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Analysis of quantitative methods to evaluate resilience in a supply chain network

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INTRODUCTION

This thesis, starting from an analysis of the existing literature, aims to identify and analyze a range of methods for the quantitative calculation of resilience in the supply chain with a focus in the event of disruption.

With the development of globally distributed supply chains, the topic has been increasingly analyzed and various approaches and methodologies have been proposed in the literature to address the complex management, improvement techniques and study of possible dangers. In fact, the activities carried out in the distribution chain have an intrinsic risk of unforeseen interruptions. This is due to factors such as an ever-increasing tendency to offer lean and just in time services, the deterioration rate in products and the uncertainty of demand that have reduced the time available to manage any unexpected events.

The need to deal with unknown events has become even more evident with the recent Covid-19 pandemic, which has forced many companies to modify or completely suspend their processes temporarily due to unforeseen interruptions such as local quarantines and lock downs, or also as drastic changes in availability of materials and transportations.

What this thesis will therefore deal with, are the quantitative methods that allow the numerical evaluation of the resilience of a supply chain. This kind of methods allows to take into consideration various aspects and characteristics of the supply chain. Some of these aspects are impacting on performance, recovery time, economic damage and time of survival. The final goal is for decision makers to have the tools to compare different chains and evaluate their own networks.

1. SUPPLY CHAIN RESILIENCE

In this modern competitive world, modern SCs are designed to be efficient and effective; supply chains are multi-tier complex networks, which are distributed and connected globally. Although these qualities enable the SC to work efficiently, it increases the SC's vulnerability to various risks.

Supply chain risks are categorized into two main types, such as operational and disruption risks (Chen et al., 2013).

As a recent example worldwide disasters, we've seen with COVID-19, can have a far-reaching and global impact upon supply chain logistics, suppliers, and workforces. Other examples of supply chain disruptions can come in the form of unexpected competition, sudden market trends, or even rapid changes in customer shopping behaviors.

In order to fully understand what the key aspects and differences that are present in the various methods of calculating resilience that will be subsequently analyzed, we must initially ask ourselves what is the concept of resilience and what are the main attributes that a company must adopt to have a resilient chain. This topic has been extensively discussed in the literature and various definitions have been proposed over time that take more or less into account various key aspects.

A first possible example of definition was given by Closs & McGarrell (2004) SC resilience is the supply chain's ability to withstand and recover from an incident. A resilient supply chain is proactive - anticipating and establishing planned steps to prevent and respond to incidents. Such supply chains quickly rebuild or reestablish alternative means of operations when the subject of an incident.

This cited definition underlines as main aspects the ability to prepare in advance for uncertain events and to restore company operations, leaving out however important details such as the quality of this new achieved state. In fact, it does not refer to the quality of the operational state to be attained and whether this should be equal to or better than the previous one.

In order to address this dilemma in the literature, different definitions have been cataloged and compared in the study by Tukamuhabwa & Benjamin R (2015) in which the two more exhaustive among those analyzed where given by Ponis and by Ponomarov.

- In the study of Ponis & Koronis (2012) the definition is: supply chain resilience is the ability to proactively plan and design the supply chain network for anticipating unexpected disruptive (negative events), respond adaptively to disruptions while maintaining control over structure and function and transcending to a post robust state of operations, if possible a more favorable one than that prior to the event, thus gaining a competitive advantage.
- The second definition was given in the paper by Ponomarov (2012): SC resilience is the adaptive capability of a firm's supply chain to prepare for unexpected events, respond to disruptions, and recover from them in a timely manner by maintaining continuity of operations at the desired level of connectedness and control over structure and function.

Looking now at the content and differences between this two, the former includes aspects related to robustness and competitive advantage but compared to the latter it lacks the aspect related to time efficiency in which the SC is supposed to reach the post-disruption state. Furthermore, neither of the two definitions considers the economic component in terms of results obtainable compared with the costs and efforts necessary to achieve them.

The reduction of costs through a rapid and effective coordination is a necessary focus of resilient supply chains (Xiao et al. 2012).

Indeed this important aspect is discussed from an interesting point of view in the Resilience index as cost of establishing resilience: here authors aim to considered that the cost of reaching a state of greater resilience, and therefore better preparation for potential disruptive events, could exceed the economic loss that a firm would have to bear facing the disruptive event with the existing SC resilience level. This is challenging the concept of improving the network allowing decision makers to evaluate investments and their potential effectiveness in the overall business frame.

A final definition was therefore proposed in the study Tukamuhabwa & Benjamin R (2015), SC resilience is the adaptive capability of a supply chain to prepare for and/or respond to disruptions, to make a timely and cost effective recovery, and therefore progress to a post disruption state of operations – ideally, a better state than prior to the disruption where adaptability means that the supply chain must have the ability to change and provide an appropriate response even to events never seen before and it is not enough to select a recovery method from a pre-existing list, this includes forecasting and anticipating cases of disruption that could be faced in order to be able to mitigate or completely avoid its effects.

Later a different approach to a definition in supply chain resilience has been given by Hosseini & Ivanov (2019) which defined SC resilience as SC capability to utilize the absorptive capacity of SC entities to repulse and withstand the impacts of perturbations, to minimize the consequences of disruptions and their propagation by utilizing adaptive capacity, and to recover performance level to normal operations in a cost-efficient manner using restorative capacity when absorptive and adaptive capacities are not sufficient.

In this new perspective, beside the definition itself, it is highlighted and explained in which steps a disruption event impacts a firm, underlining how resilience, as identified in the paper by Biringer et al. (2013), is made of three consequent different types of strategies. Absorptive capacity is the ability to absorb the disruption thanks to proactively prepare measure that does not require a system reconfiguration. The concept of absorptive capacity defines two distinct metrics: potential absorptive capacity and realized absorptive capacity.

- Potential absorptive capacity allows organizations to be more alert or cognizant of potential and realized disruptions through acquiring and assimilating knowledge (Zahra and George, 2002).
- Realized absorptive capacity allows organizations to transform and exploit knowledge created via acquisition and assimilation (Zahra and George, 2002).

This first resilience layer according to a recent study by Roth (Roth et al 2021) enables firms to better prepare for disruption and can be strengthened by improving and learning from small day to day "disrupting" events providing a different viewpoint form other literature papers where day to day risks are considered as a different category and analyzed with different approaches.

Their findings are that study also offers insight into the issue of whether learning by experience applies to the context of resilience; specifically, whether the ability to absorb low-impact disruptions gives organizations experiences and processes that better enable them to handle high-impact disruptions. Significant positive associations of low impact resilience to high impact resilience suggest strong linkages between the two levels of resilience for organizations in all the operating conditions (Roth et al 2021).

The second resilience layer is made by Adaptive capacity, this comes into action when, due to a disruption, the firm is not able to withstand it with its current system operations but have to adapt and to change its process during the disruption and the recovery period. The final part of resilience is made by restorative capacity, this comes into action after large scale events such as natural disaster or pandemic like Covid-19 where the firm has to restore and rebuild facilities, workforce and processes. However, few researches have focused on long term and global risks, such as pandemics, which generate a sudden breakdown in supply, production and demand lasting for several months, as we have seen during the first months COVID-19 containment (Ivanov and Dolgui, 2020; Ivanon 2020b).

The current crisis has given rise to a new challenge relating to the survivability of SCs, which had not been studied intensively in the pre-pandemic SC literature (Ivanov and Dolgui, 2020). The question of SC survivability goes beyond the existing state-of-the-art in SC management. It cannot be resolved within a narrow SC perspective, but rather requires an analysis on a larger scale (Ivanov, 2020a; Ivanov and Dolgui, 2020).

After Covid-19 literature is pointing out that the classical resilience capacities such as absorptive, adaptive and restorative, are no longer enough to deal with such long term disruption and a fourth concept needs to be introduced. Supply chain survivability capacity, a kind of resilience to allow the supply chain to stay alive temporary during a longer period and recover after it.

Akram's study define SC survivability as the ability to stay alive in a temporary non-viable equilibrium during a large disruption (Akram, 2022). Akram's paper found three new strategies adopted by firms during this survival period:

- the first one is called subsidies strategy which consist of asking for public financial aid. This maintains artificially the circulation of financial flows but may be ineffective if there is not a real revival in customer demand in the months following the end of the containment (Akram, 2022).

- Hibernation strategy that consists of stopping production, massively reducing expenses, and living on liquidity reserves (Akram , 2022). Hibernation could slow down the economy until the pandemic is brought under control and preserve those vital relationships for a quicker recovery. If all stakeholders share the burden of economic inactivity, firms are more likely to survive. Financing could help cover firms' reduced operational costs until the pandemic subdues (Didier et al, 2020).

- Migration strategy (Akram, 2022) which means to redirect production into manufacturing items that can support markets that are still functioning or facing a surge in demand during the long disruption.

One example of this last survival strategy is given by BACARDÍ's premium rum distillery in Puerto Rico, the largest in the world, partnered with Olein Refinery to combat the shortage of personal disinfectant by providing raw material ethanol to be used in hand sanitizers (Bacardi, 2020).

During the pandemic, also Fiat Chrysler (FCA) has begun producing ventilator parts to help Italy's Siare Engineering boosting its output production flow of the medical equipment needed to treat patients during the coronavirus crisis, the carmaker said on Friday (Reuters, 2020).

1.1. Definition and types of disruption

The risk of disruption is classified as HILF or high impact and low frequency of occurrence. It is considered difficult to predict as it consists of events such as Natural disasters, political unrest, economic crises and pandemic diseases. Its repercussions are very strong in the supply chain, making it therefore difficult to estimate and manage.

Disruption risks unpredictably vary in type, scale, and nature. They are intermittent and irregular to be identified, estimated, and forecasted well. They may have short- and long-term negative effects (Ho et al. 2015; Torabi et al. 2015; Dolgui et al. 2018; He et al. 2019; Hosseini et al. 2019a; Ivanov and Sokolov 2020).

A disruption event can cause different types of repercussions and ripple effects, the Covid-19 pandemic was one that caused and made it possible to observe different types of crises based on the sector / geographical location in which the supply chain was operating.

Subsequently we will analyze some of the main consequences on supply chains that occurred following the recent pandemic. On a high level, trying to initially grasp the overall impact, it is shown in the pie-chart, Fig. 1.1, as result of a survey that 56 percent of global retailers reported moderate disruption in their supply chains as a result of the COVID-19 pandemic, 12 percent of retailers reported heavy disruption.

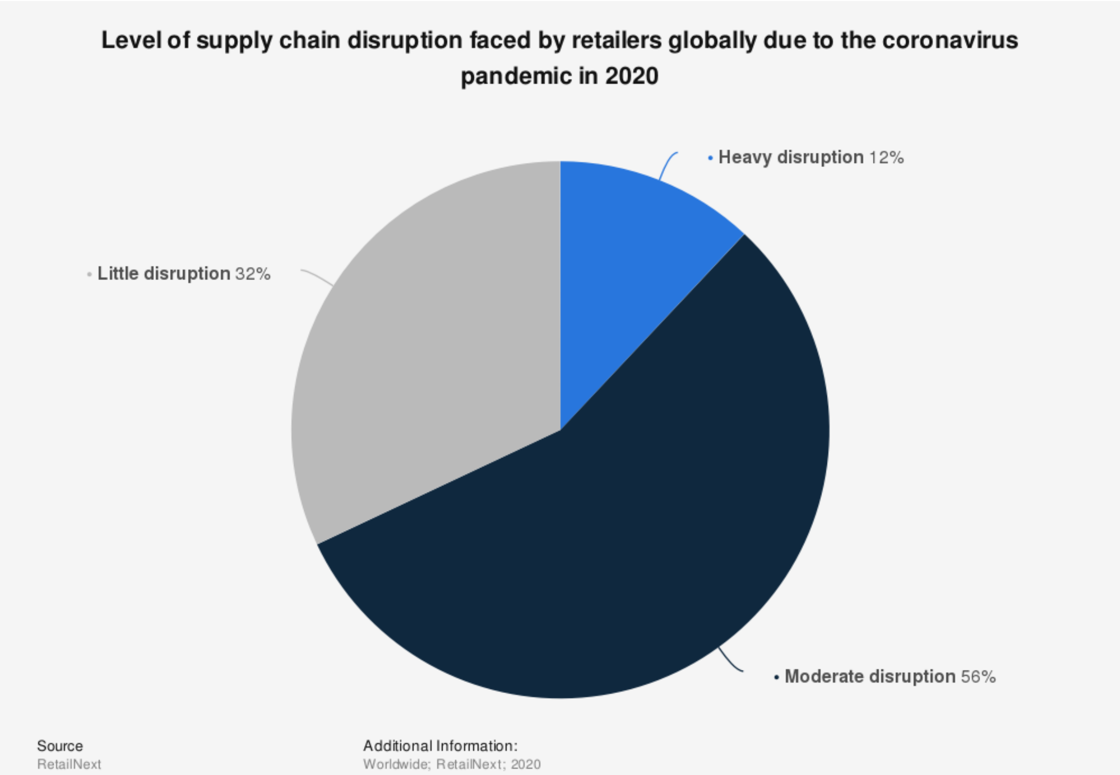

Fig. 1.1

1.1.1. Demand drops

A demand drop is defined as a decrease in a product's sales, either due to a temporary or permanent decrease in consumer demand.

The effect of demand drops in supply chain resilience is that it can create further stress for the supply chain, as well as potentially cause a cascading effect that impacts much more than just one organization. Despite all the shocks caused, the survivability of SCs with critical demand disturbances during COVID-19 remains unclarified in the literature (Schleper et al, 2021).

An extreme example can be seen in the airlines industry where, due to restrictions on travel, it saw collapses up to 95% during the first April Covid-19 compared to the same month of the previous year (Josephs, 2020). As can be seen in the Fig. 1.2 , the demand did not only drop but never recovered throughout the whole year, creating a long term survivability threat.

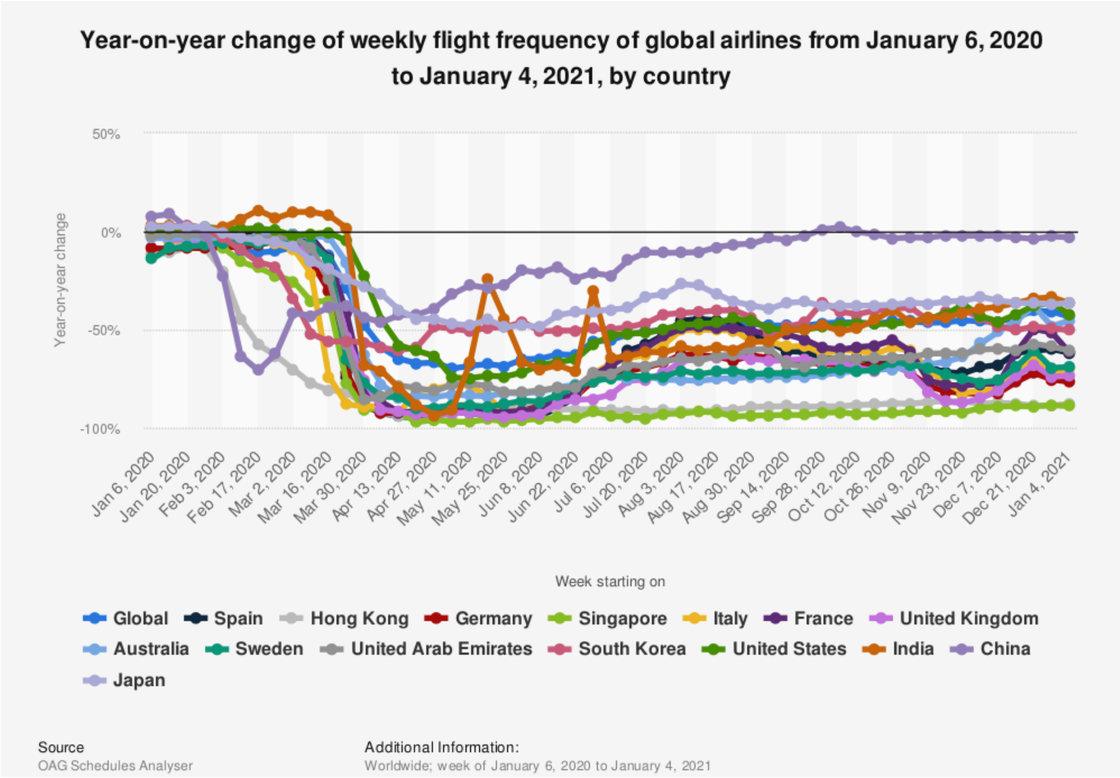

Fig. 1.2

Other examples have been reported in the textiles, clothing and fashion industry which suffered a 27% to 30% contraction of sales as reported by DeMarco (DeMarco, 2020). This sector has also experienced unprecedented demand crises which are seriously threatening the firms ‘survival and their social ecosystems (Bevilacqua et al.,2020; Majumdar et al.,2020).

1.1.2. Demand surges

Demand surges are caused by unexpected increases in the requested volume of a product or service that requires supply to meet demand in an efficient and timely manner.

This is the opposite case compare to the previous one and was seen in sectors such as toilet paper and hygiene products in the United States where, driven by the panic of the imminent quarantine, there has been an unexpected peak in demand which has led to a general shortage when no one was prepared with productions and stocks to cope with its spike.

