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A Mixed-Method Study on the Effectiveness of a Buffering Strategy in the Relationship between Risks and Resilience
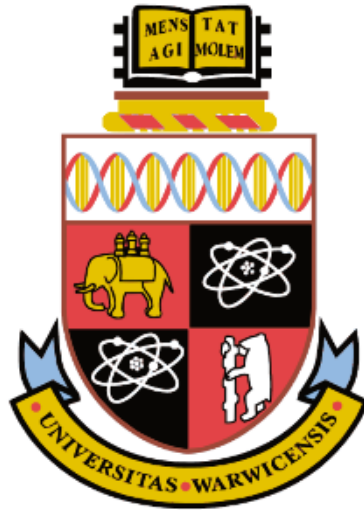
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A thesis submitted in partial fulfilment of the
requirements for the degree of
Doctor of Philosophy in Engineering

University of Warwick, Warwick Manufacturing Group (Department)
September 2017

This thesis is dedicated to my two loves in life, Angie and Manuel

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Declaration

This thesis is the original work of the author and is submitted in partial fulfilments of the requirements of the degree of Doctor of Philosophy (PhD). The research was performed at WMG department of the University of Warwick from October 2013 to September 2017, under the supervision of Dr Dawei Lu and Dr Ali Ahmad. This thesis has not ben submitted in whole or in part as consideration of any other degree qualification at this or any other university. Where other work has been used it has been acknowledged. In accordance to the Requirements for the Award of the Research Degree of the Faculty of Sciences, the length of this thesis is less than 70,000 words.

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Abstract

The present research pursues two main interrelated objectives: one the one hand, to derive a unified definition of the concept of supply chain resilience (SCRes) from which a quantitative holistic measure of SCRes that appraises both dynamic and inherent resilience can be developed; on the other, to evaluate the theoretical effectiveness—due to the use of simulated experimental data—of a buffering strategy founded on the use of on-hand inventory buffers or short-term manufacturing capacity to build up SCRes. In this sense, the review of the literature uncovered not only flaws in the existing approaches to measure SCRes, but also opposing standpoints on the theoretical effectiveness of using a buffering strategy to inhibit the frequency/impact of SC disruptions. From the literature it is also unclear in which cases or under what circumstances the unit of analysis for this research should adopt a buffering strategy as mentioned. The unit of analysis selected for these purposes is a real-world military food supply chain (MFSC) operating in a risky environment that provides subsistence items to a medium-size military force (<280,000 troop members). The research methods to address the two research objectives proposed are, first, a robust model based on discrete simulation; and second, an open-ended questionnaire administered to the staff of the MFSC. The first method—simulation—provides the data required to test the nine ex-ante hypotheses, while the second method—questionnaire—complements the previous ones by increasing their usefulness and empirical validity. The simulation experiment performed consists of subjecting the MFSC under analysis to the stepwise occurrence of three categories of risk—operational risks or R_1; natural disasters and intentional attacks or R_2; and black-swan events or R_3—while on-hand inventory buffers or short-term manufacturing capacity—the buffering strategy—are gradually increased following an efficient experimental design. To test the nine hypotheses of the research, it was necessary to apply an approach based on data mining techniques— mining causal association rules—and non-parametric methods—the Kruskal-Wallis rank sum and Binomial distribution tests, and the Wilcoxon rank sum test with continuity correction. In this way, based on a novel perspective related to the application of the concept of *tail autotomy effect* (TAE) to obtain a measure of SCRes (Re^T), the evaluation of the output data of the simulation model indicates that: (1) ceteris paribus, increases in the frequency of occurrence of seven of the nine risk events considered reduce Re^T in the MFSC with 99% confidence; (2) increases in on-hand inventory buffers positively moderate the relationship between the frequency of occurrence of risks and Re^T, with 99% confidence, regardless of the category of risk—R_1, R_2, or R_3—affecting the MFSC; (3) increases in short-term manufacturing capacity positively moderate the relationship between the frequency of occurrence of risks and Re^T, with 95% confidence for the categories of risk R_1 and R_3, and with 99% confidence for R_2; and (4) from the open-ended questionnaire, the staff of the MFSC shows a marked preference for the use of on-hand inventory buffers over short-term manufacturing capacity to avoid the occurrence of disruptions. Despite the theoretical implications of these findings, the assumptions of the simulation model, the non-inclusion of the cost factor, and the utilization of a single MFSC may limit to a certain extent their generalization to other scenarios or unit of analysis. To ameliorate these deficiencies, the construction of the simulation model incorporates nine types of risk, the evaluation of ninety configurations of the MFSC—simulation runs, and the consideration of a lengthy horizon of analysis of up to twenty years, allowing other military-SCs or even commercial-SCs can take advantage of the implications of the results of this research. Thus, from a practical point of view, this research provides (military) logisticians with clear guidelines for making decisions on when and how to use on-hand inventory buffers or short-term manufacturing capacity to create resilience or to inhibit the occurrence of disruptions caused by categories of risk R_1, R_2, and R_3. From a theoretical standpoint, this research makes an original contribution to the body of knowledge in SC management by providing a novel conceptual framework mainly applicable to MFSCs, which includes the analysis of three

categories of risk; a holistic measure of SCRes (Re^T) including dynamic and inherent resilience; and the analysis of the application of a buffering strategy based on on-hand inventory buffers and short-term manufacturing capacity. In doing so, the findings of the research provide sufficient criteria for resolving the controversy concerning the theoretical effectiveness of the aforementioned strategy to create resilience and/or to inhibit the occurrence of disruptions in SCs.

List of Abbreviations

AL   Assembly line
ARM   Association rule mining
AP   Autotomy period
CB   Combat brigades
CIA   Correlated inspection approach
CoT   Contingency theory
CSSB   Combat service support battalion
CSSU   Combat service support units
CSSR   Case study survey research
CT   Cycle time
D   Demand
DES   Discrete-event simulation
DL   Defense Logistics
DP   Disruption period
DS   Data set
DSE   Design of simulation experiment
EC   Effective capacity
FR   Fill rate
HLC   Head logistics command
I   Inventory
KS   Kolmogorov-Smirnov test
KW   Kruskal-Wallis test
LB   Logistics brigades
LOC   Line-of-communication
LT   Lead time
MaB   Maintenance battalion
MCV   Mill's method of concomitant variation
MeB   Medical battalion
MLS   Military logistics system
MFSC   Military food supply chain
OAT   Order arrival time
OPT   Order placement time
PT   Processing time
QB   Quartermaster battalion
QDM   Questionnaire data matrix
QRD   Questionnaire raw data
ROP   Re-order point
RP   Recovery period
S   Work shifts
SB   Supply battalions
SC   Supply chain
SCRes   Supply chain resilience
SDM   Simulation data matrix
SPT   Shortest processing time
SW   Shapiro-Wilk test
TAE   Tail autotomy effect
TB   Transport battalions
TC   Theoretical capacity
W   Wilcoxon rank sum test with continuity correction
WDC   Warehouse and distribution centre

Chapter 1
INTRODUCTION

Chapter 1. Introduction

1.1 "Troops' lives may be at stake without us!"

The initial idea for developing this study was born eleven years ago when the logistics chief of the Colombian Army uttered this sentence in his welcoming speech to a group of military reservists during a training course. The General intended to convince us of the key role that military logistics plays for modern armed forces, yet he did not need to strive so hard. Military logistics by itself has become the cornerstone of the strategy in modern armed forces (Prebilic, 2006). No army in the world, not even the most powerful in weaponry, can operate on short notice and/or at long distances without adequate logistical support. The most recent conflicts in the world, as well as the 'new' roles assigned to armed forces, e.g., helping in humanitarian operations, confirm this fact (Byman et al., 2000). Despite this, military history is full of cases that demonstrate what happens when logistics criteria are not properly taken into account in the planning of military operations (Cohen & Gooch, 2006). Moreover, it is sometimes overlooked that the high uncertainty that for the most part characterizes military operations also affects military supply chains (SCs) by causing logistical breakdowns, making this type of SC the most exposed to the occurrence of risks. Thereby, when a logistical breakdown occurs, the possibility of loss of human life increases. In this regard, Demchak (2010) pointed out that preserving the continuity of military operations is equivalent to being *resilient* (p.63), whilst Yoho and colleagues (2013) stressed the need to incorporate the latter concept (resilience) into military-SCs, noting furthermore the scarcity of research in the field of defence logistics. Accordingly, the subject of this study is an attempt to improve the resilience of the Colombian military's supply chain of military food (MFSC), or, in other words, to make the MFSC less disruption-prone.

1.2 Objectives and Scope of the Study

All types of SC are inevitably exposed to a wide range of risks, regardless of their structure, level of complexity, or context (Kleindorfer & Saad, 2005; Svensson, 2000). Some of these risks have the potential to become disruptive events, i.e., they can interrupt, temporarily or permanently, the flow of supplies to end-customers (Chopra et al., 2007). The occurrence of disruptive events regularly causes a negative impact on the performance, profitability, and/or shareholder value of commercial-SCs (Hendricks & Singhal, 2005; Ponomarov & Holcomb, 2009). However, for military-SCs in general, such effects can be deeper, potentially endangering the life of troops. What can a military-SC as enunciated do to reduce the frequency/impact of disruptive events?

This is not a simple question. An analysis of the literature reveals that military-SCs have emulated several of the best practices applied by their civilian counterparts, commercial-SCs. Thus, approaches such as *mass-logistics* (Wang, 2000), *velocity management* (Dumond et al., 1995), *sense* & *response logistics* (Tripp et al., 2006), or *focused logistics* (DoD, 2010), to name a few, have been applied in military-SCs in an attempt to deal with this problem. However, to judge by the criticism of these initiatives (Girardini et al., 1995; Moore & Antill, 1999; Parlier, 2011), the results have not been entirely satisfactory, and in some cases seem to have aggravated the problem (Needham & Snyder, 2009). Accordingly, I argue in this research that a robust

solution, that is, "one that works well most of the time" (Hopp & Spearman, 2008, p.250), can be achieved through the operationalization of the concept of *resilience* or "the ability to bounce back from a disruption" (Sheffi & Rice, 2005, p.41).

From a theoretical point of view, the application of the concept of resilience can be a rather effective way to reduce the incidence of disruptions in military-SCs (Tatham & Taylor, 2008; Kovács & Tatham, 2009), especially when their particular characteristics—viz., organizational goals, operating environment, customer lead-time, level of risk, nature of logistics operations, procurement system, pattern of demand, and marketing channels—are taken into account. Nonetheless, in spite of the positive comments that the concept of resilience generates, as far as I know, no new approach or administrative practice directly involving the application of the concept of resilience has hitherto been developed, nor is there evidence regarding its application in any military-SC. Thus, for the operationalization of the concept of resilience in military-SCs, several hurdles first must be overcome.

First, the huge diversity of definitions and multiple interpretations of SC-resilience (SCRes) that can be found in the literature—this research identified 24 definitions of SCRes—to some extent hinders the operationalization of the concept of SCRes. Second, despite the significant interest that the topic of SCRes has generated among scholars and practitioners, the gap between its theoretical underpinnings and attempts to operationalize the concept has yet to be filled. And third, not all the approaches for creating SCRes and/or to inhibit the occurrence of disruptions described in the literature—see e.g. Tukamuhabwa et al (2015)—can be directly applied to military-SCs, due, inter alia, to their specificities mentioned above. Indeed, of the available approaches, 'strategies based on redundancy', particularly *buffering strategies*, seems to be the best suited to application in military-SCs. Therefore, I propose in this research two main objectives:

(1) to derive a *unified conceptualization* of SCRes based on the existing definitions, research done and gaps identified in the literature review from which a quantitative *holistic measure* of SCRes that appraises both dynamic and inherent resilience can be developed; and secondly,

(2) to evaluate the theoretical effectiveness of a *buffering strategy* founded on the use of on-hand inventory buffers or short-term manufacturing capacity to build up SCRes.

In general, with respect to the stated objectives, some authors have pointed out that little empirical research has been done on the interactive effects of buffering strategies on SC-disruptions or those to respond to risks (Marley et al., 2014; Sodhi et al., 2012). Moreover, it is worth noting the existence of a theoretical conflict regarding the effectiveness of using inventory and/or capacity to make SCs more resilient. On the one hand, some authors praise the benefits of using inventory or capacity, e.g. Pettit and colleagues (2013); on the other hand, others see no advantage in their use as inhibitors of SC disruptions, e.g. Kim and colleagues (2015). To date, this debate has not been satisfactorily resolved.

1.3 Statement of the Research Problem and Research Methods

Drawing on the lack of empirical studies and theoretical discussion on the effectiveness of the aforesaid buffering strategy, the research problem is posited in the following terms:

How is the resilience level—dynamic and inherent—of a military food supply chain in a risky environment affected by increases in on-hand inventory buffers/short-term manufacturing capacity?

The formulation of the above research problem poses the derivation of a universal definition of SCRes; the development of a theoretical framework on disruptions to assess resilience in MFSCs that includes the two above-mentioned dimensions; and the use of a quite robust tool—a simulation-based method—to 'recreate' the risky environment for the MFSC under analysis, due to the absence of historical records and the inability to modify the experimental setting at convenience. The simulation tool selected for this purpose is Simulink [v.R2015b-8.6.0.26] by MATLAB®. The risky simulated environment for the MFSC consists of nine types of risk organized into three categories—operational risks, R_{1r}; natural disasters and intentional attacks, R_{2r}; and black-swan events, R_3—within a simulation horizon of up to 20 years. Due to the volume and nature of the output data of the simulation model, data mining techniques—mining causal association rules—and non-parametric methods—the Kruskal-Wallis rank sum and Binomial distribution tests, and the Wilcoxon rank sum test with continuity correction—were chosen to test the nine research hypotheses that are raised.

The results of the simulation model are supplemented with an open-ended questionnaire administered to twelve staff member of the MFSC in order to improve the internal validity of the research findings. In this way, whilst the simulation model indicates what logisticians *should* do in case R_{1r}, R_{2r}, or R_3 occurs, the questionnaire points out what logisticians *would* do if they face these categories of risk. Furthermore, given the nature of the dominant method of research used to generate data (simulation), it can be said that the 'positivist perspective'—or analytical school—is the paradigm that best characterizes the present research.

1.4 Contributions of the Study

This study can be seen as a series of interconnected contributions. In this way, the major contribution lies in the 'extended conceptual framework', which is introduced in Chapter 3, supported and analysed in Chapter 6, and later discussed in Chapter 7, respectively. Thus, the originality of the conceptual framework is not given by the individual variables included for analysis—three categories of risk, a measure of SCRes, and in the middle of the two, a buffering strategy based on on-hand inventory buffers and short-term manufacturing capacity—, but by the manner in which they were arranged and assessed as a whole, thereby providing a tangible solution for the above-mentioned research problem (question). In doing so, the conceptual framework allows a better understanding of the resilience phenomenon, as well as providing new findings on how SCRes can be improved through the application of a buffering strategy. The second main contribution of this research is contained within the aforesaid conceptual framework, and it relates to the derivation of a unified conceptualization and a novel

quantitative measure of SCRes (Re^T), both described in Chapter 5. The proposed measure of SCRes is based on a self-defence mechanism called 'tail autotomy effect' (TAE) and includes the two dimensions of the concept of resilience: 'dynamic resilience' and 'inherent resilience'. TAE's approach for SCRes offers an innovative perspective on how SCs respond to the occurrence of disruptions caused by risks. The resulting Re^T is integrated into a robust simulation model of the MFSC and the results are measured through techniques of data mining and non-parametric methods.

Last but not least, this study contributes in several ways to the underexplored field of defence logistics by typifying the internal processes of a real-world MFSC (Chapter 6); by providing theoretical explanations of why it is worth studying buffering strategies in military-SCs (Chapter 3); by giving a thorough description of the risks that most often affect military-SCs and constructing a probabilistic simulation model for these (Chapter 6); and lastly, by arguing for the need to implement and measure resilience in military-SCs (Chapter 5).

1.5 Structure of the Study

For the development and completion of the previous 'extended argument', eight chapters are required, as shown in Figure 1. Accordingly, Chapter 2 carries out a systematic literature review on how the concept of SCRes has been operationalized heretofore. As a result, several research gaps and hidden patterns within the literature are revealed, as well as the prevalent research methods for gathering and analysis of data. Chapter 3 refines the six key-variables to be studied and the presumed relationship among them—the 'conceptual framework' in which this study is based. From this conceptual framework, nine hypotheses of research are then derived. Chapter 4 draws on the results of the prior systematic review and conceptual framework, by answering two main questions: why a simulation-based method was utilised to gather data, and why data mining techniques and non-parametric statistics were used to test the nine hypotheses.

Chapter 5 derives a unified conceptualization of SCRes based on the definitions available in the literature. A universal definition of SCRes, along with TAE, is then used to construct a quantitative measure of resilience or Re^T. Chapter 6 describes each one of the steps that make up the simulation model of the MFSC, including the description of the SC under analysis, the identification and assessment of risk events that affect the SC, the assumptions of the model, the verification and validation of the model, the experimental design, and the programming code in Simulink®. Additionally, this chapter also explains how the data from the simulation model and the open-ended questionnaire administered to MFSC's staff are gathered, organized, and prepared for a further analysis and discussion in the subsequent chapter. Chapter 7 examines each one of the nine hypotheses of the research's conceptual framework by using data mining techniques and non-parametric statistics. Finally, Chapter 8 delineates the conclusions of the study from the findings and results of the previous chapter and presents the main implications and limitations of this study, as well as suggestions for further research.

Figure 1. Structure of the thesis research
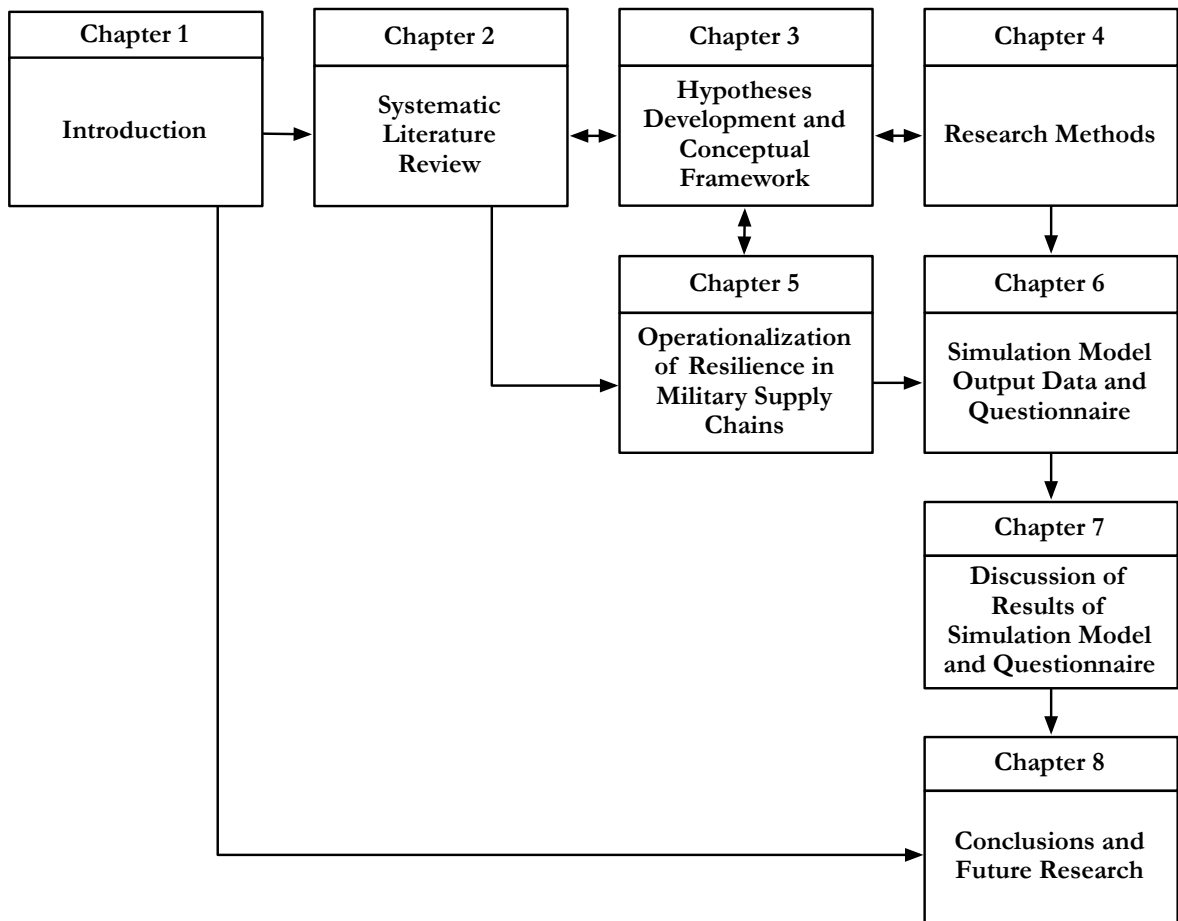
1.6 Summary of Chapter 1

This chapter laid the foundations for the present study. Beginning with the delimitation of the context, it stated the objectives and scope of the study, by emphasizing the lack of research and the existence of a theoretical conflict regarding the effectiveness of a buffering strategy to make SCs more resilient. Second, it formulated the research problem to be dealt with, as well as the research methods that will be used for the gathering and testing of data. Third, it pinpointed the main contributions of the study. Finally, it described the overall structure of the study. The following chapter develops a systematic review of the literature on the approaches used to measure the concept of resilience in military-SCs.

Chapter 2
SYSTEMATIC LITERATURE REVIEW

Chapter 2. Systematic Literature Review

2.1 Introduction

This review of the applicable literature has been developed from the perspective of the research questions raised in the introductory chapter of this investigation and comprises two main parts. The first part (section) focuses on the previous empirical studies that include the variables 'on-hand inventory buffers' and/or 'short term manufacturing capacity' with the 'occurrence of risks/disruptions' and/or 'SC-resilience'. The second part (subsequent sections) examines 'how the concept of resilience in SCs (SCRes) has been operationalized so far'. Thus, the main objective of this review is to find, analyse, and classify the existing literature on this topic, identifying previous approaches, patterns, and gaps in the body of knowledge, in order to develop a new SCRes measure. This review of the literature is guided by a 'systematic' protocol recently incorporated into the SC management field (Wilding & Wagner, 2014). This protocol aims to minimise bias in the search for information, allowing the replication of this procedure by other authors (Torgerson, 2003). *Business Source Complete®* by EBSCO was the main research engine used to access management databases, though the search process was complemented by *Google Scholar®*. A systematic literature review (SLR) for the mentioned topic identified a total of 40 documents through a five-stage process (Denyer & Tranfield, 2009). The critical analysis of each of these documents, as well as the findings and research gaps encountered, are described below.

2.2 Topical Research and Gaps

2.2.1 Topical research

Overall, the study of how the occurrence of risks affects the performance of SCs—e.g., their level of resilience—and how these develop strategies to prevent/mitigate such consequences—i.e., disruptions—is currently a theme of great interest among academics (Bode et al., 2011), and provides the theoretical underpinning of this research. Nevertheless, the literature on this subject is not entirely homogeneous. While a variety of approaches based on anecdotal evidence or self-reported data abounds in the literature—Hendricks & Singhal, 2012; Wagner & Bode, 2008—, theoretical-based models on empirical and/or verifiable hypotheses/proposals are rather scarce. To date, relatively few empirical studies (eleven) include in their conceptual frameworks the variables 'on-hand inventory buffers' and/or 'short term manufacturing capacity' with the 'occurrence of risks/disruptions' and/or 'SC-resilience'. The following is a critical analysis of the eleven empirical studies found in the literature that fulfils this condition. The hypotheses/propositions/questions of interest for the present research in each one of these studies are indicated as follow.

Zsidisin and Wagner (2010) tested the extent to which SCRes practices moderate disruption frequency, using an online questionnaire survey for various types of companies. The hypotheses of interest are: "Supply management professionals that create supply chain resiliency through [1] flexibility and [2] redundancy in response to risk perceptions, experience the effects of supply

disruption less frequently." (p.5). The authors found that both hypotheses were statistically significant. However, Zsidisin and Wagner also found that having multiple suppliers, inventory buffers, and business continuity plans might not reduce the frequency of disruptions. The authors attribute this contradictory result to the fact that companies usually overestimate the benefits of creating redundancy.

Bode and colleagues (2011) proposed a model of organizational responses to SC-disruptions, using an online questionnaire survey of European commercial businesses. These authors posed three hypotheses of interest: (1) "The greater the impact of a supply disruption on a firm, the greater its pursuit of buffering and bridging"; (2) "The positive relationship between the impact of a supply chain disruption and the pursuit of buffering is weaker when prior trust in the involved exchange partner is low than when it is high"; and, (3) "The positive relationship between the impact of a supply chain disruption and a firm's pursuit of buffering is weaker when the firm's prior experience is low than it is when prior experience is high" (pp.836-39). For all hypotheses mentioned, authors found strong statistical validity.

Colicchia and colleagues (2010) modelled a supply process of a European retailer and a manufacturing company in the presence of risks. The research question proposed in this study is: "how a company […] can increase its supply chain resilience by employing […] mitigation actions and contingency plans" (p.683). By using a Monte Carlo simulation-based model, the authors compared the effectiveness of contingency plans and mitigation actions. The results showed that contingency plans are more effective than mitigation actions; however, the highest level of resilience (lowest variability of the SC) is achieved when both approaches are utilised conjointly. Similarly, Schmitt and Singh (2012) modelled an assembly distribution system subject to the occurrence of supply disruptions and demand uncertainty. By using a discrete-event simulation, the authors developed a model to improve resilience (service level) based on inventory placement and back-up mitigation methods—inventory, capacity, and time. Two questions of interest are: (1) "Where should inventory be held in the network to minimize total costs and meet minimum average service levels?" and (2) "What is the best response type for back-up capabilities?" (p.23).

Hoffmann and colleagues (2013) studied the background of supply risk management performance using an online questionnaire survey of Germans cross-industry. The hypothesis of interest is: "Risk mitigation weakens the effect of [1] environmental uncertainty and [2] behavioural uncertainty on a buyer's supply risk management performance" (p.203). The authors found statistical evidence that supports previous hypothesis. However, they also mentioned that the moderating effect is only significant for part [1]. Boone and colleagues (2013) evaluated the impact of inventory management of service parts on the continuity and resiliency of the SC of the USAF. In their model, the term "system approach" refers to the holistic representation of all parts in the system when making inventory-level decisions and backorders disrupt the inventory flow. Thus, the two hypotheses of interest are: (1) "The system approach will reduce the duration of flow disruptions, ceteris paribus, thus enhancing resiliency"; and, (2) The system approach will reduce the duration of operational disruptions,

ceteris paribus, thus enhancing resiliency" (p.224). The authors found that both hypotheses are statistically supported.

Marley and colleagues (2014) empirically studied the interactive effects of complexity and buffering on SC disruptions in the analysis of a steel processing plant, by using the lenses of normal accident theory. These authors posed a proposition of interest: "The lower the inventory levels, the greater the likelihood of a customer experiencing a normal supply chain disruption" (p.145). Marley and colleagues found that the above proposition is not statistically supported. In other words, adding more inventories to the SC is not a useful strategy to mitigate SC-disruptions. However, in this regard, the authors noted that this result does not contradict the existing theory, but rather 'complements it.' Bradley (2015) studied the effect of capacity and inventory buffers as mitigators of catastrophic SC disruptions in manufacturing firms. Based on the review of the literature, the author argued that to use inventory buffers as mitigators of SC-disruptions, aspects such as location and capacity of warehousing of the SC need to be addressed beforehand. By using examples of SCs affected by disruptions, Bradley theorizes that characteristics of inventory buffers vary with SC location, suggesting the use of a "reservoir of stored capacity" as an alternative for alleviating the negative effects of catastrophes on the performance of the SC. Furthermore, and based on secondary information, the author evaluated the financial feasibility of a capacity and inventory buffer strategy using net income and credit worthiness.

Brandon-Jones and colleagues (2015) studied the moderating effect of production capacity and safety stock at suppliers and plants, on the relationship between the frequency of SC disruptions and plant performance. For this purpose, the authors analysed a number of British manufacturing firms through the application of a survey instrument. The hypotheses of interest in this study are: (1) "The higher the level of production capacity, the lower the negative effects of disruption frequency on plant performance"; (2) "The higher the level of safety stock at suppliers, the lower the negative effects of disruption frequency on plant performance"; and, (3) "The higher the level of safety stock at plant, the lower the negative effects of disruption frequency on plant performance." The authors found that, while extra production capacity and safety stock at suppliers positively affect plant performance, safety stock at the plant generates a negative impact on plant performance.

Park and colleagues (2016), based on an online questionnaire survey of Korean firms, found that the hypothesis "The higher the level of safety stock a firm keeps, the less frequently supply chain disruptions occur" (p.124) is not statistically significant. Despite this result, the authors argued that safety stock has only a partial negative impact on the occurrence of SC-disruptions. Finally, Brusset and Teller (2017) examined the moderating effect of risks on the relationship between external integration and flexibility capabilities, and SCRes, through an online questionnaire survey of French SCs. These authors found that the hypothesis "There is a positive relationship between the implementation of [supply chain] capabilities and the level of resilience in supply chains" (pp.61-62) is not uniformly supported. That is, there is statistical significance for the effect of integration and flexibility capabilities on SCRes, but not for the relationship between external capabilities and SCRes. Regarding the latter, Brusset and Teller

argued against this result, by pointing out that SC managers consulted do not have sufficient experience dealing with external capabilities, which means that the effects of resilience have not been observed yet.

