s + TDC_s)) - TFC \quad (A.2)$$

$$sales_s = \sum_p \sum_{pp \in ALT} \sum_{m \in PM} \sum_{t \in ST} sellprice_{pp} \times SA_{p,pp,m,s,t} \quad (A.3)$$

$$TMC_s = \sum_i \sum_j \sum_f \sum_{t \in ST} mc_{i,j} \times FSF_{i,j,f,s,t} + \sum_{p \in PF} \sum_f \sum_{t \in ST} vpc_{p,f} \times PRO_{p,f,s,t} \\ + \sum_i \sum_f \sum_{t \in ST} scosti \times SPOi_{i,f,s,t} + \sum_{p \in PF} \sum_f \sum_{t \in ST} scostp \times SPOp_{p,f,s,t} \quad (A.4)$$

$$TTC_s = \sum_i \sum_j \sum_f \sum_{t \in ST} vtcs_{i,j,f} \times FSF_{i,j,f,s,t} + \sum_{p \in PF} \sum_f \sum_r \sum_{t \in ST} vtcr_{p,f,r} \times FFR_{p,f,r,s,t} \\ + \sum_{p \in PF} \sum_f \sum_{m \in PM} \sum_{t \in ST} vtcd_{p,f,m} \times (FFM_{p,f,m,s,t} + RMF_{p,m,f,s,t}) \\ + \sum_p \sum_r \sum_{m \in PM} \sum_{t \in ST} vtc_{p,r,m} \times (FRM_{p,r,m,s,t} + RMR_{p,m,r,s,t}) \\ + \sum_{p \in PF} \sum_f \sum_d \sum_{t \in ST} vtcd_{p,d,f} \times RFD_{p,f,d,s,t} \quad (A.5)$$

$$TIC_s = \sum_i \sum_f \sum_{t \in ST} invcf_{i,f} \times INVf_{i,f,s,t} + \sum_{p \in PF} \sum_f \sum_{t \in ST} invcf_{p,f} \times INVf_{p,f,s,t} \\ + \sum_p \sum_r \sum_{t \in ST} invcr_{p,r} \times INVR_{p,r,s,t} \quad (A.6)$$

$$TDC_s = \sum_{p \in PF} \sum_f \sum_{m \in PM} \sum_{t \in ST} dcm_{p,f,m} \times FFM_{p,f,m,s,t} + \sum_{p \in PF} \sum_f \sum_r \sum_{t \in ST} dcr_{p,f,r} \times FFR_{p,f,r,s,t} \quad (A.7)$$

$$TFC = \sum_{p \in PF} \sum_f fpc_{p,f} \times E_{p,f} + \sum_f fcec_f \times XE_f + \sum_f \sum_t vcec_f \times CAPInc_{f,t} + \sum_j \sum_f ftcs_{j,f} \times Xs_{j,f} \\ + \sum_f \sum_r ftcr_{f,r} \times Xr_{f,r} + \sum_f \sum_m ftcd_{f,m} \times Xd_{f,m} + \sum_r \sum_m ftc_{r,m} \times Xm_{r,m} \quad (A.8)$$

$$Min Z_2 = \sum_s pb_s \times \left(\sum_i \sum_j \sum_f \sum_{t \in ST} (tts_{j,f} \times liunit_i \times FSF_{i,j,f,s,t}) \right. \\ + \sum_{p \in PF} \sum_f \sum_{t \in ST} pt_{p,f} \times PRO_{p,f,s,t} + \sum_{p \in PF} \sum_f \sum_r \sum_{t \in ST} (ttr_{f,r} \times lunit_p \times FFR_{p,f,r,s,t}) \\ + \sum_{p \in PF} \sum_f \sum_{m \in PM} \sum_{t \in ST} (ttd_{f,m} \times lunit_p \times FFM_{p,f,m,s,t}) \\ \left. + \sum_p \sum_r \sum_{m \in PM} \sum_{t \in ST} (ttm_{r,m} \times lunit_p \times FRM_{p,r,m,s,t}) \right) \quad (A.9)$$