As shown in the following picture, Fig. 1.3, by the end of march 2020 70% of U.S. grocery stores and online shops were out of stock (Wieczner , 2020).

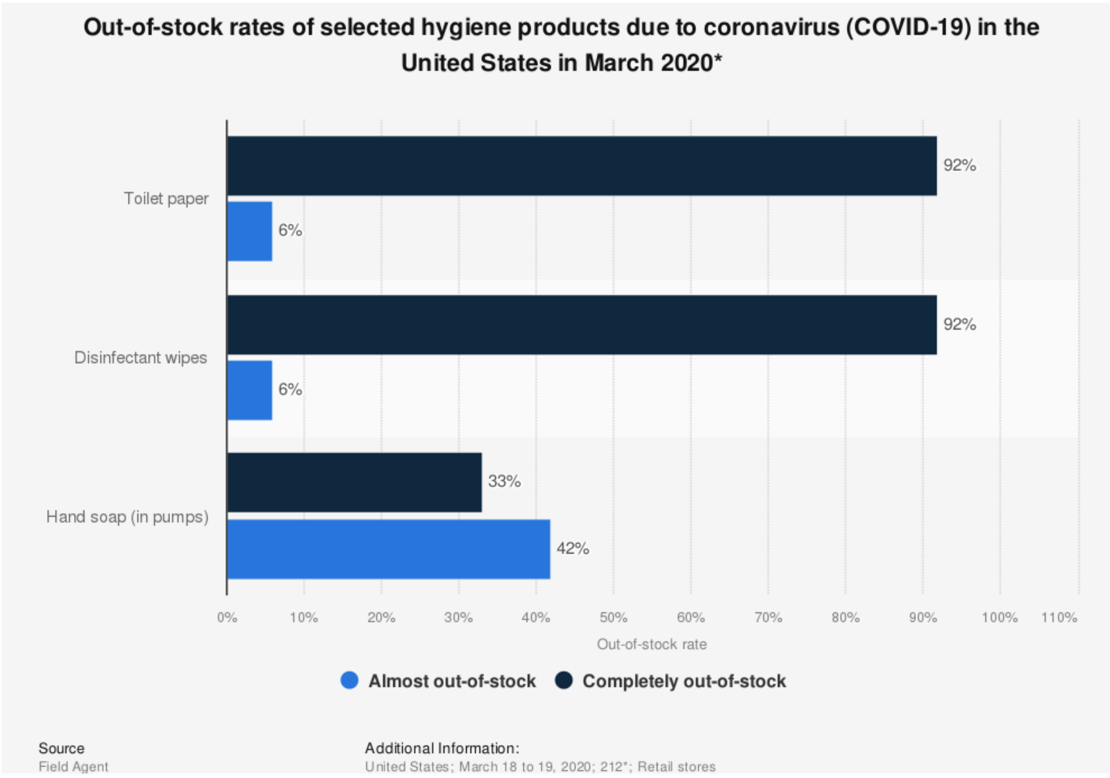

Fig. 1.3

1.1.3. Reduced productivity

Another type of effect caused is the reduced productivity. In general this can happen due to lack of manpower, lack of equipment or other events that reduce the possible output. In this case, the disease and quarantine at home, have produced a unexpected peak in worker absences and reduced psychophysical well-being given the ongoing problems.

The following chart, Fig. 1.4, shows the result of a survey among workers to report mental health challenges faced due to the pandemic that can result in reduced productivity. Examples of this can be seen at Sysco is the industry's largest distributor for food and related products. As of the end of

March 2020, Sysco had laid off or furloughed around 33%, according to the company statement due to social distancing measures implemented across the country (Mathews, 2020).

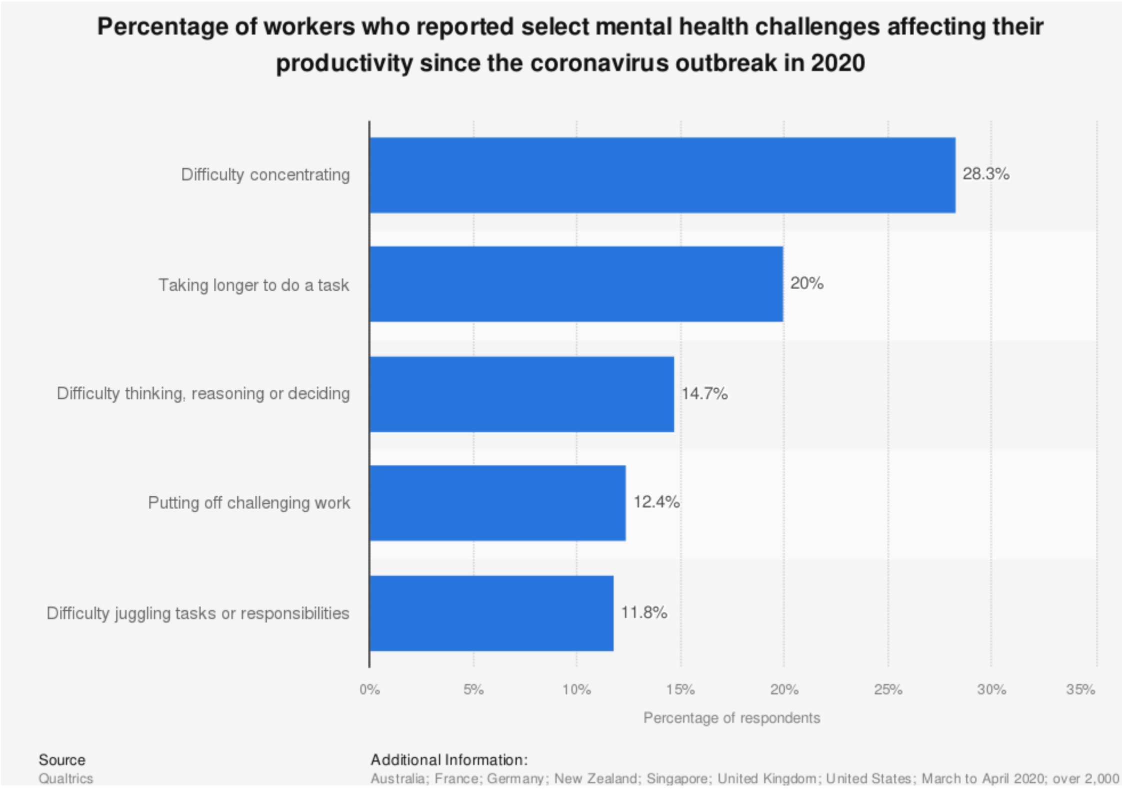

Fig. 1.4

1.1.4. Storage and access restrictions

The definition of Storage and access restrictions is a situation in which a shipment is either off-site (isolated), or not being held in a warehouse that can allow it to flow through the supply chain. This can be caused by health regulations, such as quarantine or quarantining, or if there is a need to access the product for inspection purposes.

During the pandemic, in many cases there was the impossibility of accessing and operating in production plants or warehouses due to a local outbreak of infections and temporary shutdown. This quickly obliges the firm to reconfigure the layout of the supply chain, or to use other spaces or to reconfigure the internal functioning of the systems to comply with the new distance rules and reduce the risk of contagion.

A study by Rinaldi (Rinaldi & Bottani, 2021) with an Italian logistic grocery provider, highlighted how the site manager has explained that the sense of uncertainty and the growing fear have led to the decision to provisionally close the site. Moreover, the warehouse was located in the first Italian red zone and many employees came from that area. The impact of the closure of the warehouse on the tons of products distributed compared to the previous year, forced to choose another site 200km away, out of the red area and it took the firm more than 11 weeks to move operations and restore normal working conditions.

1.1.5. Raw material shortage

A raw material shortage is the inability to acquire enough of the necessary input in a way that is timely and in sufficient quantity, to enable your business to run at maximum efficiency.

As Tom Derry (Tom Derry , 2020) the CEO of The Institute for Supply Management said during an interview “You have to realize that there’s almost no industry sector—and when I say that, I mean manufacturing and nonmanufacturing—that isn’t reliant on China in the United States”. An effect of this kind was seen during the Semiconductor Crisis for the automotive industry after Covid-19 outbreak since China was a heavily affected country and China is now the world’s largest sales market for semiconductor applications, with a market share of 35% in 2020 (Frieske, B.; Stieler, S.2022).

As their study has shown the COVID-19 pandemic and the subsequent shortage in semiconductor components proved to be a shock to the economy and the automobile industry: for the first time the entire world and almost all economic sectors were affected and supply chain disruptions will continue to negatively impact production capacities even in and beyond 2022 (Frieske, B.; Stieler, S.2022). It's found that the European automotive market suffered a ripple effect over China's production problem since the European and German automotive industries have little influence on the stability of semiconductor supply chains due to their small market share, but are heavily affected in terms of production capacities (Frieske, B.; Stieler, S.2022).

An in-depth study, Fig. 1.5, was conducted in 2021 by the consultancy firm Inverto with trade journal Handelsblatt surveying almost 100 directors and decision-makers in DACH region mainly in the production / mechanical industry: one year after covid-19 outbreak the disruption was still present as visible in the picture, raw materials prices and availability were the most impacting external factors in business performance.

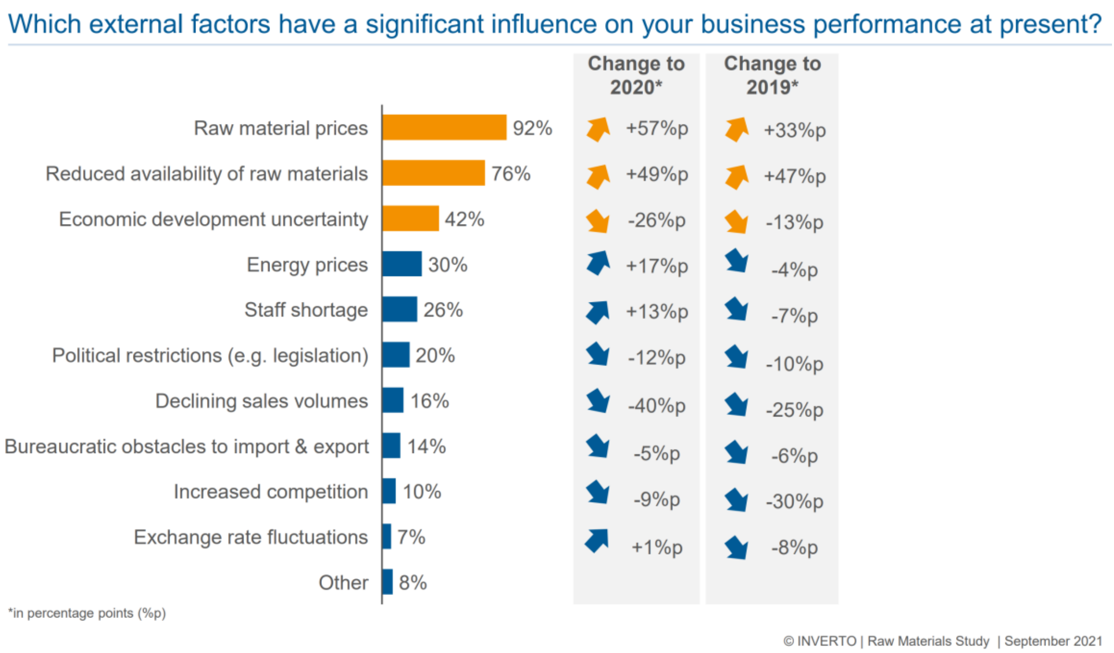

Fig. 1.5

Ultimately, a consumptive research over the effects of a rare disruptive events as Covid-19, provides valuable insights for risk management, as a risk management process is intended to anticipate risks that could arise in future operations.

The aim is to develop a method whereby all risks can be perfectly identified, even if, realistically, this is perhaps not possible. Simchi-Levi' s paper focus on the role of decision-makers and provides two dimensions of analysis by distinguishing known-unknown / unknown-unknown and controllable-uncontrollable risk (Simchi-Levi et al, 2008. Simchi-Levi, 2010).

His studies present different categories of risk status from the point of view of anticipation of potential risks and the real state of the operational system. The dimensions used to categorize risks are knowledge based. Know-known are risks predictable both in the form of what triggers them and what will the outcome be.

The known–unknowns are risks that can be predicted from analyses of past events, for example by the means of statistical data analysis, e.g. meantime to failure, supplier lead time (Simchi-Levi , 2010).

The unknown–unknowns are risks that can hardly be predicted. Terrorist attacks, epidemics, or geo-political instability are typical examples, but due to the climate change, also extreme weather events and related natural catastrophes will become harder to predict (Heckmann et al, 2015).

Controllable-uncontrollable is the second dimension provided by Simchi-Levi and refers to a firm's ability to handle risks and control their recurrence.

1.2. Drivers to Supply chain resilience

In recent years, the importance of supply chain resilience has been recognized as a critical factor in ensuring the success of organizations in the face of disruptive events. Various studies have highlighted the need to develop resilient supply chains that can withstand and recover from such events while minimizing their impact on operations.

While several enablers for supply chain resilience have been studied and explained in the literature, including redundancy, flexibility, collaboration, and agility, there has been a growing interest in leveraging big data analytics to enhance resilience. Therefore, the following section of this thesis aims to provide an overview of the key enablers for supply chain resilience identified in the literature. Such group of enablers can guide decision makers in the risk management process presenting the key points in building resilience in a SC.

1.2.1. Flexibility

Flexibility is a concept that arises from the need to decrease the adverse effects of uncertainty and risks in global supply chains (Liao,2020).

Flexibility is one of the main drivers, as is described by Tang & Tomlin can have a sort of butterfly effect in the ability to withstand disruption, minor changes in flexibility lead to a drastic reduction in disruption (Tang & Tomlin, 2008).

Supply chain flexibility can be described as the ability to change, optimize, and adapt the supply chain in response to changing market conditions (Katsaliaki et al., 2021). It provides benefits such as responding to and meeting demand changes such as seasonality, poor production periods, poor supplier performance, poor delivery performance and responding to new products, new markets or new markets (Katsaliaki et al., 2021). This can be achieved by integrating operational flexibility, systems flexibility and information technology into product development, sales and marketing activities.

Flexibility has been proven to enhance the supply chain to face those problems that also fall into the category of high frequency and small impact. Flexibility builds the capabilities and helps in sustaining the supply chain not only during disruptions, but it helps for continuous day-to-day operations (Asamoah at al, 2020; Queiroz et al, 2021).

The study made by Chirra in the implementation of flexibility among the supply chain, defined the biggest obstacle in ensuring the flexibility of global supply chains as the purchasing function of the global supply chain (Chirra et al. 2020). As in some cases the company finds itself dependent on a single component manufacturer or single geographical location from which certain raw materials are exported, this is the case of the Europe automotive industries that suffered a ripple effect due to disruption in Chinese semiconductor production.

1.2.2. Stock reserve

Reserve Capacity is the ability to absorb losses in a supply chain without impacting the business's overall ability to deliver products or services.

For example, if an organization's suppliers are suddenly unable to provide materials or service because of a disruption in trading relations or natural disaster, which could have significant consequences for the company. A firm should have buffer stock as well as back up capacity to mitigate uncertain environment (Chowdhury et al. 2017).

1.2.3. Integration

Supply chain integration is a key strategy for organizations to ensure their supply chain is robust and resilient.

To improve the company's performance, it is necessary to have a strategy to improve operational performance that is implemented through supplier integration, internal integration, and relationship management to customers (Cahyaningratri et al. 2022).

Some of the benefits include lower costs, increased efficiency, and better security. For example, integrating a supply chain increases the overall efficiency of manufacturing by reducing waste and inventory. If a shipment from overseas is delayed, it can cause some production to halt completely or at least reduce production levels in that sector.

Integration with a supply chain partner also improves quality performance, and it is a factor for the production system resilience of a business (Sun et al, 2012).

Another modern point of view for integration is software integration between different organizations, this enables real time transmissions to update multiple parties on events, messages and tracking updates which lead to an improved visibility over the real time status of the network and faster problem solving.

1.2.4. Redundancy

Redundant parts or processes are required to ensure that possible failures in the system are able to be resolved without stopping it, decreasing the impact and duration of any failure in critical areas of the system. Redundancy can also help to increase reliability by lowering the likelihood of a failure occurring, thereby improving service levels and reducing customer dissatisfaction.

Build redundancy it's considered to be expensive as the company must bear the costs of the redundant stock, capacity and workers, which can prove to be a very expensive measure. But as showed in studies by Shekarian (Shekarian et al 2020) and Ivanov and Dolgui (Ivanov, D., and A. Dolgui. 2020) flexibility and redundancy make supply chain networks less sensitive to external uncertainties.

And adding redundancy to the supply chain by designing a backup supply base, provides a better response to disruptions compared to adding volume flexibility, from the perspective of both cost and service level(Kamalahmadi et al,2022).

1.2.5. Agility

Supply chain agility is a methodology that allows organizations to understand suppliers, suppliers' customers and their ecosystems in order to make better planning, resources allocation and real-time decisions.

Christopher & Peck (Christopher M, Peck H , 2004) defined supply chain agility as the ability to respond quickly to unpredictable changes in demand or supply.This could perhaps be achieved through a rapid change to business processes and systems (Erol et al. 2010).