2.2.2 Gaps in the topical research

Overall, the eleven empirical studies previously analysed provide valuable insights to the literature on SC disruptions/resilience domains, yet they are not devoid of limitations. The first observation is related to the expanded use of qualitative research techniques for analysing the mentioned variables. Thus, in six of the theoretical frameworks described—Park et al, 2016; Zsidisin and Wagner, 2010; Bode et al, 2011; Hoffmann et al, 2013; Brandon-Jones et al, 2015; and Brusset and Teller, 2017—, the measurements of the sources and impact of risks, the occurrence of disruptions, and/or the level of the SCRes, are based on respondents' perceptions rather than on measurable objective criteria. This aspect—derived from using phenomenological methodologies—reduces the validity and reliability of these analyses and may lead to conflicting results. In this sense, a concomitant issue is the heterogeneity of the samples of individuals selected for survey application, in which cultural issues, managers' experience, or proclivity to the occurrence of risks of the industry/sector analysed, can influence the results of such studies. The type of methodology employed also limits the depth of research questions raised. For example, the hypotheses described above are presented from a broad perspective, without considering the specific impacts that each type of risk may have, and what strategies the SCs should adopt. In other words, most previous research has addressed the impact of risks as a whole, ignoring the differential effect each category of risk has on SC-performance. Furthermore, the articles' authors themselves mention shortcomings related with the reliability of surveys' respondents and the generalizability of the results by using cross-sectional data.

On the other hand, regarding the articles that used quantitative methodologies, the study by Schmitt and Singh (2012) and Colicchia and colleagues (2010) offer limited results in terms of the scope. The lack of a formal theoretical framework, i.e., presented in terms of research hypotheses or propositions, impedes the establishment of statistical significance among variables of interest. In addition, the criteria used to measure SCRes, while adequate for purposes of both studies, are poorly defined, especially if they are contrasted with available definitions of SCRes in the literature (see e.g. Table 5.1). As for the article by Marley and colleagues (2014), the reliability of the results of their research is based on the use of empirical data (with no intervention) from a working steel processing plant. The utilisation of this type of data represents the ideal scenario for conducting research (Rosenbaum, 2010). However, the inability of the researchers to modify the configurations of the plant at convenience (the experimental setting), e.g., to manipulate the policy of inventory level or to change the lot size of the order of raw materials to test the plant under 'extreme scenarios', limits to some extent the depth of this research. The same limitation is observed in the work of Boone and colleagues (2013). Lastly, the theoretical framework described in the study by Bradley (2015) is the one that most closely resembles the content of the present research. Indeed, Bradley's study included capacity and inventory buffers as elements to mitigate SC-disruptions. However, the scope of this study is limited and it points in a different direction (financial perspective), not to mention

that the variable SCRes was not included in the analysis. Finally, it is also worth mentioning that, except for the work of Boone and colleagues (2013), the other studies are based on the analysis of commercial-SCs.

2.3 Protocol for the Systematic Literature Review (SLR)

Following Denyer and Tranfield (2009), five steps make up the protocol for developing a SLR, including (1) question formulation, (2) locating studies, (3) study selection and evaluation, (4) analysis and synthesis, and (5) reporting and using the results. These steps were applied to the main stream above mentioned below.

Question formulation and locating studies

The question that will guide the review of the literature is as follows: 'how the concept of resilience in SCs (SCRes) has been operationalized so far'. In this way, by using the *Business Source Complete*® by EBSCO as the main research engine to access management databases together with *Google Scholar*® platform, were define the search strings.

The search strings considered in the SLR for this topic were 'supply chain resilience' or 'resilient supply network'. The keywords were 'evaluation', 'metric', 'index', 'measurement', 'measure', 'assessment' and 'indicator'. Others documents outside the research criteria were also included, given that there are concepts allied with SCRes such as 'supply chain robustness', 'supply chain flexibility', 'supply chain vulnerability', and 'supply chain reliability'. Both strings and keywords were examined in all fields of peer-reviewed academic journals, books, conference proceedings, and theses, for a timespan from 2001 to date (July, 2017).

Study selection and evaluation

The selection of the year 2001 as a starting point for analysis was due to the attacks of September 11 in New York City, which became a milestone in the development of the SC risk management/disruptions (Colicchia & Strozzi, 2012; Snyder et al., 2016), two disciplines closely related with the study of SCRes. Hence, despite the specificity of strings and keywords used, the initial search based on the analysis of titles and summaries retrieved 323 entries, of which 108 were discarded because they were not related directly with the established search criteria or were duplicated. Thus, from 215 documents, a closer inspection of informational content left only 43 documents. Further checks allowed including seven additional bibliographical references in the body of inspected documents, from which ten were ultimately discarded, leaving a total of 40 documents for analysis and coding. Figure 2.1 summarizes the search process of documents in relation to the guiding question above formulated. The steps 3 and 4 of the SLR corresponding to the analysis and synthesis of documents retrieved, and the report and use the results, are explained in detail in Sections 2.4 to 2.6.

Figure 2.1 Overview of the SLR for the operationalization of SCRes

323 documents	215 documents	43 documents	50 documents	40 documents
Sourcing using search strings and key words	Removing non-relevant and duplicates	Closer inspection of documents	Checking inside of documents	Final analysis and coding of documents
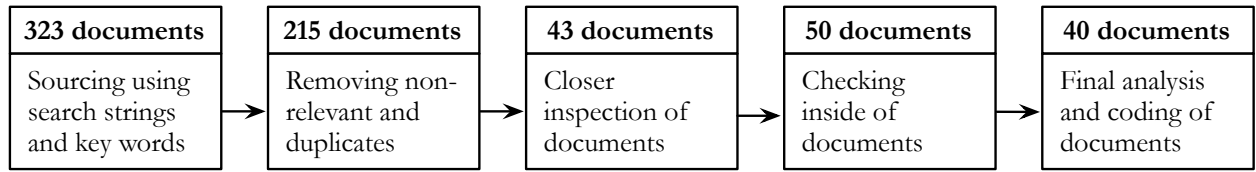
2.4 Critical Analysis of the Literature Review

The critical analysis of the 40 selected documents is described below. The documents are grouped according to the approach used to measure SCRes.

2.4.1 SCRes measurements based on resilience triangle approach

The *resilience triangle*, or the model to reduce the likelihood of failure, its consequences and the time of recovery, originally proposed by Bruneau and colleagues in the context of seismic resilience of communities (2003, 2007), has had a notable influence on the formulation of SCRes' indices/indicators in the LSCM field. For instance, Falasca and colleagues (2008) used this idea to pose a theoretical framework for assessing SCRes. Xu and colleagues (2014) complemented the resilience triangle with an additional criterion, redundancy. These authors developed a robust analytical model to predict SCRes from the analysis of a centralised SC, which is seen as a biological cell that adapts and recovers by itself from random disruptions. The SCRes measurement is tested using a simulation approach. Lastly, Zobel and Khansa (2014) extended this framework by integrating a trade-off variable between robustness and rapidity, which they called 'the predicted resilience'. As described in their article, the function of resilience is the triangle area where the (inverted) base corresponds to the time needed to recover to normal operations; and the height, the percentage of lost quality. Based on this approach, the authors extended the concept of resilience to multi-event situations such as disasters with large losses but quick recovery, smaller losses but slower recovery, and so on. Zobel and Khansa's model offers a general perspective on how to measure resilience within the framework of the occurrence of natural disasters, but more research is needed to apply these results to the specific context of SCs.

2.4.2 SCRes measurement based on graph/network theory approaches and/or simulation applications

Several authors have emphasized the use of graph/network theory and/or simulation techniques to measure SCRes. Datta and colleagues (2007) studied the performance of a manufacturing SC-network against variations in demand using an agent-based modeling methodology. The criteria used to measure the operational resilience are the customer service level, the production change over time, the average inventory, and the total average network inventory. This paper stands out not only for its findings on how to enhance the previous

criteria, but also because is the first work in the literature to propose a measurement for SCRes. Wang and Ip (2009) proposed an evaluation approach to measure resilience in aircraft maintenance and service logistics networks. These authors considered redundancy and distribution to be the factors affecting resilience. Despite the specificity of Wang and Ip's approach, the underlying idea may be replicated for other types of SCs. Also, this approach provides guidance on how to measure resilience without including disruption analysis. Ip and Wang also applied an equivalent approach to measure resilience in transportation networks (Ip & Wang, 2011). Zhao and colleagues (2011) used network topology and a simulation approach to measure resilience in a military logistic network based on the supply availability rate, the number of nodes, and the length of average and the maximum supply-path. Kim and colleagues (2015) proposed a network resilience metric based on the analysis of nine criteria, viz. network density, average degree, walks, average walk length, maximum and minimum walk lengths, connectivity, betweenness centrality, and network centralization. Their final resilience measure for supply networks is the ratio of the number of nodes or arcs disrupted to the total number of nodes/arcs.

In the same sense, Soni and colleagues (2014) developed an index to quantify SCRes from the identification of ten resilience enablers proposed by experts from industry and academy, viz. agility, collaboration, information sharing, sustainability, risks and revenue sharing, trust, visibility, culture, adaptability, and SC structure. Thus, using graph theory, these authors built up a resilience digraph for the ten enablers, from which interdependency relationships are inferred through the application of interpretative structural modeling. The calculation of the resilience index is thereby a percentage of the ideal cases from the ten enablers. Thus, from a practical perspective, Soni et al's index is a robust and meaningful approach to rank a set of SCs according to their resilience level. However, the selection of the enablers may not be generalizable to all SC types. Mari and colleagues (2015; 2015b) measured SCRes using four criteria: accesibility, robustness, responsiveness, and flexibility. The resulting metric of resilience is applied on a theoretical SC and then verified through a simulation model. More recently, Mohan and Bakshi (in press) formalised the measure of SCRes through the concept of disruption-recovery time. By using graph theory, the authors examined how quickly a SC-network can rid itself of the disruption caused by a trigger event from the application of three concepts: the ripple effect, the critical component property, and the bidirectional propagation of disruptions. Lastly, Li and colleagues (2017) defined a resilience measure from the maximum allowable recovery time, the amount of product delivered, and the average delivery distance. The above measure of resilience was applied on a mobile phone SC-network using Monte Carlo simulation.

2.4.3 SCRes measurements from attributes associated with SCs

Several authors have proposed various SCRes measurements from attributes associated with SCs. Jüttner and Maklan (2011), from a case study on three manufacturing companies, explored the relationship between SC-risk management and SC-vulnerability, and SCRes. By using structured interviews and secondary information, these authors found that flexibility, velocity, visibility, and collaboration exert a positive influence on SCRes. However, despite these

findings, the nature of these results does not allow establishing a numerical relationship between the categories analysed and SCRes. In a similar fashion, Spiegler and colleagues (2012) assessed SCRes by applying a dynamic perspective to inventory levels and shipment rates. These authors used the drivers proposed by Ponomarov and Holcomb (2009), viz., readiness, response and recovery, and combined them with the absolute error (ITAE). The resulting measure of SCRes is a robust but complex dynamic model. Carvalho and colleagues (2012), in a theoretical work, argued that before any attemp at measuring SCRes, a framework that relates the current operations, the transition states, and the vulnerability points of SCs, should be developed. In a later work applied to the automotive industry, Carvalho and collegues (2013) developed a composite index to evaluate agility and resilience practices in SCs. The authors used Delphi method to calculate the so-called *AR-index,* which is derived from a weighted sum of 14 sub-indicators, seven of which are to measure SC agile behaviour, and the remaining seven to measure resilient behaviour. Compared to other resilience measures, the so-called AR-index is intuitive and easy for managers to implement in practice. However, the idea of measuring two complex concepts at the same time (agility and resilience) may pose data aggregation problems.

Pettit and colleagues (2013) created a survey-based tool for assessing SCRes on the premise that the concept of resilience need not be accurately specified. The proposed tool or SCRAM™ integrates 21 factors and 111 subfactors that link SCs vulnerabilities and capabilities to a 'balanced resilience', an intermediate point between the 'zone of erosion of profits' and the 'risk exposure zone'. Despite the originality of this proposal, the subjectivity in the measurement of factors and subfactors coupled with the large amount of longitudinal-data required render the so-called SCRAM index difficult to benchmark with other SCs. Azevedo and colleagues (2013) integrated the assessment of greenness and resilience in a unique index using the Delphi method. This 'ecosilient-index' is the sum of the products of the green/resilient SC-practices implemented and their specific weights, the latter provided by a set of experts. Undoubtedly, the novel aspect of this proposal lies in the integration of the two concepts mentioned. Nonetheless, the identification and evaluation of what the authors call "green and resilient practices," as well as the assignation of the specific weights, hinders using the ecosilient-index as a yardstick. Cardoso and colleagues (2014) proposed a composed resilience indicator from the analysis of the design and characteristics of five SCs, although the character of this study is exploratory. In a further work (2015), these authors combined several economic-performance factors and SCRes. Thus, SCRes is measured through a set of 11 sub-indicators selected from the literature that focus on three aspects of SC-networks: design, centralization, and operational issues. More recently, Li and colleagues (2017b) used use survey data to evaluate the financial performance of a firm from 3 dimensions of SCRes: SC preparedness, SC alertness, and SC agility.

2.4.4 SCRes measurements from allied concepts

The measurement of the concepts allied to the notion of resilience has also been addressed in the literature. Thomas (2009) quantified logistics-effectiveness for contingency operations in the military context. Thomas considered a unit of analysis to be a SC-network for routing the right logistics to the right place in support of contingency operations. Thus, the approach proposed

measures SC-reliability by establishing the conditions and probabilities of failure at each link of the SC-network. Wagner and Neshat (2010) developed an index to measure vulnerability based on graph theory and a four-step algorithm. These authors constructed a SC-vulnerability index based on the analysis of the interdependencies of three groups of drivers: supply side, demand side, and SC-structure. The approach presented in this article provides a well-founded method for measuring vulnerability. However, the generalizabilty of the proposed model to other SCs is limited by the subjectivity of the method utilised (experts' opinion). Martínez and Pérez (2005) developed an index of flexibility to be applied to automotive SCs. By using an online questionnaire, the authors operationalized six variables including flexibility, environmental uncertainty, technological complexity, mutual understanding, interdependence, and supplier dependence. Similarly, Sokri (2014) proposed three independent metrics to measure flexibility in military-SCs through the analysis of two elements: flexibility in supply and capacity of delivery. The merit of this article lies in its simplicity, practicality, and pertinence in assessing the flexibility of military-SCs.

2.4.5 SCRes measurements based on conceptual approximations from other disciplines

Several attempts to operationalize SCRes have been proposed using conceptual approximations from other disciplines. Shuai and colleagues (2011) provided a quantitative measure of SCRes based on the application of 'biological cell elasticity theory'. The construction of this SCRes measurement took into account the time needed for achieving a normal state and the gap between the normal state and the original state. Shuai and colleagues' article, although novel in terms of employing an approach not previously used in the literature, is very complex and impractical in application to real SCs due to the assumptions considered. Similarly, Raj and colleagues (2015) developed a new measure of SCRes based on the so-called 'Cox proportional hazard' (Cox, 1972). Using this idea, these authors added a likelihood dimension to SCRes by aggregating the failure point function to the system. The proposed measure of SCRes is tested through a simulation model for a SC subjected to 12 different sources of disruptions. However, as with the previous model, the strong assumptions required to implement Cox's model limit its applicability to real SCs.

Munoz and Dumbar (2015) developed an approach for measuring operational resilience at the level of firm/SC from the idea of 'transient responses', or the analysis of post-disruption performance data over time. The authors quantified SCRes using a multidimensional metric that is evaluated through a linear weighted-sum aggregate index. However, again, the applicability of this metric to real-world SCs is restricted by the assumptions associated with the modelling process. Dixit and colleagues (2016) developed a measure for SCRes from the concept of the 'expected value of the fraction of demand-satisfied post-disaster'. These authors used a multi-objective stochastic mixed-integer programming model based on the percentage of unfulfilled demand and the total transportation cost post disaster, both applied to a SC-network. The results of the model were complemented with the use of genetic algorithms and surrogate models. Dixit and colleagues' work is undoubtedly a novel theoretical contribution to the operationalization of SCRes. Nevertheless, from a practical point of view, its applicability is questionable. Lastly, Sahu and Datta (2017) proposed a quantitative metric for SCRes based on

the application of the 'fuzzy set theory'. These authors analysed the case of an automobile part manufacturing company, from which numeric data (fuzzy numbers) based on qualitative experts' judgments (survey data) were collected. Despite the novelty in the use of a fuzzy-based approach to measure SCRes, the subjectivity of the input data set, and the amount of information required, also make the model impractical in application to other SCs.

2.4.6 SCRes measurements based on previous approaches

Other studies have used previous indices/indicators to measure SCRes or a combination of them. Lomax and colleagues (2013) applied the resiliency analysis support tool (RAST) to a military-SC. This approach was designed for the US military forces to use during disaster and humanitarian response operations, though it can also be used by civilian organizations. RAST's main objectives are to increase situational awareness of disasters occurrence and to support decision-making processes. To this end, RAST uses information from different sources to show in real-time the geographical position of available resources such as food, shelter, sanitation, and health supplies. Yilmaz-Börekci and colleagues (2014) set out a measurement scale to assess supplier resilience in supply networks from interviews and surveys in manufacturing and services companies. Similarly, Nikookar and colleagues (2014) evaluated well-known practices to increase SCRes in the automotive industry using interviews and surveys. In a similar fashion, Barroso and colleagues (2015) proposed an aggregated quantitative index of resilience to be applied in SCs or individual firms, by considering several settings and previous approaches to enhance resilience.

Pant and colleagues (2014) developed a set of measures of resilience to be applied in container terminals. The measurement criteria used are the time to total system restoration, the time to full system service resilience, and the time to α%-resilience. Similarly, Garcia-Herreros and colleagues (2014) analysed SCRes with risk of facility disruptions. The authors based their idea on the notion that SCRes is associated with backup capacity. Thus, using a two-stage stochastic programming approach, Herrera and colleagues constructed a robust mathematical model that allows finding the best SC-design to minimize investment and expected cost from multiples scenarios with disruptions. The measure of SCRes discussed in this article is not explicit but it is incorporated into SC-flexibility to meet customer demand despite the occurrence of disruptions. Ambulkar and colleagues (2015) proposed a qualitative scale of resilience at the firm level based on an analysis of how they develop resilience to SC-disruptions. These authors utilised the survey method to collect cross-sectional data. Firm resilience is operationalised by integrating the SC disruption orientation, the resource reconfiguration, and the risk management infrastructure. The main limitation of this analysis is related to the type of data used, which only provides a snapshot of the phenomenon being analysed at any given time, restricting the ability to infer causal relationships among the analised variables.

Lücker and Seifert (2017) developed an operational metric for quantifying resilience in the context of pharmaceutical SCs. The authors based the SCRes analysis on two mitigation levers: stockout quantity and stockout time. Finally, Pourhejazy and colleagues (2017) measured the resilience of a SC-network using data envelopment analysis (DEA). To this end, the authors

evaluated the best-practice and less-performing SC-network configurations of a liquefied petroleum gas company. Available capacity, average clustering coefficient, number of supply nodes, distance between supply and demand nodes, average node degree, and population exposure, are the 7 factors considered for the resilience index. The use of DEA for SCRes evaluation is undoubtedly a novel approach from a theoretical point of view. However, the limitations of the proposed index are proportional to the number of DEA requirements, reducing its usability.

2.5 Findings

2.5.1 Patterns found in the literature

As shown in the previous critical analysis, the operationalization of the SCRes concept has been approached from different angles, from which some initial patterns in the literature already are visible. Table 2.1 summarizes the previous classification and identifies the main methodologies for the collection (or generation) and analysis of the data, as well as the entity subject of study.

Table 2.1 Summary of patterns in the literature on the operationalization of the SCRes concept

Pattern	Authors (year)	Method for gathering data	Method for data analysis	Unit of analysis
1. Based on resilience-triangle approach	Falasca et al (2008)	Simulation	Unspecified	Generic supply chain
	Xu et al (2014)	Simulation	Comparison of system configurations	Generic supply chain
	Zobel and Khansa (2014)	Simulation	Comparison of system configurations	Populated area
2. Based on resilience graph/network theory	Datta et al (2007)	Simulation	Comparison of system configurations	Manufacturing supply network
	Wang and Ip (2009)	Assumed data	Genetic algorithm	Aircraft maintenance and service logistics networks
	Ip and Wang (2011)	Assumed data	Optimization	Transportation networks
	Zhao et al (2011)	Simulation	Comparison of system configurations	Military supply chain
	Kim et al (2015)	Simulation	Comparison of system configurations	Generic supply chain networks
	Soni et al (2014)	Case study	Interpretive structural modeling	Manufacturing supply chains
	Mari et al (2015), (2015b)	Simulation	Comparison of system configurations	Generic supply chain network
	Mohan and Bakshi (in press)	Analytical	Unspecified	Generic supply chain network
	Li et al (2017)	Simulation	Comparison of system configurations	Mobile phone supply chain network
3. From attributes associated with supply chains	Jüttner and Maklan (2011)	Survey	Content analysis + Pattern matching	Manufacturing firms
	Spiegler et al (2012)	Simulation	Comparison of system	Generic supply chain

			configurations	
	Carvalho et al (2012), (2013)	Survey	Experts' weighting results	Automotive supply chains
	Pettit et al (2013)	Survey	Mixed-method triangulation	Several firms from different industries
	Azevedo et al (2013)	Survey	Experts' weighting results	Automotive supply chains
	Cardoso et al (2014), (2015)	Case study	Expected net present value, optimization	Supply chain network
	Li et al (2017b)	Survey	Confirmatory factor analysis	Several firms from different industries
4. From allied concepts	Thomas (2009)	Assumed data	Analytical	Contingency logistics system
	Wagner and Neshat (2010)	Survey	Principal component analysis	Several firms from different industries
	Martínez and Pérez (2005)	Survey	Tau-equivalent reliability	Automotive firms
	Sokri (2014)	Analytical	Unspecified	Military supply chain
5. Based on conceptual approximations from other disciplines	Shuai et al (2011)	Analytical	Unspecified	Generic supply chain
	Raj et al (2015)	Simulation	Model coefficient estimation	Generic supply chain
	Munoz and Dumbar (2015)	Simulation	Structural equation modeling	Generic supply chain
	Dixit et al (2016)	Simulation	Comparison of system configurations	Generic supply chain network
	Sahu and Datta (2017)	Survey	Fuzzy weighting experts	Automotive firms
6. Based on existing approaches to measure SCRes	Lomax et al (2013)	Assumed data	Descriptive	Military supply chain
	Yilmaz-Börekci et al (2014)	Survey	Exploratory factor analysis	Several firms from different industries
	Nikookar et al (2014)	Survey	Critical factor index method	Automotive supply chains
	Garcia-Herreros et al (2014)	Assumed data	Optimization	Generic supply chain
	Barroso et al (2015)	Simulation	Comparison of system configurations	Automotive supply chains
	Pant et al (2014)	Simulation	Comparison of system configurations	Container terminals
	Ambulkar et al (2015)	Survey	Exploratory factor analysis	Several firms from different industries
	Lücker and Seifert (2017)	Survey, past records	Optimization	Pharmaceutical supply chain
	Pourhejazy et al (2017)	Case study	Data envelopment analysis	Petroleum-gas firm

2.5.2 Classification by type of journal and publication year

Table 2.2 shows the number of articles per journal and its respective rating per the most recent Academic Journal Guide ABS guide. Similarly, Figure 2.1 shows the number of publications on the operationalization of the SCRes concept over time.

Table 2.2 Distribution of the publications on the operationalization of the concept of SCRes with respect to journals

Journal	# publications	ABS rating*
IEEE Systems Journal	4	n.f.
Computers & Industrial Engineering	3	★★
Journal of Operation Management	2	★★★★
International Journal of Production Research	2	★★★
Omega	2	★★★
Sustainability	2	n.f.
International Journal of Logistics Systems and Management	2	n.f.
International Journal of Operations & Production Management	1	★★★★
International Journal of Production Economics	1	★★★
Informs	1	★★★
Computers & Operations Research	1	★★★
Supply Chain Management: An International Journal	1	★★★
International Journal of Logistics: Research and Applications	1	★★
Benchmarking: An International Journal	1	★
International Journal of Agile Systems and Management	1	★
Journal of Change Management	1	★
Management Research Review	1	★
International Journal of Systems Science: Operations & Logistics	1	n.f.
Industrial Engineering and Engineering Management	1	n.f.
Journal of Cleaner Production	1	n.f.
Journal of Modelling in Management	1	n.f.
International Journal of Industrial Engineering	1	n.f.
Management and Production Engineering Review	1	n.f.
International Journal of Business Logistics	1	n.f.
Industrial & Engineering Chemistry Research	1	n.f.
Others (proceedings, theses, and book chapters)	5	n.a.
Total	40	-

Academic Journal Guide 2015 (1390 total entries). Retrieved from:
https://charteredabs.org/academic-journal-guide-2015-view/
n.f.: no matching records found; n.a.: no applicable

Figure 2.2 Number of publications on the operationalization of the concept of SCRes by year (2001-2017*)
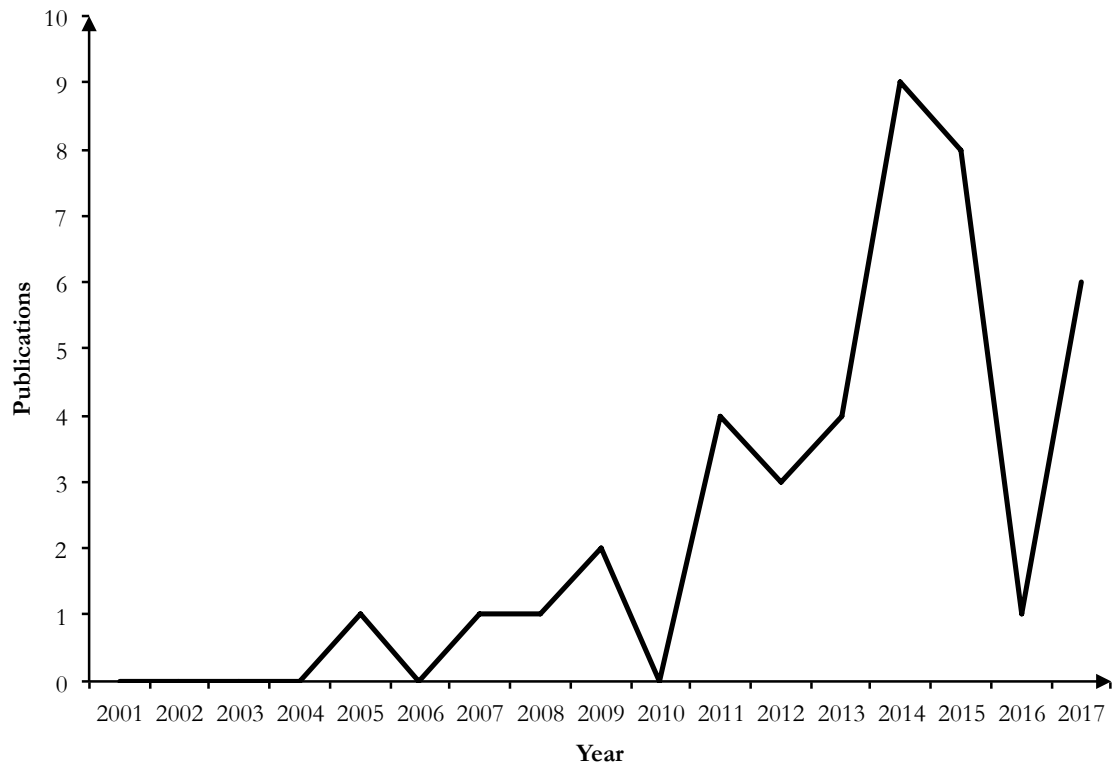
* Up to July, 2017.

2.5.3 Classification by research approach and level of suitability of SCRes

Based on the works of Beamon (1999), Latva-Koivisto (2001), and Modrak and colleagues (2013), the level of suitability of the SCRes indices/indicators described in the publications analysed is evaluated taking into account four criteria: (1) *validity* or the measure of the inclusion of all pertinent aspects of the notion of SCRes, from 1-none to 5-all; (2) *ease of implementation* or the measure of the difficulty in implementing the index/indicator of SCRes, from 1-very difficult to 5-very easy; (3) *universality* or the measure of how comparable the SCRes' results are when different examiners use it; from 1-not comparable to 5-very comparable; and (4) *intuitiveness* or the measure of how easy is to understand the index/indicator of SCRes, from 1-very difficult to 5-very easy. Likewise, the list of publications is classified by the research approach. The results of this evaluation are shown in Table 2.3.