Constraints

$$pmin_{p,f} \times W_{p,f,t} \leq PRO_{p,f,s,t} \leq pmax_{p,f} \times W_{p,f,t} \quad \forall (p,f) \in PF, (s,t) \in ST \quad (A.10)$$

$$\sum_{p \in PF} (PRO_{p,f,t} \times ireq_{p,i}) = CON_{i,f,t} \quad \forall i, f, (s,t) \in st \quad (A.11)$$

$$\sum_{p: pt=0 \wedge p \in PF} PRO_{p,f,s,t} \leq CAP_{f,tt} \quad \forall f, (s,t) \in ST \quad (A.12)$$

$$\sum_{p \in PF} \sum_{s \in ST} \sum_{preS} \sum_{dt: dt=tt-t} ONG_{p,f,s,ss,tt} \leq CAP_{f,tt} \quad \forall f, (ss,tt) \in ST \quad (A.13)$$

$$ONG_{p,f,s,ss,tt} = PRO_{p,f,s,t} \quad \forall (p,f) \in PF, (s,t) \wedge (ss,tt) \in ST \cap fwS, \quad t \leq tt < t + pt_{p,f}, \\ dt = tt - t, \quad (A.14)$$

$$CAP_{f,t} = CAP_{f,t-1} + CAPInc_{f,t-stime_f} \quad \forall f, t > 1 \quad (A.15)$$

$$CAP_{f,t} = icap_f + CAPInc_{f,t-stime_f} \quad \forall f, t = 1 \quad (A.16)$$

$$pcemin \times icap_f \times XE_f \leq \sum_t CAPInc_{f,t} \leq pcemax \times icap_f \times XE_f \quad \forall f \in F_{own} \quad (A.17)$$

$$ocemin \times XE_f \leq \sum_t CAPInc_{f,t} \leq ocemax \times XE_f \quad \forall f \in F_{out} \quad (A.18)$$

$$INVfi_{i,f,s,t} = \sum_{(ss,dt) \in preS \wedge dt=1} INVfi_{i,f,ss,t-1} - CON_{i,f,s,t} + \sum_j \sum_{(ss,dt) \in preS \wedge dt=tts} FSF_{i,j,f,ss,t-tts_{j,f}} \\ + (1 - dis) \times \sum_{p \in PF} \sum_{m \in PM} \sum_{(ss,dt) \in preS \wedge dt=ttd} (RMF_{p,m,f,ss,t-ttd_{f,m}} \times ireq_{p,i}) \quad \forall i, f, (s,t) \in ST, t > 1 \quad (A.19)$$

$$INVfi_{i,f,s,t} = invinf_{i,f} - CON_{i,f,s,t} + \sum_j \sum_{(ss,dt) \in preS \wedge dt=tts} FSF_{i,j,f,ss,t-tts_{j,f}} \\ + (1 - dis) \times \sum_{p \in PF} \sum_{m \in PM} \sum_{(ss,dt) \in preS \wedge dt=ttd} (RMF_{p,m,f,ss,t-ttd_{f,m}} \times ireq_{p,i}) \quad \forall i, f, (s,t) \in ST, t = 1 \quad (A.20)$$

$$INVfp_{p,f,s,t} = \sum_{(ss,dt) \in preS \wedge dt=1} INVfp_{p,f,ss,t-1} + \sum_{(ss,dt) \in preS \wedge dt=pt} PRO_{p,f,ss,t-pt_{p,f}} - \sum_r FFR_{p,f,r,s,t} \\ - \sum_{m \in PM} FFM_{p,f,m,s,t} \quad \forall (p,f) \in PF, (s,t) \in ST, t > 1 \quad (A.21)$$

$$INVfp_{p,f,t} = invinf p_{p,f} + \sum_{\substack{(ss,dt) \in preS \wedge dt=pt \\ \in PF, (s,t) \in ST, t=1}} PRO_{p,f,ss,t-pt_{p,f}} - \sum_r FFR_{p,f,r,s,t} - \sum_{m \in PM} FFM_{p,f,m,s,t} \quad \forall (p,f) \quad (A.22)$$