Christopher & Peck (Christopher M, Peck H , 2004) suggested that supply chain agility is mainly composed of visibility and velocity. Supply chain visibility refers to the ability to see through the entire supply chain. It enables a clear view of the whole chain, which may help in detecting signals of impending disruptions. Visibility implies having knowledge of the status of a supply chain's assets and environment (Pettit et al. 2013).

Thereby also helping to avoid overreactions, unnecessary interventions and ineffective decisions in circumstances of risk (Christopher & Lee 2004).

1.2.6. Recovery

Supply chain recovery is defined as the strategic and tactical processes to identify, develop and implement solutions to restore an organization s supply chain capability. Recovery efforts are directed at responding to the short-term volatility, that can occur following the disruption of one or more activities within a company s supply chain system.

A key purpose of supply chain recovery is to evaluate damage, prevent further damage, identify critical information and processes needed to respond effectively, develop repair plans, implement fixes and minimize future impact.

1.2.7. Collaboration

Collaboration in supply chain refers to when two or more independent firm works closely and implement appropriate supply chain strategies toward common aim (Scholten and Schilder, 2015).

Supply chain Collaboration is the ability of entities in the supply chain to actively communicate and share information so that they can better understand their own operations, and those of their partners. This allows them to mobilize, adapt and respond in order to ensure delivery of end products and services on time.

Lack of information sharing leads to vulnerability and increases the bullwhip effect throughout the supply chain (Yang and Fan, 2016).

The goal of supply chain collaboration is to facilitate communication, reduce costs associated with processing and certification, and enhance customer experience, thus increasing the competitiveness of both commodities and their final receiver.

1.2.8. Data analytics

Data analytics has considerably become an important tool in this optimization process. Despite increasing popularity, the academic literature on data analytics capability is still underdeveloped (Srinivasan and Swink,2018; Hazen et al. 2018).

The major areas where data analytics is used, include inventory management and ordering as well as real-time visibility, planning and forecasting of raw material requirements and production cycles. The purpose of data analytics is to understand data and uncover new aspects that otherwise would be invisible. Data analytics can be used to build robust models that can respond quickly, accurately and reliably to business requirements. Data analytics capability provides insights based on big data processing, on what to change to match environmental uncertainty (Srinivasan and Swink, 2018).

The study by Dubey (Dubey et al. 2021) reconciles the independent contributions of two well-established streams in the literature: studies that explain the use of data analytics capability to increase the data processing capacity and those that focus on supply chain resilience and competitive advantage. Finding support to their hypothesis and therefore relationships connecting those two aspects.

2. SUPPLY CHAIN RESILIENCE INDEX

Supply chain disruptions can have severe consequences for organizations, including financial losses, reputational damage, and customer dissatisfaction. As a result, there is a growing interest in developing strategies to improve the resilience of supply chain networks.

One approach to this challenge, is the use of supply chain resilience indexes, which provide a way to measure and compare the resilience of different supply chain networks.

In this chapter, we will explore the concept of supply chain resilience indexes, their advantages and limitations, and their potential applications.

A clear need for the improvement of decision-making tools so as to provide better and trustworthy information to decision makers was identified, which can only be achieved by developing more comprehensive quantitative models that represent real scenarios (Pires Riberio and Barbosa Povoa, 2018).

A supply chain resilience index is a measure of the ability of a supply chain network to withstand and recover from disruptions. It is calculated based on a set of indicators that capture different aspects of the supply chain's resilience, such as the robustness of the network, the flexibility of the operations, the redundancy of the inventory, and the agility of the response. The indicators can be weighted and aggregated into a single score, which represents the overall resilience of the supply chain network.

One of the advantages of using a supply chain resilience index is that it can summarize many aspects of the supply chain's resilience in one single number. This makes it easier for decision-makers to assess and compare the resilience of different supply chain networks, they may acquire an estimation on the resilience performance of the alternative options, that is, they will know which option performs the best in terms of resilience (Alexopoulos et al, 2022).

Another advantage of using a supply chain resilience index is that it can help identify weak parts in the supply chain network. By analyzing the indicators that contribute the most to the resilience score, decision-makers can pinpoint the areas of the supply chain that are most vulnerable to disruptions and prioritize their efforts to strengthen them. For example, if the inventory indicator has a low score, it may indicate that the supply chain network is overly reliant on a single supplier or lacks sufficient safety stock.

The index past simply being a means for assessing the network resilience; can be further transforms into a tool that upgrades the network and determines step-by-step network improvement decisions (Ahmadian et al 2020).

Supply chain resilience indexes can also be used to compare the resilience of different supply chains, such as those of competitors or suppliers. By benchmarking their own supply chain network against others, organizations can identify best practices, learn from others' experiences, and enhance their own resilience strategies. Additionally, by sharing their resilience scores with partners and stakeholders, organizations can build trust, promote transparency, and foster collaboration.

Despite their advantages, supply chain resilience indexes also have some limitations. For example, they may oversimplify the complexity of the supply chain network and fail to capture all the nuances and interactions among different components. Additionally, they may be influenced by the choice of indicators and weights, which can be subjective and context dependent. Finally, they may not be able to predict all potential disruptions, particularly those that are unforeseeable or outside of an organization's control.

In conclusion, supply chain resilience indexes offer a valuable tool for assessing, comparing, and improving the resilience of supply chain networks. While they have their limitations, they provide a useful framework for decision-makers to evaluate the strengths and weaknesses of their supply chain networks.

In the preceding section, will be provided broad research to the concept of supply chain resilience indexes, it will delve into the details of some new resilience indices that have emerged in the literature since the COVID-19 outbreak in early 2020. The aim is to present a comprehensive analysis of the latest proposed methods, focusing on their mathematical foundations and practical implications. By doing so, will be provided a deeper understanding of the current state-of-the-art in this rapidly evolving field.

The analysis of optimization models of SCR models show that future research efforts could explore multi-objective optimizations. We recommended potential future research avenues, which are divided into two classes: methodology based and subject based (Hosseini and Ivanov 2019).

The analysis will cover a range of resilience indices, each representing different ways to deal with supply chain performance in the face of disruptions. Will be explored how these indices can be used to identify weak points in supply chains, compare different supply chains, and evaluate the effectiveness of resilience strategies. To achieve this, will be examined the mathematical foundations and illustrate its practical implications through examples.

The purpose is that this detailed analysis of the latest resilience indices will be valuable to researchers, practitioners, and decision-makers alike. Ultimately, the goal is to contribute to the growing body of knowledge on supply chain resilience and help advance understanding of this critical field.

2.1. POC penalty of change

Alexopoulos's team (Alexopoulos et al. 2022), with their research, aims to provide a new method to calculate a supply chain resilience index that combines both technological and economical terms and does not require large and complex amounts of data for calculations.

It's base on the POC, penalty of change, the POC method expresses the expected cost of accommodating potential changes in the operating environment. The formula for the calculation of the penalty of change can be interpreted as the expected value of cost if a change occurs.

The definition of supply chain resilience, as explained by Hosseini & Ivanov (Hosseini, S.; Ivanov , 2019), states that the first defense against a disruption is the absorptive capacity, so that a firm doesn't have to change its operations to withstand the disruption and only if this is not enough the firm has to use adaptive capacity and restorative capacity Strategies, which will require an economic investment to adapt and change disrupted operations.

Based on this logic, the penalty of change is used as an index to measure supply chain resilience and it's flexibility based on the fact that ideally a supply chain would have a Poc of 0 because it could sustain whichever disruption, while a non-resilient one would have a higher Poc, because a cost in investments would be needed to change and survive during a disruption. This concept translates in: the lower the Poc, the more resilient a supply chain is.

The POC can be calculated by the following formula by Chryssolouris (Chryssolouris and Lee 1992; Chryssolouris 2006) which allows to create a probabilistic model that weights the impact of possible events, which makes the assumptions more realistic(Alexopoulos et al. 2022).

$$\text{POC} = \sum_{i=1}^{D} \text{Pn}\,(X_i)\text{Pr}\,(X_i)$$

Where D is the number of potential changes.

Xi is the i-th potential change.

Pn(Xi) is the penalty (cost) of the i-th potential change.

Pr(Xi) is the probability of the i-th potential change to occur.

With this single formula, it is possible to create different disruption scenarios taking also into account the ripple effect created by a an operational interruption over the rest of the system.

For example, representing evolutions of one/more disruption/s with a tree diagram decision-makers, can build a probabilistic model in which level 1,2,3… branches represent the probability of an event to propagate in many possible ways, an example is shown in Fig 2.1.

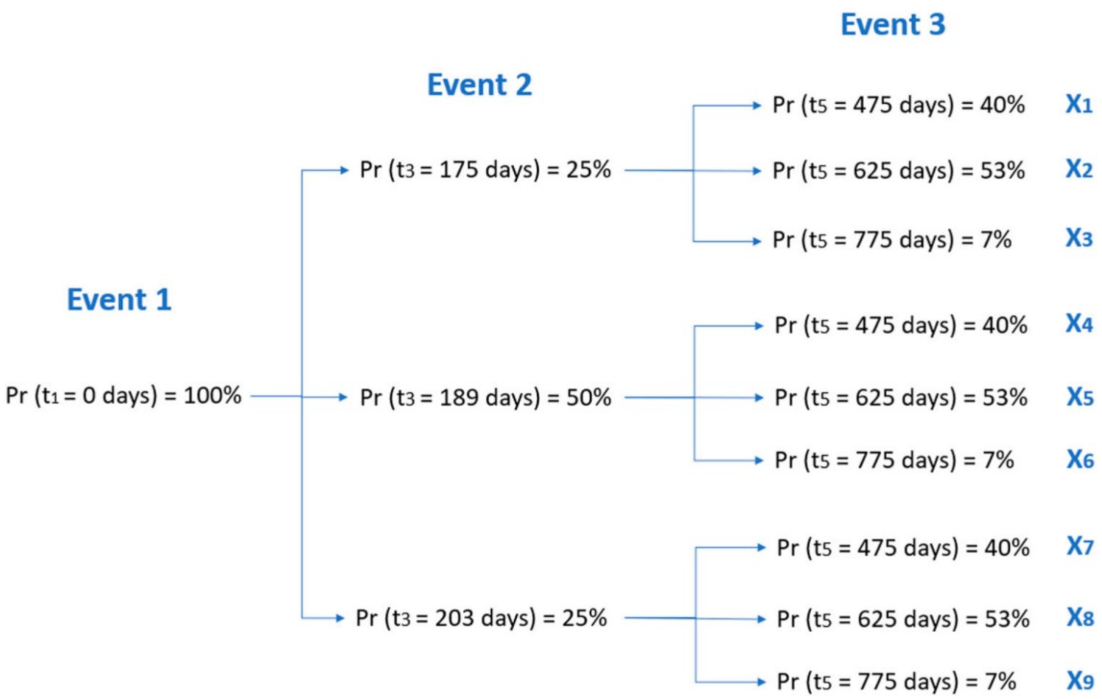

Fig. 2.1

In this tree diagram, each Xi final branch is associated to a Pn(Xi) cost, which can be represented in costs such as unmet demand, production loss or other valuable parameters for the company. At the end of this process N different alternatives will be created so that Xi | I belong to N to populate the whole diagram with the ramifications in scope for the resilience analysis.

This methodology presents strengths as being straightforward and generic, characteristics which make it user-friendly to apply and very customizable based on company's objectives. It also proposes a probabilistic model that allows to weight different assumptions and scenarios compared to other deterministic ones.

One of the weaknesses of the method is that its reliability is on subjective assumptions on the possible events and estimations on the probabilities of these events to occur. However, in some cases, the subjective estimation could be based on previous data or have multiple subjective estimations, from different experts or groups of experts, and utilise the average value(Alexopoulos et al. 2022).

2.2. Resilience index as cost of establishing resilience

A different cost driven supply chain resilience index is proposed by Liwei Chen, introducing as a parameter the cost of establishing resilience to evaluate whether the economic loss endured during a disruption in the supply chain is grater or lower that the incurred cost to build resilience measures. Such index can help decision makers to compare and evaluate which are the most cost-effective strategies to maximize resilience value.

The performance of the supply chain in the interruption without resilience is composed of three parts: the cost of order loss, the cost of order backlog and the sales revenue (Liwei Chen et al 2020).

Introducing then the new parameter, the study takes into account four cost types of performance:

Cost of order loss = Cost incurred after a time t_w when the customer can no longer wait and decide to cancel the order.

Cost of order backlog = Time related cost due to supply chain inability to satisfy customer demand.

Sales revenue = Revenue generated from demand during the disrupted time.

Cost of resilience = Cost to establish resilience techniques and cost of production (using settled resilience measures) during disrupted time.

Based on these definitions and the model's parameters in Document B the resilience index $EA(t_w)$, t_w time customer can wait, is defined by Liwei (Liwei Chen et al 2020) as:

$$EA(t_w) = \frac{UFC(t_w) - FC(t_w)}{C_f(t_w)}$$

Where $UFC(t_w)$ represents the performance of the supply chain without resilience ability under demand flow of different t_w after interruption.

$FC(t_w)$ represents the performance of the supply chain with resilience ability under demand flow of different t_w after interruption.

$C_f(t_w)$ is the cost of establishing resilience under demand flow of different t_w (Liwei Chen et al 2020).

Therefore, if $EA(t_w)$>=0 for each t_w, the supply chain is in complete resilience state which means that in all cases costs related to implement resilience measures are lower than losses that those measures are able to recover during disruption. Since customers could have different needs for some t_w can happen that $EA(t_w)$<0, in such case the overall EA can be measured by the sum of $EA(t_w)$ for different flow of t_w multiplied by their weight :

$$EA = \int_0^{\infty} EA(t_w) \times p_{t_w} dt_w$$

where :

$$p_{t_w} = \frac{d(t_w)}{\int_0^{\infty} d(t_w) dt}$$

and $d(t_w)$ is the number of demands per unit time for the demand flow in which the time that customers can wait is t_w. This allows to calculate the comprehensive cost recover enabled by a combination of resilience procedures.

The mathematical model to elaborate each factor is:

$$UFC(t_w) = C_{ufc}(t_w) - P_2(t_w) = C_{ufc1}(t_w) + C_{ufc2}(t_w) - P_2(t_w)$$

$$FC(t_w) = C_f(t_w) + C_{fc}(t_w) - P_1(t_w) = C_f(t_w) + C_{fc1}(t_w) + C_{fc2}(t_w) - P_1(t_w)$$

$$EA(t_w) = \frac{C_{ufc}(t_w) - C_f(t_w) - C_{fc}(t_w) + P_1(t_w) - P_2(t_w)}{C_f(t_w)}$$

Assuming that the loss recovered by resilience ability is $C_d(t_w)$. The loss recovered by the resilience includes the cost of the order backlog of the recovered products, the cost of order loss and sales revenue, which can be expressed as (Liwei Chen et al 2020) :

$$C_d(t_w) = C_{ufc1}(t_w) + C_{ufc2}(t_w) - C_{fc1}(t_w) - C_{fc2}(t_w) + P_1(t_w) - P_2(t_w)$$

$$EA(t_w) = \frac{C_d(t_w) - C_f(t_w)}{C_f(t_w)} = \frac{C_{ufc1}(t_w) + C_{ufc2}(t_w) - C_{fc1}(t_w) - C_{fc2}(t_w) + P_1(t_w) - P_2(t_w) - C_f(t_w)}{C_f(t_w)}$$

The example presented in the paper evaluates the use of three resilience procedures: additional inventory and subsequently agility as first resilience measures, later dual sourcing to kick-in when the extra inventory is consumed. Those are compared with a non-resilient network that from t0 is impacted by the disruption.

In order to elaborate the method UFC , FC , Cf have to be determined for each of the three stages, which means that different measures of t_w needs to be estimated: t_w during the initial additional inventory , t_w during the mid agility phase and last t_w during the dual sourcing final phase up to the end of disrupted time frame.

This methodology presents two innovative aspects:

- the customer expectation is considered as an indicator, which can be integrated into the measurement of the entire resilience indicator
- then the differences of the supply chain resilience measurement are analyzed under different types of customer needs(Liwei Chen et al 2020).

Moreover it allows decision makers to calculate the index applying different resilience enablers/processes to identify the best cost effective combination for the supply chain. It can provide valuable information weather establishing resilience may only increase costs or if different types of resilience ability might substitute one another and provide the same overall result in the supply chain.

2.3. The resilience triangle: Readiness, Response, Recovery

The quantitative model presented by Ahmadian, proposes to calculate supply chain resilience in a network by analyzing it's components (nodes) and flows connecting nodes (arcs).

This is based on the assumption that if the network components (nodes and arcs) are resilient, the whole network is also resilient. Therefore, we focus our attention on the resilience of network components, and define the resilience index for each component (Ahmadian et al, 2020).

Based on this logic, the amount of data and the difficulty with which the calculation is made depends on the desired detail level, a supply chain network can be broken down in to majors nodes like production plants, warehouses and suppliers to obtain an approximate resilience value for each component or node. Can be defined on a smaller scale, such as single processes or even part of processes to achieve a more detailed but complex solution.

The first step is then to create a diagram in which each node (i) with its supply (s_i) and demand (d_i) is connected to others with arcs (f_{ji} flow from node i to node j). This arcs represents the inbound and outbound flow to and from each node. The resilience of each component is quantified as the functionality loss in the network, this concept comes from the assumption that each disruption translates in a monetary consequence due to a decrease in the network system throughput.