Table 2.3 Classification of the publications according to the level of suitability of SCRes

Authors (year)	Quantitative	Qualitative	Suitability level of SCRes index/indicator (0-lowest, 1-highest)
Wang and Ip (2009)	•		0.80
Kim et al (2015)	•		0.80
Ip and Wang (2011)	•		0.80
Xu et al (2014)	•		0.75
Sokri (2014)	•		0.75
Wagner and Neshat (2010)		•	0.70
Soni et al (2014)		•	0.65
Ambulkar et al (2015)		•	0.65
Zobel and Khansa (2014)	•		0.65
Carvalho et al (2013)		•	0.65
Cardoso et al (2015)	•		0.65
Mari et al (2015)	•		0.65
Thomas (2009)	•		0.65
Mari et al (2015)	•		0.65
Jüttner and Maklan (2011)		•	0.60
Garcia-Herreros et al (2014)			0.60
Spiegler et al (2012)	•		0.60
Datta et al (2007)	•		0.60
Azevedo et al (2013)		•	0.60
Lückera and Seiferta (2017)	•		0.60
Mohan and Bakshi (2017)	•		0.60
Pant et al (2014)	•		0.60
Barroso et al (2015)	•		0.55
Pourhejazy et al (2017)	•		0,55
Sahu et al (2017)	•		0.50
Martínez and Sánchez (2005)		•	0.50
Dixit et al (2016)	•		0,50
Zhao et al (2011)	•		0,50
Li et al (2017)		•	0.50
Pettit et al (2013)		•	0.45
Munoz and Dunbar (2015)	•		0.45
Yilmaz-Borekci et al (2014)		•	0.45
Nikookar et al (2014)		•	0.45
Carvalho (2012)		•	0.40
Raj et al (2015)	•		0.40
Falasca et all (2008)	•		0,35
Shuai et al (2011)	•		0.35
Cardoso et al (2014)	•		0.30
Lomax et al (2013)	•		0.30
Percentage	70.0%	30.0%	-

Figure 2.3 Classification of publications according to research approach
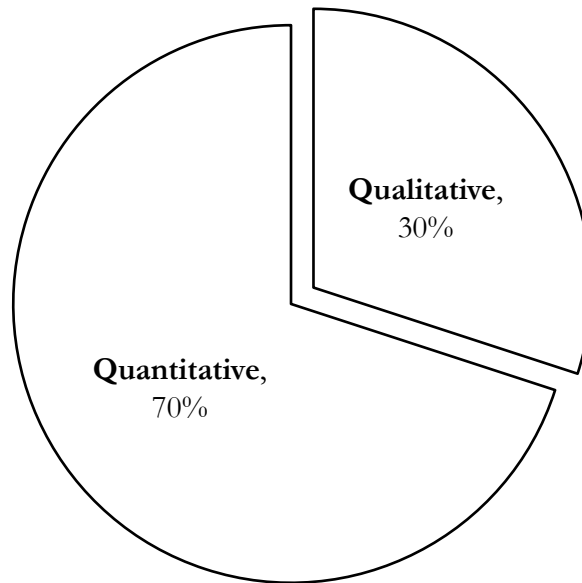
2.6 Research Gap

The review of the literature on the operationalization of the SCRes concept has uncovered several gaps that are promising for the development of future research. The first aspect to highlight is the unusual interest in studying 'how to measure SCRes' that has been created among academics and professionals. The new realities and changing scenarios faced by SCs are perhaps the main motivation for studying resilience (Cardoso et al., 2015). In fact, as can be seen in Table 2.2, not one of the top-journals in the field of LSCM has remained oblivious to this phenomenon, and the number of articles published on this topic points to a growing trend (see Figure 2.1). However, the current number of articles on this matter remains relatively low, pointing to a need for more research. In spite of the rather low numbers, the review of existing studies allowed identification of some preliminary patterns in the literature, as described in Table 2.1. Some of these patterns seem to be 'depleted', e.g. 'the triangle-based approach to resilience', while others offer new and interesting avenues for making practical contributions on the subject, e.g. 'the approaches based on conceptual approximations from other disciplines', but still with some aspects in need of improvement (e.g. suitability).

Regarding the approaches employed, one aspect in common among all the attempts to measure SCRes lies on their marked eclecticism in the derivation of decision variables. Most of the studies listed in Table 2.1 combined different methodologies and concepts to obtain a 'better approximation of resilience'. However, the excessive use of the 'eclectic approach'—especially in quantitative approaches—may result in intricate and impractical indices or indicators. In Table 2.3, the suitability of the previous attempts to operationalize the concept of SCRes is evaluated, and only a small fraction of them (5/40) could be classified in the first quartile of the sample. This result indicates that, from my perspective, there is room to propose new simplified

low-complexity indexes or indicators of SCRes, without falling into simplistic approaches. In addition, Figure 2.3 shows the clear dominance of quantitative approaches (70.0%) over qualitative approaches (30.0%). Regarding the latter, it can be said that, while the survey-based method is a research methodology with a long tradition in LSCM (Sachan & Datta, 2005), when it is used as a criterion for assessing SC-attributes as SCRes, the validity and reliability of the resulting index/indicator is significantly less than when using quantitative methods. This is because such methodologies add a component of subjectivity that cannot be easily replicated in other contexts or types of SCs (Spiegler et al., 2012).

A third aspect is related to the separation between the concept of SCRes and the attempts to operationalize it. In most of the SCRes measures described in Table 2.1, the decision variables or component elements of the index or indicator do not seem to be closely related to any of the definitions of SCRes. This gap between the 'theory and practice' is more pronounced in the conceptual approaches from other disciplines (pattern 5 in Table 2.1) than in those approaches based on attributes associated with SCs (pattern 3). In other words, if the elements that shape the notion of SCRes, viz. readiness, response, recovery, and growth (Hohenstein et al., 2015) are studied in-depth, it can be concluded that several of the SCRes measures listed in Table 2.1 and 2.3 are not totally consistent with the concept itself. Moreover, 'inherent resilience' or the strength that a SC holds from the available resources (Azadegan, 2017), is another missing element in many of the indices or indicators analysed. Finally, the plurality of approaches described in the literature is a clear indication that there is not a single best method for measuring SCRes. This remark leads us to think about the need to create specific resilience measures adjusted to specific types of SCs.

2.7 Summary of Chapter 2

The application of a systematic protocol for the review of the literature allowed the identification of 40 publications directly related to the operationalization of the concept of SCRes. The in-depth analysis of these documents revealed the existence of six patterns associated with the approach used to measure resilience, which are applied to a wide variety of SCs, logistics systems, and individual firms. The research approaches utilised are predominantly quantitative in nature. In this regard, the most prevalent method for collecting data is simulation-based tools, and for the analysis of data, the comparison of system configurations. The review of the literature also uncovered several research gaps promising for exploration: (1) Unusual interest among academics and practitioners in measuring SCRes, (2) the excessive complexity of the existing SCRes measures, (3) the clear prevalence of quantitative approaches over qualitative approaches, (4) the gap between the theoretical underpinnings of SCRes and the attempts to operationalize the concept, and (5) the missing element in several of the proposed SCRes measures: inherent resilience. The following chapter constructs the conceptual framework and research hypotheses.

Chapter 3
HYPOTHESES DEVELOPMENT AND CONCEPTUAL FRAMEWORK

Chapter 3. Hypotheses Development and Conceptual Framework

3.1 Introduction

The purpose of this research is to understand to what extent the application of a buffering strategy affects the relationship between the occurrence of risks and the level of resilience in a SC of military food (MFSC). In this sense, the main motivation is to advance the debate in the literature around the theoretical effectiveness of this kind of SC strategy to create resilience and/or to inhibit the occurrence of disruptions, both in the context of military-SCs. To this end, this chapter constructs a conceptual framework that relates three main categories of risk—operational (R_{1r}), natural disasters-and-intentional-attacks (R_{2r}), and black-swan events (R_{3r})—to SC-resilience (SCRes); and, acting as contingent factors, on-hand inventory buffers and short-term manufacturing capacity. The development of this conceptual framework is addressed through the lens of *contingency theory* (CoT). The rest of the chapter is organized as follows. The second section provides arguments as to why buffering strategies in military-SCs deserve to be studied. The third section outlines previous empirical works in commercial-SCs—due to the lack of previous works on resilience applied to military-SCs—related to the analysis of the aforementioned variables, from which gaps and a conceptual model based on CoT are both identified. The fourth section derives and presents research hypotheses and a conceptual framework. Lastly, fifth section integrates the constituent elements of the research.

3.2 Why Study Buffering Strategies and Why in Military Supply Chains?

Existing literature outlines a number of strategies to improve resilience in commercial-SCs. For instance, Tukamuhabwa and colleagues (2015) categorised these into strategies (1) that increase flexibility, (2) based on redundancy, (3) are for building collaborative relationships, and (4) aim to improve agility. The buffering strategy described in this research can be seen as a safeguard that protects the military-SC under analysis from the occurrence of disruptions in order to gain stability (Bode et al., 2011); i.e., it falls into the category of SC strategies based on the creation of *redundancy*. In this regard, in a recent paper, Marley and colleagues (2014) pointed out that not many works have examined empirically the interactive effects between complexity and buffering strategies on SC disruptions, and Sodhi and colleagues (2012) underlined the need for more empirical studies on how SCs should use buffering strategies to respond to risks. Therefore, the little empirical research to evaluate the 'theoretical effectiveness' of this type of strategy presents an important gap that must be filled. Apart from this controversy, which will be further explored, the reason for studying a buffering strategy lies in the very nature of the unit of analysis (military). It is important to note that by 'theoretical effectiveness' in this context is meant the use simulated data instead of empirical data for testing the research hypotheses due to the lack or nonexistence of the latter (Davis & Bingham, 2007).

For military-SCs, the possibility of 'switching a buffering strategy on/off' is almost 'instantaneous' in practice. Thus, increasing on-hand inventory buffers or adding more short-term manufacturing capacity to deal with disruptions is easily executable (Waters, 2007). However, this is not the case for the other categories of strategies, which advocate the

implementation of several practices such as standardization of finished products, utilization of a flexible supply base, exchange of information with partners, and real-time tracking of assets and deliveries to customers (Tang, 2006). Moreover, not all these strategies can be easily implemented in military-SCs. For instance, regarding the first practice suggested for a MFSC, troops' nutritional requirements fit the characteristics of combat scenarios, thereby producing generic combat rations, which might be considered an issue of inconvenience as regards the physical performance of soldiers on the frontline. Continuing with the example, due to the governmental character of military-SCs, the acquisition of raw materials and inputs is subject to rigorous procurement procedures, making them less opaque to the public eye, but less flexible for the selection of suppliers. This 'rigidity' in the procurement process relates to the reluctance of military-SCs to share information with their stakeholders, including their suppliers (Schwartz, 2014; Walden, 2005; Fox, 2011). Finally, the hostile environment of military-SCs is a major impediment for monitoring their performance in real-time, particularly in downstream operations. This problem is accentuated when the theatre of operation moves away from the supply units.

An additional issue to be mentioned is the high operational cost of setting up buffering strategies in SCs (Christopher & Peck, 2004). It is a fact that the activation of more work-shifts or holding/replenishing more inventory will negatively impact the cost structure in SCs. Thus, for a commercial-SC, the decision of whether to implement a buffering strategy is relatively simple: 'choose the lowest cost between applying this strategy and not doing it (shortage cost)'. However, for a military-SC operating in conditions of war, the costs of shortage, i.e., the cost associated with non-compliance with the mission and/or the loss of human lives is, by rule of thumb, usually higher than labour or inventory costs. Consequently, aspects related to the costs of implementing a buffering strategy will be considered marginal within this context.

3.3 Topical Research, Gaps, and Conceptual Model

3.3.1 Theoretical model from contingency theory lens (CoT)

The Section 2.2 outlined the prior studies that directly resemble the present research insofar as the variables analysed. This section describes the lens through which the present research framework is examined: the *contingency theory* (CoT). The origins of CoT go back to the research by Lorsch and Lawrence (1970), Chandler (1969), and Burns and Stalker (1994), on the performance of organizations in their environments, though some authors pointed out that its starting point was Bertalanffy's systems theory (Skyttner, 2005). CoT conceives of organizations as open-systems that are influenced by their environment (or contingencies), allowing them to adapt continuously through the acquisition of new capabilities (Woodward, 1980). In this sense, the literature about this topic considers organizational structures and administrative systems to be based on environmental and organizational factors, without implying a causal relationship between them (Donaldson, 2001). CoT offers a robust perspective for analysing military-SCs operating in hostile environments, since it provides a context in which the relationship between two variables is contingent upon some third variable (Tosi & Slocum, 1984; Fynes et al., 2005). For instance, Mikes and Kaplan (2014) developed a contingency framework that hypothesizes

the 'fit' between risks and observable variations in the mix of enterprise risk management, as well as organizational effectiveness. Using the same approach, Tomlin (2006) pointed out that companies can use two tactics to deal with disruptions: mitigation and contingency tactics, or response actions after the occurrence of disruptions.

Drawing on CoT, Figure 3.1 describes the conceptualization of a military-SC. In this figure, a military-SC provides combat rations to the troops in a hostile environment. The main objective of this SC is to guarantee continuity of military operations by minimizing the frequency and/or duration of disruptions in the flow of supplies. The occurrence of disruptions is due to both external/internal factors (risks) immersed in a complex and heterogeneous environment, outside the reach of the SC. In response, the SC develops adaptive and survival mechanisms (congruency mechanisms), which increase the effectiveness of the SC logistics processes. Thus, lesser and/or shorter disruptions in the flow of supplies are evaluated through performance measures that verify the fit between congruence mechanisms and independent variables. The practical contributions of CoT to the theoretical model in Figure 3.1 are (1) the examination of the context of the military-SCs from (2) the identification of contingent variables (management practices), by giving as a result (3) an effective organizational design (e.g. a more resilient military-SC). The theoretical model of Figure 3.1 provides a useful starting point for the subsequent development of the *ex ante* hypotheses and conceptual framework.

Figure 3.1 Performance of a military-supply chain in presence of risks and congruent mechanisms from contingency-based theory
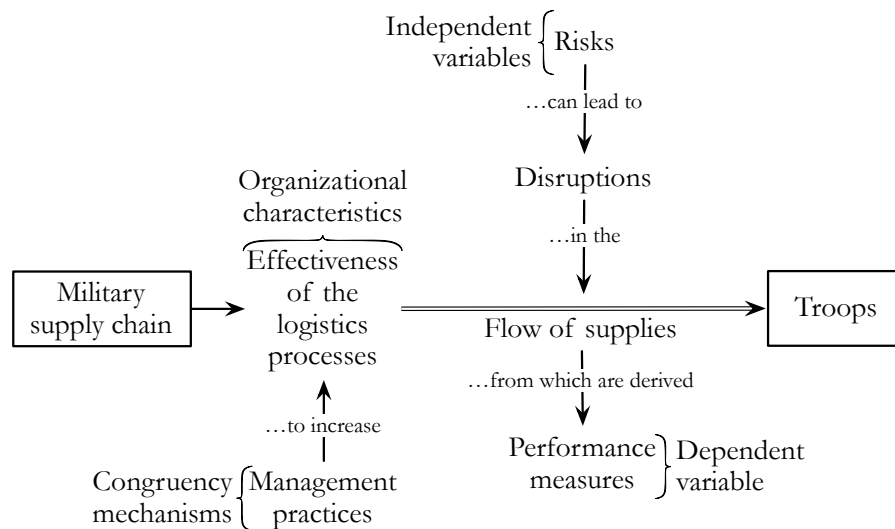
3.4 Hypotheses Development and Conceptual Framework

Three independent sets of interrelated hypotheses upon military-SCs are presented as follows. Each set of hypotheses—three in each set—represents an *assumed* relationship within the conceptual framework on which this research is based. The first set of hypotheses (H_{1a}, H_{1b},

and H_{1c}) describes the direct effect between increases in the frequency of occurrence of three categories of risk (R_{cr}) and the level of resilience of the military-SC under analysis (SCRes). Although this relationship denotes the extant theory, i.e., it should be taken as true, it will be subject to statistical validation. The second set of hypotheses (H_{2a}, H_{2b}, and H_{2c}) describes the interactive effect that increases to the levels of on-hand inventory buffers ($I_{t,S}$) may have on the relationship between risks and SCRes. Lastly, the third set of hypotheses (H_{3a}, H_{3b}, and H_{3c}) describes the interactive effect that increases in short-term manufacturing capacity (S) may have on the relationship between risks and SCRes. In the three mentioned cases, the effect of risks on the SC (disruptions) is assessed individually (by categories of risk), following the suggestion of Sheffi (2005) who stated, "each type of disruption should be anticipated and defended against differently" (p.13). In this sense, it is worth mentioning that the analysis of the previous empirical works in commercial-SCs described in Section 3.3 serves as starting point and reference framework for the above three sets of hypotheses on military-SCs. Nonetheless, for their formulation, the perspective selected in this research is *Plato's approach* or *carving at the joints* (Van de Ven, 2007), i.e. juxtaposing or comparing competing explanations regarding the utilisation of $I_{t,S}$ or S to increase SCRes in the light of the author's findings.

3.4.1 Hypotheses concerning the direct effect of increases in the frequency of occurrence of risks on the measure of resilience in supply chains: Hypotheses H_{1a}, H_{1b}, and H_{1c}

What is the linkage between risk and resilience? Few authors have explored in depth the implications of this relationship, perhaps due to its 'obvious' nature. Kahan and colleagues (2010), in a study for the U.S. Department of Homeland Security, examined the scope of this association from both qualitative and quantitative points of view. According to this study, risk and resilience are inversely related to each other. Thus, the more resilient a system is, the less prone it is to facing risks. On the other hand, the fewer/more risks a system faces, the higher/lower its level of resilience is.

In a broad sense, the notion of resilience might be interpreted as a measure of the performance of a system within a risky environment. From this perspective, the study by Wagner and Bode (2008) sheds lights on this relationship (risk and resilience) in the context of SCs. These authors developed survey-based empirical research in which they examined the relationship between the occurrence of five types of risk—demand side, supply side, regulatory, legal and bureaucratic; and catastrophic—and SC-performance. The results of this study, however, are somewhat disconcerting; while there is statistical significance for demand and supply side risks, the statistical support for regulatory, legal and bureaucratic, and catastrophic risks is weak. Wagner and Bode argued that this outcome is due to the fact that high-level executives underestimate the occurrence of these risks by considering them as exceptional events with a low likelihood of occurrence.

Hopp and Spearman (2008) posed a principle applicable to all manufacturing systems that underpins the linkage between risk and resilience. According to these authors, increases in variability negatively affect the performance of production systems. Hopp and Spearman

termed this relationship *variability law*. The variability is, in this context, the result of a mixture of predictable and unpredictable randomness with disruptive effects. More recently, Brandon-Jones and colleagues (op. cit., 2015) hypothesised a negative relation between the frequency of SC disruptions and the performance of manufacturing plants. In this regard, the authors confirmed this hypothesis, though subject to interaction effects. Therefore, based on previous works and studies outlined in the topical research, it can be said there are arguments to posit the following three hypotheses:

Hypothesis 1a (H$_{1a}$): 'Ceteris paribus, increases in the frequency of occurrence of operational risks (R$_{1r}$) reduce the measure of resilience in supply chains (Re^T).'

Hypothesis 1b (H$_{1b}$): 'Ceteris paribus, increases in the frequency of occurrence of natural-disasters-and-intentional-attacks (R$_{2r}$) reduce the measure of resilience in supply chains (Re^T).'

Hypothesis 1c (H$_{1c}$): 'Ceteris paribus, increases in the frequency of occurrence of black-swan events (R$_3$) reduce the measure of resilience in supply chains (Re^T).'

3.4.2 Hypotheses concerning the moderating effect of on-hand inventory buffers in the relationship between the frequency of occurrence of three categories of risk and the measure of resilience in supply chains: Hypotheses H$_{2a}$, H$_{2b}$, and H$_{2c}$

The first scientific reference on inventory management dates back to the second decade of the 20th century (Harris, 1913). Since then, hundreds of articles and entire treatises on this topic have been written, e.g., *Analysis of Inventory Systems* (Hadley & Within, 2012). The first works that considered inventory to prevent SC disruptions focused on "the single/multiple-supplier problem" or *supply side*, that is, interruptions in the supply of raw materials/components for the production/assembly of finished products, e.g., Goyal, 1977; Parlar & Perry, 1996; or to handle natural variations in demand which occur at the retailer stage of the SC or *demand side*, e.g., Ross, 2015. Nevertheless, the discussion of inventory as a mechanism for enhancing resilience and/or mitigating a broader range of SC disruptions is more recent. To date, inventory is the most prevalent buffering method used by SC managers because it does not need to be coordinated with suppliers or customers (Lapide, 2008). Despite this, two contradictory points of view in the literature coexist regarding the real effectiveness of inventory to prevent the occurrence of disruptions in SCs.

The first view argues that '*inventory can indeed enhance the level of resilience in SCs, and, as result, prevent the occurrence of disruptive events*'. Within this perspective, several nuances can be found. Rice and Caniato (2003), Lee and Wolfe (2003), and Jüttner and colleagues (2003) were the first authors to suggest increases in stockpiling and buffer inventory as a mechanism for creating resilience in SCs and/or mitigating disruptions. Chopra and Sodhi (2004), and Lockamy and McCormack (2010) pointed out that increasing inventory reduces delays and procurement and capacity risks, but also increase inventory risks. Christopher and Peck (2004) indicated that the selective use of inventory provides "slacks" that create more resilient SCs. Zsidisin and colleagues (2005) pointed out that the use of inventory to prevent SC disruptions is conditioned to low levels of

waste and variance. In a similar fashion, Boone and colleagues (2013) pointed out that inventories are a necessary component of an effective SC strategy, but that they can have detrimental effects on the SC when the inventory approach is misused. Similarly, Tomlin and Wang (2012) mentioned that a buffering strategy based on stockpile inventory is not without limitations, and that therefore, four factors should be considered for its application: risk profile, detection, isolation, and recovery. These authors recommended the use of inventory for frequent-but-short disruptions, and for rare-but-long disruptions, whenever, in the latter, a disciplined process for maintaining the stockpile exists.

Faden (2014) showed that the use of inventory buffers should be higher when the production forecast is less reliable. Sheffi (2002), and Sheffi and Rice (2005) recommended that SCs should keep "strategic emergency stock" in a fashion similar to the way U.S. strategic oil reserves are administered. These authors pointed out that this stock should not be used for day-to-day fluctuations, but only in case of the occurrence of an extreme disruption. A similar idea is proposed by Tang (2006), Pickett (2006), and Bode and colleagues (2011), who suggested the use of "shock absorbers" at certain strategic locations along the SCs—such as warehouses, logistics hubs, and distribution centres—to avoid inventory holding and obsolescence costs. Complementing this approach, Son and Orchard (2013) suggested using strategic inventory reserves instead of inventory buffers due to the lower holding cost of the former. Finally, Stecke and Kumar (2009) and Pettit and colleagues (2013) mentioned that SCs should carry extra inventory as a coping strategy to mitigate the negative effects of disruptions and/or to deal with demand fluctuations.

In contrast to above studies, the second view postulates in general that *'inventory does not create SCRes, nor is it and effective way to prevent the disruptions in SCs.'* Christopher and Lee (2004) discussed how the utilisation of inventory buffers is a clear indication of lack of visibility and control in the SC. These authors also pointed out that the worst-case scenario occurs when a SC holds high levels of inventory buffers and the demand decreases at the same time. In the same line of thinking, Bandaly and colleagues (2012) indicated that SCs face the risk of obsolescence when they keep inventory buffers for the mitigation of demand-side uncertainty. Tomlin (2006), by analysing a hypothetical SC with two suppliers—one unreliable, and the other reliable but more expensive—concluded that inventory mitigation does not work well when disruptions are rare and long. Zsidisin and Wagner (2010) compared redundancy and flexibility practices in SCs. According to the results found, redundancy—based on the use of safety stock, multiples suppliers, and low capacity utilization rates—is a less effective practice to reduce risks than flexibility. In a similar fashion, Hopp and colleagues (2012) concluded regarding the use of inventory as a protective mechanism for SC disruptions that it can mitigate disruptions and its use depends on the SC environment, but it is not sufficient by itself to protect against rare-but-long disruptions.

In a study on how to mitigate SC disruptions, Marley and colleagues (2014) argued that high inventory should not be considered an effective countermeasure, since it may increase the number of downstream disruptions in SCs. The main argument of these authors revolves around the idea of "complexity in systems". These authors indicated that increasing inventory

exacerbates the complexity of the SCs by increasing the likelihood of occurrence of "normal disruptions" in complex processes. Kim and colleagues (2015), researching structural relationships among entities within a SC network, contended that, first, redundancy—based on the use of inventory buffers—as a mitigation strategy for disruption needs to be understood in a holistic and integrative manner; and second, redundancy does not necessarily create higher resilience. Lastly, in a similar vein, Cardoso and colleagues (2015) found evidence indicating that in not all the cases adding more redundancy—in the form of more inventories—through mitigation strategies leads to more resilient SCs. The analysis of these authors shows that aspects such as the type and probability of disruptions, as well as the structure of the supply network are concomitant factors that should be taken into account. Thereby, by weighting both points of view, there are arguments to posit the following hypotheses:

Hypothesis 2a (H$_{2a}$): 'On-hand inventory buffers (I$_{t,S}$) moderate the relationship between the frequency of occurrence of operational risks (R$_{1r}$) and the measure of resilience in supply chains (Re^T), with the relationship being enhanced by increases in the levels of I$_{t,S}$.'

Hypothesis 2b (H$_{2b}$): 'On-hand inventory buffers (I$_{t,S}$) moderate the relationship between the frequency of occurrence of natural-disasters-and-intentional-attacks (R$_{2r}$) and the measure of resilience in supply chains (Re^T), with the relationship being enhanced by increases in the levels of I$_{t,S}$.'

Hypothesis 2c (H$_{2c}$): 'On-hand inventory buffers (I$_{t,S}$) moderate the relationship between the frequency of occurrence of black-swan events (R$_3$) and the measure of resilience in supply chains (Re^T), with the relationship being enhanced by increases in the levels of I$_{t,S}$.'

3.4.3 Hypotheses concerning the moderating effect of increases in the levels of short-term manufacturing capacity in the relationship between the frequency of occurrence of three categories of risk and the measure of resilience in supply chains: Hypotheses H$_{3a}$, H$_{3b}$, and H$_{3c}$

Short-term manufacturing capacity is based on the number of available work shifts in the SC. Several of the authors who suggested the use of on-hand inventory buffers also recommended the utilisation of this mechanism to enhance SCRes and/or prevent the occurrence of disruptive events (Rice & Caniato, 2003; Christopher & Peck, 2004; Chopra & Sodhi, 2004; Lapide, 2008; Cardoso et al., 2015). Likewise, researchers appear to be more predisposed to recommending increases in manufacturing capacity than to building inventory buffers to mitigate disruptions, due especially to the cost of the latter. For instance, Christopher and Peck (Ibid., 2004) mentioned that capacity is a more flexible mechanism than inventory, with both essential to SCRes. Lapide (Op.cit., 2008) pointed out that using SC capacity to prevent disruptions is as effective as using inventory. Simchi-Levi and colleagues (2007) suggested that the use of a redundant strategy (including increases in capacity) might be effective against risks of the type "unknown-unknowns" type. Zsidisin and Wagner (2010) found that a low capacity utilization rate reduces risks but not as much as flexibility does. Hendricks and Singhal (2012) and Hopp and colleagues (2012) pointed out that reducing overcapacity makes SCs more prone to

disruptions. Thus, similarly to the previous analysis, there are arguments to posit the following hypotheses:

Hypothesis 3a (H₃ₐ): 'Short-term manufacturing capacity (S) moderates the relationship between the frequency of occurrence of operational risks (R_{1r}) and the measure of resilience in supply chains (Re^T), with the relationship being enhanced by increases in the levels of S.'

Hypothesis 3b (H₃ᵦ): 'Short-term manufacturing capacity (S) moderates the relationship between the frequency of occurrence of natural-disasters-and-intentional-attacks (R_{2r}) and the measure of resilience in supply chains (Re^T), with the relationship being enhanced by increases in the levels of S.'

Hypothesis 3c (H₃c): 'Short-term manufacturing capacity (S) moderates the relationship between the frequency of occurrence of black-swan events (R_3) and the measure of resilience in supply chains (Re^T), with the relationship being enhanced by increases in the levels of S.'

3.4.4 Conceptual framework of the research

All previous hypotheses constitute the conceptual framework of this research and are applicable to military-SCs, as shown in Figure 3.2. Two basic patterns are distinguishable in the conceptual framework described: (1) the direct effect between the three categories of risk (R_{cr}) and the measure of resilience for military-SCs (Re^T), and, (2) the interaction of a buffering strategy ($I_{t,S}$, S) in the relationship between R_{cr} and Re^T.