$$INVr_{p,r,s,t} = \sum_{(ss,dt) \in preS \wedge dt=1} INVr_{p,r,ss,t-1} + \sum_{f \in PF} \sum_{(ss,dt) \in preS \wedge dt=ttr} FFR_{p,f,r,ss,t-ttr_{f,r}} + \sum_{m \in PM} \sum_{(ss,dt) \in preS \wedge dt=ttr} RMR_{p,m,r,ss,t-ttr_{r,m}} - \sum_{m \in PM} FRM_{p,r,m,s,t} \quad \forall p,r, (s,t) \in ST, t > 1 \quad (A.22)$$

$$INVr_{p,r,s,t} = invinr_{p,r} + \sum_{f \in PF} \sum_{(ss,dt) \in preS \wedge dt=ttr} FFR_{p,f,r,ss,t-ttr_{f,r}} + \sum_{m \in PM} \sum_{(ss,dt) \in preS \wedge dt=ttr} RMR_{p,m,r,ss,t-ttr_{r,m}} - \sum_{m \in PM} FRM_{p,r,m,s,t} \quad \forall p,r, (s,t) \in ST, t = 1 \quad (A.23)$$

$$(\mincol + rvar_s) \times (nconf + rvar_s) \times \sum_{p \in ALT \wedge PM} SA_{p,pp,m,s,t} \leq \sum_r RMR_{pp,m,r,s,t} \leq (nconf + rvar_s) \times \sum_{p \in ALT \wedge PM} SA_{p,pp,m,s,t} \quad \forall (pp,m) \in PM, (s,t) \in ST, t \quad (A.24)$$

$$(\mincol + rvar_s) \times \sum_{p \in ALT \wedge PM} \sum_{(ss,dt) \in preS \wedge dt=lt} SA_{p,pp,m,s,t-lt_p} \leq \sum_{f \in PF \wedge F_{own}} RMF_{pp,m,f,t} \leq \sum_{p \in ALT \wedge PM} \sum_{(ss,dt) \in preS \wedge dt=lt} SA_{p,pp,m,s,t-lt_p} \quad \forall (pp,m) \in PM, (s,t) \in ST, t \quad (A.25)$$

$$\sum_d RFD_{p,f,d,t} = dis \times \sum_{m \in PM} \sum_{(ss,dt) \in preS \wedge dt=ttd} RMF_{p,m,f,t-ttd_{f,m}} \quad \forall (p,f) \in PF \wedge F_{own}, (s,t) \in ST \quad (A.26)$$

$$fmin \times Ys_{j,f,t} \leq \sum_i FFS_{i,j,f,s,t} \leq fmax \times Ys_{j,f,t} \quad \forall j,f, (s,t) \in ST \quad (A.27)$$

$$fmin \times Yr_{f,r,t} \leq \sum_{p \in PF} FFR_{p,f,r,s,t} \leq fmax \times Yr_{f,r,t} \quad \forall f,r, (s,t) \in ST \quad (A.28)$$

$$fmin \times Yd_{f,m,t} \leq \sum_{p \in PF \cap PM} FFM_{p,f,m,s,t} \leq fmax \times Yd_{f,m,t} \quad \forall f,m, (s,t) \in ST \quad (A.29)$$

$$fmin \times Ym_{r,m,t} \leq \sum_{p \in PM} FRM_{p,r,m,s,t} \leq fmax \times Ym_{r,m,t} \quad \forall r,m, (s,t) \in ST \quad (A.30)$$

$$fmin \times Ync_{m,r,t} \leq \sum_{p \in PM} RMR_{p,m,r,s,t} \leq fmax \times Ync_{m,r,t} \quad \forall r,m, (s,t) \in ST \quad (A.31)$$