This functionality loss was introduced by Bruneau with this equation, (Bruneau et al., 2003; Tierney & Bruneau, 2007) :

$$R^B = \int_{t_0}^{t_1} [100 - Q^B(t)]dt$$

where Q^B is the percentage of infrastructure quality at time t and R^B is the resulting loss of resilience.

The functionality loss concept and how it changes over time during a disruptive event can be represented with the resistance triangle in Fig 2.2.

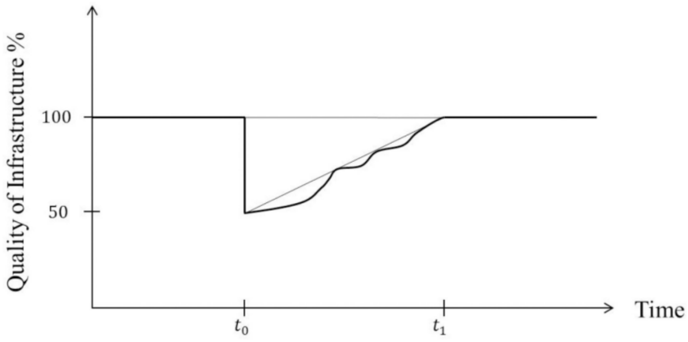

Fig. 2.2

Ahmadian's study is proposing a new way to calculate the area taking into account 4 factors: Readiness: the probability of disruption, Response: consequences of those disruptions, Recovery: recovery to the normal state, and Criticality: the ability of the network system to perform in case of component failure.

If there is no substitution for the component in the case of disruption, it is considered more critical (Ahmadian et al, 2020).

In order to explain formulas to calculate the loss in each step of the recovery time some definitions have to be introduced, the complete nomenclature list for variables use in the method can be found in Document F.

Impact of a Node Disruption (I_i^n), the impact of a node disruption on the network, I_i^n is the total loss when node i is disconnected from the network (Ahmadian et al, 2020).

$$I_i^n = \sum_j f_{ji} + s_i = \sum_k f_{ik} + d_i \qquad \forall i \in \mathcal{N}$$

This formula explains that the impact of a disrupted node in the supply chain is equal to the inbound flows to the node, plus the outbound supply that the node used to provide to the network.

Impact of an Arc Disruption $\left(I_{ij}^a\right)$, the impact of an arc disruption on the network is defined as the total loss in the case of disconnecting the arc from the network (Ahmadian et al, 2020).

$$I_{ij}^a = f_{ij} \forall (i,j) \in \mathcal{A}$$

The impact equals the incoming and outgoing flows that were in the disrupted path.

Repair Ratio Function $Q(t)$ is a function of time, is defined as a cumulative function of the repair function r, which yield the area of the resilience triangle for node i and arc (i, j), respectively (Ahmadian et al, 2020).

$$Q_i^n(t) = \int_0^t r_i^n(x)dx \qquad \forall (i) \in \mathcal{N}$$
$$Q_{ij}^a(t) = \int_0^t r_{ij}^a(x)dx \qquad \forall (i,j) \in \mathcal{A}$$

Node and Arc Criticality (C_i^n) measured as the network loss in a time period during which the evaluated component is disrupted.

The criticality of each component is calculated before a disruption happens, by predicting the impact of the component disruption on the network and considering possible alternatives for performing the operation of the disrupted component (Ahmadian et al, 2020).

$$C_i^n = \text{minimize} \sum_{k \in \mathcal{N}} l_k$$

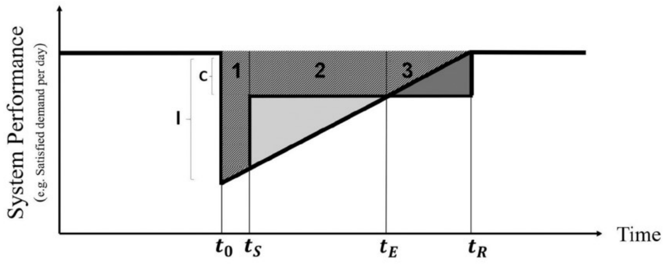

Fig. 2.3

Represented in Fig. 2.3, the functionality loss is made of three stages, initially a disruption in t_0 creates the performance drop that will last until t_S, this initial time is needed by the firm to implement an alternative solution in the network.

The loss related to this first period of time can be calculated utilizing φ damage level and $\mathcal{L}$ likelihood of disruption:

$$L_1 = \int_{t=t_{0i}n}^{t_{Si}n} I_i^n \varphi_i^n \mathcal{L}_i^n (1 - Q_i^n(t))dt \qquad \text{for a node}$$

$$L_1 = \int_{t=t_{0ij}^a}^{t_{Sij}^a} I_{ij}^{a*} \varphi_{ij}^a \mathcal{L}_{ij}^a \left(1 - Q_{ij}^a(t)\right)dt \qquad \text{for an arc.}$$

The middle stage from t_x to t_e represents the time in which the alternative solution is being used, a factor C [0,I] is introduced to evaluate the quality of the plan:

C=0 if the alternative perform as good as the pre-existing system, instead C increase if the solution is worst , up to C=I if the impacted component is critical and there is no alternative to replace it.

$$L_2 = C_i^n \mathcal{L}_i^n (t_{Ei}^n - t_{Si}^n) \qquad \text{for a node}$$

$$L_2 = C_{ij}^a \mathcal{L}_{ij}^a \left(t_{Eij}^a - t_{Sij}^a\right) \qquad \text{for an arc.}$$

The final stage stands for the time range te to tr needed to switch from the backup plan to a full recovery with the original system.

$$L_3 = \int_{t=t_{Ei}^n}^{t_R^n} I_i^n \varphi_i^n \mathcal{L}_i^n (1 - Q_i^n(t))dt \qquad \text{for a node}$$

$$L_3 = \int_{t=t_{Eij}^a}^{t_{Rij}^a} I_{ij}^a \varphi_{ij}^a \mathcal{L}_{ij}^a \left(1 - Q_{ij}^a(t)\right)dt \qquad \text{for an arc.}$$

The component resilience index is then obtain as

$$\text{CRI} = \frac{\text{1-Demand loss}}{\text{Demand in the network during the time}}$$

$$\text{So CRI} = \frac{\text{1 - (L1 L2 L3)}}{\text{Total demand}}$$

The result is than a dimensionless value that can range from 0, no demand loss and perfect component resilience, to 1 which stands for no resilience.

The method allows a firm to find the weakest component in the network, according to the study we represent the network resilience as the resilience of the weakest component(s). Hence, improving the resilience of the weakest component(s) increases the overall network resilience (Ahmadian et al 2020). Thanks to this approach, is possible for decision makers to assess resilience and optimize the use of financial resources identifying and focusing on the bottleneck component in the supply chain, thus increasing the network resilience by evaluating the as-is state and introducing criticality as a parameter to evaluate alternative strategies.

In the same way as for the POC index, the weakness of this approach is the subjective source used to determine which are the possible improvement scenarios to assess the criticality, and the estimation of probabilities for events to occur.

2.4. The resilience triangle: Severity and Recovery time

Carvalho's study presents a quantitative supply chain resilience index which aims to propose an index that enables companies to assess their resilience of on-time delivery to the two most common SC failure modes (i.e., capacity shortage and material shortage) based on the resilience practices they deploy (Carvalho et al, 2022).

Resilience practices are actions that are deployed by managers and decision-makers to prevent or mitigate SC disturbances and failure modes.

These practices are normally deployed to reduce the disturbance severity by improving the visibility and redundancy SC capabilities, for instance, sharing information with SC partners and using substitutes for production.

The second goal is to minimize the recovery time by improving the flexibility, responsiveness, and collaboration SC capabilities; for instance, altering the production/delivery schedules, or planning a SC common response (Carvalho et al, 2022).

The proposed model is built, as the previous study, using the resilience triangle originally conceived by Bruneau, Fig 2.4 (Bruneau et al., 2003; Tierney & Bruneau, 2007).

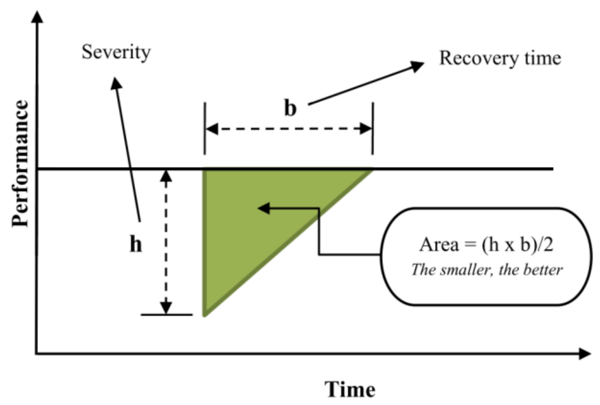

Fig. 2.4

In this case the triangle is not split in time phases as for the former approach but considered as a whole, since here the area of the triangle represents the loss of performance due to supply chain failure the resilience index, is calculated as:

Resilience index$_z$ = (severity × recovery time)/2

where

$$\text{Severity}_{z} = 1 - \frac{\sum_{S=1}^{N_{ZS}} X_{ZS}}{A * N_{ZS}}$$

$$\text{Recovery time}_{Z} = 1 - \frac{\sum_{r=1}^{N_{zr}} Y_{zr}}{A * N_{zr}}$$

The following table is used to visualize and explain each factor:

z = chosen failure mode

A = maximum assignable resilience score to each metric

Xzs= score assigned to the s supply chain state metric which contributes to minimize severity of the failure mode z	Yzr= score assigned to the r supply chain state metric which contributes to minimize recovery time due to the failure mode z
Nzs= Total number of supply chain state metrics evaluated to minimize failure z	Nzr= Total number of supply chain state metrics evaluated to minimize recovery time due to z

The obtainable resilience index is related to a selected failure mode and is in the range of [0, 1/2]. Where 0 is maximum resilience, since either the severity impact or recovery time are 0 (no disturbance effects), and ½ means no resilience toward the select z failure mode.

In order to calculate the index a theoretical framework of resilience practices, supply chain variables and metrics have to be created and evaluated.

In order to create a framework that explain the process of the index calculations, the study is focused on on-time delivery and highlights two main failure modes that lead to creating negative disturbance:

- capacity shortage, which occurs when the available resources are not enough to meet the demand
- material shortage, which occurs when there is not enough material to meet the demand (Carvalho et al, 2022).

Given a failure mode caused by a disruption as capacity shortage, the steps to create the index starts with a questionnaire and literature investigation to gather information about relevant supply chain practices, which are then are organized into techniques to reduce severity and techniques to reduce recovery time.

Each practice is than broken down into its variables and then again into metrics. Metrics through a questionnaire or expect opinions receive a score [0, A], where 0 means the metrics is very low/difficult to assess and 5 that it is very high/easy to achieve.

As an example to better explain this scoring process, in the resilience enabler section, redundancy was explained as a practice that can reduce the severity in case of a system failure due to disruption. This practice could be for the company divided into two different variables, the availability of alternative processes and the availability of secondary production plants.

Lastly, taking into consideration the first variable, alternative processes can be obtained by different “metrics”: outsourcing, versatile production lines and redundant production line. To each of these metrics a score [0, A] is assigned to allow the calculation of the final index.

In this approach resilience practices were selected based on experts’ knowledge and evidence from literature and developed in a framework to obtain an index capable of measuring resilience at an individual company level, and thus it can also be used by companies that operate in rather disintegrated SC settings (Carvalho et al, 2022).

This comes with some limitations as more resilience variables might have emerged if different types of SCs or different disruptions are considered, the result becomes then case specific and may not always apply to different SC tiers, industry sectors, and countries.

2.5. The resilience triangle: multi-stage optimization stochastic model

Goldbeck, by proposing a multi-stage optimization method for initial investments in network capacity and subsequent dynamic network flows, aims to provide more comprehensive decision support for improving the resilience of interdependent supply chains (Goldbeck at al, 2020).

Establishing a different method to assess supply chain resilience through a stochastic model that calculate the area of the resilience loss triangle RLT as the resilience triangle captures various aspects including robustness, redundancy, recovery time and resourcefulness (Bruneau et al., 2003; Tierney & Bruneau, 2007).

The idea is to model asset failure and disruption propagation over sequential time periods with a scenario tree, this is organized in t ∈ [1, T] subsequential time steps and in each step nodes are identified as S ∈ [1 , St] so that the total number of scenarios if the sum of “leaves” at the end of the tree.

$$\mathrm{RLT} = \sum_{t=1}^{T} \sum_{s=1}^{S_t} p^{t,s} \left(1 - \frac{\sum_{i \in V} c_i^{\mathrm{r}} u_i^{t,s}}{\sum_{i \in V} c_i^{\mathrm{r}} \breve{u}_i^{t}}\right)$$

where RLT measures the total loss in system performance in terms of ability to satisfy users demand as weighted sum of loss in each time step across nodes.

p is the probability related to a time-node in the tree.

c is the economic value of satisfying one unit of demand at node i.

ŭ end user demand in a time-node of the tree.

u supply to user in a time-node of the tree.

v vertices (node) of a graph G (V, E) used to represent the supply chain as nodes connected by links E.

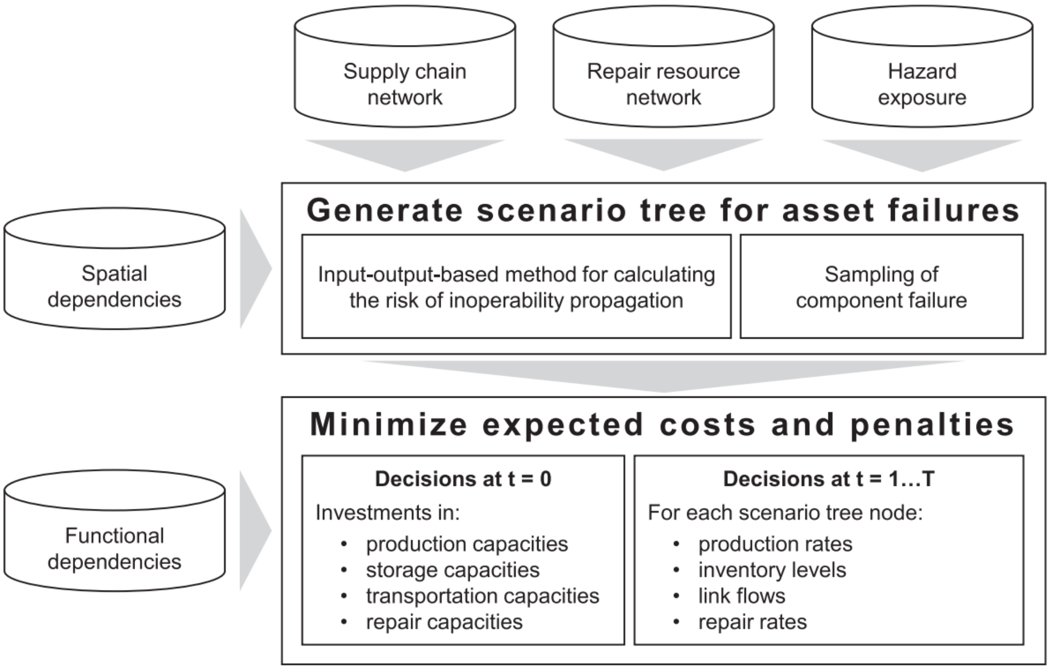

Fig. 2.5

A scenario tree generation algorithm is bult following the structure in Fig. 2.5: it captures asset damage uncertainty and has to consider the risk of cascading failure, represented by failure propagation dependencies (Goldbeck at al, 2020). For this reasons the inoperability input-output model by Haimes (Haimes et al, 2001) is used since it can model bi-directional/circular dependencies which happens when a node A is dependent on a node B and B is either dependent on A or a node C that is dependent on A

$x = Ax + c$

$x = (I - A)^{-1} c$

where A is the matrix characterizing the level of dependancy between supply chain assets and c is the perturbation vector that describes inherent or independent inoperability.

Once solved, X rappresents a vector which measures the probability and degree of inoperability in the supply chain. Goldbeck's method adapt this model to a supply chain system that consider costs and operational aspects in two ways (Goldbeck at al, 2020):

1. use the input-output model only for dependency relations that cannot be modelled as network flows, namely stochastic failure propagation or correlation effects;

2. model distinguishes between the probability and degree of inoperability so that it can be used for generating random samples rather than calculating expected outcomes. This is achieved by considering the perturbation vector c and interdependency matrix A to be composed of random variables.

The scenario tree is built by assigning random values to gather different scenarios identified by the corresponding inoperability vector

$\mathrm{x}^{t,s} = (\mathrm{I} - \mathrm{A}^{t,s})^{-1}\mathrm{c}^{t,s}$

and iterating the process for each time step tc t ∈ 1 to T using the mathematical model formulation:

$$\text{minimize} \sum_{(j,k)\in E} \bar{c}^{\mathrm{f}}_{j,k}\bar{f}_{j,k} + \sum_{i\in V}\left(\bar{c}^{\mathrm{g}}_{i}\bar{g}_i + \bar{c}^{\mathrm{h}}_{i}\bar{h}_i\right) + \sum_{t=1}^{T}\sum_{s=1}^{S_t} p^{t,s}\left(\sum_{(j,k)\in E} c^{\mathrm{f}}_{j,k}f^{t,s}_{j,k} + \sum_{i\in V}\left(c^{\mathrm{g}}_{i}g^{t,s}_{i} + c^{\mathrm{h}}_{i}h^{t,s}_{i} + c^{\mathrm{q}}_{i}q^{t,s}_{i} + c^{\mathrm{r}}_{i}r^{t,s}_{i}\right)\right)$$

The objective function, mathematical formulation in Procedure E, seeks to minimize capital expenditure in the first stage and operational costs in the subsequent T stages (Goldbeck at al, 2020).