Figure 3.2 Conceptual framework for the three categories of risk (R_{cr}), the measure of resilience for military-SCs (Re^T), and a buffering strategy ($I_{t,S}$, S)
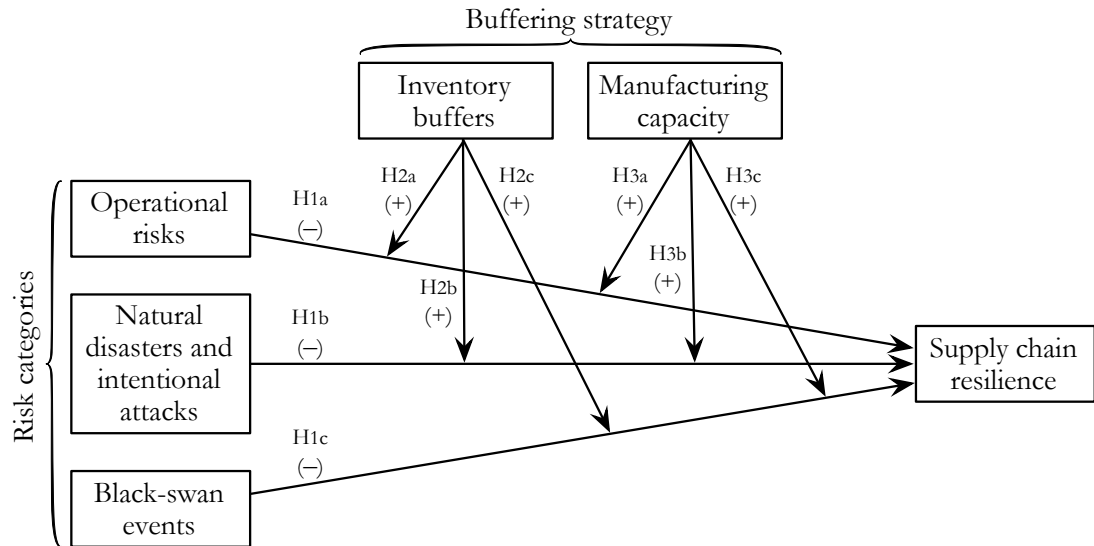
3.5 Comprehensive Research Perspective

Within the context of defense logistics area, the definition of the research problem—central question—emerged mainly from a preliminary approximation to the LSCM literature; and second, from the previous knowledge and experience of the researcher upon military-SCs. Thus, while the initial literature review allowed the identification of the topic of the research— *What is the most appropriate strategy to increase supply chain resilience or SCRes?*—, the analysis and observation of the performance of military-SCs and the background of the researcher enabled the selection of the unit of analysis for the research—*military food supply chain* or MFSC.

The designation of the topical research and the unit of analysis led to new questions: What is the most suitable definition of SCRes? How to measure resilience in military-SCs? Is it different from doing it in commercial-SCs? What aspects within the SCRes literature need more attention? In a nutshell, how to raise the level of resilience in MFSCs and what is the most appropriate strategy? Thereby, a deeper review of the literature from the objectives of the research that could cover all these aspects was needed.

With these questions in mind, the objectives of the research were clearly stated. In this way, the first research objective relates to the derivation of a universal conceptualization of SCRes and its subsequent operationalization; and the second objective, with the evaluation of the effectiveness of a buffering strategy in the context of MFSCs. The systematic review of the literature revealed gaps and patterns in the SCRes literature that, together with the previous identification of topical research and the selection of the unit of analysis, allowed deriving the research hypotheses, and subsequently, the conceptual framework of the research. Figure 3.3 summarizes the above.

Figure 3.3 Blueprint of the research
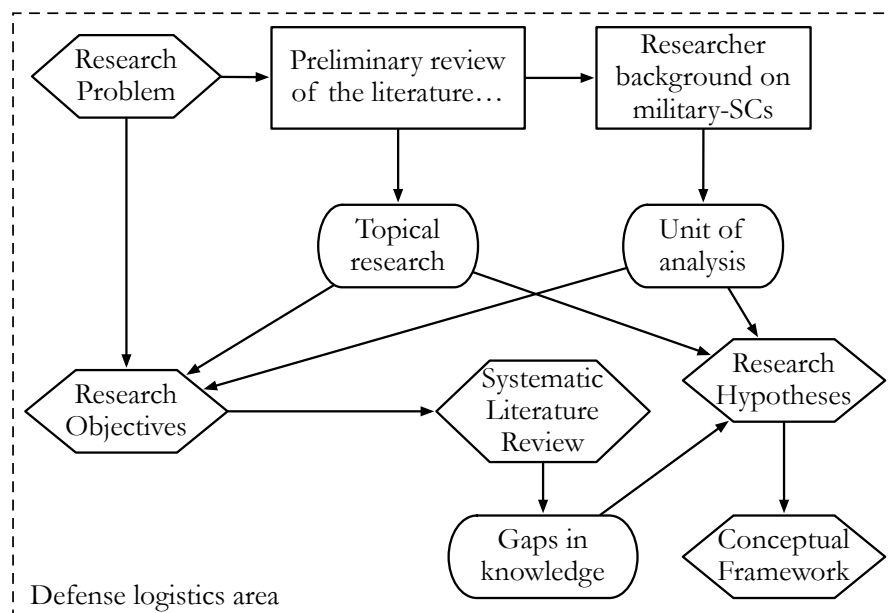
3.6 Summary of Chapter 3

The conceptual framework above described allows articulating four major stages of this research: review of the literature, operationalization of the concept of resilience, formulation of a simulation model, and analysis and results. For this purpose, in this chapter presented a solid justification of the interest in studying buffering strategies in military-SCs. Second, it developed a thorough review of previous empirical work related to risks/disruptions affecting the performance of SCs in overall and the buffering strategies used. Third, it obtained a theoretical model from CoT theory lenses, which serves as a starting point for the derivation of the nine research hypotheses applied to military-SCs. Lastly, it constructed a novel and comprehensive conceptual framework, which is the basis of this research. As described in the topical research, several of the variables considered in this conceptual framework have already been studied in previous theoretical or empirical works. However, how the variables of interest were arranged, as well as how they will be further evaluated and analysed, make this conceptual framework an original solution approach for the research problem posited in the introductory chapter.

Chapter 4
RESEARCH METHODS

Chapter 4. Research Methods

4.1 Introduction

The purpose of this chapter is to explain how and why the research methods for generating and analysis of data required for testing the research hypotheses were selected. To this end, this chapter is splitted up into two main sections. The first section focuses on the research methods for gathering of data, and the second section, on the research methods for their analysis. Building off the patterns found in the review of the literature in Chapter 2, each of these sections describes the research methods available in the literature, the research methods selected for each case, and the underlying reasons that justified their adoption for the purposes of the present research.

4.2 For the Collection of the Data

As was set forth in Chapter 1, the research problem proposed in this study comprises two main, integrated objectives: (1) to derive a unified conceptualization of SCRes based on the existing definitions, research done and gaps identified in the literature review from which a quantitative holistic measure of SCRes that appraises both dynamic and inherent resilience can be developed; and secondly, (2) to evaluate the theoretical effectiveness of a buffering strategy founded on the use of on-hand inventory buffers or short-term manufacturing capacity to build up SCRes.

To attain the first objective, a whole theoretical framework upon the operationalization of the SCRes concept and a text-mining algorithm were developed respectively, as will be explained in Chapter 5. To reach the second objective, two interrelated aspects must be addressed: First, we must examine the performance of a real-world military food SC (MFSC) in a hostile and changing environment; and second, we need to evaluate the effectiveness of a buffering strategy as described on the level of SCRes, as will be explained both in Chapter 6. Under ideal circumstances (Rosenbaum, 2010), the information needed to assess both aspects should come from an observational study in which the occurrence and impact of risk events on the SC under analysis are available and sufficiently detailed over time; and secondly, the information should be based on changes made for convenience from the levels of on-hand inventory buffers and short-term manufacturing capacity, or through randomized controlled trials, with the aim of measuring in situ the effect of these adjustments on the resilience of the SC.

Yet, the above conditions are difficult to achieve in practice. Firstly, there are few organizations with robust information systems to collect this type of data, let alone that are willing to disclose it to third parties (Tang, 2006). The situation described applies particularly to military-SCs, in which the information availability for risk analysis is usually limited, unreliable, or unavailable (Freier, 2008; Birkemo, 2013). And secondly, it is not feasible to modify the internal parameters of an actual SC at the expense of obtaining experimental results. Concerning the MFSC under analysis, there are no detailed historical records of the occurrence of risks/disruptions over time

nor studies that relate the effects that adjustments on the internal parameters/policies of the SC, e.g. outsourcing of logistical functions, may cause on its performance. Despite these information gaps, the author of this study had direct access to technical records of the SC related to characteristics and types of rations assembled, supplier and raw material information required, production capacity, internal SC-configuration, number of workers, times of delivery and distribution, and quantity and frequency of rations demanded, among other technical aspects.

Thus, if the research objectives and information constraints mentioned above are taken into account, what is the most appropriate modeling approach for gathering data from a military-SC operating in a risky environment? To answer this question, Table 4.1 characterizes the main approaches outlined in the literature for modeling disruptions in SCs, while Figure 4 summarizes the most common research methods used to collect data for the operationalization of the concept of SCRes, from the information provided in Table 2.1.

Table 4.1. Modeling approaches for SC-disruptions

Modeling approach	Characteristics and main assumptions	Problem-solving capability	Information requirements
1. Analytic Stochastic Models, e.g. King and Wallace (2012)	- Discrete and continuous probability functions - Very flexible to model - Model decisions have to be made before collecting data - Computationally difficult to solve - Wide range of applications and approaches	This approach allows determination of the optimal structure of an SC under uncertainty in the face of unexpected events or disruptions.	High
2. Bayesian Networks, e.g. Darwiche (2009), Donaldson (2010)	- Compact representation - Use of conditional probabilities - Robust to simulate small disruptions - Operational flexibility with different variables - Past information determines the future - Variety of applications	This approach enables modeling disruptions and causal relationships for SCs in a context of uncertainty through the use of (incomplete) historical data.	Moderated
3. Behavioural, e.g. Croson and Donohue (2002)	- Complete rationality of decision makers - Principles for modeling are based in social science - Disruptions and unexpected events are mainly based on behavioural factors - Few applications in literature	This approach allows analysing human behaviour within SCs, and how their actions can reduce the impact of unexpected disruptions.	High

4. Game theoretical—non-cooperative and cooperative game, e.g. Papapanagiotou and Vlachos (2012)	- Set of players - Strategy space - Payoff functions - Multiples goals - Constrains and conflicting objectives	This approach enables analysing SC-disruptions, emphasizing the interactions between suppliers and retailers under stochastic conditions and policies of risk sharing.	High
5. Networks based—Petri-Nets' variants—Girault and Valk (2003)	- High level of abstraction - Graphical and mathematical methods - Very flexible for modeling different logistics problems - Unsuitable for large-scale systems - Varied applications in literature	This approach is considered a kind of simulation-based tool. It allows examining settings of concurrency, asynchrony, parallelism and distribution in non-deterministic and/or stochastic SCs.	Moderated
6. Principal Agent, e.g. Swaminathan and Smith (1998)	- High level of abstraction - Flexible and reusable framework to develop models - Robust but complex to apply - Few applications in literature	This approach is considered a kind of simulation-based tool. It enables understanding sequential and hierarchical disruptions in different types of SCs based on generic, modular and reusable structures.	High
7. Simulation—Discrete and Dynamics, e.g. Chung (2004) and Sterman (2000)	- Experimentation in compressed time - Flexible but costly in terms of time - Discrete, dynamic or both - Graphical and mathematical methods - Few analytic requirements - Very sensitive to data collection - Appropriate to analyse complex problems	This approach allows evaluating the impact of different disruptive events along the SC at researcher's own convenience, according the level of detail desired—system oriented or process oriented.	Moderated

Figure 4.1 Commonly used research methods to collect data for the operationalization of the concept of SCRes

As is derived from Table 4.1, each modeling approach described therein comes along with a set of characteristics, assumptions, and problem-solving capability that define its scope of application. In this way, 'analytic stochastic models' are not appropriate for application to the research problem since the purpose of the study is not to find an overall/local optimum solution; the 'Bayesian networks' approach requires a certain amount of historical data to produce reliable outcomes that, as mentioned above, are not available at the MFSC; a 'behavioural' approach is used to address research problems that directly involve the representation of human decision-making regarding SC-disruptions, a scope of application away from the present research problem; the 'game theoretical' approach has been used to study the interaction of entities within the SC, but as with the previous option, it is far removed from the present research problem; 'petri-nets variants' is a family of graphical approaches within discrete-event simulation tools with a varied number of applications in SC-disruptions that do properly fit to the present research problem, particularly *coloured petri-nets* (Jensen & Kristensen, 2009), but with a limited number of robust software packages available; the 'principal agent' approach is a simulation-based tool used to represent the behaviour of individual decision makers—or *autonomous agents*—at a micro level of the SC, a level of analysis not required to solve the research problem; lastly, the 'simulation' approach—system dynamics and discrete-events simulation—enables the modeling of SC-disruptions from a macro and a process-oriented perspective, which makes it suitable, especially with the latter perspective, for the research problem at hand. It should be noted that, from a practical point of view, the key difference between a 'simulation' approach and 'petri-nets variants' is that for the former, the number and robustness of the software packages is higher, though their results are equivalent to each other.

Furthermore, Figure 4 describes the pattern of dominance of the 'simulation approach' over other research methods for the collection of data to operationalize the concept of SCRes. Thereby, from a total of 40 publications analysed, in 14 of them the paradigm 'discrete-event simulation' (DES) was the main research methodology chosen by predecessor studies for the

collection of the data. This result confirms the presumption of several authors that simulation-based studies are the dominant paradigm for SCRes analysis (Mandal, 2014; Datta & Christopher, 2011). Needless to say that the remaining research methodologies included in Figure 4.1 do not fit with either the nature of the data required nor with the information constraints mentioned.

Therefore, based on the previous arguments, DES, in the form of the software *Simulink* [v.R2015b-8.6.0.26] by MATLAB®, was the tool selected for the collection (or generation) of the data for the MFSC, which is implemented in Chapter 6 and the program code described in Annex B. It is advisable at this point briefly to mention the main uses and limitations of the DES within the context of the SC-disruption/SCRes. For instance, Dong and colleagues (2009) pointed out that DES is a proper tool to assess robustness and resilience to disruptions of a supply network; Al-Aomar and colleagues (2015) affirmed that DES can be used to design, improve, and validate ex-ante the performance of manufacturing systems; and Melnyk and colleagues (2009) indicated that DES can be applied in modeling the risks that trigger the disruptions in SCs, building up the simulation model itself, establishing appropriate policies and parameters in the SC, and analysing the output data of the simulation runs.

By contrast, Behdani (2013) argued that when DES is applied for analysing SC-disruptions, the micro-level entities of the SC are "passive objects with no decision-making capability"; and Fishman (2001) pointed out that the results of the simulation have a limited range of applicability that need to be confronted with reality. Thus, in an attempt to minimise such limitations of DES and increase the usefulness and validity of the findings of this study, the output data of the DES were complemented with the results of an open-ended questionnaire administered to the MFSC staff under analysis. By virtue of the foregoing, this study can be considered *mixed-method research* (Johnson et al., 2007). The results of the open-ended questionnaire and details on how was conducted are described in Section 6.10 of this research. The following section explains the criteria utilised for the selection of the research methods for the analysis of the output data of the simulation model.

4.3 For the Analysis of the Data

The selection of the research methods required for the analysis of the output data of the simulation model was influenced by three aspects: First, the review, analysis and derivation of a unified definition of SCRes from the existing conceptualizations in the literature; second, the adoption of the 'simulation paradigm' or DES to generate the dataset required for examining the research hypotheses; and third, the nature of the research problem as a whole. Regarding the first aspect, the problem consisted of synthesizing a new conceptual approach of SCRes that, although novelty itself, contained the 'DNA of the twenty-four definitions' identified in the review of the literature in Chapter 2 of this research. In other words, the purpose was not only to obtain a new definition of SCRes, but also to derive one that was universal. The approaches for qualitative-information analysis available in literature—e.g. *grounded theory* (Charmaz, 1983), *thematic synthesis* (Thomas & Harden, 2008), or *framework synthesis* (Pope et al., 2000), among others—seemed to be inappropriate to address this problem since the high number of SCRes

conceptualizations that must be analysed. Another alternative solution approach considered was to define an inclusive criterion from the available definitions on SCRes—e.g. choose the SCRes' definition most cited in the scientific literature—and then use it as a reference in the construction of the new unified concept of SCRes. However, the use of this approach involved the risk of bias in the selection of one of the existing definitions of SCRes over the others. Therefore, a robust and neutral analysis-approach based on objective criteria that would allow the easy extraction of the underlying components common to the twenty-four definitions of SCRes was required. The method selected was *text-mining data*, and the results of its application are described in detail in Subsection 5.4, and the algorithm used in Annex A.

Regarding the second aspect, the adoption of a DES model to collect the data required for testing the research hypotheses restricts the use of statistical methods to only one: *non-parametric statistical methods*. This is because, by definition, the output variables of DES models are not normally distributed (Kleijnen, 2015). This assumption is statistically verified in the study in Subsection 7.2.2. Lastly, concerning the third aspect, the nature of the research problem posited in Chapter 1 aims to 'compare' the resilience of the MFSC according to the levels of on-hand inventory buffers/short-term manufacturing capacity and the categories of risk considered. Thereby, taking into account both factors, the resulting question is, what are the *non-parametric statistical methods* best suited to *comparing* the resilience levels of a military-SC under distinct configurations? The answer to the above question is summarized in Table 4.2.

Table 4.2. Non-parametric methods to compare data series

Setting	Non-parametric method
One sample	Wilcoxon rank signed test
Two independent samples	Wilcoxon rank sum test with continuity correction
Several independent samples	Kruskal-Wallis rank sum test

Hence, from Table 4.2, the two main tests adopted for the analysis of the output data of the simulation model are the *Kruskal-Wallis rank sum test* and the *Wilcoxon rank sum test with continuity correction*. The first test is used to verify if the univariated time series examined come from different populations, while the second test is used to verify if one of the univariated time series is lower than the other (Wassermann, 2006). The application of the above tests guarantees the verification of the sets of hypotheses 2 (H_2) and 3 (H_3), as described in Sections 7.3 and 7.4, respectively. In those cases in which the application of the Kruskal-Wallis rank sum test is not conclusive, an additional test is applied: the *Binomial test*.

In the analysis of the set of hypotheses 1, given that the comparison to be made is between the frequency of occurrence of several types of risk and the level of resilience of the SC, the approach chosen is different from that applied in the analysis of the sets of hypothesis 2 and 3. Thus, a technique for data mining is selected for this purpose: *association rule mining*. The application of this technique allows finding the degree of relationship and the relation of causality if any between the frequency of occurrence of risks and the level of resilience of the SC, which involves analysing a high volume of data. In this regard, Zhang and colleagues (2016) stated that compared with traditional exploratory data analysis, "association rule mining is

superior in investigating multiway interactions between numerous entities that are hard to represent by a single model." (p.1). The application of the above test guarantees the verification of the set of hypothesis 1 (H$_1$), as explained in Section 7.2. Lastly, Figure 4.2 summarizes the way in which the different research methods described above concur to the achievement of the first (a) and second (b) research objectives.

Figure 4.2 Research design and research objectives
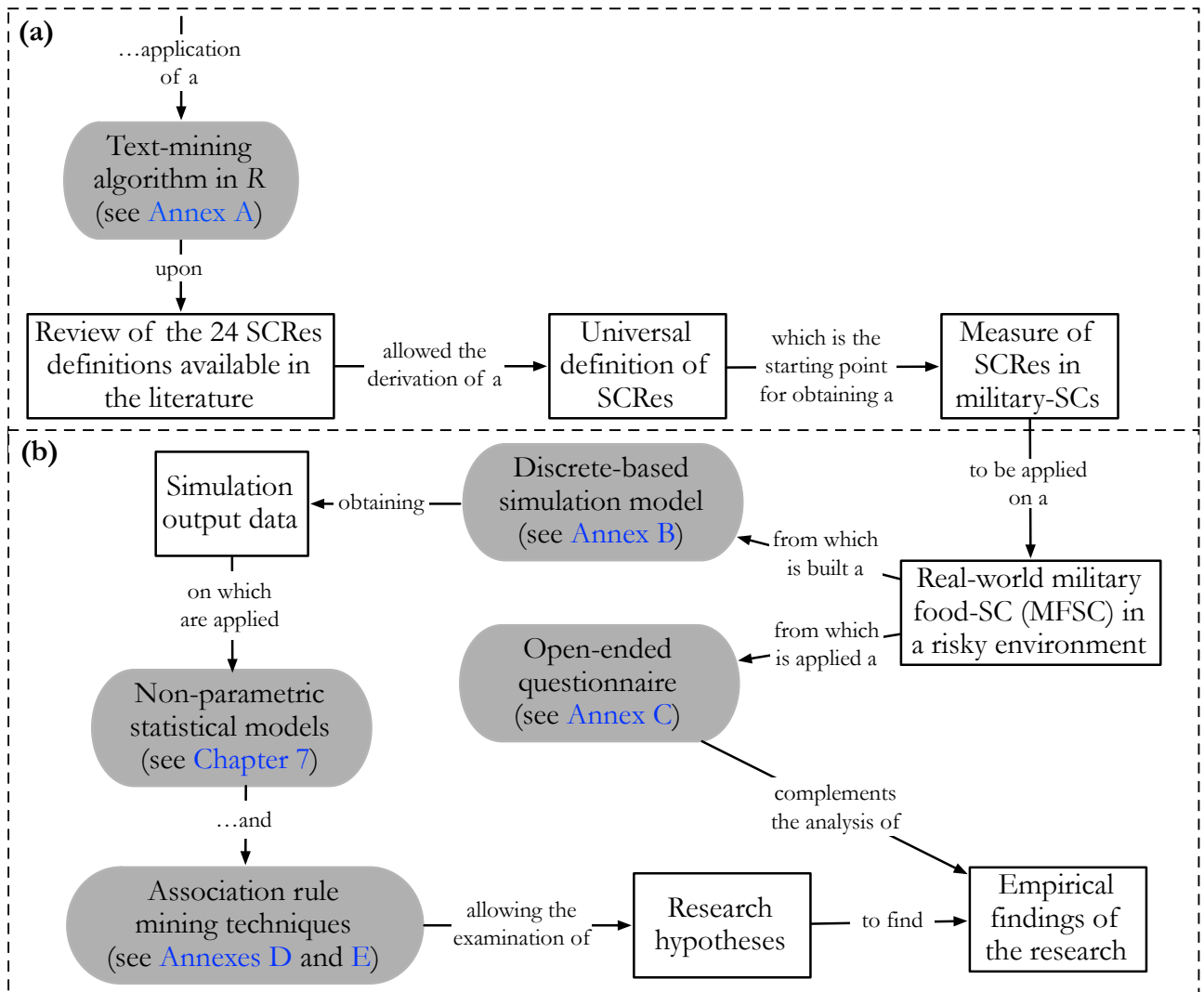
4.4 Summary of Chapter 4

This chapter provided the arguments on how and why the research methods for gathering and analysis of the data were selected. For the collection of data, the main research method selected was *discrete-event simulation* (DES), and as complement to the above, *an open-ended questionnaire* was administered, making this study *mixed-method research*. Two fundamental reasons motivated the adoption of DES: first, the impossibility of experimenting with a real-world military-SC, and second, the limitations of information of the variables analysed. Similarly, for the analysis of data, the research methods selected were *association rule mining* for testing the set of hypothesis 1 (H_1) given the efficiency of this technique in the analysis of high volume of data; and the *Kruskal-Wallis sum rank* and *Binomial distribution tests*, and the *Wilcoxon sum rank test with continuity correction* for the testing the sets of hypothesis 2 and 3, respectively, given the non-normality of the output data of the simulation model.

Chapter 5
OPERATIONALIZATION OF RESILIENCE IN MILITARY SUPPLY CHAIN

Chapter 5. Operationalization of Resilience in Military Supply Chains

5.1 Introduction

SC-performance measures are essential for managers to make right decisions (Gunasekaran & Kobu, 2007), and measuring SC-resilience (SCRes) has become key in recent years. In this regard, it can be said that SC-managers need better methods to assess the determinant factors of SC-proneness to disruptions (Kleindorfer & Saad, 2005; Bode & Wagner, 2015). The review of the literature in Chapter 2 of this research evidenced a limited number of publications concerning the quantification of SCRes. As far as known, the notion of SCRes was first mentioned in the literature by Rice and Caniato (2003) and first-measured by Datta and colleagues (2007), which makes this subject in relatively new area of research. Since then, researchers have actively tried to operationalize this concept with relative success, although the existing measures of SCRes pose several weaknesses that need to be improved. This chapter proposes a new quantitative measure of SCRes (Re^T) based on the gaps found in the review of the literature, but could be used for any type of SCs. Re^T is based on the *tail autotomy effect* (TAE) and includes the two dimensions of the concept of resilience: *dynamic resilience* and *inherent resilience*. Thus, the chapter is organized as follows: the first part describes the characteristics and justification of implementing a measure of resilience in military-SCs. In the second part, a text-mining algorithm is used to derive a unified definition of SCRes. In the third part, the fundamentals of disruption analysis in military-SCs are presented through the TAE lens. The chapter ends with the introduction of the analytical measure of resilience or Re^T.

5.2 Characteristics of Military Supply Chains

Military-SCs are framed in the field of defense logistics (DL). The post-Second War II perspective of the DL refers to how the country's armed forces are supplied timely and continuously with goods and services, or more specifically, how military personnel and/or equipment are mobilized to theatres of operation that demand their presence. Several authors and organizations have widely theorized in this regard, e.g., Eccles (1959), Falk (1986), DoA (2008), Kress (2016), and Zeimpekis and colleagues (2015). However, the essence of the DL has barely varied in the last 60 years, due to perhaps to the lack of interest of the topic among researchers (Yoho et al., 2013). Military-SCs are not monolithic organizations. In fact, they can be significantly different depending on several factors: volume and weight of cargo, operational context of the battlefield, mission assigned, and, especially, the branch of the military forces they supply. Operations manuals of the military powers (DoD, 2008; NATO, 2012) point out that the logistics supplies for ground troops are made up of massive amounts of food and ammunition, which are mobilized by land, sea, or inland waterways. Troops deployed on the sea (naval forces) need mostly food, fuel, and ammunition, which are carried mainly by marine transports, and, in exceptional cases, by air. Last but not least, crews of pilots and air-support personnel chiefly demand fuel, ammunition, and repair parts, which are usually mobilised by aerial means. As a general rule, the volume and amount of supplies sent to the Navy or Air force are smaller than to the Army due to the lower number of men in service. Likewise,

between ground and aerial delivery, the latter is the preferred method for re-supplying forward-operation bases because it is safer, though more expensive. An appropriate way to characterize military-SCs is to compare them with their civilian counterparts, commercial-SCs. As is known, both SCs share many similarities such as having a common origin (Southern, 2011; La Londe et al., 1971). For instance, their logistics processes—suppliers, procurement, operations, distribution and customers—are fairly similar (McGinnis, 1992; Christopher, 2011). However, because they supply dissimilar end-customers and operate in different environments, their differences seem to be deeper than their commonalities.

The most notable divergence is related to the *objectives of the organization*. Thus, whereas the emphasis of military-SCs is on responsiveness and preparation for war (Wang, 2006; Moore et al., 1991), the objective of commercial-SCs is to contribute to long-term profitability and maximize shareholder value (Hopp, 2008; Wilhite et al., 2014). Gansler and Lucyshyn (2006) pointed out this disparity of objectives as "losing sales vs. losing lives". In this sense, a concomitant factor is the *customer lead-time*. The customer lead-time in military-SCs is determined by the characteristics of the mission and/or the operational conditions of the terrain, but not by the competitors of the market, as is the case with commercial-SCs. This aspect makes it such that the lead-times of the military-SCs are short and inflexible to changes, which restricts the use of this dimension (time) as an alternative or buffering in case of disruptions in the flow of finished items.

The *level of risk* to which both SCs are exposed is another differential factor. Comparatively, the military-SC environment is characteristically uncertain, complex, and hostile, not to mention that there is a constant possibility of loss of human life. Thus, "how do you hide logistics?" is a recurrent question on the battlefront (Pagonis & Krause, 1992). It could be said, on the other hand, that commercial-SCs face some degree of uncertainty in their operations, but never comparable to the level of risk involved in military operations. One of these risks is related to the nature of cargo transported. Military-SCs carry a wide range of hazardous materiel, including explosives, fuel, ammunition and heavy equipment, over long distances (Spellman, 2007). The transportation of war materiel usually includes the mobilization of troops to the theatre of operations/war, and, if necessary, the return of this materiel from the theatre to the source of supply or point of disposal, in what is called *retrograde operations* (Klinghoffer et al., 2015). The above capabilities are rarely observed in commercial-SCs. The same apply for the range of items in inventory, which regularly exceeds 50,000 SKU in military-SCs (Tatham, 2005).

Finally, the *procurement system* for the acquisition of raw materials and components in military-SCs can be considered rather rigid compared to commercial-SCs. Due to their governmental nature, military-SCs must follow a set of regulations designated to ensure transparency and impartiality with the selection of suppliers. However, as a side effect, the application of these rules reduces the flexibility and efficiency of the procurement system (Rutner et al., 2012). Other differences between military and commercial-SCs worth mentioning are the variability of the pattern of demand (Wang, 2000), the hierarchy of organizational structure (Bjørnstad, 2011), and the absence or presence of marketing channels (Kim, 1996).

5.3 The Need to Implement and Measure Resilience in Military Supply Chains

Despite the large number of studies and detailed analyses about the detrimental effects that risks may have on the performance of SCs—e.g., Hendricks & Singhal, 2005; Zsidisin & Ritchie, 2009; Wagner & Bode, 2008; Ivanov et al., 2014—, managers do not seem to be fully engaged in building up resilience, to judge from how SCs continue to be impacted by risk events. A recent report on business interruptions over the period 2010-2014 indicates a growing incidence of risks in SCs (AGCS, 2015). An illustrative case is the aftermath of the series of explosions in the Chinese port city of Tianjin, which killed 173 people, resulting in estimated losses of US$3.3 billion, as well as massive logistical delays in several global supply networks for months. Bode and colleagues (2011) attribute this 'managers inattention' to the uncertainty associated with the identification and evaluation of risks, while Hendricks and Singhal (2012) affirm that it is due to the poor understanding of the magnitude and persistent effect of disruptions on financial performance. But at the end of the day, how important is the notion of resilience to military logisticians? Would it make a difference to military personnel if the resilience level of the SC were increased on average, say, 20%? What would be the consequences if the resilience level decreased in the same proportion? How much resilience do military-SCs need?