$$fmin \times Yel_{m,f,t} \leq \sum_{p \in PF \cap PM} RMF_{p,m,f,s,t} \leq fmax \times Yel_{m,f,t} \quad \forall f,m, (s,t) \in ST \quad (A.32)$$

$$invminfi_{i,f} \leq INVfi_{i,f,s,t} \quad \forall i,f, (s,t) \in ST \quad (A.33)$$

$$invminfp_{p,f} \leq INVfp_{p,f,s,t} \quad \forall (p,f) \in PF, (s,t) \in ST \quad (A.34)$$

$$\sum_{p \in PF} INVfp_{p,f,t} + \sum_i INVfi_{i,f,t} \leq invmaxf_f \quad \forall f, (s,t) \in ST \quad (A.35)$$

$$invminr_{p,r} \leq INVr_{p,r,s,t} \quad \forall p,r, (s,t) \in ST \quad (A.36)$$

$$\sum_p INV_{p,r,s,t} \leq invmaxr_r \quad \forall r, (s,t) \in ST \quad (A.37)$$

$$\sum_s pb_s \times \left(\frac{\sum_p \sum_t INV_{p,r,s,t}}{tnum} \right) \leq \sum_s pb_s \times \left(\frac{\sum_p \sum_{m \in PM} \sum_t FRM_{p,r,m,s,t}}{turn} \right) \quad \forall r \quad (A.38)$$

$$\sum_{pp:(pp,m) \in PM \wedge (p,pp) \in ALT} SA_{p,pp,m,s,t} \leq DEM_{p,m,s,t} \quad \forall (p,m) \in PM, (s,t) \in ST \quad (A.39)$$

$$DEM_{p,m,s,t} = 0 \quad \forall (p,m) \in PM, (s,t) \in ST, t < 8 \quad (A.40)$$

$$DEM_{p,m,s,t} = idem_{p,m} \quad \forall (p,m) \in PM, (s,t) \in ST, t = 8 \quad (A.41)$$

$$DEM_{p,m,s,t} = \sum_{(ss,dt) \in preS \wedge dt=1} (DEM_{p,m,ss,t-1}) \times var_{s,t} \quad \forall (p,m) \in PM, (s,t) \in ST, t > 8 \quad (A.42)$$

$$\begin{aligned} & \sum_{p:(p,m) \in PM \wedge (p,pp) \in ALT} SA_{p,pp,m,s,t} \\ &= \sum_{f \in PF} \sum_{ss \in preS \wedge dt=ttd} FFM_{pp,f,m,ss,t-ttd_{f,m}} \\ &+ \sum_r \sum_{ss \in preS \wedge dt=ttm} FRM_{pp,r,m,ss,t-ttm_{r,m}} \quad \forall (pp,m) \in PM, (s,t) \in ST \end{aligned} \quad (A.43)$$

$$DEM_{p,m,s,t} - \sum_{pp:(pp,m) \in PM \wedge (p,pp) \in ALT} SA_{p,pp,m,t} = LS_{p,m,s,t} \quad \forall (p,m) \in PM, (s,t) \in ST \quad (A.44)$$

$$\sum_p \sum_{m \in PM} \sum_s \sum_{t \in ST} pb_s \times LS_{p,m,s,t} \leq ds \times \sum_p \sum_{m \in PM} \sum_s \sum_{t \in ST} pb_s \times DEM_{p,m,s,t} \quad (A.45)$$

$$\sum_t W_{p,f,t} \leq tnum \times E_{p,f} \quad \forall (p,f) \in PF \quad (A.46)$$

$$\sum_t Y_{s_j,f,t} \leq tnum \times X_{s_j,f} \quad \forall j, f \quad (A.47)$$

$$\sum_t Y_{d_{f,m},t} \leq tnum \times X_{d_{f,m}} \quad \forall f, m \quad (A.48)$$

$$\sum_t Y_{r_{f,r},t} \leq tnum \times X_{r_{f,r}} \quad \forall f, r \quad (A.49)$$

$$\sum_t Y_{m_{r,m},t} \leq tnum \times X_{m_{r,m}} \quad \forall r, m \quad (A.50)$$