Where capital expenditure is the sum of operations and decision taken in the immediate future, the first step of the planning scope and operational costs represents the sum of sustained costs across the scenario tree weighted by probabilities.

This model introduces the concept of repair resources, it can be modelled in a similar way as the core supply chain logistics compared to current models which assume fixed repair budgets and cannot optimize pre-disruption investments in the supply chain (Goldbeck at al, 2020). The output of the model allows to find, through a scenario tree, the optimal combination of investments in repair capability against savings from avoided disruption thanks to those initial investments.

The downside of such approach is that, to completely create the scenario, it’s assumed that decision makers have knowledge of the whole tree and fully capture in it all possible failure propagation needed to calculate the probability of each different outcome. In real life applications this may not be the case as high impact disruption are rare events with insufficient data to model the behavior and impact.

Moreover, a limitation of their work is that distributed and individual decision making by different SC members is not considered to be a factor, which limits the application of the model to mainly analyzing well-integrated SCs where all the SC members are committed to collaborating and sharing information (Carvalho et al, 2022).

2.6. Fuzzy 3R Python model: Resources, Risks, Resilience

The quantitative resilience method proposed by Saloua, aims to provide sociotechnical systems with a decision-making tool that supports them in assessing the resilience of their processes (Saloua et al 2020). A fuzzy model is used to create a framework that can incorporate the 3R process: Resource, Risk, and Resilience.

- Resources that can be considered, among others (time, budget, regulations…) as a constraint that may limit the achievement of the process objective (Llamas et al,2016).
- Risks, which are undesirable events that may happen several times can have a negative impact on the process (D. Ristic ,2013).
- Resilience, which is the ability of a system to manage disturbances and to adapt to changes without ceasing the activity (O. Gluchshenko,2012).

The 3r process is made in two stages, a definition of parameters and subsequently the resilience assessment that is achieved using a fuzzy model elaborated via a python algorithm.

2.6.1. Parameters definition

For the first stage the study try to assess how difficult it is for a firm to overcome a disruptive event, the paper propose 4 key parameters needed to evaluate the impact of a disruption:

- MTPD Maximum Tolerable Period of Disruption = Time in which a process can keep functioning before being critically impacted by a disturbance
- WIT Workaround Implementation Time = Time requested by a

previously analyzed alternative process to be adopted after the original one can no longer operate

- WMTTL Workaround Maximum Tolerable Time Length = Time frame in which the alternative process can work normally
- RT recovery time = Time needed by the network to resume a normal state

2.6.2. Resilience assessment

Starting from this definitions the 3R process is built assigning a selected process-disruption combination time ranges that should be defined and the process criticality level should be identified based on these intervals (Saloua et al 2020). This part relies on the human factor and expertise to create a proper scale.

For example using a 5 criticality levels scale a process's MTPD can be chosen due to the selected disruption to analyze over a time range [0 to infinite[days. Following this example selecting random time brackets, the process criticality level would then look like:

level	Description
1 very low	MTPD app]4,infinite[the risk of failure is very low since the process can operate in case of disruption for more than 4 days
2 low:	MTPD app]3,4] the risk of failure is low since the process can operate in case of disruption for 3 to 4 days
3 medium:	MTPD app]2,3] the risk of failure is medium

since the process can operate in case of disruption for 2 to 3 days

4 high: MTPD app]1,2] the risk of failure is very high since the process can operate in case of disruption for 1 to 2 days

5 very high: MTPD app [0,1] the risk of failure is very high since the process can operate in case of disruption for a maximum of one day

WIT,WMTTL and RT will be then defined over the same 5 levels scale and each level defined on an appropriate time range based on the related parameter. For each parameter, the definition of their levels is the output of an assessment of resources, threats and workarounds related to the combination of process-disruption in evaluation by decision makers. Such information can be obtained via expects opinions, industry survey and data analysis.

Once all the data is gathered the research suggests to use a triangular membership function to elaborate the fuzzy model. The mode can be implemented via python programming language (Document A) using fuzzy sets as master data and evaluated parameters as input to the algorithm.

If we keep following the example of a N=5 levels scale, the output is a numeric resilience index of 5 levels in a range [0, N-1]; where 0 means that the process is not resilient and easily subject to failure in case of disruption; 4 means optimal resilience level.

In short, the major advantages of this process are summarized as follows:

- this is a generic method that can be applied to any system and help it to define the key indicators, related to resistance (MTPD), recovery

(RT) and anticipation (WIT and WMTTL) which are the three functions of a resilience process, and can help to identify most effective strategies;

- it provides a resilience score and a rating as per the resilience scale, which can be useful for detecting and improving weaknesses and also increasing strength and effectiveness to deal with adverse events (Saloua et al 2020).

From a vulnerabilities point of view, this method inherits the flaws of fuzzy logic, human knowledge is often incomplete and episodic as compared to systematic way; sometime rules may be mismatched and/or non-coherent so broad testing over HILF disruptions, which is hard to assess, would be needed to prove the effectiveness of the approach in evaluating resilience.

2.7. Fuzzy multi criteria decision making model

A different approach to create a supply chain resilience index using a fuzzy decision-making model is proposed by Morteza, a novel fuzzy Multi Criteria Decision Makin (MCDM) model based on the Best-Worst Method (BWM), fuzzy Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS). The method's scope is to evaluate key supply chain players against several risk factors (Morteza et al 2022).

The aim of this index is to evaluate different frims/actors in a network against several disruption organized in risk criteria, thanks to the fuzzy model each supply chain component can be connected to a comprehensive risk value and ranked from most to least resilient.

The process starts splitting the network into key players or nodes and selecting the list of disruptions / risks criteria to consider based on literature and experts opinions. The Best Worst Method (BWM) is a multi-criteria decision-making method that uses two vectors of pairwise comparisons to determine the weights of criteria. Rezaei (Rezaei J., 2015) (Rezaei J., 2016). The output of BWM is an assessment over the relative weight of each disruption in the list of selected risks, to rank most to least impacting

A pool of experts is needed to provide an evaluation about the most important criterion, the worst, how the best compare to the others and how others compare to the worst using a scale 1 to N.

Steps for the Best Worst Method by Rezaei (Rezaei J., 2015) (Rezaei J., 2016) are:

1. identify best and worst criterion;
2. create vectors via pairwise comparison aij which shows how much the decision-maker prefers criterion i over criterion j. In a scale 1 to 9 aij=1 means that j is equally important as i and aij=9 that i is extremely more

important than j, a visual representation in Fig. 2.6.

Preferences of the best criterion over others: Ab = (Ab1, Ab2, …, Abn)

Preferences of the worst criterion over others: Xw = (A1w, A2w, …, Anw)

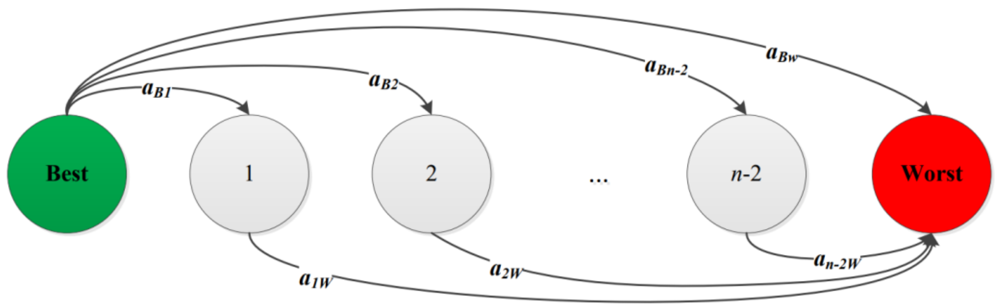

Fig. 2.6

3. Optimal weights assigned to each criterion (W1,W2, …, Wn) are define as:

$$w_B/w_j = a_{Bj}$$

$$w_j/w_W = a_{jW}$$

and calculated solving the optimization model

$$min\xi$$

s.t.

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi, \text{ for all } j$$

$$\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi, \text{ for all } j$$

$$\sum_j w_j = 1$$

$w_j \geq 0$, for all j

ξ^* consistency ratio is obtained based on the table in Document C.

Once disruption risks are defined, the MARCOS method elaborated by Stevi´c (Stevi´c et al. 2020) is implemented via a series of nine steps described in Procedure D. It allows to create a matrix Xmn of m alternatives which represents key players in the supply chain, evaluated against n risks criteria. Again a pool of experts is needed to provide an evaluation, expressed in a fuzzy scale 1 to N, about how each alternative m endorse risk n, this questionnaire provide the input data for the complete initial matrix Xmn. The output result of Procedure D establishes a quantitative ranking order, most to least vulnerable supply chain player against selected disruptions.

The MARCOS method is implemented under an uncertain environment through fuzzy triangular numbers. to empower decision makers to express their opinions and judgments according to the uncertainties of parameters in real-life cases and to ensure reliable decision solutions to address the resiliency and risk factors in an SC network (Morteza et al 2022).

This method proposed by Morteza carry the disadvantages of fuzzy implementation, such as the heavy dependency on experts reliability in both evaluating the risks that the network may face and later judging key players against those same risks. Nevertheless this approach provides a useful framework to address the improvement of cooperation in a supply chain, evaluating different firms/organizations like suppliers, distributors, logistic platforms and retailers to identify possible improvements in the network.

2.8. Resilience index: optimization recovery approach

Nguyen proposes a stochastic model to provide a framework to develop supply chain resilience indices, concerning the performance against potential large-scale disruptions for MEASC (multi-echelon assembly supply chain) networks(Nguyen et al 2021).

Based on the optimization recovery approach of Nguyen; which considering as values to minimize orders tardiness and time to recover (TTR); consider the theoretical approach that each supplier can optimize its own local recovery/scheduling problem and the solutions will propagate to the overall optimal recovery plan (Nguyen et al 2020).

A multi-echelon supply chain is a network that ends in a final assembly, and is made of multiple levels of suppliers which can be spread in different countries. They can be subject to disruptions of different natures and ripple effects caused by interruptions in an upper node/s of the supply chain. The network is analyzed as a combination of location-event scenarios, sampling combinations of Li locations with Ej type of disruptions.

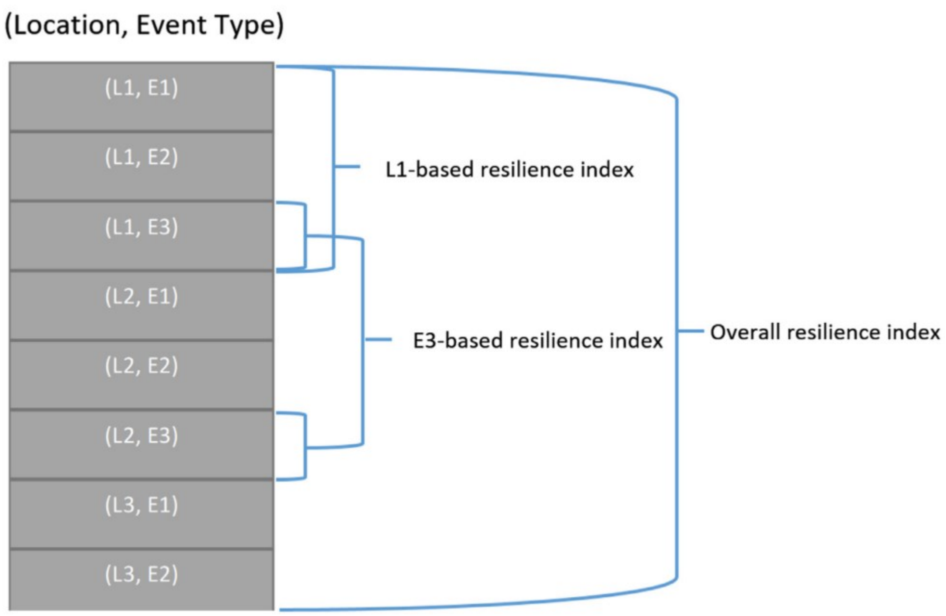

Fig. 2.7

As shown in Fig. 2.7 this sampling approach allows to create a location index by aggregation of different events happening in a Li location, or similarly an event index by aggregation of different locations to understand the impact of a particular Ei disruption.

An overall index can be calculated in two different ways:

- aggregation of all location/event indexes by their weighted average. This is computationally easy but doesn't provide statistical values as variance, confidence and tolerance intervals and distribution
- the other method is to evaluate the whole supply chain as one single location/event scenario where all locations and disruptions are sampled together which will give a more relevant statistical result but it's more expensive to perform.

Once the aim of the index is decided the process follows three main steps:

1. first is to sample potential scenarios at a supplier level to evaluate whether a supplier is disrupted and the possible time range of disruption: for example in case of a hurricane from historical data it's possible to extract a frequency index based on the geographic location and a strength index;
2. given the disruption range the second step is to generate multiple disruption scenarios from the combination of randomly generated disruption times from the individual suppliers from a normal distribution of mean x and standard deviation y (Nguyen et al 2021). Since a Monte Carlo simulation is used to compute the resilience index a minimum N number of scenarios is required to obtain a statistically significant output. N is calculated with Conover formula (Conover WJ, 1999)

$$N \approx \frac{1}{4}\chi_{(1-\alpha)}\frac{1+q}{1-q}+\frac{1}{2}(r+m-1)$$

3. the final step is to use random generated scenarios metrics as input for the Monte Carlo simulation, whose output is the performance index. In a Monte Carlo simulation a random value is repeatedly assigned to the uncertainty-related variable to face uncertainty while making a forecast. The variable in question is given many different values while the mathematical process is repeated over and over. After the simulation is finished, the results are averaged to produce an estimate. (Bonate, 2001).

To elaborate such metrics the firm have to create/use a mathematical model recovery plan to calculate based on which factors are relevant to measure the impact of a disruption. In the paper, studying the case of multi-echelon assembly supply chain networks, the recovery algorithm is provided in Nguyen study (Nguyen et al 2020) which aims to the minimum maximum tardiness or the minimum time to recover as resilience measures, which allows to calculate the necessary input data for the Monte Carlo simulation.

The individual resilience indices are derived using the mathematical terms in proof of the decision rules, Ti out and TTRi , which represent the impact of disruptions that can be attributed to a supplier and its subtier networks.

Applying these individual supplier indices to the different suppliers within the network shows the vulnerable suppliers, which is useful for supplier selection, capacity expansion and safety stock allocation strategies(Nguyen et al 2021).

Looking at drawbacks of the just described method, it’s using a recovery algorithm, Nguyen’s in this case, as black-box to feed the Monte Carlo simulation. Decision makers have to provide input variables as disruption frequencies and disruption times, obtaining as output the performance metrics of the MEASC network. These requirements can generate inconsistent results due to necessity of selecting the correct recovery algorithm for company needs and availability of raw data relevant for the considered disruption.

2.9. Resilience index: graph theory approach

Agarwal proposes a graph theory-based supply chain resilience index, it quantifies supply chain ability to prepare for unexpected events, respond and recover from them to an improved state of operations (Agarwal et al, 2021).

This approach made of the digraph representation, the adjacency matrix formulation and calculation of the permanent function (Jain et al., 2017. Tan et al., 2019) allows researchers and decision makers to have the flexibility to include new drivers as they evolve with changing global conditions (Kaur set al., 2006).

The process to calculate the index starts investigating through empirical investigation methods such as experts opinions and surveys which are the enablers to supply chain resilience and the level of dependence between factors.

To achieve this the Exploratory Factor Analysis (EFA) is used, the broad purpose of EFA is to enable relationships and patterns between data to be easily interpreted. It enables variables to be regrouped into factors based on shared variance and therefore helps to isolate underlying concepts (Forrester et al., 2020).

In the paper's the case study is presented analyzing through EFA the supply chain of an automotive company, for this example scenario enablers as outcome of EFA are categorized into three main groups: strategic level, operational level and tactical level. Grouping enabler allows decision makers to gather both focused indexes about each level for insightful evaluation and an overall high level index representing the network.