Overall, it can be said that there are not many studies in the literature on SCRes that provide satisfactory answers to these questions, since the assumptions on which they are based are not fully compatible with the characteristics and context of military-SCs. Thus, arguments such as gaining a competitive advantage (Ponomarov & Holcomb, 2009; Sheffi, 2015), improving the sustainability of operations (Fiksel, 2006), increasing innovation (Golgeci & Ponomarov, 2013), increasing the market share (Hohenstein et al., 2015), or reducing costs/increasing sales (Park et al., 2016), seem at first glance attractive arguments for adopting resilience paradigm in commercial-SCs, but not very convincing or even applicable for military-SCs. As noted previously, military-SCs are not looking for better financial performance or market position, but rather for a continuity of operations.

An analysis of the tenets that underlie the main work philosophies implemented by military-SCs confirms this lack of attention to resilience. Thus, the *mass-logistics approach* consists of prepositioning massive stockpiles of supplies and weapons systems, or the so-called "iron mountains" of supplies, to cope with demand uncertainty (Wang, 2000; Girardini et al., 1995). *Precision logistics* & *integrated logistics capability* rests on a simple methodology: "define-measure-improve" (Fricker & Robbins, 2000). *Velocity management initiative* is a concept based on high-velocity processes tailored to meet the needs of customers (Dumond et al., 1995; Dumond et al., 2001). *Sense* & *response logistics* is an approach based on highly adaptive, self-synchronizing and dynamically reconfigurable demand to support network-centric operations and mitigate support shortfalls (Tripp et al., 2006). *Customer wait time* is an approach designed to optimize system readiness and to meet performance goals for a weapons system through long-term support arrangements (Gansler & Lucyshyn, 2006; DAU, 2005). *Lean sustainment initiative* is a set of practices including maintenance, repair and overhaul that keep the systems operating and up-to-date throughout their entire life cycle (Mathaisel et al., 2009). Lastly, *focused logistics* is an integral strategy that combines information, logistics and transportation technologies to provide rapid

response in critical situations, to track key assets, and to deliver tailored logistics packages and sustainment at all levels of military operations (DoD, 2010).

All the approaches above are based on the application of lean and/or agile principles but not on a resilience paradigm, which is evidence of the apparent disinterest or unknowingness of the military logisticians about the importance of this concept. Some specialists from the academy have begun to highlight the need for implementing resilience into military-SCs. Dowdall (2004), by examining the UK defence industry supply system, underscored the importance of resilience for facing the demands of highly competitive environments. Similarly, Tatham and Taylor (2008), by analysing the British military-SC model, emphasized the necessity of the resilience as a mechanism to avoid or absorb shocks through stocks. Demchak (2010) suggested that military-resiliency is embedded in the mechanisms of learning—e.g., manuals, precepts, or doctrine—that serve as a guide to survival during combat operations. Parlier (2011) incorporated the notion of resilience into a multidisciplinary conceptual model applied to the U.S. Army. More recently, Yoho and colleagues (2013), in a review paper on defence logistics, pointed out the relevance of including a resilience paradigm as a research cluster due to the need of military-SCs to withstand the high degree of uncertainty associated with the environment in which they operate.

Accordingly, military-SCs need to be more resilient than their civilian counterparts. Being very exposed to the occurrence of risks makes them prone to interruptions in the flow of supplies that could endanger the life of troops. This is a strong argument for implementing the notion of resilience in military-SCs. In this sense, this research argues that the more resilient the military-SCs are, the less likely they are to suffer the negative impacts of risks, and as a result, the frequency and intensity of disruptions will be reduced. Hence, resilience in military-SCs must be interpreted as the SC-ability to accomplish the mission. For instance, if the supplied items are of the type Class I—subsistence and commercially bottled water—or Class V—ammunition—, fewer interruptions will mean more lives saved. Similarly, the need to quantify resilience can be summarized in the well-known principle of quality, "if you can't measure it, you can't improve it." This means that, without a proper measure of resilience, it is not possible to evaluate the effectiveness of resilience-building strategies implemented (Tang & Tomlin, 2008); in other words, SCRes cannot be improved if it cannot be measured.

5.4 Toward a Universal Definition of Supply Chain Resilience (SCRes)

The SCRes concept must be accurately defined prior to any attempt to measure it. However, the review of the literature revealed no less than 24 definitions about SCRes, as shown in Table 5.1. Which of these definitions is the best descriptor of the SCRes concept? In an effort to avoid bias in the selection of any of these characterizations, a text-mining algorithm in *R* (2013) (see Annex A) based on Feinerer and colleagues (2008) was applied to the set of definitions in Table 5.1. The general idea of applying an algorithm of this type is to find the frequency of occurrence of key words, from which a unified definition of SCRes can be derived. Connectors and superfluous words such as 'the,' 'and,' 'in,' 'to,' 'for,' 'or,' and so on, are not taken into account within the selection. Figure 5.2 shows the plot of the results of the text mining analysis. The

most frequent words used by the authors of Table 5.1 apart from 'supply,' 'chain,' and 'network,' are 'ability' (24 times), 'disruption' (16 times), 'state' (9 times), 'operations' (7 times), 'original' (6 times), 'return' (6 times), 'respond' (6 times) and 'unexpected' (5 times).

Table 5. Definitions of supply chain resilience (SCRes)

No.	Author(s) (year)	Definition of SCRes
1	Rice and Caniato (2003)	Resilience in the supply network environment is the ability to react to unexpected disruption and restore normal supply network operations.
2	Christopher and Peck (2004)	Resilience is the ability of the supply chain to return to its original state or move to a new, more desirable state after being disturbed.
3	Closs and McGarrell (2004)	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 re-establish alternative means of operations when the subject of an incident.
4	Christopher and Rutherford (2004)	Resilience is the ability of a system to return to its original (or desired) state after being disturbed.
5	Sheffi (2005)	Resilience in terms of the corporate world is the ability of the company to bounce back from a large disruption including the speed with which it returns to a normal level of performance.
6	Gaonkar and Viswanadham (2007)	Resilience is the ability of a supply chain to maintain, resume and restore operations after a disruption.
7	Datta (2007)	SCRES is not only the ability to maintain control over performance variability in the face of disturbance but also a property of being adaptive and capable of sustained response to sudden and significant shifts in the environment in the form of uncertain demands.
8	Datta et al (2007)	Resilience of the supply network is the ability of the production–distribution system to meet each customer demand for each product on time and to quantity.
9	Falasca et al (2008)	Resilience is the ability of a supply chain to reduce the probabilities of a disruption, to reduce the consequences of those disruptions when they occur and to reduce the time to recover normal performance.
10	Longo and Oren (2008)	Resilience is a critical property that, in a context of supply chain change management, allows the supply chain to react to internal/external risks and vulnerabilities, quickly recovering an equilibrium state capable of guaranteeing high performance and efficiency levels.
11	Ponomarov and Holcomb (2009)	Resilience is the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function.
12	Barroso et al (2010)	SCRES is the supply chain's ability to react to the negative effects caused by disturbances that occur at a given moment in order to maintain the supply chain's objectives.
13	Pettit et al (2010)	SCRES is the ability to survive, adapt and grow in the face of turbulent change.
14	Guoping and Xinqiu (2010)	Resilience is the ability of the supply chain to return to its original or ideal status under emergency risk environment.
15	Carvalho et al (2011)	SCRES is concerned with the system's ability to return to its original state or to a new more desirable one after experiencing a disturbance and avoiding occurrence of failure modes.
16	Shuai et al (2011)	Resilience is defined as the rapid recovery ability to equilibrium after the supply chain is attacked by a disturbance and we use the recovery time to measure the ability.
17	Christopher (2011)	Resilience is the ability of the supply chain to cope with unexpected disturbances.
18	Xiao et al (2012)	Resilience is the supply chain's ability to return to the original or ideal status after external disruption and includes both the abilities of adaptability to the environment and recovery from the disruption.
19	Yao and Meurier (2014)	SCRES is defined as the ability to bounce back from disruptions and to permanently deal with and respond to the changing environment.
20	Ponis and Koronis (2012)	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 favourable one than that prior to the event, thus gaining a competitive advantage.
21	Brandon-Jones et al (2014)	SCRES is defined as the ability of a system to return to its original state, within an acceptable period of time, after being disturbed.
22	Hohenstein et al (2015)	SCRES can be defined as the ability to prepare for, respond to, and recover from potential disruptions, and increase market share.
23	Tukamuhabwa et al (2015)	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.
24	Kim et al (2015)	Supply network resilience is a network attribute to withstand disruptions that may be triggered at the node or arc level.

Figure 5.1 Plot of the results of the text-mining analysis of SCRes definitions available in the literature

Thus, from the previous analysis, the 'universal definition' of SCRes derived is as follows:

> The adaptive ability of the supply chain/network to respond to/react to/resist to unexpected operational disruptions, recover from them and return to the original/desired state.

This result is adopted in the subsequent sections of this research as the unified definition of SCRes, and it is used in particular as a reference point for the selection of the variables that make up the proposed analytical measure of resilience.

5.5 Disruptions in Military Supply Chains

Disruptions in SCs are by and large regarded as "unplanned events that may occur in the supply chain, which might affect the normal or expected flow of materials and components" (Svensson, 2000, p.731). In the same sense, Handfield and colleagues (2008) defined disruption as "a major breakdown in production or distribution nodes that impacts other nodes in the supply chain" (p.34). Wagner and Bode (2006, 2009) adopted a different perspective by defining SC disruption as the trigger that leads to SC risk. In a later work, these authors (2015) extended the definition of SC-disruption to an unintended event occurring upstream, inbound or in the sourcing of the supply network that seriously threatens the continuity of operation at the level of the firm. Rice and Caniato (2003) affirmed that disruptions have the potential to cause entire SC-networks to fail, and Ivanov and colleagues (2014) emphasised its unpredictability. Kim and colleagues (2015), by using graph theory, affirmed that a supply network disruption occurs when "the network no longer has a walk from the source to the sink node due to disruptions" (p.53). Chopra and colleagues (2007) distinguished between disruptions—interruption of supply—and delays—recurrent risks, by underlining the importance of this differentiation in the implementation of mitigation strategies. Ambulkar and colleagues (2015), in an analysis of firm resilience, identified four types of disruptions, including supply disruption, logistics/delivery disruptions, inhouse/plant disruptions, and natural hazards/regulatory and political issues. Craighead and colleagues (2007) argued that SC disruptions are unavoidable, and Blackhurst and colleagues (2011) pointed out that the impact of disruptions depends on the level of SCRes.

All this research expands our understanding of the phenomenon of disruption, particularly on how disruptions originate, how they spread throughout SCs' structure, and how they affect the performance of SCs. However, more in-depth analysis is needed regarding how SCs respond to disruptions (Zsidisin & Wagner, 2010). In fact, none of these studies addresses the equivalence of the *tail autotomy effect* (TAE) as an internal mechanism of response to the occurrence of risks. This mechanism of self-defence has been observed by zoologists in some species of lizards, who induce the separation of their own tail from their trunk to distract predators and to escape dangerous situations (Vitt et al., 1977; Niewiarowski et al., 2017). Figure 5.2a describes the initial situation without risk to the lizard. In Figure 5.2b, the lizard's tail detaches from the trunk before the imminent attack of a predator. The interesting aspect of this prodigy of nature lies in the autotomy of movement of the lizard's tail after the blood flow is interrupted as a result of a complex neuromuscular control system, as described in Figure 5.2c. The autotomic movement

continues for up to 30 minutes due to the energy reserves stored in the tail (glycogen). Finally, after months, the lizard's tail recovers and returns to its original size and shape, as described in Figure 5.2d.

Figure 5.2 Tail autotomy effect in lizards (TAE)
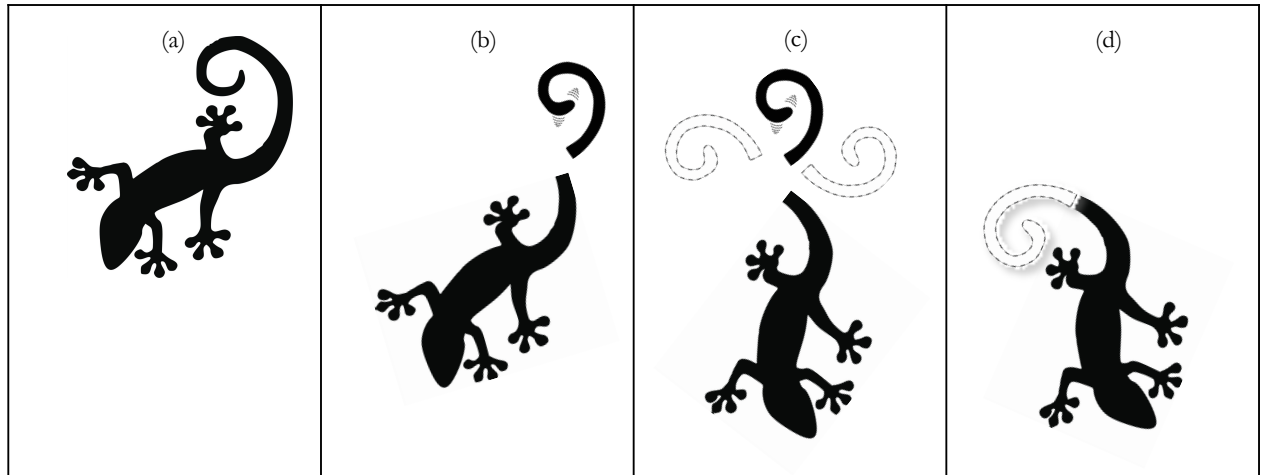
The application of this animal defensive mechanism is relevant for this research since it provides an alternative perspective on how SCs respond to the occurrence of disruptions caused by risks. Therefore, the TAE is observed in SCs when, due to an increase in the frequency of occurrence of risks and/or its level of impact, the SC manufacturing capacity is oversaturated or the physical assets of the SC are seriously damaged. The materialization of the risks can literally cut or separate the SC into two parts—the first, from the point of impact of the risk, upstream through the end of the chain, and the second, from the point of impact of the risk, downstream through the other end of the chain—without implying that the 'movement' of supplies to the end-users is interrupted. This behaviour is similar to that observed in Figure 5.2 when 'the tail of the chain'—the second part—continues moving autonomously for a given period, after which it returns to its original state. A deeper analysis of the TAE in SCs enables the characterization of the following two types of SC-disruptions.

5.5.1 Partial disruption

A *partial disruption* occurs when fluctuations in the demand for finished items and/or disturbances in facilities, lines-of-communication, processes, workstations or machines do *not* interrupt the flow of supplies to end-users, i.e., the SC cycle time of the a order j is equal to its lead time ($CT_j = LT_j$). During this *period of autotomy*, the SC achieves the maximum level of resilience, or, in a particular case, the resilience of the MFSC prevents the disruptive events from interrupting completely the flow of rations to military personnel, as shown in Figure 5.3. Thus, once the impact of the risks ends, the SC will return progressively to the previous state of non-disruption that existed before the occurrence of the risk (continuous line). But, if a new risk affects the SC, it may continue in the same state (dotted line), or degenerate rapidly into total disruption (segmented line).

Figure 5.3 Partial disruption in the supply chain (SC)
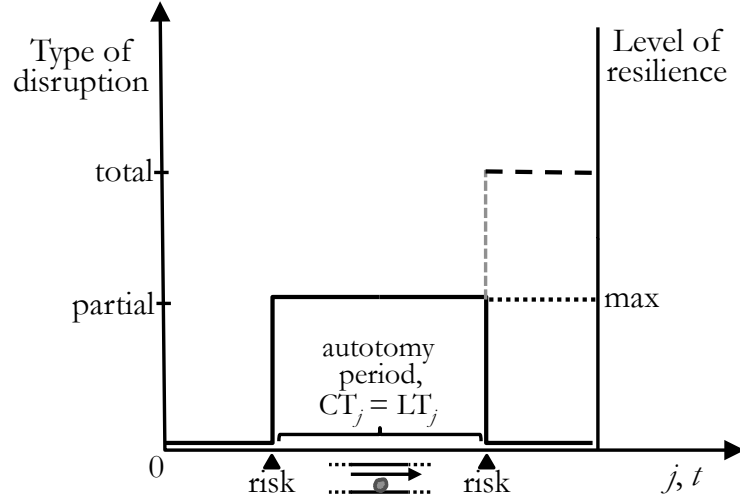
The period of autotomy of the SC occurs within the SC cycle time for each order j (CT_j). Thus, the length of the period of autotomy for an order j (AP_j) is equal to the sum of the impacting times of the risks on the SC ($\sum R_{cr}$) minus their overlapping times ($\sum R_{1r} \cap \cdots R_{c4}$). An algorithmic solution to calculate AP_j in the simulation model is provided below.

Algorithm 1: Determining the period of autotomy of the order j-th (AP_j)
1: LET $CT_j = (OAT_j - OPT_j)$, $LT_j = \overline{LT}$, R_{cr}: $[R^0_{cr}, R^f_{cr}]$ with $j = 1\ldots6{,}000$, $c = 1\ldots3$, $r = 1\ldots4$, and $\Omega = \{R_{11}, R_{12}\ldots R_{cr}\}$
2: IF the impact of at least one $R_{cr} \in \Omega$ manifests within the interval $[OPT_j, OAT_j]$ AND $CT_j = LT_j$,
3: THEN, $AP_j = \sum R_{cr} - \sum (R_{1r} \cap \ldots R_{c4})$

5.5.2 Total disruption

In the same way as with the previous typology, a *total disruption* occurs when fluctuations in the demand for finished items and/or disturbances in facilities, lines-of-communication, processes, workstations or machines interrupt the flow of supplies to end-users, causing the SC cycle time to be greater than the lead time ($CT > LT$). Theoretically, during this period of disruption, the resilience level is at its lowest since the SC cannot withstand the negative effects of fluctuations in the demand and/or disturbances along the chain, as shown in Figure 5.4a. However, once the occurrence of the risk is detected (R^0_{cr}) within the disruption period, a recovery process starts to reverse this condition and return to the previous state of non-disruption prior the occurrence of the risk (segmented line). The SC can also change in state back to the period of autotomy (dotted line). Thus, the *period of recovery* is contained within the *period of disruption* ($RP \leq DP$), as is depicted in Figure 5.4b.

Figure 5.4 Total disruption in the supply chain
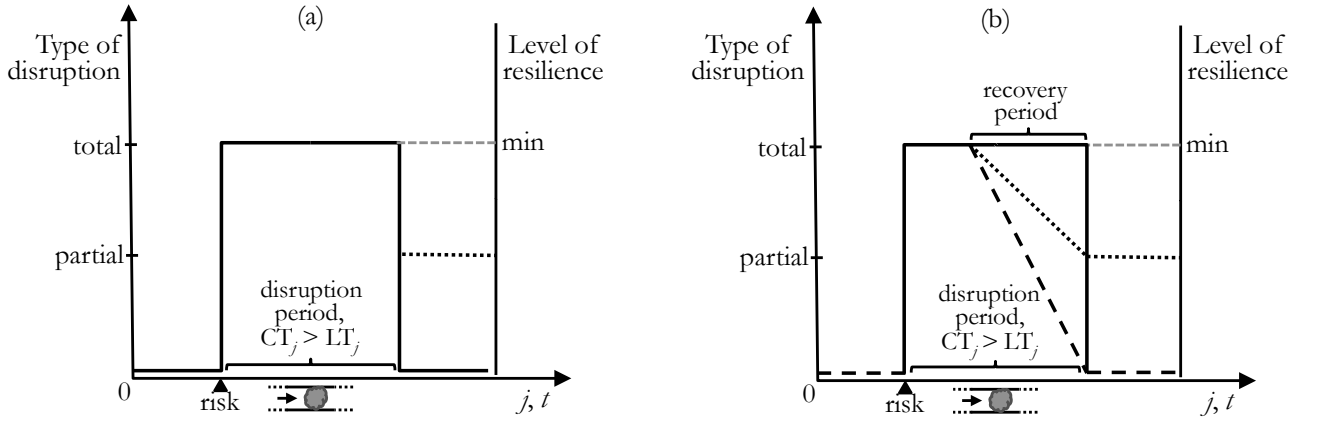
This 'containerization' occurs because the SC does not change from one state (of total disruption) to another (of non-disruption/partial disruption) abruptly, but rather this process occurs gradually. The gradualness in returning to a new, more desirable state is indeed the recovery period. Its importance lies in that during this time, the SC exhibits a resilience level higher than zero but lower than in the AP. Thus, the length of the period of recovery for an order j-th (RP_j) is given by the difference between the order arrival time of the j-th order (OAT_j) and the first-time of the occurrence/detection of a risk (R^0_{cr}), while the period of disruption for an order j-th is equal to the cycle time (CT_j). Algorithmic solutions to calculate RP_j and DP_j in the simulation model are presented below.

Algorithm 2: Determining the period of recovery of order j-th (RP_j)
1: LET $CT_j = (OAT_j - OPT_j)$, $LT_j = \overline{LT}$, R_{cr}: $[R^0_{cr}, R^f_{cr}]$ with $j = 1\ldots6,000$, $c = 1\ldots3$, $r = 1\ldots4$, and $\Omega = \{R_{11}, R_{12}\ldots R_{cr}\}$
2: IF the impact of at least one $R_{cr} \in \Omega$ manifests within the interval $[OPT_j, OAT_j]$ AND $CT_j > LT_j$,
3: THEN, $RP_j = (OAT_j - \text{first-}R^0_{cr})$

Algorithm 3: Determining the period of disruption of order j-th (DP_j)
1: LET $CT_j = (OAT_j - OPT_j)$, $LT_j = \overline{LT}$, R_{cr}: $[R^0_{cr}, R^f_{cr}]$ with $j = 1\ldots6,000$, $c = 1\ldots3$, $r = 1\ldots4$, and $\Omega = \{R_{11}, R_{12}\ldots R_{cr}\}$
2: IF the impact of at least one $R_{cr} \in \Omega$ manifests within the interval $[OPT_j, OAT_j]$ AND $CT_j > LT_j$,
3: THEN, $DP_j = CT_j$

5.5.3 An analytical example of supply chain disruptions

In order to clarify the previous analysis, Figure 5.5 describes the three cases that may occur within the simulation model of SC-disruptions. Consider the time horizon of an SC for three

orders, $j = 1…3$. Order 1 is placed at OPT_1 and delivered at OAT_1 within the set period LT_1, i.e., $CT_1 = LT_1$. Also, as noted, no risks occur during CT_1. This fact implies that it is not feasible to estimate the level of SCRes, since this can only be measured when the SC is affected by the occurrence of risks. Therefore, the *non-disruption period* for the order 1 (N-DP$_1$) is the time between OPT_1 and OAT_1.

Similarly, order 2 is placed at OPT_2 and expects to be delivered at the end of LT_2. However, the unforeseen occurrences of the risks R_A, R_B and R_C affect the performance of the SC by making CT_2 higher than LT_2, or in simpler terms, Order 2 is delivered late. Hence, the *period of recovery* for order 2 (RP$_2$) is the time between the first occurrence of a risk (R^0_A) and the arrival time of the order (OAT_2); and the *period of disruption* (DP$_2$) is the difference between OAT_2 and OPT_2. Lastly, order 3 is placed at OPT_3 and delivered at OAT_3, within the set period LT_3, i.e., $CT_3 = LT_3$. It should be noted that, although during CT_3 the risks R_A, R_B and R_C impact SC performance, order 3 is delivered on time, i.e., $CT_3 = LT_3$. Hence, the *period of autonomy* for order 3 (AP$_3$) is the sum of the individual impacts of risks R_A ($R^f_A - OPT_3$), R_B ($R^f_B - OPT_3$) and R_C ($R^f_C - R^0_C$), minus the overlapping times between R_A and R_B ($R^f_A - OPT_3$).

Figure 5.5 Supply chain disruptions
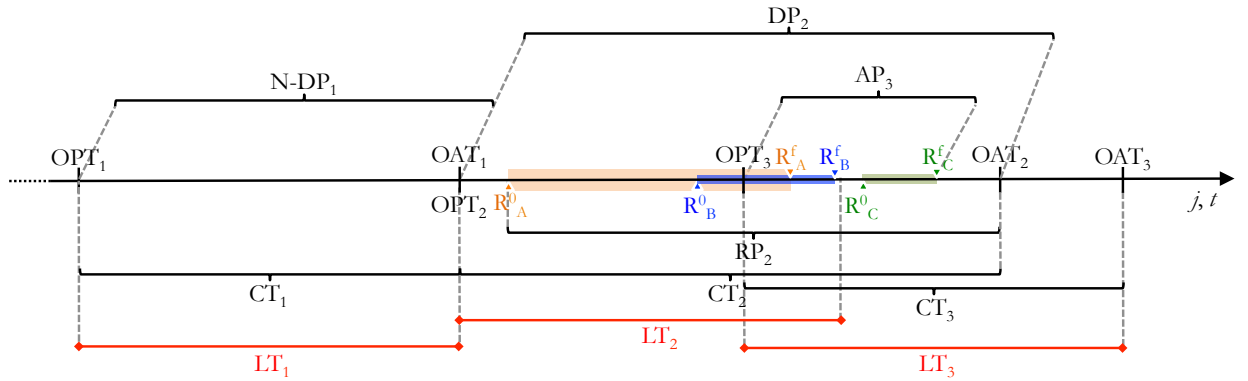
5.6 Measuring Resilience in Military Supply Chains

A new SCRes measure should be constructed to fill the gaps and shortcomings found in the review of the literature developed in Chapter 2, which can be summarized as follows: (1) the measure should be based on 'conceptual approximations from other disciplines' (pattern 5 found at the SLR); (2) the approach should be simplified and easy to apply; (3) it should be an objective-quantitative assessment measure; (4) it must be consistent with accepted definitions of SCRes; (5) it must include a way to measure inherent-resilience; and finally, (6) it should be specific to a particular type of SC. In addition, as Pettit and colleagues suggested (2013), the measurement of SCRes cannot be seen as a single event, but as a process over time.

5.6.1 Variable selection

In order to guarantee consistency of the proposed measure of SCRes with the concept itself, two key aspects are identified from the 'universal definition' presented in Section 5.4: (1) 'to respond to/react to/resist unexpected operational disruptions', and (2) 'to recover from them (disruptions) and return to the original/desired state.' This first aspect of the definition of SCRes refers to the ability of an SC to resist/cope with the consequences of potentially damaging random risks. In other words, the stochastic nature of disruptions caused by risks makes them unavoidable (an exogenous variable), but their impact can be reduced/minimized, depending on the level of SCRes. Thus, theoretically, the SC is resilient when it experiences *periods of autotomy*; on the other hand, it is not resilient during *periods of disruption*. From this perspective, these concepts seem to be opposed to each other, but the second aspect of the definition of SCRes—or the ability of the SC to recover from the occurrence of disruptions as quickly as possible, which involves the condition of resilience, is in fact included within the period of disruption. That is, based on the premise of the inevitability of disruptions (Craighead et al., 2007; Burns, 2015), the SC is also resilient when it rapidly recovers from the disturbing state and returns to the previous state (or an even better one) before the impact of the risk is felt. This SC capability is operationalized throughout the *period of recovery*. In this way, the proposed measure is completely consistent with the unified definition of SCRes presented above, and with the basic set of attributes of SC disruption management (Ivanov et al., 2014). The analytical measure of resilience in military-SCs is thereby obtained from the following sub-indicators:

(1) The period of autotomy for each order j (AP_j) in units of time t
(2) The period of recovery for each order j (RP_j) in units of time t
(3) The period of disruption for each order j (DP_j) in units of time t

It should be clarified that the three sub-indicators mentioned above are consistent with the concepts of SCRes in Table 5.1, as well as with the unified definition derived from them. However, these sub-criteria do not measure the inherent resilience in the design features of the SCs, i.e., during periods of non-disruption. This is, in fact, a failure in the definitions on SCRes described in the literature. The measure of inherent or static resilience will be discussed later.

5.6.2 Weighting and derivation of sub-indicators

There are two key questions that must be solved in order to weight the three above sub-indicators of SCRes. First, when does a military-SC reach its maximum/minimum level of resilience? Regarding this question, in a risky scenario, the military-SC achieves resilience's maximum value ($\overline{Re}^{max}$) when it is able to resist the impact of risks, avoiding the total interruption of flow of supplies to the troops (AP_j). Conversely, the military-SC reaches the resilience's minimum value ($\overline{Re}^{min}$) when the occurrence of risks causes a total interruption of the flow of supplies to the troops except during the period of recovery ($DP_j - RP_j$). During the period ($DP_j - RP_j$), the flow of supplies to the troops is interrupted by the impact of risks, but the recovery process has not started yet. Finally, the SC achieves an intermediate level of

resilience ($\overline{\mathrm{Re}}$) during the period of recovery (RP$_j$). It should be noted that, the three sub-indicators of SCRes do not need to be normalized since all of them are expressed in the same unit of time. Figure 5.6 summarizes the allocation of weights for each state of the SC.