Annex B: Results for response strategy analysis of the deterministic model

Point A'

Table 25: Deterministic model results with different response strategy, fixing decisions of point A

Sol	Res Metric	Flow Time	Profit	SL	Revenue	TMC	TTC	TDC	TIC	TEC
Ref	1,000	51 124	396 403	1,00	632 683	175 121	54 260	4 323	326	2 250
<i>2 Weeks Disruption</i>										
Supply	0,288	27 971	153 676	0,90	557 028	341 382	33 621	5 984	2 786	19 580
Prod	0,288	27 971	153 823	0,90	556 894	341 449	33 611	6 069	2 779	19 164
Transp	0,288	27 971	153 587	0,90	560 123	344 299	33 631	6 153	2 786	19 667
<i>4 Weeks Disruption</i>										
Supply	0,287	27 971	153 304	0,90	556 597	341 562	33 599	5 934	2 720	19 479
Prod	0,288	27 971	153 788	0,90	556 893	341 488	33 608	6 069	2 777	19 164
Transp	0,287	27 971	153 304	0,90	556 597	341 562	33 599	5 934	2 720	19 479
<i>4 Weeks Disruption with Delay</i>										
Supply	0,255	28 862	140 805	0,90	554 885	346 884	36 184	5 961	2 724	22 326
Prod	0,273	31 350	147 656	0,90	554 865	341 299	37 527	5 595	2 358	20 431
Transp	0,321	32 572	166 896	0,90	560 508	327 895	38 127	5 628	2 362	19 602

SL: Service Level; TMC: Manufacturing Cost; TTC: Transportation Cost; TDC: Duties Cost; TIC: Inventory Cost; TEC: Capacity Expansion Cost

Point B'

Table 26: Deterministic model results with different response strategy, fixing decisions of point B

Sol	Res Metric	Flow Time	Profit	SL	Revenue	TMC	TTC	TDC	TIC	TEC
Ref	0,146	7 987	97 666	0,900	561 713	428 093	10 466	7 034	335	18 118
<i>2 Weeks Disruption</i>										
Supply	0,597	27 754	240 907	0,989	625 032	317 040	30 613	7 774	310	28 387
Prod	0,588	27 785	240 576	0,981	619 398	312 664	30 833	7 291	265	27 769
Transp	0,597	28 349	241 957	0,986	623 046	314 140	31 349	7 401	327	27 873
<i>4 Weeks Disruption</i>										
Supply	0,591	26 320	238 484	0,989	624 852	320 545	29 125	8 366	273	28 059
Prod	0,577	28 976	239 557	0,973	614 357	307 801	31 890	7 112	299	27 698
Transp	0,596	28 183	241 703	0,986	623 130	314 682	31 240	7 393	324	27 788
<i>4 Weeks Disruption with Delay</i>										
Supply	0,540	22 955	218 095	0,990	623 465	340 063	25 773	8 478	268	30 788
Prod	0,505	23 962	211 473	0,972	612 772	332 011	26 762	7 600	224	34 703
Transp	0,528	23 869	217 660	0,979	617 426	335 254	26 694	7 779	252	29 788

Point C'

Table 27: Deterministic model results with different response strategy, fixing decisions of point C