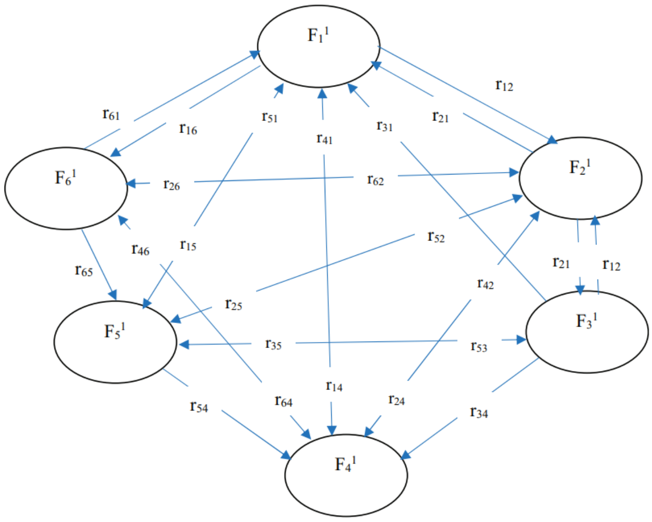

Fig. 2.8

Once enablers are evaluated a graph for, as Fig. 2.8, each category can be plotted the following step is the creation of the adjacency matrix. Assumed a digraph with N enablers, having no self-loops, it can be represented by matrix $F = [f_{ij}]$ where r_{ij} represents the interaction of the ith enabler with jth enabler (Scanlon and Deo, 1999). The inheritance of each practice F_i^1 and their interdependencies r_{ij} are quantified through discussion with the industry experts using a decided scale [0, N] (Agarwal et al, 2021).

$$F = \begin{bmatrix} F_1^1 & r_{12}^1 & r_{13}^1 & r_{14}^1 & r_{15}^1 & r_{16}^1 \\ r_{21}^1 & F_2^1 & r_{23}^1 & r_{24}^1 & r_{25}^1 & r_{26}^1 \\ r_{31}^1 & r_{32}^1 & F_3^1 & r_{34}^1 & r_{35}^1 & r_{36}^1 \\ r_{41}^1 & r_{42}^1 & r_{43}^1 & F_4^1 & r_{45}^1 & r_{46}^1 \\ r_{51}^1 & r_{52}^1 & r_{53}^1 & r_{54}^1 & F_5^1 & r_{56}^1 \\ r_{51}^1 & r_{62}^1 & r_{63}^1 & r_{64}^1 & r_{65}^1 & F_6^1 \end{bmatrix}$$

(example digraph and related matrix of a group containing six enablers)

In order to explicate matrices into a single index the permanent function equation proposed by Marcus(Marcus et al, 1962) is used:

$$\text{per } (A) = \sum_{\sigma \in S_n} \prod_{i=1}^{n} a_{i,\sigma(i)}$$

where Sn is the group off all n! permutations of N = {1, 2, ..., n}. This formulae requires summing over all n! permutations with N multiplications for each sum.

The resilience index in finally calculated as the permanent function of the digraph-matrix enclosing the function of each level as node and the dependency between levels.

This representation includes all the information regarding the inheritance of coordination mechanisms and their interactions. Hence, it is useful in calculating a composite index since no information is lost while calculating a permanent function value.

The value of the RI obtained through permanent function value facilitates comparison which is difficult if only qualitative information is present (Agarwal et al 2021). It allows to create a best and a worst case indexes assuming fixed interdependencies within the industry field and changing inheritance to the highest or lowest vale, thus benchmarking the firm against competitors in the scale worst case to best case.

3. CATEGORIZATION OF SUPPLY CHAIN RESILIENCE INDEXES

The evaluation and comparison of supply chain resilience indices has become increasingly relevant in recent years, as companies seek to better understand and manage the risks that can impact their supply chain operations.

In the beginning of the previous chapter, a general introduction was given about the potential benefits and applications of a quantitative supply chain resilience index, to quote again an interesting research suggestion made by Hosseini in his review of quantitative methods for supply chain resilience analysis published before Covid-19, we recommended potential future research avenues, which are divided into two classes: methodology based and subject based (Hosseini and Ivanov 2019).

Starting with this proposition, it’s possible to observe how the previously discussed collection of state-of-the-art resilience indexes is united by the same scope, expressing a resilience measure through a unique number representative of the whole supply chain. This goal, during the executions of those methods, is achieved in different ways: specific enablers/metric are taken into consideration, various kind of data sources are used and many mathematical approaches are utilized.

In this final part, we will categorize them based on two classes, trying to provide valuable insights for researchers and decision makers, presenting different groups of indexes arranged by the scope for what they are suitable for. In other words, organizing them based on which real life applications they are suitable for and can provide information to evaluate and improve resilience.

To achieve this result, a visual representation is built, Fig. 3.1. The most effective way to represent this, is using a sort of cartesian graph where the abscissa is the scope of the index and the ordinate is the objectivity level of input data needed to elaborate the mathematical process.

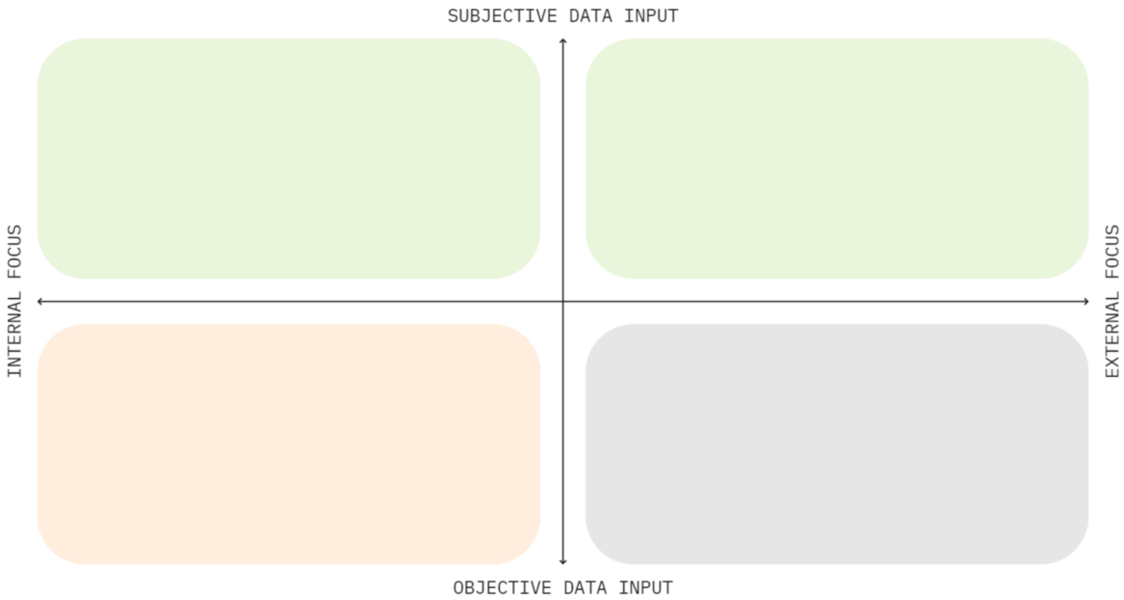

Fig. 3.1

3.1.1. Abscissa scope

There are two main opposite scopes that can be seen among resilience indexes: an internal or external focus.

- Internal is described as the quantitative evaluation and comparison of a company's internal processes, nodes and costs optimization. With the focus not on a firm's representative number, but on identifying the weakest part to optimize investments and to improve resilience.

- External focus is the main objective of evaluating the whole network faced, with a single or multiple disruptions, through a unique number that can be used to compare the company with competitors or used to establish resilience between firms in partnership within the same supply chain.

3.1.2. *Ordinate data objectivity level*

The second class to evaluate and to group is about the input data necessary to calculate the index. As we have seen in earlier analysis, there are two opposite starting points to obtain the final resilience number.

- Subjective data input. These models use expert's opinions, questionnaire and evaluation over nonmathematical objects as relevance of supply chain enablers. The relative mathematical approach translates this information into variables needed to calculate the output index.

- Objective data input. These models require a series of parameters as costs/investments, productions levees, inventory data, material flows, demand/supply etc… Specific company variables, which requires data analysis of the company metrics, historical data on disruptions and knowledge in the industry/geographical risks.

Considering the two classes, indexes are categorized in the chart shown in the following Fig. 3.2. Will then be discussed only groups 1 and 3 given their opposite features and to avoid redundancy as group 2 and 4 share a different combination of the same strengths and weaknesses as the first pair.

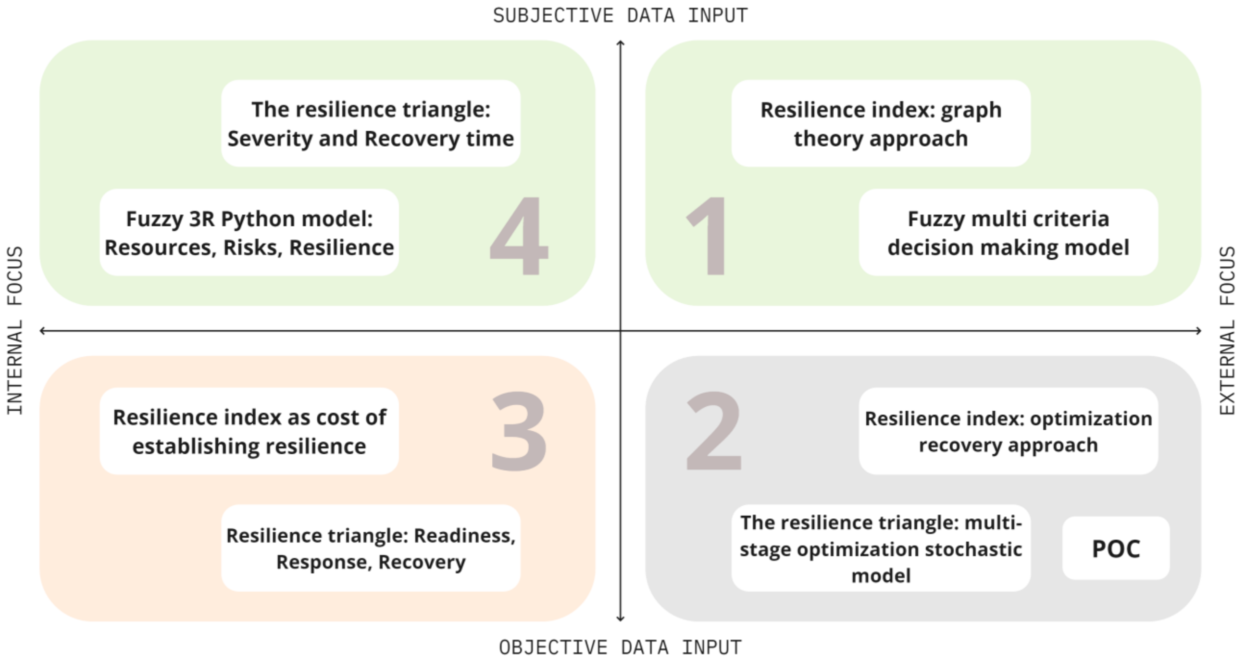

Fig. 3.2

Group 1 is made of the "graph theory approach" by Agarwal and the "multi criteria decision making model" by Morteza. Both this indexes, in real life scenarios, allow decision makers to select a panel of industry relevant qualitative attributes, the previously discussed supply chain enablers, measuring how the company performs compared to partners and competitors in case of disruption. The calculation process itself emphasize which enablers are more significant providing guidance on which aspects the risk management should focus. The outcome of these methods grand knowledge of how the company is positioned within the industry sector in terms of resilience against those disruption evaluated in the process.

The major drawbacks of indexes in this area of the chat are related to the board of selected expects as the output may result inconsistent and vary based on the audience questioned. The other point is the degree of freedom granted in the data gathering as the result may depend which risk are considered, if all possible risks are evaluated and which enabler are included in the questionnaire.

Group 3 is made of “index as cost of establishing resilience” by Liwei and “The resilience triangle: readiness, response, recovery” by Ahmadian. These indexes enable decision makers to measure resilience investigating processes performance during different time stages of a disruption. They consider variables such as customer demand, investment costs, customer expectations, damage and repair capabilities, to model multiple possible scenarios and to identify the most cost-resilience effective strategy to implement. They then provide understanding of which are the weak links in the company.

The disadvantage of such mathematical model is the availability of raw data and accuracy of data analysis to obtain variables, most of all probabilities of disruptive events to occur and how their propagation will affect the firm. Also due to the high demand in input data these methods result not suitable in benchmarking the overall supply chain against partner/competitors as the required data would not be available and accurate enough to get a consistent result.

Conclusion

The thesis project has started examining how the concept of supply chain resilience has evolved over the last decade, from a descriptive ideal behavior in which some enablers were mentioned, to the introduction of different disruptive phases and the capabilities needed in each one.

Recent literature concluded that absorptive capacity, adaptive capacity and restorative capacity are not enough to withstand a long-lasting disruption as Covid-19, as per Ivanov's findings: the current crisis has given rise to a new challenge relating to the survivability of SCs, which had not been studied intensively in the pre-pandemic SC literature (Ivanov and Dolgui, 2020). This new fourth survivability capacity has been introduced and discussed with some modern strategies for firms to survive during a long-term lasting disruption.

The consideration of Covid-19, an unprecedented disruptive event, lead the continuation of the thesis initially over the analysis of its multiple impacts and ripple effects among many supply chains in very diverse industries. As understanding how such event developed over time and which are the broad range of consequent risks, is the fundamental information needed to develop scenarios and strategies needed as input data for resilience indexes calculation. Later lead to a literature inquiry about which are the drivers to supply chain resilience, these are the primary conceptual aspects that decision makers should focus on to build resilience in a network. Recognizing which are the enablers and their effects, permit the creation of the framework needed during the execution of indexes' mathematical models.

Subsequently to understanding the effects of Covid-19 on resilience and the drivers to resilience, the thesis focused into the investigation of the state-of-the-art supply chain resilience indexes. Trying to find a new comprehensive approach, that incorporates modern knowledge/approaches previously discussed and allows decision makers to evaluate the supply chain against high impact low frequency risks.

Nine indexes have been discussed and analyzed, revealing new interesting approaches and including new metrics in their models, each with some strengths and weaknesses. Liwei, in his cost optimization model, includes the evaluation of costs to establish resilience compared to the forecasted cost suffered in case resilience is not established. Ahmadian, Carvalho and Goldbeck, present different approaches to calculate the functionality loss expressed by the resilience triangle theory. Morteza and Agarwal focus the resilience measure relying on framework of enablers.

Given the absence of a single comprehensive approach, the final part of the thesis has organized the state-of-the-art indexes based on two dimensions: scope and input data required, finding four groups that best fit different applications of resilience calculation. Thus providing a first framework to categorize resilience indexes methods, allowing decision makers and future researchers in real case scenarios to identify suitable indexes that can provide valuable information.

Appendix Documents of the Procedures

Document A – Code of Fuzzy Python model by Saloua (Saloua, et al 2020)

```
import numpy as np

import skfuzzy as fuzz

from skfuzzy import control as ctrl

MTPD = ctrl.Antecedent (np.arange (8), 'MTPD')

WIT = ctrl.Antecedent (np.arange (8), 'WIT')

WMTTL = ctrl.Antecedent (np.arange (8), 'WMTTL')

RT = ctrl.Antecedent (np.arange (8), 'RT')

Echelon = ctrl.Consequent (np.arange (0, 5, 1), 'echelon')

MTPD.automf (5)

WIT.automf (5)

WMTTL.automf (5)

RT.automf (5)

Echelon['Unconscious'] = fuzz.trimf(Echelon.universe, [0, 0, 1])

Echelon['Informed'] = fuzz.trimf(Echelon.universe, [1, 1, 2])

Echelon['Aspiring'] = fuzz.trimf(Echelon.universe, [2, 2, 3])

Echelon['Progressing'] = fuzz.trimf(Echelon.universe, [3, 3, 4])

Echelon['Expert'] = fuzz.trimf(Echelon.universe, [4, 4, 5])
```

```
MTPD['Very high'] = fuzz.trimf(MTPD.universe, [0, 0, 0.16])

MTPD['High'] = fuzz.trimf(MTPD.universe, [0.16, 0.16, 1])

MTPD['Medium'] = fuzz.trimf(MTPD.universe, [1, 3, 3])

MTPD['Low'] = fuzz.trimf(MTPD.universe, [3, 5, 5])

MTPD['Very low'] = fuzz.trimf(MTPD.universe, [5, 7, 7])

WIT['Very low'] = fuzz.trimf(WIT.universe, [0, 0, 1])

WIT['Low'] = fuzz.trimf(WIT.universe, [1, 1, 3])

WIT['Medium'] = fuzz.trimf(WIT.universe, [3, 3, 5])

WIT['High'] = fuzz.trimf(WIT.universe, [5, 5, 7])

WIT['Very high'] = fuzz.trimf(WIT.universe, [7, 7, 8])

WMTTL['Very high'] = fuzz.trimf(WMTTL.universe, [0, 0, 1])

WMTTL['High'] = fuzz.trimf(WMTTL.universe, [1, 1, 3])

WMTTL['Medium'] = fuzz.trimf(WMTTL.universe, [3, 3, 5])

WMTTL['Low'] = fuzz.trimf(WMTTL.universe, [5, 5, 7])

WMTTL['Very low'] = fuzz.trimf(WMTTL.universe, [7, 7, 8])

RT['Very low'] = fuzz.trimf(RT.universe, [0, 0, 1])

RT['Low'] = fuzz.trimf(RT.universe, [1, 1, 3])

RT['Medium'] = fuzz.trimf(RT.universe, [3, 3, 5])

RT['High'] = fuzz.trimf(RT.universe, [5, 5, 7])

RT['Very high'] = fuzz.trimf(RT.universe, [7, 7, 8])
```

```
resiliencescale_ctrl = ctrl.ControlSystem ([rule1, rule2,.., rule n])

resiliencescale.input ['MTPD'] = *inpunt by user

resiliencescale.input ['WIT'] = *inpunt by user

resiliencescale.input ['WMTTL'] = *inpunt by user

resiliencescale.input ['RT'] = *inpunt by user

resiliencescale.compute ()

print (resiliencescale.output['echelon'])

    Echelon.view(sim=resiliencescale)
```

Document B – Parameters for mathematical model by Liwei (Liwei Chen et al, 2020)

t_w	Time customers can wait
P	Transaction price on the market per unit product
C_1	Cost of order backlog per unit time per unit product
C_2	Cost of order loss per unit product
τ	Production ability of agility
$\tau(t_w)$	Production ability of agility in the supply chain under demand flow of different t_w
ρ	Production ability of dual sourcing procurement
$\rho(t_w)$	Production ability of dual sourcing procurement in the supply chain under demand flow of different t_w
X	Amount of additional inventory
$X(t_w)$	Amount of additional inventory in the supply chain under demand flow of different t_w
C_{fix}	Fixed cost for establishing agility
C_{var}	Variable cost for establishing agility
C_{outf}	Fixed cost for establishing dual sourcing procurement
C_{outv}	Variable cost for establishing dual sourcing

	procurement
C_{rmif}	Fixed cost for establishing additional inventory
C_{rmiv}	Variable cost for establishing additional inventory
d	Total demand of product generated per unit time
$d(t_w)$	Demand of product per unit time under demand flow of different t_w
EA	Supply chain resilience
$EA(t_w)$	Supply chain resilience to establish resilience ability under demand flow of different t_w
$UFC\ (t_w)$	Performance of supply chain without resilience when interruption occurs under demand flow of different t_w
$FC(t_w)$	Performance of supply chain with resilience when interruption occurs under demand flow of different t_w
$C_f(t_w)$	Cost of establishing resilience under demand flow of different t_w
$C_{fc}(t_w)$	Loss of supply chain with resilience at interruption under demand flow of different t_w
$C_{ufc}(t_w)$	Loss of supply chain without resilience at interruption under demand flow of different t_w
$P(t_w)$	Income from orders at t_w after supply chain recovery under demand flow of different t_w
$C_d(t_w)$	The redeemed loss by establishing resilience

under demand flow of different t_w

f(I) The number of orders that can be satisfied when the supply chain is interrupted

Document C – Consistency Index by Rezaei (Jafar Rezaei, 2014)

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency Index (max ξ)	**0.00**	**0.44**	**1.00**	**1.63**	**2.30**	**3.00**	**3.73**	**4.47**	**5.23**

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

Consistency ratio (CR) ∈ [0 , 1]. The lower the CR the more consistent the comparison, hence the more reliable results.