Figure 5.6 Weighting levels of SCRes
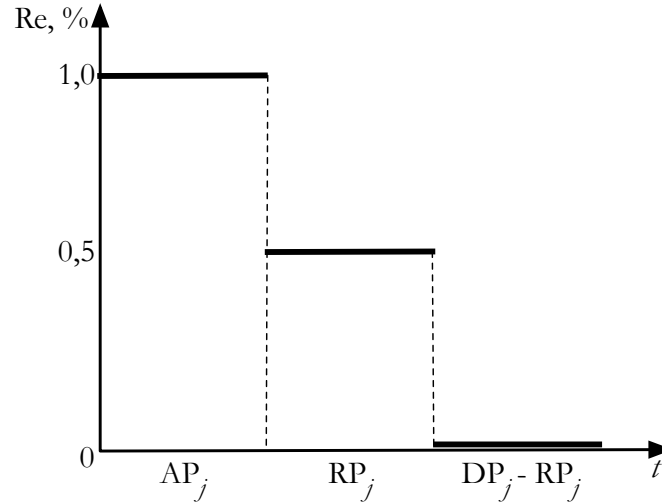
In the three states an SC can operate as described in Figure 5.6, the sine qua non condition is 'the occurrence of risks.' This is the usual way that SCRes has been measured in the literature (Christopher & Peck, 2004; Blackhurst et al., 2011; Klibi et al., 2010; Kim et al., 2015), and is the basis for the application of TAE. This dynamic-resilience approach is based on the emphasis in the SCRes definitions on the occurrence of risks as triggering factors of disruptions, as seen in Table 5.1. But, what happens to SCRes in the absence of risks (disruptions)? Is it measurable? If the perspective on resilience as an intrinsic SC-ability linked to its internal strengths and capabilities is accepted (Pettit et al., 2010; Wang & Ip, 2009), measurement of SCRes under 'non-risks' conditions is also necessary. Rose (2007) calls this *static resilience*. Unfortunately, few studies in the LSCM field have examined in detail how to measure resilience or what factors should be considered in an environment of non-occurrence of risks, e.g., Craighead et al (2007). Consequently, both perspectives of resilience are adopted in this research. First, this research measures dynamic resilience through the TAE lens, i.e., when the SC experiences periods of autotomy (AP$_j$), recovery (RP$_j$) or non-recovery (DP$_j$ – RP$_j$). And second, we measure static resiliency through the *fill rate* (FR). Several authors have used this SC-performance index as measure of the resilience in SCs (Schmitt & Singh, 2012; Barroso et al., 2011; Xanthopoulos et al., 2012). We integrate FR to obtain a more robust measure of SCRes.

Hence, AP$_j$, RP$_j$, DP$_j$ and FR$_t$ are the four sub-indicators for measuring resilience in military-SCs (Re^T). The first three are calculated for each order j over time from the procedures explained in Algorithms 1, 2 and 3, respectively. In the proposed model, AP$_j$ is an independent and disjointed measure of DP$_j$ and RP$_j$. By virtue of this independence, a variation of AP$_j$ does not affect the value of DP$_j$ or RP$_j$. The range of values of AP$_j$ is $0 < AP_j \leq LT$, whenever CT$_j$ = LT$_j$.

Figure 5.7 describes the level of resilience as a function of AP_j, with $\overline{Re}^{max}$ and $\overline{LT}$ fixed, from Equation 5.1. Hence, the longer the AP_j, the greater the resilience of the SC.

Figure 5.7 Resilience as function of the autotomy period, AP_j
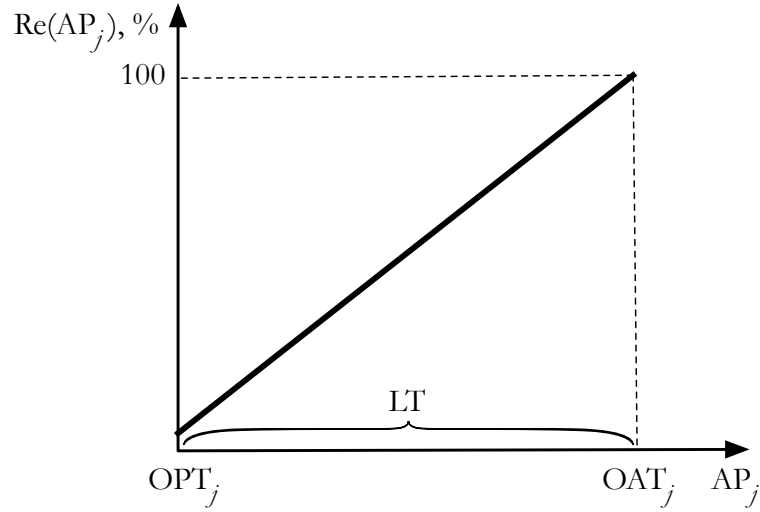
$$Re(AP_j) = \overline{Re}^{max}\left(\frac{AP_j}{\overline{LT}}\right) \qquad (5.1)$$

In the proposed model, the SC is also resilient—but less than during the AP_j—when it is recovering from the impact of risks. The range of values of RP_j is $0 < RP_j \leq CT_j$, whenever $CT_j > LT_j$. The RP_j is in practice contained within the DP_j (or CT_j), and is assumed that it lasts from when the occurrence of the first risk is detected (R^0_{cr}) until the order j is delivered (OAT_j). Regarding its mathematical expression, this study adopts the suggestion of Blackhurst and colleagues (2011), who affirm that "the resiliency of a supply chain and the recovery time from a disruption should be inversely related" (p.376). Figure 5.8 describes the level of resilience as a function of RP_j, with $\overline{Re}$ fixed, from Equation 5.2. Hence, the shorter the RP_j, the greater the resilience of the SC.

Figure 5.8 Resilience as function of the recovery period, RP_j
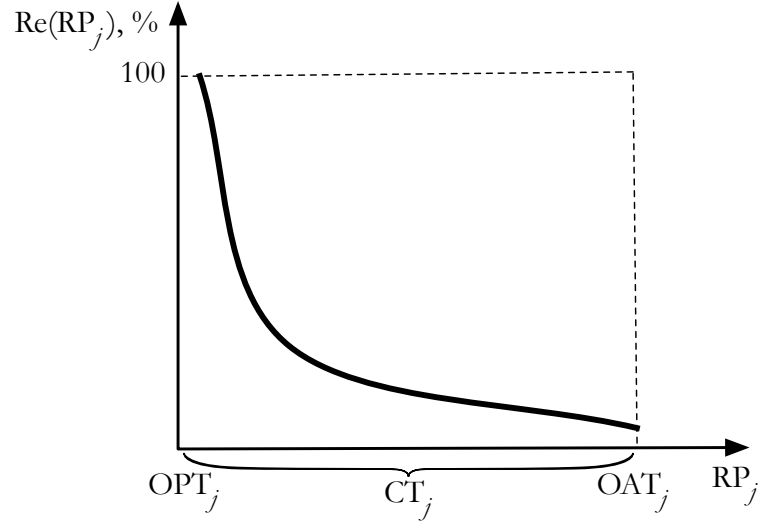
$$Re(RP_j) = \overline{Re}\left(\frac{1}{RP_j}\right)$$ (5.2)

The third sub-indicator for measuring SCRes is actually the subtraction of RP_j from DP_j. This time corresponds to a period of non-resilience or highest vulnerability of the SC (Asbjørnslett, 2009; Sheffi & Rice, 2005). The range of values of $(DP_j - RP_j)$ is $0 < DP_j - RP_j \leq CT_j$, whenever $CT_j > LT_j$. This sub-indicator is included within the measurement of resilience in order to maintain the consistency of the model, though the value of resilience is zero in all cases due to the weighting parameter assigned ($\overline{Re}^{min}$), as shown in Figure 5.9, from Equation 5.3.

Figure 5.9 Resilience as function of the non-recovery period $(DP_j - RP_j)$
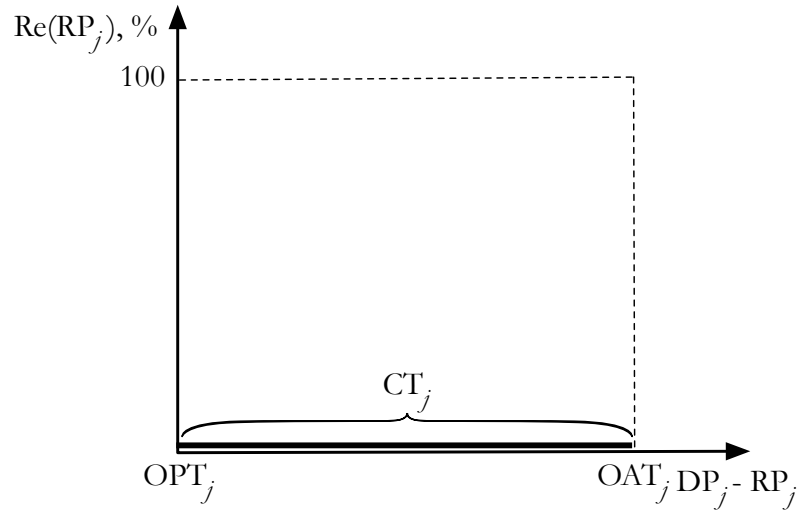
$$Re(DP_j, RP_j) = \overline{Re}^{\min}\left(\frac{DP_j - RP_j}{CT_j}\right) \tag{5.3}$$

The last sub-indicator for measuring SCRes is the *fill rate* (FR_t), which is a modification of the Cachon and Terwiesch's formula (2008), $FR = 1 - \frac{E(B_t)}{E(D_t)}$. The original formula evaluates the FR over time from the expected backorder and the expected demand. The purpose is to measure the expected fraction of orders that are served. This study uses the same logic but a new variable is added to the formula: the number of lost or unattended orders j in period t (U_t). Thus, the proposed formula to measure resilience as function of the SC-performance (FR_t) is given in Equation 5.4. An increase in the number of backorders (B_t) or lost orders (U_t) in relation to the total number of orders demanded (D_t) is a clear indication of lower resilience in the SC, with $B_t + U_t \leq D_t$. Equation 5.4 also describes a function with memory; that is, B_t accumulates overtime, and after a certain period (order cancellation time), B_t are categorized as U_t, without disappearing from the calculation of resilience. Figure 5.10 depicts the relationship between resilience and the fill rate (FT_t)—the latter as a function of B_t, U_t, and D_t.

Figure 5.10 Resilience as function of the fill rate, FT_t
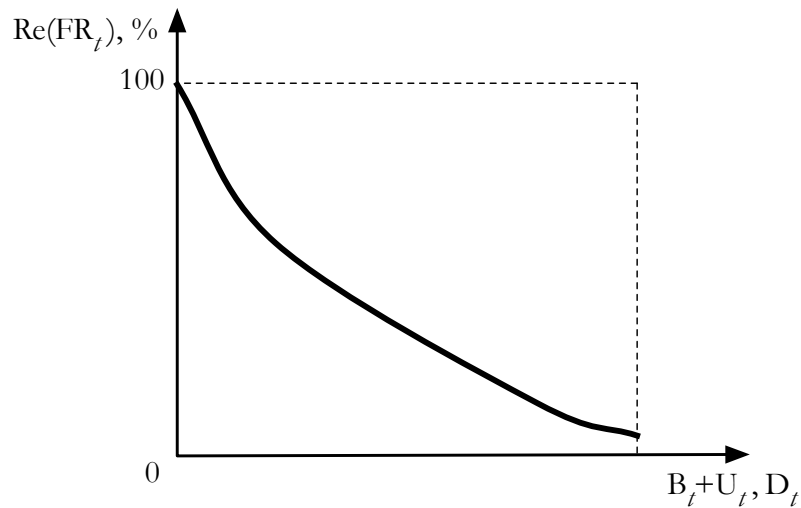
$$Re(FR_t) = 1 - \left(\frac{B_t + U_t}{D_t}\right) \tag{5.4}$$

In the following sub-section the aggregation of the measurement of resilience (Re^T) is introduced based on the previous sub-indicators.

5.6.3 An analytical measure of resilience for military supply chains, Re^T

Following the above framework, a conditional function is selected for the four sub-indicators of the analytical measure of resilience (Re^T). Re^T is a time-dependent function that can be applied to any type of SC. Re^T is normalized on a 0 to 1 scale and the four sub-indicators are expressed on a ratio scale to make them compatible with the axioms of measurement theory (Tversky et al., 1988). The frequency of measurement is determined by the regularity of work orders j. Thus, the level of Re^T for each order j is obtained from the individual measures of AP$_j$, RP$_j$ and/or (DP$_j$ – RP$_j$), or FR$_t$, as is described in Equation 5.5. Figure 5.11 summarises the derivation of Re^T.

$$
\text{Re}^T = \begin{cases}
\overline{\text{Re}}^{\textbf{max}}\left(\frac{\text{AP}_j}{\overline{\text{LT}}}\right) & \text{AP}_j \\[2mm]
\overline{\text{Re}}\left(\frac{1}{\text{RP}_j}\right) & \text{RP}_j \\[2mm]
\overline{\text{Re}}^{\textbf{min}}\left(\frac{\text{DP}_j - \text{RP}_j}{\text{CT}_j}\right) & \text{DP}_j - \text{RP}_j \\[2mm]
1 - \left(\frac{\text{B}_t + \text{U}_t}{\text{D}_t}\right) & \text{N-DP}_j
\end{cases}
\tag{5.5}
$$

Figure 5.11 Steps involved in deriving the measure of resilience for military supply chains, Re^T

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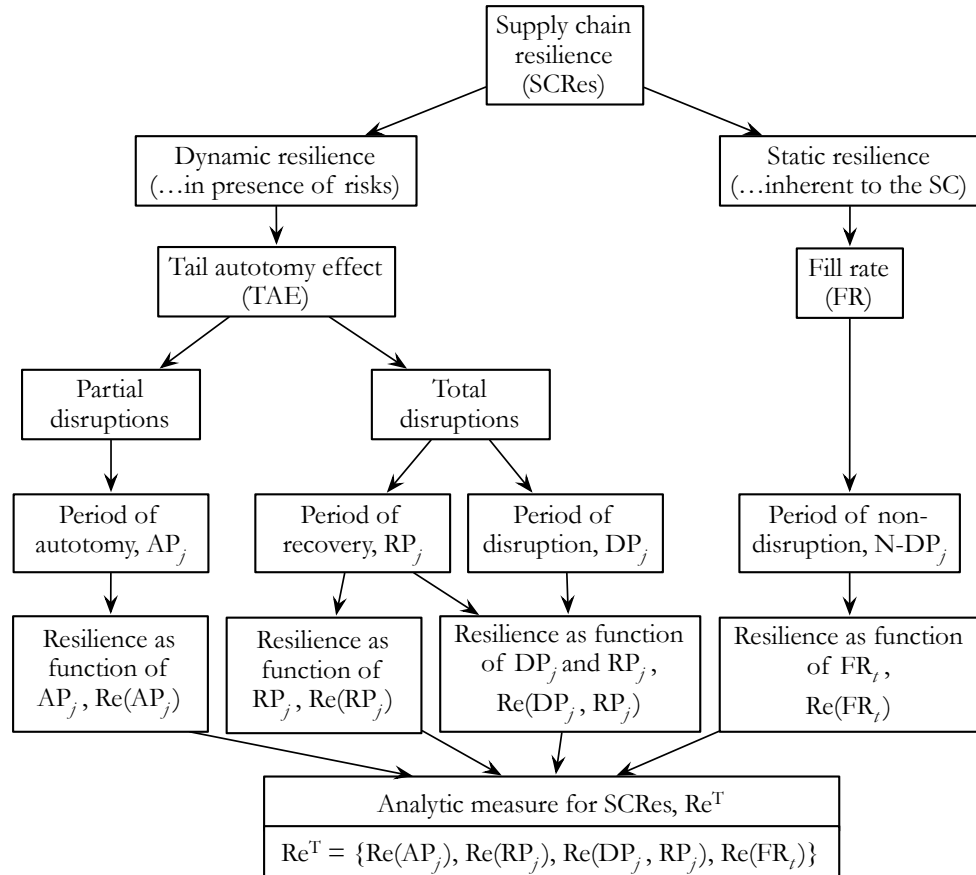
5.7 Summary of Chapter 5

This chapter contributed to the literature on the operationalization of the concept of SCRes in several ways. First, it fully characterized military-SCs in light of their peers, commercial-SCs. In this sense, new arguments such as the need to implement and measure SCRes were introduced and later discussed. Secondly, it derived a universal definition of SCRes from the analysis of the various conceptual approaches in the existing literature. The application of a text-mining tool to the set of SCRes-theoretical approximations avoided biases in the selection of a reference definition. Thirdly, the chapter developed a theoretical framework to assess resilience in military-SCs through the *tail autonomy effect*. This novel perspective offers an alternative way of understanding disruptions in (military) SCs. Last but not least, from this framework and the shortcomings previously identified in the review of literature in Chapter 2, this chapter offered a holistic measure of SCRes that appraises both dynamic and inherent dimensions. The resulting measure of SCRes, or Re^T, will be integrated into the results of the simulation model in the next chapter.

Chapter 6
SIMULATION MODEL OUTPUT DATA AND QUESTIONNAIRE

Chapter 6. Simulation Model Output Data and Questionnaire

6.1 Introduction

This research is based on two main sources of information: a non-terminal *simulation model* for the military food supply chain or MFSC, and second, an open-ended *questionnaire* administered to twelve staff members of an MFSC. The first seven subsections of this chapter describe in detail the stages of *simulation model* (Banks, 1999; Law, 2003) for a real-world military food supply chain (MFSC), which is responsible for the provision of subsistence items, particularly combat rations. The primary objective of these subsections is to model the three scenarios of research hypotheses proposed in Chapter 3, that is: (1) increases in the frequency of occurrence of risks; (2) increases in the levels of on-hand inventory buffers in the presence of risks; and (3) increases in the short-term manufacturing capacity in the presence of risks. Thus, the first and second sections describe the military logistics system (MLS) and the operations that make up the MFSC. The third section illustrates the analysis of risks that affect the MFSC. The fourth section sets out the assumptions that were considered for simulation of the MFSC. The fifth section explains the processes of verification and validation of the simulation model. The sixth section details the experimental design in which the research hypotheses are based. And, the seventh section defines the simulation run length, the warm-up period, and the output data of the model.

Unlike the previous ones, sections eight and ninth of this chapter explain how data from both sources of information—simulation model and questionnaire—were gathered, organized, and prepared to facilitate subsequent data analysis. This way, the eighth section sets out the output data of the simulation model, and the ninth section presents the raw questionnaire data. Lastly, but not less important, Annex B contains the programming code in *Simulink*® and details regarding how the simulation model was built, which were left out of the chapter due to their length.

6.2 Description of the Military Logistics System (MLS)

Military-SCs do no operate in isolation but rather are an integral part of a macro-system called the *military logistics system* (MLS). The main objective of the MLS is to provide timely and continuous support to all members of the military forces of a country. An MLS lends joint logistical support to all branches of the military including the Army, the Navy and the Air Force, in relation to their needs and requirements for the fulfilment of assigned tasks. However, the existence of a single MLS to meet the needs of all branches of the military is not the observed pattern in all the countries. In some geopolitically influential countries with powerful military forces, such as the USA, each branch of the military forces works as an independent entity with its own MLS, which may promote a healthy competition among them by reducing the impact of intentional attacks on the logistics system, at the expense of achieving economies of scale and efficiency.

The general structure of the MLS under analysis consists of two major operational units, *logistics brigades* (LBs) and *combat brigades* (CBs), as described in Figure 6.1. In this structure, LBs derive their existence from the CBs (Kress, 2016). However, the performance of the latter depends substantially on the former. Thus, the points of contact between them are the plans for purchasing raw materials, production of items, maintenance of machinery and equipment, and storage and distribution of finished products.

The LBs are the backbone of the military logistics strategy (Pagonis & Krause, 1992), and their number may vary from country to country depending on the size and capabilities of the military forces they supply. In the MLS under study, two LBs are currently in operation. Within structure of a LB, the *head logistics command* (HLC) is the unit responsible for formulating and supervising the mentioned plans, and the *military logistics agency* (MLA) leads the execution of those plans. *Combat service support battalions* (CSSBs) receive, classify, store, and distribute raw materials. *Quartermaster battalion* (QB) is a mega-factory (six SCs) that manufactures intendancy material such as ammunition and explosives, uniforms, wood and metal articles, footwear, and food. *Supply battalions* (SBs) are in charge of storing, transporting, and distributing finished products. *Transport battalions* (TBs) provide the physical means for transporting finished products. *Maintenance battalion* (MaB) repairs military equipment, weapon systems, machinery, and facilities. Lastly, *medical battalion* (MeB) is responsible for the medical rehabilitation of personnel wounded in combat, reverse logistics, and humanitarian operations. Note that, in Figure 6.1, first-tier suppliers are not part of the MLS.

Combat brigades (CBs) are the other major operating unit of a MLS, as is described in Figure 6.1. CBs are the largest military unit deployed in case of warfare or any threat that requires a rapid military response. Although CBs are military units specialized in war operations, their internal structures include tactical logistics units named *combat service support units* (CSSUs). CSSUs have the task of receiving and storing finished products, and then carry them into the theatre of operations. CSSUs act as the cross-docking point between the LBs and the end-users of the MLS. This process is carried out through several means of transport—by land, sea, o air—according to the level of urgency of the military operation and the availability of equipment.

Figure 6.1 Description of the military logistics system (MLS)
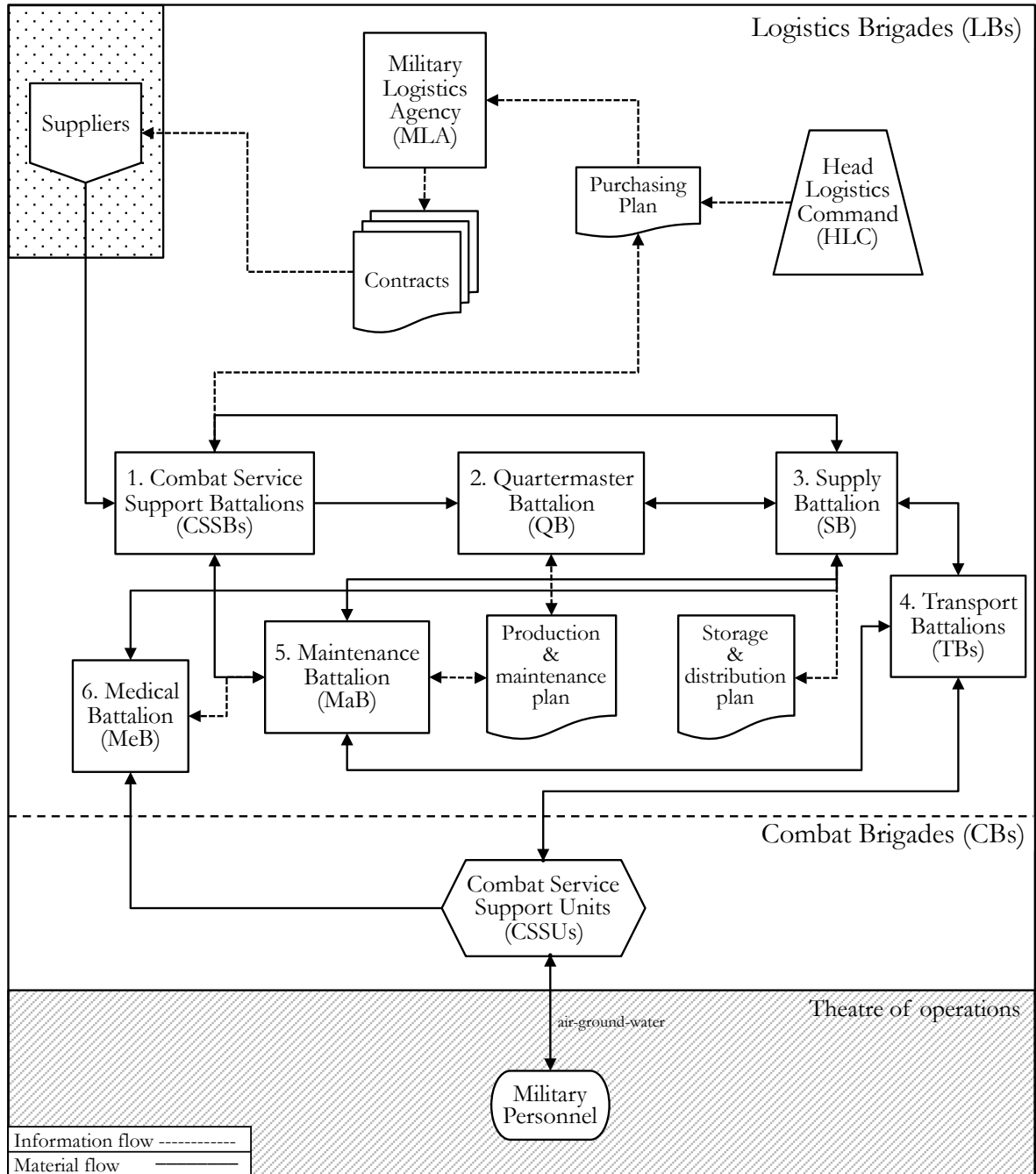
6.3 The Supply Chain of Military Food (MFSC)

The statement "An army marches on its stomach!" attributed to Napoleon is more pertinent than ever before. All armies need a regular provision of food in order to carry out the mission and keep on fighting. Without food, troops' morale and performance fall. This is main reason why the SC of military food (MFSC) was chosen for analysis, among the six SCs that make up the MLS. The main objective of a MFSC is to provide troops "the right meal at the right place and at the right time" (DOA, 2010, p.vi). MFSCs conventionally provide a broad range of subsistence items, including regular food not-ready-to-eat, to be prepared in kitchen areas or ration C1; individual combat rations delivered in special packaging and to be consumed by a soldier during a day or ration C2; and a group of combat rations normally designed for six men or ration C3. This research will focus only on rations of type C2.

In most of cases, troops cannot sit down for a hot cooked meal, but must pick up the food and move ahead, so troops rely on ready-to-eat food. Combat rations ensure adequate physical and cognitive performance by military personnel in different settings (NATO, 2010). Combat rations are part of the Class I items—Subsistence and commercially bottled water—and are primarily used in combat or training operations, for airborne personnel, in difficult-to-reach areas, or in the absence of field kitchen equipment. The food for soldiers no only has to be tasty but has to remain in optimal conditions. Combat rations are non-perishable food for up to three years at 27ºC or less, odourless, packaged in airtight and labelled bags resistant to adverse climatic conditions—temperatures ranging -10ºC to 50ºC, easy-to-open without specific tools, and ready-to-eat by troops. Rations must meet strict technical protocols based on the NATO-Stanag-2937 (NATO, 2013) or an equivalent technical standard, e.g. Military Technical Standard-0065-A4 in the case of this study.

Each pack of combat ration contains three meals, each one with the 1,300 calories; macronutrients—carbohydrates, protein and fat; micronutrients—vitamins, minerals, and trace elements—and the fibre needed for a high performance athlete (soldier) for 24 hours. Combat rations must be as light and compact as possible. A combat ration pack must not exceed 1,400 grams of weight in order to facilitate its air transport, airdropped operations, or relocation by the soldier himself. Typically, a soldier carries an average of five rations in a combat bag-pack for personal consumption, though this figure depends on the length of mission and frequency of re-supply. In the following subsections, the macro-operations that make up the MFSC are described in detail.

6.3.1 Raw materials (*rm*)

Currently, the MFSC assembles 21 types of combat rations based on the nutritional requirements of troops and climatic conditions in which military operations are carried out. However, to simplify the analysis, we will assume that MFSC produces only one type of combat rations, the 'Cold weather combat ration # 1'. Table 6.1 lists the 12 raw materials (*rm#*) required for their manufacture.

Table 6.1 Raw materials required for the assembly of the 'Cold weather combat ration # 1'

Raw material	Breakfast	Raw material	Lunch	Raw material	Dinner	Raw material	High-calorie products
rm_1	1 portion of meat pastry (150 gr)	rm_4	1 portion of chickpeas soup (180 gr)	rm_7	1 portion of meat goulash (180 gr)	rm_{10}	1 can of condensed milk (100 gr)
rm_2	1 bar of chocolate with cheese (25 gr)	rm_5	1 sachet of hydrating drink (36 gr)	rm_8	1 piece of fruit bread (100 gr)	rm_{11}	1 bag of peanuts with sesame (100 gr)
rm_3	1 piece of wheat bread (100 gr)	rm_6	1 piece of corn bread (100 gr)	rm_9	1 bar of sugar cane (125 gr)	rm_{12}	1 bag of mixed fruit (50 gr)

6.3.2 Manufacturing capacity of the assembly line (AL)

Table 6.2 describes the theoretical capacity (TC_S) and effective capacity (EC_S) of the assembly line expressed in hours according to the number of active work-shifts (S), and under deterministic conditions—no risks occur. TC indicates the production capacity of the AL without discounting the time required for maintenance of machines and installations, i.e., operating 7 days per week continuously, while EC is equal to TC less time for maintenance—24 hours each week, with TC > EC. Table 6.2 shows the values for TC and EC according the number of S, assuming that 1 shift (S = 1) is equal to 8 hours, 1 day is equal to 3 shifts, 1 week is equal to 7 days, 1 month is equal to 4 weeks, 1 semester is equal to 6 months, and 1 year is equal to 2 semesters.

Table 6.2 Theoretical capacity (TC_S) and effective capacity (EC_S) of the AL in hours

Period	TC_1	EC_1	TC_2	EC_2	TC_3	EC_3
Year	2,688	2,304	5,376	4,608	8,064	6,912
Semester	1,344	1,152	2,688	2,304	4,032	3,456
Month	224	192	448	384	672	576
Week	56	48	112	96	168	144
Day	8		16		24	
Shift			8			

Similarly, Table 6.3 describes TC_S and EC_S for the AL expressed in rations according to the number of active work shifts (S). To date, the MFSC operates at an assembly rate (λ) equal to 320.5 rations/hour and 1 active work shift (S = 1). At that production level, MFSC can assemble up to 738,432 rations/year, provided no risk occurs.