Sol	Res Metric	Flow Time	Profit	SL	Revenue	TMC	TTC	TDC	TIC	TEC
Ref	0,642	18 771	254 643	1,00	628 612	324 923	21 116	13 194	263	14 473
<i>2 Weeks Disruption</i>										
Supply	0,186	10 880	113 246	0,90	555 783	394 217	13 549	9 258	365	25 148
Prod	0,180	10 880	111 012	0,90	562 438	401 344	13 660	9 380	435	26 607
Transp	0,184	10 880	112 363	0,90	558 922	397 882	13 575	9 242	348	25 511
<i>4 Weeks Disruption</i>										
Supply	0,185	10 880	112 948	0,90	558 434	396 814	13 590	9 327	372	25 383
Prod	0,175	10 880	108 944	0,90	562 049	403 723	13 622	8 628	376	26 756
Transp	0,180	10 880	110 978	0,90	561 582	401 806	13 647	9 053	315	25 783
<i>4 Weeks Disruption with Delay</i>										
Supply	0,180	10 880	111 134	0,90	555 808	394 324	13 639	9 269	375	27 067
Prod	0,139	10 895	94 877	0,90	560 755	414 940	13 638	8 707	346	28 247
Transp	0,128	10 883	90 380	0,90	562 483	421 458	13 625	9 389	339	27 291

SL: Service Level; TMC: Manufacturing Cost; TTC: Transportation Cost; TDC: Duties Cost; TIC: Inventory Cost; TEC: Capacity Expansion Cost

Annex C: Results for response strategy analysis of the stochastic model

Point A'

Table 28: Stochastic model results with different response strategy, fixing decisions of point A

Sol	Res Metric	Flow Time	Profit	SL	Revenue	TMC	TTC	TDC	TIC	TEC
Ref	0,984	48 674	414 620	0,99	643 841	171 061	53 452	3 895	639	174
<i>2 Weeks Disruption</i>										
Supply	0,34	27 234	183 028	0,90	586 987	342 702	33 882	6 089	2 537	18 750
Prod	0,34	27 234	183 446	0,90	586 750	342 288	33 895	6 096	2 645	18 380
Transp	0,34	27 234	183 611	0,90	587 435	342 109	33 983	5 897	2 744	19 090
<i>4 Weeks Disruption</i>										
Supply	0,33	27 234	178 411	0,90	586 459	343 026	33 868	6 304	2 724	22 127
Prod	0,30	27 234	167 972	0,90	582 260	349 821	35 914	5 423	2 426	20 704
Transp	0,34	27 234	183 156	0,90	586 875	342 577	33 915	6 093	2 631	18 503
<i>4 Weeks Disruption with Delay</i>										
Supply	0,31	28 089	170 281	0,90	584 679	347 672	36 377	5 862	2 388	22 099
Prod	0,32	30 218	174 367	0,90	584 585	344 648	37 719	5 831	2 350	19 671
Transp	0,35	30 973	187 848	0,90	587 189	334 311	38 013	5 472	2 328	19 216

SL: Service Level; TMC: Manufacturing Cost; TTC: Transportation Cost; TDC: Duties Cost; TIC: Inventory Cost; TEC: Capacity Expansion Cost

Point B'

Table 29: Stochastic model results with different response strategy, fixing decisions of point B

Sol	Res Metric	Flow Time	Profit	SL	Revenue	TMC	TTC	TDC	TIC	TEC
Ref	0,200	8 271	124 653	0,900	584 403	421 932	11 952	7 154	245	18 466
<i>2 Weeks Disruption</i>										
Supply	0,627	26 898	270 612	0,976	636 831	300 343	30 880	7 447	350	27 199
Prod	0,604	27 572	268 964	0,956	623 750	292 434	31 694	6 494	368	23 796
Transp	0,623	27 518	271 638	0,969	631 403	296 486	31 796	6 648	322	24 513
<i>4 Weeks Disruption</i>										
Supply	0,625	27 096	269 755	0,976	636 898	300 737	31 277	7 544	344	27 242
Prod	0,604	28 441	268 697	0,957	624 393	292 201	32 480	6 349	425	24 240
Transp	0,623	27 672	271 554	0,969	631 776	296 530	31 956	6 692	329	24 715
<i>4 Weeks Disruption with Delay</i>										
Supply	0,568	22 778	245 914	0,976	637 675	324 295	26 321	8 663	331	32 150
Prod	0,536	23 962	242 403	0,953	622 599	314 875	27 515	7 535	308	29 963
Transp	0,538	22 936	239 840	0,960	626 206	324 476	26 675	7 309	318	27 589