Peocedure D – MCDM method by Stevi´c (Stevi´c, 2020)

1. Fuzzy decison matrix

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdot & \tilde{x}_{1n} \\ \tilde{x}_{21} & & & \tilde{x}_{2n} \\ \cdot & \ddots & & \cdot \\ \cdot & & & \cdot \\ x_{m1} & \cdots & & \tilde{x}_{mn} \end{bmatrix}$$

2. Fuzzy decision matrix is extended by Fuzzy idea(AI) and fuzzy anti-idea(AAI)

$$\widetilde{AAI} = \min_{\mathrm{i}} \tilde{x}_{\mathrm{ij}} \quad \text{if j} \in \text{B}, \quad \max_{\mathrm{i}} \tilde{x}_{\mathrm{ij}} \quad \text{if j} \in \text{C}$$

$$\widetilde{AI} = \max_{\mathrm{i}} \tilde{x}_{\mathrm{ij}} \quad \text{if j} \in \text{B}, \quad \min_{\mathrm{i}} \tilde{x}_{\mathrm{ij}} \quad \text{if j} \in \text{C}$$

3. Fuzzy decision matrix is normalized using equatiuons:

$$\tilde{n}_{\mathrm{ij}} = \frac{\tilde{x}_{\mathrm{ai}}}{\tilde{x}_{\mathrm{ij}}} \quad \text{if j} \in \text{C}$$

$$\tilde{n}_{\mathrm{ij}} = \frac{\tilde{x}_{\mathrm{ij}}}{\tilde{x}_{\mathrm{ai}}} \quad \text{if j} \in \text{B}$$

4. Fuzzy weighted matrix is created using results of BWM. Vij fuzzy weighted normalized value of alternative i compared to criterion j.

$$\tilde{V}_{\mathrm{ij}} = \tilde{n}_{\mathrm{ij}} \tilde{w}_{\mathrm{ij}}$$

5. Calculate fuzzy sum of the weighted matrix for each alternative i

$$\tilde{S}_{\mathrm{i}} = \sum_{\mathrm{j}=1}^{\mathrm{n}} \tilde{V}_{\mathrm{ij}}$$

6. Calculate the degree of utility of each alternative

$$\widetilde{K}_{\mathrm{i}^-} = \frac{\tilde{S}_{\mathrm{i}}}{\tilde{S}_{\mathrm{aai}}}$$

$$\widetilde{K}_{\mathrm{i}^+} = \frac{\tilde{S}_{\mathrm{i}}}{\tilde{S}_{\mathrm{ai}}}$$

7. Calculate utility function for each alternative based on AI and AAI

$$\mathrm{F}\left(\widetilde{K}_{\mathrm{i}^-}\right) = \frac{\widetilde{K}_{\mathrm{i}^+}}{\widetilde{K}_{\mathrm{i}^+} + \widetilde{K}_{\mathrm{i}^-}}$$

$$\mathrm{F}\left(\widetilde{K}_{\mathrm{i}^+}\right) = \frac{\widetilde{K}_{\mathrm{i}^-}}{\widetilde{K}_{\mathrm{i}^+} + \widetilde{K}_{\mathrm{i}^-}}$$

8. Calculate final utility function of each alternative

$$\mathrm{F}\left(\widetilde{K}_{\mathrm{i}}\right) = \frac{\widetilde{K}_{\mathrm{i}^+} + \widetilde{K}_{\mathrm{i}^-}}{1 + \frac{1 - \mathrm{F}\left(\widetilde{K}_{\mathrm{i}^+}\right)}{\mathrm{F}\left(\widetilde{K}_{\mathrm{i}^+}\right)} + \frac{1 - \mathrm{F}\left(\widetilde{K}_{\mathrm{i}^-}\right)}{\mathrm{F}\left(\widetilde{K}_{\mathrm{i}^-}\right)}}$$

9. Defuzzification to determine ranking order

$$\text{Defuzzification } = \frac{l + 4m + u}{6}$$

Procedure E - multi-stage optimization model, Goldbeck (Goldbeck at al, 2020)

Global decision variables	$\bar{f}_{j,k}$	Nominal link flow capacities
	$\bar{g}_i$	Nominal production capacities
	$\bar{h}_i$	Nominal storage capacities
Stochastic variables	$x_{j,k}^{t,s}$	Damage to links
	$x_i^{t,s}$	Damage to nodes
Time and scenario dependent decision variables	$\tilde{f}_{j,k}^{t,s}$	Available link flow capacities
	$\breve{f}_{j,k}^{t,s}$	Repair of link flow capacities
	$f_{j,k}^{t,s}$	Link flows
	$\tilde{g}_i^{t,s}$	Available production capacities
	$\breve{g}_i^{t,s}$	Repair of production capacities
	$g_i^{t,s}$	Production rates
	$\tilde{h}_i^{t,s}$	Available storage capacities

$\breve{h}_i^{t,s}$	Repair of storage capacities
$h_i^{t,s}$	Inventory levels
$u_i^{t,s}$	Supply to end-users
$v_i^{t,s}$	Supply to dependent assets
$q_i^{t,s}$	Supply shortfalls below service level targets
$r_i^{t,s}$	Suply shortfalls below demand

$$\text{minimize} \sum_{(j,k)\in E} c_{j,k}^{\mathrm{f}} \bar{f}_{j,k} + \sum_{i\in V} \left(c_i^{\mathrm{g}} \bar{g}_i + c_i^{\mathrm{h}} \bar{h}_i \right) + \sum_{t=1}^{T} \sum_{s=1}^{S_t} p^{t,s} \left(\sum_{(j,k)\in E} c_{j,k}^{\mathrm{f}} f_{j,k}^{t,s} + \sum_{i\in V} \left(c_i^{\mathrm{g}} g_i^{t,s} + c_i^{\mathrm{h}} h_i^{t,s} + c_i^{\mathrm{q}} q_i^{t,s} + c_i^{\mathrm{r}} r_i^{t,s} \right) \right)$$

Subject to:

capacity utilization

$$f_{j,k}^{t,s} \leqslant \tilde{f}_{j,k}^{t,s} \leqslant \bar{f}_{j,k} \leqslant \hat{f}_{j,k} (j,k) \in E, t = 1 \dots T, s = 1 \dots S_t$$

$$g_i^{t,s} \leqslant \tilde{g}_i^{t,s} \leqslant \bar{g}_i \leqslant \hat{g}_i i \in V, t = 1 \dots T, s = 1 \dots S_t$$

$$h_i^{t,s} \leqslant \tilde{h}_i^{t,s} \leqslant \bar{h}_i \leqslant \hat{h}_i i \in V, t = 1 \dots T, s = 1 \dots S_t$$

loss and recovery of capacity

$$\left(1 - x_{j,k}^{t,s}\right)\left(\tilde{f}_{j,k}^{\Delta t,s(1)} + \breve{f}_{j,k}^{\Delta t,s(1)}\right) = \tilde{f}_{j,k}^{t,s}(j,k) \in E, t = 1 \dots T, s = 1 \dots S_t$$

$$\left(1 - x_{i}^{t,s}\right)\left(\tilde{g}_{i}^{\Delta t,s(1)} + \breve{g}_{i}^{\Delta t,s(1)}\right) = \tilde{g}_{i}^{t,s} i \in V, t = 1 \dots T, s = 1 \dots S_t$$

$$\left(1 - x_{i}^{t,s}\right)\left(\tilde{h}_{i}^{\Delta t,s(1)} + \breve{h}_{i}^{\Delta t,s(1)}\right) = \tilde{h}_{i}^{t,s} i \in V, t = 1 \dots T, s = 1 \dots S_t$$

net flow for each node over connected links

$$\sum_{(j,i)\in E} f_{j,i}^{\Delta_{t,s}(\delta_{j,i})} - \sum_{(i,j)\in E} f_{i,j}^{t,s} + h_i^{\Delta_{t,s}(1)} - h_i^{t,s} + g_i^{t,s} - u_i^{t,s} - v_i^{t,s} = 0$$

$$i \in V, t = 1 \dots T, s = 1 \dots S_t$$

$q_i^{t,s}$, $r_i^{t,s}$ respectively express how much the supply to end-users falls below the service level target and demand

$$\beta_i \breve{u}_i^t - u_i^{t,s} \leqslant q_i^{t,s} \quad i \in V, t = 1 \dots T, s = 1 \dots S_t$$

$$\breve{u}_i^t - u_i^{t,s} \leqslant r_i^{t,s} \quad i \in V, t = 1 \dots T, s = 1 \dots S_t$$

supply to dependent nodes

$$v_i^{t,s} = \sum_{(j,k)\in E:(i,j,k)\in D} \left(\alpha_{i,j,k}^{\mathrm{f}} f_{j,k}^{t,s} + \alpha_{i,j,k}^{\breve{\mathrm{f}}} \breve{f}_{j,k}^{t,s}\right) + \sum_{k\in V:(i,k)\in D} \left(\alpha_{i,k}^{\mathrm{g}} g_k^{t,s} + \alpha_{i,k}^{\mathrm{h}} h_k^{t,s} + \alpha_{i,k}^{\breve{\mathrm{g}}} \breve{g}_k^{t,s} + \alpha_{i,k}^{\breve{\mathrm{h}}} \breve{h}_k^{t,s}\right)$$

$$i \in V, t = 1 \dots T, s = 1 \dots S_t$$

set all decision variables to be non-negative

$\bar{f}_{j,k} \geqslant 0 (j,k) \in E$

$\tilde{f}_{j,k}^{t,s}, \breve{f}_{j,k}^{t,s}, f_{j,k}^{t,s} \geqslant 0 (j,k) \in E, t = 1 \dots T, s = 1 \dots S_t$

$\bar{g}_i, \bar{h}_i \geqslant 0 k \in V$

$\tilde{g}_i^{t,s}, \breve{g}_i^{t,s}, g_i^{t,s}, \tilde{h}_i^{t,s}, \breve{h}_i^{t,s}, h_i^{t,s}, q_i^{t,s}, r_i^{t,s}, u_i^{t,s}, v_i^{t,s} \geqslant 0 \qquad k \in V, t = 1 \dots T, s = 1 \dots S_t$

Document F – Nomenclature of parameters for mathematical modelling (Ahmadian et al, 2020).

G=(N,A)	Network with a set of nodes N and a set of arcs A
f_{ji}	Flow of arc $(i,j) \in \mathcal{A}$
T	Standard time interval
d_i	Demand of node $i \in \mathcal{N}$
s_i	Supply of node $i \in \mathcal{N}$
γ_{ij}	Capacity of arc $(i,j) \in \mathcal{A}$
I_i^n	Demand loss of node $i \in \mathcal{N}$
φ_{ij}^a	Estimated damage level on arc $(i,j) \in \mathcal{A}$ caused by a disruption on the same arc
$\tilde{\varphi}_{ijn}^a$	Estimated damage level on arc $(i,j) \in \mathcal{A}$ caused by a disruption on node $n \in \mathcal{N}$
r_i^n	Repair rate function of node $i \in \mathcal{N}$
r_{ij}^a	Repair rate function of arc $(i,j) \in \mathcal{A}$
Q_i^n	Cumulative repair rate of node $i \in \mathcal{N}$
Q_{ij}^a	Cumulative repair rate of arc $(i,j) \in \mathcal{A}$
I_i^n	Impact of node $i \in \mathcal{N}$ disruption on the network
I_{ij}^a	impact of arc $(i,j) \in \mathcal{A}$ disruption on the network

C_i^n	Criticality of node $i \in \mathcal{N}$
C_{ij}^a	Criticality of arc $(i, j) \in \mathcal{A}$
$\mathcal{L}_i^n$	Likelihood of having disruption on node $i \in \mathcal{N}$
$\mathcal{L}_{ij}^a$	Likelihood of having disruption on arc $(i, j) \in \mathcal{A}$
R_i^n	Resilience of node $i \in \mathcal{N}$
R_{ij}^a	Resilience of arc $(i, j) \in \mathcal{A}$

Images LIST

Fig. 2.3 – The resilience triangle, system performance brake down. (Ahmadian et al, 2020)

Fig. 2.4 – The resilience triangle, impact on performance as “Severity” and “Recovery time”. (Carvalho et al, 2022)

Fig. 2.5 – Overview of modelling multi-stage optimization method. (Goldbeck at al, 2020)

Fig. 2.6 – BWM method: Determine the preference of all the criteria over the worst criterion using a number between 1 to N scale. (Rezaei J., 2015)

Fig. 2.7 – Schematic rocedure to create overall resilience index (Nguyen et al 2021).

Fig. 2.8 – Example Digraph of strategic level enablers. (Agarwal et al, 2021)

Fig. 3.1 – Cartesian graph to categorize supply chain indexes

Fig. 3.2 – Categorization of supply chain resilience indexes

Bibliography and Sitography

[1]Chen, J., Sohal, A. S., & Prajogo, D. I. (2013). Supply chain operational risk mitigation: A collaborative approach. International Journal of Production Research, 51(7), 2186–2199 https://doi.org/10.1080/00207543.2012.727490

[2] Closs, D., and McGarrell, E., 2004. Enhancing Security Throughout the Supply Chain. IBM Center for the Business of Government, Special Report Series: 1-52 http://www.businessofgovernment.org.

[3] Tukamuhabwa, Benjamin R., Stevenson, Mark, Busby, Jerry and Bell, Marta (2015) Supply chain resilience: definition, review and theoretical foundations for further study. International Journal of Production Research, 53 (18). pp. 5592-5623 http://dx.doi.org/10.1080/00207543.2015.1037934

[4] Ponis, S., and Koronis, E., 2012. Supply Chain Resilience: Definition of Concept and Its Formative Elements. Journal of Applied Business Research 28(5):921-930

[5] Ponomarov, S., 2012. Antecedents and consequences of supply chain resilience: A Dynamic Capabilities Perspective. PhD Dissertation, University of Tennessee-USA.

[6] Xiao, R., Yu, T., and Gong, X., 2012. Modeling and simulation of ant colony's labor division with constraints for task allocation of resilient supply chains. International Journal on Artificial Intelligence Tools 21(3):1-19

[7] Hosseini, S.; Ivanov, D.; Dolgui, A. Review of quantitative methods for supply chain resilience analysis. Transp. Res. E.-Log.2019, 125, 285–307.

Ivanov, D., & Sokolov, B. (2020). Simultaneous structural-operational control of supply chain dynamics and resilience. Annals of Operations Research, 283(1), 1191–1210.

[8] Joseph. (2020). US airlines are losing money for the first time in years as coronavirus ends travel boom. www.cnbc.com

[9] Schleper, M. C., Gold, S., Trautrims, A., & Baldock, D.(2021). Pandemic-induced knowledge gaps in operations and supply chain management: COVID-19'simpacts on retailing. International Journal ofOperations & Production Management,41(3), 193–205. https://doi.org/10.1108/IJOPM-12-2020-0837

[10] DeMarco, A. (2020).McKinsey issues dismal post-pan-demic forecast for $2.5 trillion fashion industry. Forbes.