Table 6.3 Theoretical capacity (TC_S) and effective capacity (EC_S) for the AL in rations

Period	TC_1	EC_1	TC_2	EC_2	TC_3	EC_3
Year	861,504	738,432	1723,008	1,476,864	2,584,512	2,215,296
Semester	430,752	369,216	861,504	738,432	1,292,256	1,107,648
Month	71,792	61,536	143,584	123,072	215,376	184,608
Week	17,948	15,384	35,896	30,768	53,844	46,152
Day	2,564		5,128		7,692	
λ			320.5			

6.3.3 Process of assembling combat rations

In this research, as a convention, a *process* is the set of operations designed to accomplish a specific task or to prepare/receive/transport raw materials, work-in-progress inventory (WIP) or finished items within a period. A process may include workers, workstations, materials, and working methods. An *operation,* on the other hand, indicates a sequence of activities and methods of work performed by a single person/work-team in workstations to achieve specific tasks.

The assembly process of combat rations in the MFSC is depicted in Figure 6.2. This process follows a dual policy of production, that is, *assembly-to-stock* from operation 1 at MLA to operation 9 at SB, and *assembly-to-order* from the latter to operation 13 at the theatre of operations. Regarding the inventory policy, the re-order point (ROP) of the chain is of the type (ROP, Q), i.e., a fixed quantity of raw material/finished items is placed whenever the inventory position in each operation falls below ROP. The description of each of the 13 operations that make up the process of assembly of combat rations is detailed below.

Operation 1 ($Op_{1,j}$): *Contracting of suppliers*

Operation 1 ($Op_{1,j}$) is performed by the MLA. This operation involves the contracting of raw material suppliers for the assembly and distribution of combat rations. The time needed to prepare, evaluate, select and contract 12 suppliers through public tenders is one month (PT = 672 hours). The output of the $Op_{1,j}$ is 12 contracts for the same number of suppliers (Q = {$cntr_1…cntr_{12}$}), which must be renewed twice a year (F = biannual or every 4,032 hrs). $Op_{1,j}$ may be subject to 'delays in contracting with suppliers' (R_{12}).

Operation 2 ($Op_{2,j}$): *Preparation and shipping of raw materials to the warehouse and distribution centre*

Operation 2 ($Op_{2,j}$) is performed by external *suppliers*. This operation consists of preparing and sending the necessary quantities of raw materials for the assembly of combat ration packs (see Table 6.1). The processing time for the delivery of inputs is one day (PT = 24 hours). $Op_{2,j}$ ends when the shipment of raw materials required for a working month and an active shift (S = 1) is delivered to the *warehouse* a*nd distribution centre* (WDC), with Q = {190,000 rm_1…190,000

rm_{12}} and a monthly reorder point (ROP = every 672 hours). Failures during $Op_{2,j}$ may cause 'shortages of raw materials and components' (R_{13}).

Operation 3 ($Op_{3,j}$): *Reception, verification and storage of raw materials*

Operation 3 ($Op_{3,j}$) is carried out at the WDC installations. This operation consists of the reception, verification and storage of the 12 raw materials for the assembly of combat ration packs. The processing time of raw materials is one day (PT = 24 hours), and there is no raw material stored at the beginning of the operation ($I_{t,1} = 0$). Weekly, WDC prepares the shipment of raw material required for a workweek and an active shift (S = 1) to AL, i.e., Q = {15,500 rm_1…15,500 rm_{12}} and ROP = every 168 hours. $Op_{3,j}$ is subjected to the incidence of 'natural disasters' (R_{21}).

Operation 4 ($Op_{4,j}$): *Transport and delivery of raw materials to assembly line*

Operation 4 ($Op_{4,j}$) is executed through a *line-of-communication* (LOC). This operation consists of the transportation and delivery of the 12 raw materials necessary for the assembly of combat ration packs from WDC to the AL. The delivery time for the inputs is one day (PT = 24 hours). The quantity of raw material transported corresponds to the requirements of a workweek and an active shift (S = 1) to the AL, i.e., Q = {15,500 rm_1…15,500 rm_{12}} and ROP = every 168 hours. $Op_{4,j}$ is vulnerable to 'terrorist attacks' (R_{22}).

Operation 5 ($Op_{5,j}$): *Pre-assembly of high-calorie products for combat rations*

Operations 5, 6 and 7 form part of the AL of combat rations. $Op_{5,j}$ is the first operation of the AL and consists of the pre-assembly of high-calorie products for each combat ration. At an assembly rate (λ) of 320.5 rations/hour, the processing time for each pre-assembly of combat ration is 0.003125 hours (PT = $1/\lambda$), and the delivery frequency of pre-assemblies to the following workstation is immediate (ROP = every 0.003125 hours), one after the other (Q = 1). After a work shift of 8 hours, $Op_{5,j}$ will have transferred a total of 2,564 pre-assemblies to the next workstation. There is no raw material stored at the beginning of $Op_{5,j}$ ($I_{t,1} = 0$). $Op_{5,j}$ is prone to experiencing 'breakdowns in workstations' (R_{11}), 'natural disasters' (R_{21}), and 'black-swan events' (R_3).

Operation 6 ($Op_{6,j}$): *Assembly of combat rations*

Operation 6 ($Op_{6,j}$) is the second operation of the AL and consists of the manual assembly of combat rations. The processing time of each pack of combat ration is 0.003125 hours (PT = $1/\lambda$), and the frequency of delivery of assemblies to the following workstation is immediate (ROP = every 0.003125 hours), one after the other (Q = 1). After a work shift of 8 hours, $Op_{6,j}$ will have transferred a total of 2,564 assemblies to the next workstation. $Op_{6,j}$ is prone to experiencing 'breakdowns in workstations' (R_{11}), 'natural disasters' (R_{21}), and 'black-swan events' (R_3).

Operation 7 ($Op_{7,j}$): *Quality control of combat rations*

Operation 7 ($Op_{7,j}$) is the last operation of the AL and consists of the verification and final packaging of combat rations in boxes of 10 units. The time required to check and package combat rations is 0.003125 hours/unit (PT = 0.003125 hours), and the frequency of shipments to the *supply battalion* (SB) is every 2 days (ROP = every 48 hours). The shipment of combat rations to SB occurs only when the batch size achieves 5,000 rations (Q = when batch size achieves 5,000 rations). Due to its nature, $Op_{7,j}$ can individually be impacted by 'quality problems' (R_{14}), and along with $Op_{5,j}$ and $Op_{6,j}$ by 'natural disasters' (R_{21}) and 'black-swan events' (R_3). It should be noted that the processing times of $Op_{5,j}$, $Op_{6,j}$, and $Op_{7,j}$ describe a balanced AL ($PT_5 = PT_6 = PT_7$).

Operation 8 ($Op_{8,j}$): *Transportation and delivery of combat rations to supply battalion*

Operation 8 ($Op_{8,j}$) is executed through an LOC. This operation consists of the transportation and delivery of combat rations from the AL to the SB. The delivery time for the combat ration packs is one day (PT = 24 hours) and shipments occur only when the batch size achieves 5,000 rations (Q = 'when batch size achieves 5,000 rations'), every two days (ROP = 48 hours). $Op_{8,j}$ is vulnerable to 'terrorist attacks' (R_{22}).

Operation 9 ($Op_{9,j}$): *Receipt, classification, and storage of combat rations*

Operation 9 ($Op_{9,j}$) is carried out at the SB installations. This operation consists of the receipt, classification, and storage of combat ration packs. The processing time of combat ration packs is one day (PT = 24 hours), and there are no finished items stored at the beginning of the operation ($I_{t,1} = 0$). $Op_{9,j}$ ends when batch sizes in the range of 2,400 to 2,600 rations (Q = 2,400 to 2,600 rations) are sent to the *combat service support units* (CSSUs), at a daily freight rate (ROP = 24 hours). $Op_{9,j}$ can be individually impacted by 'natural disasters' (R_{21}), and together with $Op_{3,j}$, $Op_{5,j}$, $Op_{6,j}$, and $Op_{7,j}$ by 'black-swan events' (R_3).

Operation 10 ($Op_{10,j}$): *Transportation and delivery of combat rations to combat service support units*

Operation 10 ($Op_{10,j}$) is performed through an LOC. This operation consists of the transportation and delivery of combat rations from SB to CSSUs. The delivery time for the combat ration packs is one day (PT = 24 hours). Shipments occur in batch sizes ranging from 2,400 to 2,600 rations at a daily freight rate (ROP = 24 hours). $Op_{10,j}$ is vulnerable to 'terrorist attacks' (R_{22}).

Operation 11 ($Op_{11,j}$): *Delivery and distribution of combat rations*

Operation 11 ($Op_{11,j}$) is carried out at the CSSU installations. This operation consists of the receipt, delivery, and distribution (in less than 1 hour) of combat rations to the troops deployed in the theatre of operations. Because of its temporal nature, the processing time is considered a

nuisance factor (PT = 0). Shipments occur in batch sizes ranging from 2,400 to 2,600 rations at a daily freight rate (ROP = 24 hours). $Op_{11,j}$ can be impacted by 'terrorist attacks' (R_{23}).

Operation 12 ($Op_{12,j}$): *Transportation and dispatching of food rations for troops*

Operation 12 ($Op_{12,\ j}$) is performed through a LOC. This operation consists of the transportation and final delivery of combat rations from CSSUs to troops in the theatre of operations. The delivery time for combat ration packs is one day (PT = 24 hours). Shipments occur in batch sizes ranging from 2,400 to 2,600 rations at a daily freight rate (ROP = 24 hours). $Op_{12,j}$ is vulnerable to 'terrorist attacks' (R_{22}).

Operation 13 ($Op_{13,j}$): *Military personnel in operations waiting for the delivery of combat rations*

The theatre of operations is the physical place on the ground, sea, or air where military actions are carried out. In this thesis, the words 'troops' or 'military personnel' are used interchangeably to refer to any warfighter of any military branch in need of combat rations. The closest supply units to the troops in the theatre of operations are the CSSUs. These units use all the resources available to support the theatre-feeding mission, i.e., terrestrial, aerial, and maritime means, which presupposes having an adequate logistical structure. Although careful planning of any military action, including the determination of the number of rations to be consumed during the development of military operations, is a standard in modern armies, the battlefield involves enormous asymmetries of information or uncertainty. Hence, $Op_{13,j}$ is subjected to contingent orders for combat rations (R_{24}).

Table 6.4 Regular demand for military rations (D^{rg})

Function	Description	Distribution parameters	Model assumptions
Demand for combat rations	Regular demand for combat rations is originated in the last link of the MFSC, ranging between 2,400 and 2,600 every day, during 6 days per week.	Uniform distribution $U(X \in Z^+, a = 2,400, b = 2,600)$ for $a \leq x \leq b$	(1) The probability that the demand takes any value within the considered range is identical in all cases, and, (2) the demand for rations is placed every 24 hours, 6 days per week.

Figure 6.2 Initial configuration of the MFSC (Cf$_0$: S = 1, I$_{t,1}$ = 0, and R$_{1r}$, or R$_{2r}$, or R$_3$ enabled)
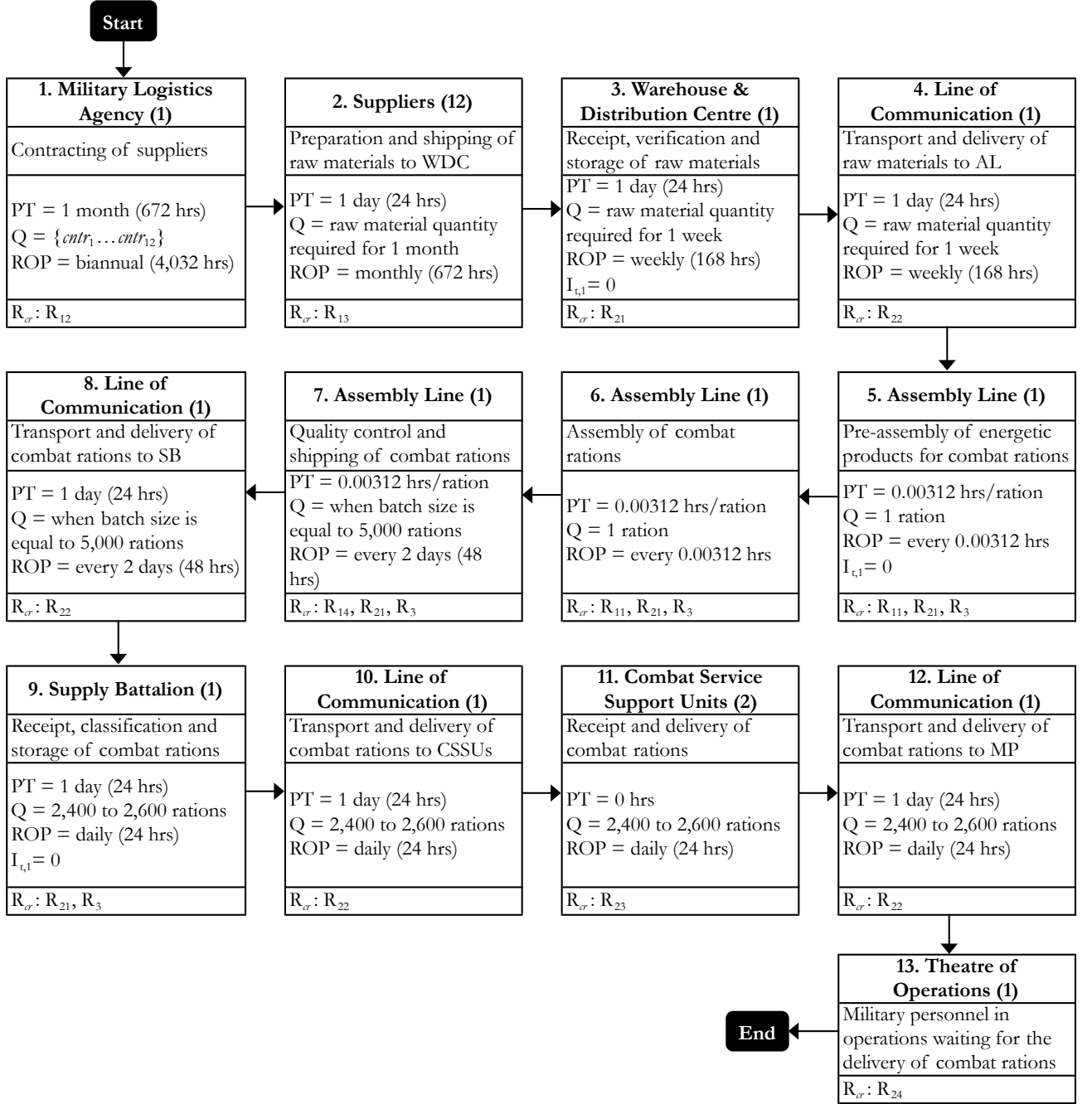
6.3.4 Demand for combat rations (D$_t$)

The pattern of demand for military items is highly variable (Wang, 2000), and combat rations are no exception. In the MFSC under analysis, the demand for combat rations originates at the last operation or *theatre of operations*, as shown in Figure 6.2. From the historical records of aggregate annual demand, its stochastic nature is modelled through a *uniform distribution U(X ∈*

Z$^+$) with parameters $a = 2,400$ and $b = 2,600$, for $a \leq x \leq b$. This means that the MFSC handles regular orders j of size Q ranging from 2,400 to 2,600 rations/day for six days a week. Thus, theoretically, the expected annual demand for combat rations fluctuates from 691,200 to 748,800 rations/year. The first figure represents the best scenario under regular conditions (D^{rg}_{best}), and the second, the worst scenario (D^{rg}_{worst}). In addition, troops can potentially face contingent military operations (Thomas, 2009), i.e., unforeseen military actions as a response to stochastic events of varied nature (R_{24}). This type of military operations generates sudden orders for combat rations that must receive priority attention to ensure a rapid deployment and mobilization of troops. These contingency requirements also range from 2,400 to 2,600 rations/*month*, that is, 28,800 additional rations/year in the best-case scenario (D^{cn}_{best}) and 31,200 additional rations/year in the worst-case scenario (D^{cn}_{worst}). Therefore, if the MFSC manufacturing capacity in deterministic conditions ($I_{t,1} = 0$ and R_{cr} = all disabled) and S = 1 is compared with the average annual demand for rations (regular and contingent), the result is that the first one (738,432 combat rations/year) is slightly lower than the second (750,000 combat rations/year). Table 6.4 describes the distribution parameters and assumptions of D^{rg} for combat rations.

6.4 Risk Analysis in the MFSC

Carpenter and colleagues (2001) pointed out two aspects that should be taken into account when a system's resilience is being measured: (1) Which configuration makes a system resilient, and (2) What kind of threats could affect a system? This section is related to the latter question, i.e., what the main risks are that may cause disruptions in military SCs and how these can be modelled.

6.4.1 An overview of risks affecting supply chains

The most elemental notion of the concept of risk involves two elements: *uncertainty* and *damage* (Kaplan & Garrick, 1981). The literature on the types of risk that can affect an SC is vast and heterogeneous, to the extent that some authors have suggested reorienting research efforts to different areas rather than continue to propose 'new' risk classifications (Hoffmann et al., 2013). Table 6.5 confirms this fact and provides a sample of the different risk classifications existing in the literature, which were developed from the analysis of commercial-SCs.

Table 6.5 Exemplary review of risk classification in SCs

Author(s)	Risk sources/levels/types
Johnson (2001)	- Demand risks
	- Supply risks
Jüttner et al (2003)	- Environmental
	- Network related
	- Organizational
Giunipero and Eltantawy (2004)	- Political events
	- Product availability
	- Transportation distances
	- Changes in technology and labour markets
	- Financial instability
	- Management turnover
Paulsson (2004)	- Operational disturbances
	- Tactical disruptions
	- Strategic uncertainties
Christopher and Peck (2004)	- Internal to the firm
	- External to the firm but external to the SC-network
	- External to the network
Chopra and Sodhi (2004)	- Disruptions
	- Delays
	- Systems
	- Forecasts
	- Intellectual property
	- Procurement
	- Receivables
	- Inventory
	- Capacity
Peck (2005)	- Value stream/product or process
	- Assets and infrastructure dependencies
	- Organisations and inter-organisational networks
	- Environmental
Kleindorfer and Saad (2005)	- Risks from coordination of supply and demand
	- Risks from disruptions to normal activities
Tang (2006)	- Operational risks
	- Disruption risks
Craighead et al (2007)	- Supply chain density
	- Node criticality
Manuj and Mentzer (2008)	- Supply
	- Demand
	- Operational
	- Security risks
Tang and Tomlin (2008)	- Supply risks
	- Process risks
	- Demand risks
	- Intellectual property risks

Wagner and Bode (2008)	- Behavioural risks
	- Political/social risks
	- Demand side
	- Supply side
	- Regulatory, legal and bureaucratic
	- Catastrophic
Trkman and McCormack (2009)	- Endogenous uncertainty
	- Exogenous uncertainty
Ellis et al (2010)	- Magnitude of supply chain disruption
	- Probability of supply chain disruption
	- Overall supply chain disruption risks

The risk classifications described in Table 6.5 provide a preliminary framework for studying risks in the MFSC under analysis. However, these classifications are based on assumptions applicable primarily to commercial-SCs, and therefore they do not fully fit the context and characteristics of military-SCs (see discussion in Section 5.2). In fact, the type of uncertainty that most characterizes the environment of military-SCs is not repeatable, not observable, or both (Cohen et al., 1991). As a result, three specific criteria based on the SC risk-management framework proposed by Handfield and McCormack (2008) are used for the identification, analysis, and estimation of risks considered in the simulation model.

First, historical records of risk occurrence in the MFSC under study were collected. This process included visits to the combat ration assembly plant and the main supply centres, the review of procedures manuals and interviews with staff personal. In addition, operations manuals of the Colombian Army and official reports from the Ministry of Defense also were consulted (NAC, 2010; NAC, 2013; MNDC, 2014). All these documents provided relevant information about the risk factors that could affect the development of logistical operations on the frontline. Second, previous approaches applied to military-SCs and/or equivalent scenarios were taken as a reference point (Loredo et al., 2015; Moore et al., 2015; Thadakamaila et al., 2004; Birkemo, 2013; Ezell et al., 2010; Colicchia et al., 2010). The review of these studies allowed including risks that might represent potential threats for the MFSC under study, but that have not materialized yet. And third, the two previous analyses were complemented with secondary sources of information related to the country risk of the MFSC (Richani, 2013; Ghesquiere et al., 2006; Cardona & Carreño, 2011; GFDRR, 2012). Thus, the country's propensity for natural disasters and the existence of terrorist groups provided additional criteria for quantifying the impact of risks (distributional parameters) affecting the MFSC under study.

The result of the joint application of the above-mentioned criteria allowed a better characterization of the nine types of risk, which were grouped into three categories, as described in Tables 6.6, 6.7 and 6.8, respectively. This categorization adopted as classification criterion the degree of uncertainty that accompanies each risk, i.e. the quantity and quality of information available that from each risk, from the lowest to the highest level (Wideman, 1992; Jorion, 2009; Rumsfeld, 2003).

6.4.2 Known-knowns: Operational risks or risks inherent to the supply chain (R_{1r})

Kleindorfer and Saad (2005) defined operational risks as equipment malfunctions, unforeseen discontinuances of supply, and human-centred issues from strikes to fraud. This category describes risk events for which there is strong evidence of its occurrence (*known-knowns*). This means that their distributions of probability and impact on SC-performance are relatively known, or can be estimated reliably.

Thus, R_{1r} are inherent in all types of SCs and have been widely discussed in the literature, e.g. Hopp and Spearman (2008) or Girling (2013). Usually, their frequency of occurrence is high and their impact is moderate, though occasionally the occurrence of R_{1r} may represent a major threat to SCs (Rice & Caniato, 2003; Craighead et al., 2007). In the present analysis, this category of risk encompasses the occurrence of 'breakdowns in machines or workstations (R_{11})', 'delays in contracting with suppliers (R_{12}), 'shortages of raw materials and components (R_{13})', and 'quality problems (R_{14})'. Table 6.6a describes their underlying causes and effects on the performance of the SC under study, while Table 6.6b characterizes the probability distributions and assumptions adopted for their modeling.

Table 6.6a Description, causes, and foreseeable effects of R_{1r} at the MFSC

Type of risk	Notation (R_{cat_type})	Description	Possible causes	Foreseeable (alleged) effects on the MFSC
Breakdowns in machines or workstations	R_{11}	One or more machines or workstations interrupt their operations without previous notice. Machines or workstations cannot be immediately restarted after the interruption.	Unforeseen technical failures, inadequate maintenance and/or inappropriate use of equipment.	Declines in production. After a time, the affected machine or workstation returns to normality.
Delays in contracting with suppliers	R_{12}	The contracting process of raw materials is delayed in any of its phases.	Lack of offerers, or the occurrence of legal problems during preparatory, pre-contractual, or contractual phases.	The contract required by the supplier for the delivery of raw materials is not finished in time, causing delays in the procurement process.
Shortages of raw material and components	R_{13}	Planned deliveries of materials and components are delayed.	Attributable to the suppliers as result of inadequate planning, machines failures, strikes or environmental factors, among others.	Raw materials and other components required for the assembly process are not delivered in time causing delays in operations.
Quality problems	R_{14}	Quality control problems in the assembly process.	Technical or human failures during the process of assembly.	Some WIP inventories have to be re-processed increasing the times of operation, which causes declines in production.

Table 6.6b Probability distributions and assumptions for modelling R_{1r} at the MFSC

Type of risk	Probability distribution	Distributional parameters	Modeling assumptions
R_{11}	*Uniform-discrete*, *U*(*x*: occurrence of a breakdown at the workstation in an interval of 168 hours; *a*: the lower bound of the interval of time in hours; *b*: the upper bound of the interval of time in hours). *Exponential*, *exp*(*x*: time in hours before the machine is repaired, β: average time in hours before the machine is repaired). The average time in hours before the machine or workstation is repaired is equal to two hours.	$U(x \in Z^+, a: 1, b: 168)$ for $a \leq X \leq b$; $exp(x \in R^+, \beta: 2)$ for $\beta > 0$	(1) The negative effects of breakdowns at Op_5 and Op_6 are all equivalent, (2) the probability of occurrence of any workstation's breakdown is identical along of the interval of time, and (3) the average time in hours before the machine/workstation is repaired is independent for each event.
R_{12}	*Binomial*, *B*(*x*: number of contracts delayed in *n* contracting processes; *n*: number of contracting processes, *p*: likelihood that one contract is delayed).	$B(x \in Z^+, n: 12, p: 1/11)$ for $n \geq 1$ and $0 \leq p \leq 1$	(1) The likelihood of delays in Op_1 remains constant for each of *n* contracting processes ($p = 1/11$), (2) which are considered independent of each other, and (3) if one of the contracting process is delayed, one week (168 hours) is added to MLA processing time.
R_{13}	*Binomial*, *B*(*x*: number of delayed deliveries in *n* planned deliveries; *n*: number of planned deliveries; *p*: likelihood that one delivery is delayed).	$B(x \in Z^+; n: 12, p: 1/10)$ for $n \geq 1$ and $0 \leq p \leq 1$	(1) The likelihood of delays in Op_2 remains constant for each of *n* deliveries (*p*: 1/10), (2) which are considered independent of each other, and (3) if one delivery is delayed, one day (24 hours) is added to each supplier's processing time.
R_{14}	*Binomial*, *B*(*x*: number of non-conforming products, *n*: number of units produced per shift; *p*: probability that one non-conforming product is produced).	$B(x \in Z^+, n: 2,564, p: 3/100)$ for $n \geq 1$ and $0 \leq p \leq 1$	(1) The likelihood of non-conforming products in Op_7 remains constant for each shift (*p*: 3/100), (2) the number of units produced is independent of each other, and (3) if any defective product is detected, the item is returned to the previous operation for re-processing.

6.4.3 Known-unknowns: Natural disasters and intentional attacks (R_{2r})

The second category consists of two types of risk, *natural disasters* and *intentional attacks*. This unified risk category describes events with asymmetric information (Hintsa et al., 2009), i.e. although there is evidence of their occurrence, their frequency, location, and impact on the SC is imprecise, incomplete, or insufficient (*know-unknowns*). Compared with the previous category of risk, their frequency of occurrence is smaller but their impact is greater.

Natural disasters (R_{21}) encompass a wide range of risks with a common origin: "mother nature" (Stecke & Kumar, 2009). In the present analysis, the incidence of R_{21} in the military-SC can be

direct, e.g., earthquakes, storms or floods; or indirect, e.g., when fires, explosions, power outages or any other related events are caused by natural disasters (Altay & Ramírez, 2010). The other typology of risk considered in the same category is *intentional attacks* ($R_{22...24}$). These risk events are characteristic of military-SCs, but not exclusive to them (Willis et al., 2005). In the MFSC under analysis, this type of risk describes deliberate actions perpetrated by terrorist groups against facilities, means of transport, or even civilian targets (Paté-Cornell & Guikema, 2002). In the present analysis, this category of risk includes 'attacks to lines-of-communication (R_{22})', 'attacks on forward-support logistics units (R_{23})', and 'contingent demand (R_{24})'. Table 6.7a describes the underlying causes and their effects on the performance of the MFSC under study, while Table 6.7b characterizes the probability distributions and assumptions adopted for their modeling.

Table 6.7a Description, causes, and foreseeable effects of R_{2r} at the MFSC

Type of risk	Notation (R_{cat_risk})	Description	Possible causes	Foreseeable (alleged) effects on the MFSC
Earthquakes, storms, floods, fires, and power cuts.	R_{21}	Natural phenomena that may cause serious damage to SC facilities.	Multiples causes beyond the control of the SC or so-called 'mother nature'.	Warehouses and the assembly line are taken out of operation causing delays in the delivery of raw materials and finished items. After a time, affected facilities return to normality.
Attacks on the lines-of-communication	R_{22}	The lines-of-communication that connect the nodes of the SC are taken out of operation.	Mostly terrorist attacks caused by rebels or terrorist groups.	The means of transport are destroyed, causing delays in the delivery of raw material or finished items. After the attack, the lines-of-communication are restored.
Attacks on forward logistics-support units	R_{23}	Severe damage or complete destruction of forward-logistics support units.	Mostly terrorist attacks caused by rebels or terrorist groups.	The destruction of forward logistics support units may produce shortages in the delivery of finished items to troops. After the attack, a new forward stock position is re-activated.
Contingent demand	R_{24}	Unforeseen small or mid-range military operations involving the rapid mobilization of combat units and the means for their support.	Several triggers such as military incursions into towns, attacks on aircrafts or military installations, armed harassment, ambushes, and illegal roadblocks, among others, cause the mobilization of troops.	Unexpected mid-range demand fluctuations (growth) of finished items.