[11] Bevilacqua, M., Ciarapica, F. E., Marcucci, G., & Mazzuto,G. (2020). Fuzzy cognitive maps approach for analyzing the domino effect of factors affecting supply chain resilience: A fashion industry case study. International Journal of Production Research,58(20), 6370–6398. https://doi.org/10.1080/00207543.2019.1680893

[12] Majumdar, A., Shaw, M., & Sinha, S. K. (2020). COVID-19 debunks the myth of socially sustainable supply chain: A case of the clothing industry in South Asiancountries.Sustainable Production and Consumption,24,150–155. https://doi.org/10.1016/j.spc.2020.07.001

[13] WIECZNER. (2020). The case of the missing toilet paper: How the coronavirus exposed U.S. supply chain flaws. Fortune.com

[14] Mathews. 2020. Sysco lays off, furloughs workers as COVID-19 disrupts operations . Huston business journal

[15] Rinaldi, M.; Murino, T.; Bottani, E.2021. The Impact of COVID-19 On Logistic Systems: An Italian Case Study. IFAC Pap.2021,54,1035–1040. https://www.researchgate.net/deref/http%3A%2F%2Fdoi.org%2F10.1016%2Fj.ifacol.2021.08.123

[16] O'Leary. 2020. The Modern Supply Chain Is Snapping. Theatlantic.com

[17] Frieske, B.; Stieler, S. 2022. The Semiconductor Crisis as a Result of the COVID-19 Pandemic and Impacts on the Automotive Industry and Its Supply Chains. World Electr. Veh. J. , 13, 189. https://doi.org/10.3390/wevj13100189

[18] Liao,Y. 2020. An integrative framework of supply chain flexibility. Int. J. Prod. Perform. Mang. 69 (6), 1321-1342. https://www.emerald.com/insight/content/doi/10.1108/IJPPM-07-2019-0359/full/html

[19] Tang, C. and Tomlin, B. (2008), The power of flexibility for mitigating supply chain risks, International Journal of Production Economics, Vol. 116 No. 1, pp. 12-27.

[20] Katsaliaki, K., Galatesi, P., Kumar, S., 2021. Supply chain disruptions and resilience: a major review and future research agenda. Ann. Oper. Res. 1-38 https://www.scopus.com/record/display.uri?eid=2-s2.0-85144243787&origin=inward

[21] Asamoah, D., Agyei-Owusu, B. and Ashun, E. (2020), Social network relationship, supply chain resilience and customer-oriented performance of small and medium enterprises in a developing economy, Benchmarking: An International Journal, Vol. 27 No. 5, pp. 1793-1813.

[22] Queiroz, M.M., Wamba, S.F. and Branski, R.M. (2021), Supply chain resilience during the COVID-19: empirical evidence from an emerging economy, Benchmarking: An International Journal, Vol. ahead-of-print No. ahead-of-print.

[23] Chirra, S., Raut, R.D., Kumar, D., 2020 Barriers to sustainable supply chain flexibility during sales promotions. Int. J. Prod. Res. 1-19

https://www.scopus.com/record/display.uri?eid=2-s2.0-85118816761&origin=inward

[24] Chowdhury, M.M.H. and Quaddus, M. (2017), Supply chain resilience: conceptualization and scale development using dynamic capability theory, International Journal of Production Economics, Vol. 188, pp. 185-204. https://www.researchgate.net/publication/315997286_Supply_Chain_Resilience_Conceptualization_and_Scale_Development_Using_Dynamic_Capability_Theory

[25] Cahyaningratri, C & Naylah, M. (2023). The effect of supply chain operational capabilities in consolidating organizational compatibility of supply chain process integration and business performance. Uncertain Supply Chain Management, 11(1), 95-102.

[26] Sun, H. and Ni, W. (2012), The impact of upstream supply and downstream demand integration on quality management and quality performance, International Journal of Quality and Reliability Management, Vol. 29 No. 8, pp. 872-890.

[27] Shekarian, M., S. V. R. Nooraie, and M. M. Parast. 2020. An Examination of the Impact of Flexibility and Agility on Mitigating Supply Chain Disruptions. International Journal of Production Economics 220: 107438

[28] Ivanov, D., and A. Dolgui. 2020. Viability of Intertwined Supply Networks: Extending the Supply Chain Resilience Angles Towards Survivability. A Position Paper Motivated by COVID-19 Outbreak. International Journal of Production Research 58 (10): 2904–2915.

[29] Masoud Kamalahmadi, Mansoor Shekarian & Mahour Mellat Parast (2022) The impact of flexibility and redundancy on improving supply chain resilience to disruptions, International Journal of Production Research, 60:6, 1992-2020, DOI: 10.1080/00207543.2021.1883759

[30] Christopher M, Peck H (2004) Building the resilient supply chain. Int J Logist Manag 15(2):1–14 https://dspace.lib.cranfield.ac.uk/handle/1826/2666

[31] Erol, O., Sauser, B., and Mansouri, M., 2010. A framework for investigation into extended enterprise resilience. Enterprise Information Systems 4 (2):111-136

[32] Pettit, J., Croxton, K., and Fiksel, J., 2013. Ensuring Supply Chain Resilience: Development and Implementation of an Assessment Tool. Journal of Business Logistics 34(1):46–76.

[33] Christopher, M. and Lee, H., 2004. Mitigating supply chain risk through improved confidence. International Journal of Physical Distribution & Logistics Management 34 (5): 388 – 396.

[34] Scholten, K. and Schilder, S. (2015), The role of collaboration in supply chain resilience, Supply Chain Management: An International Journal, Vol. 20 No. 4, pp. 471-484.

[35] Yang, T. and Fan, W. (2016), Information management strategies and supply chain performance under demand disruptions, International Journal of Production Research, Vol. 54 No. 1, pp. 8-27.

[38] Roh, J.; Tokar, T.; Swink, M.; Williams, B. Supply chain resilience to low-/high-impact disruptions: The influence of absorptive capacity. Int. J. Logist. Manag. 2021, 33, 214–238. http://doi.org/10.1108/IJLM-12-2020-0497

[39] Ivanov, D., 2020b. Predicting the impacts of epidemic outbreaks on global supply chains: a simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transport. Res. E Logist. Transport. Rev. https://doi.org/10.1016/j. tre.2020.101922

[40] Ivanov, D., 2020a. Viable supply chain model: integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic. Ann. Oper. Res. https://doi.org/10.1007/s10479-020-03640-6. Springer US.

[41] Akram El Korchi, 2020.Survivability, resilience and sustainability of supply chains: The COVID-19 pandemic, Journal of Cleaner Production, Volume 377, 134363, ISSN 0959-6526, https://doi.org/10.1016/j.jclepro.2022.134363.

[42] Biringer, B.E., Vugrin, E.D., Warren, D.E., 2013. Critical infrastructure system security and resiliency. In: Critical Infrastructure System Security and Resiliency. CRC Press Taylor & Francis. https://doi.org/10.1201/b14566

[43] Bacardi, 2020. Bacardi makes hand sanitizer. https://www.bacardi.com/culture/sanitizer/

[44] Reuters. 2020. Fiat Chrysler starts ventilator component output in Italy. https://www.reuters.com/article/us-health-coranavirus-fiat-chrysler-vent-idUSKBN21L1FA

[45] Didier, Huneeus,Larrain,Schmuker. 2020. Financing Firms in Hibernation during the COVID-19 Pandemic. https://documents1.worldbank.org/curated/en/228811586799856319/pdf/Financing-Firms-in-Hibernation-During-the-COVID-19-Pandemic.pdf

[46] Ho, W., Zheng, T., Yildiz, H., & Talluri, S. (2015). Supply chain risk management: A literature review. International Journal of Production Research, 53(16), 5031–5069.

[47] Torabi, S. A., Baghersad, M., & Mansouri, S. A. (2015). Resilient supplier selection and order allocation under operational and disruption risks. Transportation Research – Part E, 79, 22–48.

[48] Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: An analysis and recent literature. International Journal of Production Research, 56(1–2), 414–430.

[49] He, J., Alavifard, F., Ivanov, D., & Jahani, H. (2019). A real-option approach to mitigate disruption risk in the supply chain. Omega: The International Journal of Management Science, 88, 133–149.

[50] Hosseini, S., Ivanov, D., & Dolgui, A. (2019a). Ripple effect modeling of supplier disruption: Integrated Markov Chain and Dynamic Bayesian Network Approach. International Journal of Production Research. in press.

[51] D. Simchi-Levi, P. Kaminsky and E. Simchi-Levi. 2008. Designing and managing the supply chain, McGraw-Hill/Irwin, New York

[52] David Simchi-Levi. 2010. Operations rules. MIT Press

[53] Iris Heckmann, Tina Comes, Stefan Nickel. 2015. A critical review on supply chain risk – Definition, measure and modeling, Pages 119-132, https://doi.org/10.1016/j.omega.2014.10.004

[54] Srinivasan, R., and M. Swink. 2018. An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics:

AnOrganizational Information Processing Theory Perspective. Production and Operations Management27 (10): 1849–1867.

[55] Hazen, B. T., J. B. Skipper, C. A. Boone, and R. R. Hill. 2018. Back in Business: Operations Research in Support of Big Data Analyticsfor Operations and Supply Chain Management. Annals of Operations Research270 (1-2): 201–211.

[56] Rameshwar Dubey, Angappa Gunasekaran, Stephen J. Childe, Samuel Fosso Wamba, David Roubaud & Cyril Foropon (2021) Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience, International Journal of Production Research, 59:1, 110-128, DOI: 10.1080/00207543.2019.1582820

[57] Alexopoulos, Kosmas & Anagiannis, Ioannis & Nikolakis, Nikolaos & Chryssolouris, George. (2022). A quantitative approach to resilience in manufacturing systems. International Journal of Production Research. 60. 1-16. 10.1080/00207543.2021.2018519.

[58] Chryssolouris, G. 2006. Manufacturing Systems Theory and Practice. 2nd Edition. New York: Springer-Verlag.

[59] Chryssolouris, G., and M. Lee. 1992. An Assessment of Flexibility in Manufacturing Systems. Manufac Turing Review 5 (2): 105–116.

[60] Navid Ahmadian, Gino J. Lim, Jaeyoung Cho, Selim Bora, A quantitative approach for assessment and improvement of network resilience, Reliability Engineering & System Safety, Volume 200, 2020, 106977, ISSN 0951-8320, https://doi.org/10.1016/j.ress.2020.106977.

[61] Said, Saloua & Bouloiz, Hafida & Gallab, Maryam. (2020). Resilience Assessment of System Process Through Fuzzy Logic: Case of COVID-19 Context. Advances in Science Technology and Engineering Systems Journal. 5. 1247-1260. 10.25046/aj0505150.

[62] V. Llamas, T. Coudert, L. Geneste, J. Romero-Bejarano, A. de Valroger, Proposition of an agile knowledge-based process model, IFACPapersOnLine, 49(12),1092-1097, 2016.

[63] D. Ristic, A TOOL FOR RISK ASSESSMENT, Safety Engineering, 3(3), 2013.

[64] O. Gluchshenko, Defnitions of Disturbance, Resilience and Robustness in ATM Context DLR Report IB 112-2012/28, DLR,Institute of Flight Guidance, Germany, 2012

[65] Helena Carvalho, Bardia Naghshineh, Kannan Govindan, Virgílio Cruz-Machado, The resilience of on-time delivery to capacity and material shortages: An empirical investigation in the automotive supply chain, Computers & Industrial Engineering, Volume 171, 2022, 108375, ISSN 0360-8352, https://doi.org/10.1016/j.cie.2022.108375.

[66] Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., … Von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. Earthquake Spectra, 19(4), 733–752. https://doi. org/10.1193/1.1623497

[67] Tierney, K., & Bruneau, M. (2007). Conceptualizing and measuring resilience: A key to disaster loss reduction. (250): TR news.

[68] Liwei Chen, Hongyan Dui, Chi Zhang,

A resilience measure for supply chain systems considering the interruption with the cyber-physical systems, Reliability Engineering & System Safety, Volume 199, 2020, 106869, ISSN 0951-8320, https://doi.org/10.1016/j.ress.2020.106869.

[69] Morteza Yazdani, Ali Ebadi Torkayesh, Prasenjit Chatterjee, Alireza Fallahpour, Maria Jose Montero-Simo, Rafael A. Araque-Padilla, Kuan Yew Wong,

A fuzzy group decision-making model to measure resiliency in a food supply chain: A case study in Spain, Socio-Economic Planning Sciences, Volume 82, Part B, 2022, 101257, ISSN 0038-0121, https://doi.org/10.1016/j.seps.2022.101257.

[70] Jafar Rezaei, Best-worst multi-criteria decision-making method, Omega, Volume 53, 2015, Pages 49-57, ISSN 0305-0483, https://doi.org/10.1016/j.omega.2014.11.009.

[71] Jafar Rezaei, Best-worst multi-criteria decision-making method: Some properties and a linear model, Omega, Volume 64, 2016, Pages 126-130, ISSN 0305-0483, https://doi.org/10.1016/j.omega.2015.12.001.

[72] Huy Nguyen, Thomas C. Sharkey, Shamus Wheeler, John E. Mitchell, Willam A. Wallace, Towards the development of quantitative resilience indices for Multi-Echelon Assembly Supply Chains, Omega, Volume 99, 2021, 102199, ISSN 0305-0483, https://doi.org/10.1016/j.omega.2020.102199.

[73] Huy Nguyen, Thomas C. Sharkey, John E. Mitchell & William A. Wallace (2020) Optimizing the recovery of disrupted single-sourced multi-echelon assembly supply chain networks, IISE Transactions, 52:7, 703-720, DOI: 10.1080/24725854.2019.1670372

[74] Conover WJ. Practical Nonparametric Statistics. 3rd ed; 1999. New York: Wiley

[75] Bonate, Peter. (2001). A Brief Introduction to Monte Carlo Simulation. Clinical pharmacokinetics. 40. 15-22. 10.2165/00003088-200140010-00002.

[76] Nils Goldbeck, Panagiotis Angeloudis, Washington Ochieng,

Optimal supply chain resilience with consideration of failure propagation and repair logistics, Transportation Research Part E: Logistics and Transportation Review, Volume 133, 2020, 101830, ISSN 1366-5545, https://doi.org/10.1016/j.tre.2019.101830.

[77] Haimes, Y.Y., Jiang, P., 2001. Leontief-based model of risk in complex interconnected infrastructures. J. Infrastruct. Syst. 7, 1–12. https://doi.org/10.1061/(ASCE) 1076-0342(2001) 7:1(1).

[78] Agarwal, Nishtha & Seth, Nitin & Agarwal, Ashish. (2021). Evaluation of supply chain resilience index: a graph theory based approach. Benchmarking: An International Journal. ahead-of-print. 10.1108/BIJ-09-2020-0507.

[79] Jain, V., Kumar, S., Soni, U. and Chandra, C. (2017), SC resilience: model development and empirical analysis, International Journal of Production Research, Vol. 55 No. 22, pp. 6779-6800.

[80] Tan, W.J., Zhang, A.N. and Cai, W. (2019), A graph-based model to measure structural redundancy for SC resilience, International Journal of Production Research, Vol. 57 No. 20, pp. 6385-6404.

[81] Kaur, A., Kanda, A. and Deshmukh, S.G. (2006), A graph theoretic approach for SC coordination, International Journal of Logistics Systems and Management, Vol. 2 No. 4, pp. 321-341

[82] Forrester, D., Killian, M., Westlake, D. and Sheehan, L. (2020), Patterns of practice: an exploratory factor analysis of child and family social worker skills, Child and Family Social Work, Vol. 25 No. 1, pp. 108-117.

[83] Scanlon, J. and Deo, N. (1999), Graph-theoretic algorithms for image segmentation, in 1999 IEEE International Symposium on Circuits and Systems (ISCAS), IEEE, Vol. 6, pp. 141-144

[84] Marcus, M., & May, F. (1962). The Permanent Function. Canadian Journal of Mathematics, 14, 177-189. doi:10.4153/CJM-1962-013-4

[85] Stevi´c Z, ˇ Pamuˇcar D, Puˇska A, Chatterjee P. Sustainable supplier selection in healthcare industries using a new MCDM method: measurement of alternatives and ranking according to Compromise solution (MARCOS). Comput Ind Eng 2020;140: 106231

[86] RetailNext . (2020). Level of supply chain disruption faced by retailers globally due to the coronavirus pandemic in 2020 , CEO Retailer Pulse #2 April 2020, page 6 , retailnext.net/resources

[87] OAG Schedules Analyser. (2021) . Year-on-year change of weekly flight frequency of global airlines from January 6, 2020 to January 4, 2021 by country . oag.com/coronavirus-airline-schedules-data

[88] Field Agent. (2020). Coronavirus Wipes Out Shelves: Out-of-Stocks Across All 50 States. blog.fieldagent.net/coronavirus-wipes-out-shelves-stock-levels-across-all-50-states

[89] Qualtrics. (202). The other COVID-19 crisis: Mental health. https://www.qualtrics.com/blog/confronting-mental-health

[90] Inverto. (2021). Raw Materials Study 2021 Results from the survey by INVERTO and trade journal Handelsblatt. https://test.inverto.com/wp-content/uploads/2021/10/INVERTO-Raw-Materials-Study2021-EN.pdf

[91] Pires Riberio, H., Barbosa_Povoa, A., 2018. Supply chain resilience: definitions and quantitative modeling approaches- A literature review.