Table 6.7b Probability distributions and assumptions for modelling R_{2r} at the MFSC

Type of risk	Probability distribution	Distributional parameters	Modeling assumptions
R_{21}	*Uniform-discrete*, $U(X$: occurrence of a natural disaster in an interval of 16,128 hours; a: the lower bound of the interval of time in hours; b: the upper bound of the interval of time in hours). *Exponential* $exp(x$: time in hours before the assembly line returns to operation, β: average time in hours before the plant returns to operation). The average re-entry time in operation is equal to 120 hours (5 days).	$U(x \in Z^+, a$: 1, b: 16,128) for $a \leq X \leq b$; $exp(x \in R^+, \beta$: 120) for $\beta > 0$.	(1) The likelihood of occurrence of natural disasters is identical along the simulation horizon; (2) when a natural disaster happens Op_3, Op_5, Op_6, Op_7 and Op_9 are simultaneously affected; and (3) the average re-entry time in operation is independent for each operation.
R_{22}	*Uniform-discrete*, $U(x$: destruction of one line-of-communication in a interval of 4,032 hours*; a*: the lower bound of the interval of time in hours, b: the upper bound of the interval of time in hours). *Exponential*, $exp(x$: time in hours before the affected line-of-communication is rehabilitated*, β:* average time in hours before the line-of-communication is rehabilitated). The average time of rehabilitation is equal to 24 hours (1 day).	$U(x \in Z^+, a$: 1, b: 4,032) for $a \leq x \leq b$; $exp(x \in R^+, \beta = 24)$ for $\beta > 0$	(1) The likelihood that Op_4, Op_8, Op_{10} and Op_{12} are destroyed is identical along the period considered, and (2) rehabilitation times for each line-of-communication are independent of one another.
R_{23}	*Uniform-discrete*, $U(x$: destruction of the forward logistics support unit in an interval of 8,064 hours, a: the lower bound of the interval of time in hours, b: the upper bound of the interval of time in hours). *Exponential*, $exp(x$: time in hours before the affected forward logistics support unit is re-activated, β: average time in hours before the forward logistics support unit is re-activated). The average time of re-activation is equal to 120 hours (5 days).	$U(x \in Z+, a$: 1, b: 8,064) for $a \leq x \leq b$; $exp(x \in R^+, \beta$: 120) for $\beta > 0$;	(1) The likelihood that Op_{11} is destroyed is identical for any week along the simulation horizon, (2) the mean duration of re-activating an affected forward logistics support unit is independent for each case, and (3) the likelihood that a single re-entry occurs in non-overlapping intervals is independent of the number of re-entries that occur in any other disjointed time interval.
R_{24}	*Uniform-discrete* 1, $U_1(x$: time of a sudden increase in demand in an interval of 672 hours, a: the lower bound of the interval of time in hours, b: the upper bound of the interval of time in hours). *Uniform-discrete* 2, $U_2(D^{cn}$: size of a sudden increase in demand between 2,400 to 2,600 rations/672 hours; c: the lower bound of the contingent demand in rations, d: the upper bound of the contingent demand in rations).	$U1(x \in Z^+, a$: 1, b: 672) and $U2(D^{cn} \in Z^+, c$: 2,400, d: 2,600) for $a \leq x \leq b$ and $c \leq D^{cn} \leq d$	(1) The likelihood of occurrence of an increase in the demand (Op_{13}) is identical for any week along the simulation horizon, and (2) the likelihood associated with the size of the demand is the same for the indicated range.

6.4.4 Unknown-unknowns: Black-swan events (R₃)

The last category of risk considered in the analysis (*black-swans events*) is the most complicated to characterize since, by definition, there are no previous records of their occurrence (*unknown-unknowns*). According to Taleb (2010), a black-swan is an atypical event (outlier) that cannot be related to any past event, and whose occurrence carries a critical impact. In line with this definition, and based on real war games to which this author had access (IHSND, 2007), a black-swan event (R_3) occurs in the MFSC under analysis when the AL ($Op_{5...7}$) and the SB

(Op$_9$) are taken out of operation because of an air-strike launched by the aviation of a neighbouring country. It should be noted that, even though this scenario has never yet occurred, military experts consider it a likely outcome in a border conflict with a neighbouring country. Table 6.8a describes the underlying causes of this risk and its effects on the performance of the MFSC under study, while Table 6.8b characterizes the probability distribution and assumptions adopted for its modeling.

Table 6.8a Description, causes, and foreseeable effects of R$_3$ at the MFSC

Type of risk	Notation (R$_{cat\_risk}$)	Description	Possible causes	Foreseeable (alleged) effects on the MFSC
Black-swan events	R$_3$	Surprising and premeditated airstrikes launched by the air force of a neighbouring country against critical logistics facilities such as quartermaster battalions and military warehouses.	A sudden border conflict with a neighbouring country motivated by political or economic reasons, in which air power is used.	The assembly line and the military warehouses of the SC are temporarily taken out of operation, after which time these facilities return to normality.

Table 6.8b Probability distributions and assumptions for modelling R$_3$ at the MFSC

Notation (R$_{cat\_risk}$)	Probability distribution	Distributional parameters	Modeling assumptions
R$_3$	*Uniform-discrete*, $U(x$: time of occurrence of a black-swan event in a interval of 161,280 hours, a: the lower bound of the interval of time in hours, b: the upper bound of the interval of time in hours).	$U(x \in Z^+, a = 1, b = 161,280)$ for $a \leq x \leq b$	(1) The probability of occurrence of a black-swan event is the same along the simulation horizon; (2) when a black-swan event occurs, Op$_5$, Op$_6$, Op$_7$ and Op$_9$ are simultaneously taken out of operation during 672 consecutive hours; and (3) operations affected return to normality after this time.

6.5 Assumptions of the Simulation Model

The simulation model of the MFSC incorporates eight key assumptions. All these premises were posed to avoid including unnecessary details, to reduce the execution time, and to emphasize some characteristics of the real-world MFSC under analysis.

6.5.1 Operation mode and end-users

In real environments, military-SCs meet the needs of a range of end-customers such as military personnel, civilians, civil response organizations, and humanitarian relief forces. This responsiveness ability depends on the operating-mode of the military-SC. Generally speaking, in war mode; effectiveness is preceded by efficiency and cost criteria, while in peace mode the opposite occurs (Tatham, 2005). In this analysis, it is assumed that the MFSC functions in war mode, i.e. it meets only the needs of the troops.

6.5.2 Proactive strategy to mitigate the impact of risks

Risks cannot be totally avoided due to their stochastic nature, but their effects can be reduced (Kaplan & Garrick, 1981, p.12). This is indeed one of the key assumptions on which the SCRes paradigm rests (Jüttner & Maklan, 2011). SCs may choose to take some action in advance of risks, or to respond to them only if they occur. In this research it is assumed that the MFSC does not react post hoc to the materialization of risks, but that the MFSC adopts a proactive strategy (buffering strategy).

6.5.3 Single and homogeneous product

Real-world SCs manufacture a wide range of products in actual practice. Indeed, as previously indicated, the MFSC assembles 21 types of combat ration. However, to simplify the analysis, it will assume that the MFSC manufactures only one type of ration, the 'Cold weather combat ration # 1'.

6.5.4 Backorders and scheduling rule

When troops' demands are not met within the stipulated lead-time, they are labelled as *backorders*. This is because military-SCs cannot outsource/subcontract military items by restrictions in the law. In the simulation model, backorders are demands for military rations that have not yet been delivered. Hence, each SC-configuration (Cf_i) begins with zero backorders; and they then accumulate in a list of pending orders to be delivered according to the MFSC's capability. Each new backorder is entered on a list of up to 60 delayed orders, so that if a new backorder is created, the last order in the list is removed and labelled as *lost* or *unattended order* (U_l). As all backorders have equal weight, they are scheduled according to the shortest processing time rule (SPT rule), i.e., 'do backorders in increasing order of their size.' The SPT rule allows minimisation of the average completion time, the average flow time, and the average wait time (Bernus et al., 2007). The only exception to the SPT rule occurs when new orders are placed as result of contingent military operations (see R_{24} in Table 6.7b). This type of order (contingent demand) has priority over regular demands.

6.5.5 Lines-of-communication and warehouses

Two entities play a crucial role in the MFSC under study: lines-of-communication (LOCs) and storage locations (WDC, SBs and CSSBs). With regard to LOCs, the availability of distribution vehicles and the planning/analysis of routes are taken for granted. Similarly, storage capacities of WDC, SBs and CSSBs are assumed to be unlimited along the simulation horizon of the model.

6.5.6 Suppliers, placement orders, and fulfilment of raw material deliveries

Three assumptions are made for simplifying the simulation model. First, the number of hired suppliers is equal to the number of raw materials required. Second, the order placement time of

combat rations is instantaneous. And lastly, partial deliveries of raw material/finished products, incomplete and inaccurate documentation to support the order, or last-minute changes in orders/productions plans are not allowed.

6.5.7 Preparation of machines, worker strikes, and maintenance times

The simulation model does not consider machine preparation times or worker strikes. The first assumption is reasonable since the MFSC only assembles a single item; thereby production losses at the end of each shift or at the beginning of the next shift are negligible. Regarding the second assumption, the nature of the MFSC under study precludes the strike of workers because in the origin country of the military-SC, this activity is considered a violation of the law. Lastly, the maintenance of machines and installations is done once every 7 days for 24 hours.

6.5.8 Non-terminating simulation with steady state parameters

The simulation of the MFSC is considered a non-terminating simulation with steady state parameters. The above means that the length of a simulation run—established in up to 20 years—is not determined by the occurrence of any event. In addition, the parameters of the model distributions remain unchanged during this period. This assumption exerts a significant influence on the results of the simulation model.

6.6 Verification and Validation of the Simulation Model

The verification and validation of simulation models are two processes independent of each other but complementary in nature. Thus, while the purpose of verification is to ensure that the code of the simulation software works as intended, the purpose of the validation is to confirm that the simulation output data is an adequate representation of reality (Chung, 2004). Both processes are described in detail below.

6.6.1 Verification of the simulation model

Verification of the simulation model is carried out through the *run-time model verification library* of Simulink®. This software functionality comprises several block libraries that can be used to substantiate the performance of a simulation model. In this analysis, only three of them were used (see Figure 6.3). The parameters utilised for the verification of the simulation model were the SC-*manufacturing capacity* (see Table 6.3) and the *frequency of risks* (Tables 6.6b, 6.7b, and 6.8b). The three block libraries shown in Figure 6.3 point out what happens when some of the two mentioned parameters abandon their limits or intervals of occurrence.

Figure 6.3 Simulink® run-time model verification library
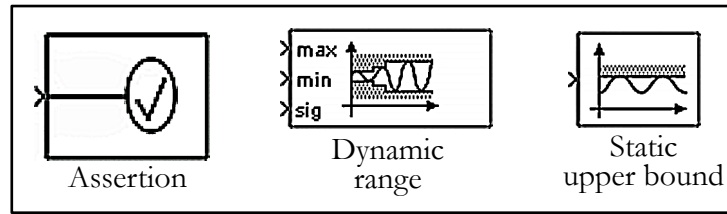
The verification experiment consisted of 42 simulation-runs that examined the consistency of the MFSC model. Each check-block depicted in Figure 6.4 was applied to the indicated parameters. For example, as indicated in Table 6.9, for the first block of verification (assertion), 12 simulation runs were carried out to verify that the throughput of the MFSC (amount of rations produced per unit of time) is not zero at any time, and 9 simulation runs were carried out to verify that none of the risks considered 'is not zero' (occurs) at any time of the simulation horizon of the model. The application of the two remaining blocks (dynamic range and static upper bound) is detailed in the same table. The results of the 42 simulation-runs confirm that the MFSC model is structurally correct.

Table 6.9 Verification criteria for simulation of the MFSC

Simulink verification blocks	According to the supply chain manufacturing capacity (Table 6.3)	Runs	According to the frequency of occurrence of risks (Table 5.10)	Runs
Assertion	Verify that the throughput is not zero in any period.	12	Verify that none of the risk events in the simulation horizon is not zero.	9
Dynamic range	Check that the throughput falls inside the specified shift ranges.	12	n.d.	0
Static upper bound	n.d.	0	Check that the frequency of each type of risk is equal or less than the specified upper bound in the simulation horizon.	9

n.d.: not defined

6.6.2 Validation of the simulation model

The purpose of the validation process is to confirm that the output data of the simulation model adequately characterizes the data obtained from the real-world system (MFSC); in other words, simulation output data must be within a "satisfactory range of accuracy" (Sargent, 2013, p.12). The foregoing implies making use of classical statistical tests such as F, Kolmogorov-Smirnov, t, Mann-Whitney, Schruben-Turing, χ^2, among the most used, for examining the similarity between the two sets of data (Smith et al., 1996) (Sandikci & Sabuncuoglu, 2006). Yet

the problem with this approach is that output data from both simulation models and real-world systems are characteristically non-stationary and highly auto-correlated, which limits the application of such statistical tests (Smith et al., 1996; Sandikci & Sabuncuoglu, 2006). Thus, instead of removing the non-stationarity and autocorrelation patterns from both data sets, the validation of the simulation model for this research was assessed through the *correlated inspection approach* (CIA) proposed by Law and Kelton (1991).

This validation procedure has been used widely in the literature of several disciplines to evaluate the validity of the output data of simulation models with respect to real-world systems, e.g. (Graham et al., 2006; Sivakumar & Chong, 2001; Chen & Wang, 2016). Figure 6.4 describes the CIA used in this research. As shown in the figure below, the simulation model is constructed on the basis of the same input data from the real-world SC, which allows comparing both output data under equivalent circumstances or *replicative validity* (Troitzsch, 2017)

Figure 6.4 Correlated inspection approach (CIA) for validation of the simulation model
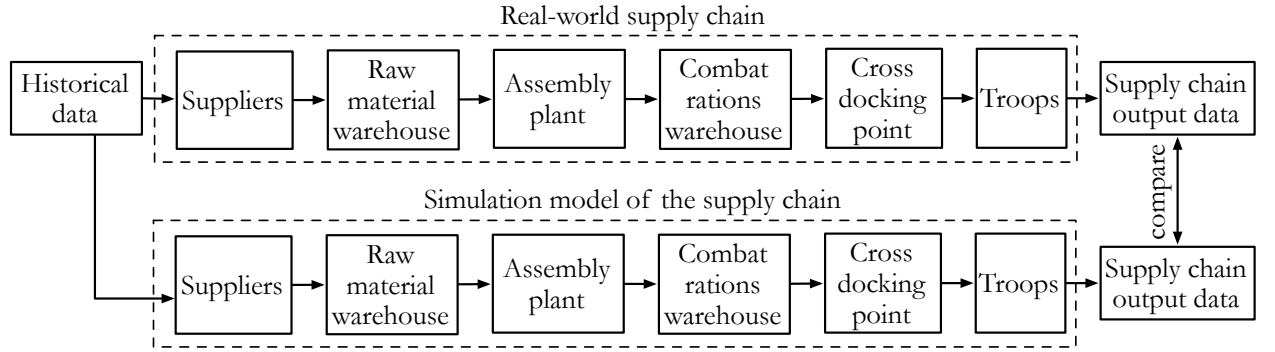
The 'number of rations per year delivered to the troops' is the output variable chosen for validating the simulation model for the MFSC. This variable is an appropriate indicator to measure the overall performance of the MFSC. Thus, the CIA consists of comparing the actual quantity of rations delivered to the troops during one year (P_t) with its equivalent result in the simulation model ($EC_{S=1}$). The records of P_t describe the historical performance of the MFSC over the last eight years ($P_1…P_8$), while each value of EC_S is the average of three simulation runs, each one with a different seed. With the values of the two parameters, the percentage change of P_t with respect to EC_S for each case is estimated (%Δ). The analysis is then complemented with the calculation of the RMSE on the square difference between P_t and EC_S. All the above is detailed in Table 6.10.

Table 6.10 Comparison of the quantity of rations per year actually delivered to military personnel (observed data P_t vs. simulated data EC_S)

Quantity of rations delivered to military personnel	Year								RMSE
	1	2	3	4	5	6	7	8	
P_t	711,808	901,131	806,454	719,344	731,016	629,429	707,203	728,878	
$EC_{S=1}$	725,021	773,675	735,389	771,434	888,776	712,315	732,883	801,239	87,918
$P_t - EC_S$	-13,213	127,456	71,065	-52,090	-157,760	-82,886	-25,680	-72,361	
%Δ	-1.86%	14.14%	8.81%	-7.24%	-21.58%	-13.17%	-3.63%	-9.93%	

Figure 6.5 Percentage change of P_t with respect to EC_S (%Δ)
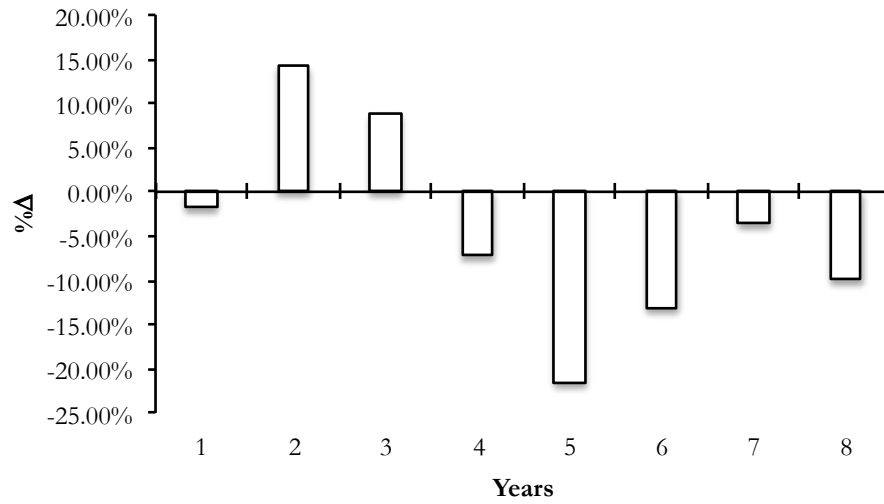
The values of %Δ in Table 6.10 are plotted in Figure 6.5 for greater clarity. With respect to this figure, the main observation is that the differences between the two variables are within the range of values found in the simulation of similar logistics systems (Merkuryev et al., 2009), though in some cases these differences appear to be high, e.g. year 5 in Figure 6.5. This is due to the fact that the simulation model does not capture all aspects involved in P_t, such as decisions of discretionary nature on variations in the production rate or trend and/or seasonality of the demand function. The modelling assumptions described in Section 5.5 of this thesis also contribute to have in some cases a larger %Δ. In addition to applying the CIA to the data, knowledgeable engineers of the MFSC reviewed the simulated data by using an approximation of the Turing test (Turing, 1950) and obtained equally satisfactory results.

6.7 Design of the Simulation Experiment

The design of simulation experiment (DSE) is based on three main scenarios: (1) increases in the frequency of occurrence of the three categories of risk, (2) increases in the levels of on-hand inventory buffers, and (3) increases in the levels of short-term manufacturing capacity. The simulation of these three scenarios provides the output data needed to calculate the measure of resilience (Re^T) for the nine hypotheses obtained in Chapter 3. The flexibility of the simulation tool allows configuration of parameters of the MFSC as well as a switching of each category of risk to on/off as required. The three scenarios of simulation are explained below.

6.7.1 Notation

This section details the notation adopted throughout the DSE and subsequent sections:

Indices

j	Job order j^{th} of combat ration packs in the simulation horizon, $j = 1\ldots6{,}000$
k	Number of operation, $k = 1\ldots 13$
t	Number of hours in the simulation horizon, $t = 1\ldots161{,}280$
c	Category of risk, $c = 1\ldots3$
r	Type of risk, $r = 1\ldots4$
i	Number of runs in the simulation experiment, $i = 1\ldots102$
λ	Assembly rate of rations per hour, $\lambda = 320.5$ rations/hour
$cntr_{\#}$	Supplier contract, $cntr_{\#} = cntr_1\ldots cntr_{12}$
$rm_{\#}$	Raw material, $rm_{\#} = rm_1\ldots rm_{12}$

Parameters

WIP	Work-in-progress inventory (sub-assemblies)
MFSC	Supply chain of military food
SCRes	Supply chain resilience
MP	Military personnel (end-users) of the MFSC
$\text{Op}_{k,j}$	Operation k-th of order j-th in the MFSC
PT_{Op}	Processing time of operation k-th
ROP_{Op}	Re-order point of operation k-th
Q	Quantity of contracts/raw material/WIP/rations in the MFSC
TC_S	Theoretical capacity of assembly line in units of t or rations according to the number of work shifts S
EC_S	Effective capacity of assembly line in units of t or rations according to the number of work shifts S
P_t	Historical data of the number of rations per year delivered to the troops
R_{cr}	Type of risk r of category c during CT_j
R_{1r}	Operational risks, $r = 1\ldots4$
R_{2r}	Natural disasters and intentional attacks, $r = 1\ldots4$
R_3	Black-swan events
R^0_{cr}	Time detection of risk R_{cr}
R^f_{cr}	Final time of impact of risk R_{cr}
$R^f_{cr} - R^0_{cr}$	Period of impact of risk R_{cr}

$I_{t,S}$	On-hand inventory buffers of raw material/rations for a period t and work shifts S
S	Number of shifts, S = 1…3
Cf_0	Current configuration of the MFSC with 1 work shift (S = 1), no stocks in operations 3, 5 and 9 ($I_{t,1}$ = 0), and some R_{cr} category enabled
Cf_i	Configuration i of the MFSC with respect to $I_{t,S}$, S, or any external operating condition related to the frequency of occurrence of R_{cr}
Ω	Set of risks R_{cr} in the simulation horizon, Ω = {R_{11}, R_{12}…R_{cr}}
D_t	Demand for rations in period t
OPT_j	Order placement time of order j-th
OAT_j	Order arrival time of order j-th
CT_j	Supply chain cycle-time of order j-th
LT_j	Supply chain lead-time (fixed) of order j-th
$\overline{Re}^{max}$	Maximum resilience weighting factor
$\overline{Re}$	Mean resilience weighting factor
$\overline{Re}^{min}$	Minimum resilience weighting factor

Variables

AP_j	Autotomy period of order j-th
DP_j	Disruption period of order j-th
RP_j	Recovery period of order j-th
$DP_j - RP_j$	Non-recovery period of order j-th
N-DP_j	Non-disruption period of order j-th
B_t	Backorders in period t
U_t	Number of lost or unattended orders j in period t
FR_t	Fill rate or percentage of orders j that are not backordered (B_j) and/or unattended (U_j) from the stock in the supply battalion in period t
Re^T	Measure of SCRes over time for the order j-th

6.7.2 Scenario I: Increasing the frequency of occurrence of the risk categories

The DSE for the first scenario consists of subjecting MFSC to a higher frequency of occurrence of the three categories of risk described in Tables 6.6, 6.7, and 6.8, respectively. The output data obtained are the input to calculate the four sub-indicators (AP_j, RP_j, DP_j-RP_j, and N-DP_j) that make up the measure of resilience (Re^T) introduced in Chapter 5, and for testing the set of hypotheses 1 (H_{1a}, H_{1b}, and H_{1c}). Set of hypotheses 1 indicates in general that 'increases in the frequency of occurrence of risks (R_{1r}, R_{2r}, and R_3) are negatively related to the measure of SCRes.' To provide output data needed for testing these hypotheses, Table 6.11 consolidates the frequency of risks per year/simulation run built up from Tables 6.6, 6.7, and 6.8. For example, 'quality problems' (R_{14}) is the most frequent risk—442,368 events in 20 years, and 'black-swan events' (R_3), the least frequent—1 event every 20 years.

Table 6.11 Frequency of occurrence of the three categories risk ('current level of risk')

Type of risk	Unit of measure	Events per year	Estimated events in a simulation run[*]
R_{11}	Breakdowns	48	960
R_{12}	Delayed contracts	2 1/6	44
R_{13}	Delayed deliveries	58	1,152
R_{14}	Defective products	22,153	443,059
R_{21}	Natural disasters	1/2	10
R_{22}	Attacks	2	40
R_{23}	Attacks	1	20
R_{24}	Contingent orders	12	240
R_3	Destructive attacks	1/20	1

*Up to 20 years or 161,280 hours

The levels described in Table 6.11 represent 'the current level of risk' that MFSC faces. The internal parameters of the MFSC, including inventory and capacity, were kept fixed at a constant level—*ceteris paribus* condition—during the time of simulation (up to 20 years or 161,280 hours), with $S = 1$ and $I_{t,1} = 0$. Table 6.12 summarizes the factor coding for the three categories of risk considered (R_{cr}), in which the column with the symbol '−' 'represents the current level of risk that the MFSC faces, and the column with the symbol '+', a higher level of risk.

Table 6.12 Factor coding for R_{cr}

Notation	− (current risk level)	+ (increased risk level)
R_{11}	$U(a{:}\ 1, b{:}\ 168)$	$U(a{:}\ 1, b{:}\ 42)$
R_{12}	$B(n, p{:}\ 1/11)$	$B(n, p{:}\ 4/11)$
R_{13}	$B(n, p{:}\ 1/10)$	$B(n, p{:}\ 4/10)$
R_{14}	$B(n, p{:}\ 3/100)$	$B(n, p{:}\ 8/100)$
R_{21}	$U(a{:}\ 1, b{:}\ 16{,}128)$	$U(a{:}\ 1, b{:}\ 4{,}032)$
R_{22}	$U(a{:}\ 1, b{:}\ 4{,}032)$	$U(a{:}\ 1, b{:}\ 1{,}344)$
R_{23}	$U(a{:}\ 1, b{:}\ 8{,}064)$	$U(a{:}\ 1, b{:}\ 1{,}344)$
R_{24}	$U(a{:}\ 1, b{:}\ 672)$	$U(a{:}\ 1, b{:}\ 336)$
R_3	$U(a{:}\ 1, b{:}\ 161{,}280)$	$U(a{:}\ 1, b{:}\ 80{,}640)$

Tables 6.13, 6.14 and 6.15 are derived from Table 6.12. Thus, Tables 6.13 and 6.14 describe the design of the matrix for R_{1r} and R_{2r}, respectively. In these two cases, a full factor design is used with ten different configurations (Cf_i). Similarly, Table 6.15 describes the design of the matrix for R_3, with two levels (−/+) and six replications per pattern, for a total of ten simulation runs. Each Cf_i is run with a different seed. The simulation horizon for each Cf_i in Tables 6.13 and 6.14 is 10 years, while for the Cf_i in Table 6.15 it is 20 years.

Table 6.13 Design matrix with increased levels of R_{1r} (H_{1a})

Cf_i	R_{11}	R_{12}	R_{13}	R_{14}	Cf_i	R_{11}	R_{12}	R_{13}	R_{14}
Cf_1	−	−	+	+	Cf_6	+	+	−	+
Cf_2	−	+	−	−	Cf_7	+	−	−	+
Cf_3	+	−	+	+	Cf_8	+	−	−	−
Cf_4	+	+	+	−	Cf_9	−	+	+	+
Cf_5	−	−	+	−	Cf_{10}	−	+	−	+

Table 6.14 Design matrix with increased levels of R_{2r} (H_{1b})

Cf_i	R_{21}	R_{22}	R_{23}	R_{24}	Cf_i	R_{21}	R_{22}	R_{23}	R_{24}
Cf_{11}	+	−	+	+	Cf_{16}	−	+	−	−
Cf_{12}	+	−	−	−	Cf_{17}	−	+	+	−
Cf_{13}	+	+	−	+	Cf_{18}	−	−	+	−
Cf_{14}	+	+	+	−	Cf_{19}	−	+	−	+
Cf_{15}	−	−	+	+	Cf_{20}	+	+	+	+

Table 6.15 Design matrix with increased levels of R_3 (H_{1c})

Cf_i	R_3	Cf_i	R_3
Cf_{21}	−	Cf_{26}	−
Cf_{22}	+	Cf_{27}	−
Cf_{23}	+	Cf_{28}	−
Cf_{24}	+	Cf_{29}	+
Cf_{25}	+	Cf_{30}	−

6.7.3 Scenario II: Increasing the levels of on-hand inventory buffers

Starting from configurations described in Tables 6.13, 6.14, and 6.15, the DSE for the second scenario consists of elevating the levels of on-hand inventory buffers of the MFSC ($I_{t,S}$) at three specific points along the chain ($Op_{3,j}$, $Op_{5,j}$, and $Op_{9,j}$). The choice of operations 3, 5 and 9 is because they are in practice critical storage points of raw material/finished products. The output data obtained are the input to calculate Re^T and to test the second set of hypotheses (H_{2a}, H_{2b}, and H_{2c}), which in general indicate that 'increases in the levels of on-hand inventory buffers ($I_{t,S}$) moderate the relationship between risks and the level of SCRes.' For this purpose, Table 6.16 describes the five different levels of on-hand inventory evaluated ($I_{168,1}$, $I_{336,1}$, $I_{504,1}$, $I_{672,1}$, and $I_{1344,1}$) at the three operations mentioned ($Op_{3,j}$, $Op_{5,j}$, and $Op_{9,j}$).

Table 6.16 On-hand inventory buffers ($I_{t,S}$) held at critical points of the MFSC ($Op_{3,j}$, $Op_{5,j}$, and $Op_{9,j}$)

$Op_{k,j}$	Type of I	$I_{168,1}$	$I_{336,1}$	$I_{504,1}$	$I_{672,1}$	$I_{1344,1}$
$Op_{3,j}$	$rm_1 \dots rm_{12}$	15,360	30,720	46,080	61,440	122,880
$Op_{5,j}$	$rm_1 \dots rm_{12}$	15,360	30,720	46,080	61,440	122,880
$Op_{9,j}$	rations	15,750	31,500	47,250	63,000	126,000

The level of $I_{t,S}$ associated with each Cf_i described in Tables 6.17, 6.18 and 6.19 represents the on-hand inventory buffers of raw material/rations for t = 168, 336, 504, 672, or 1,344 hours; and S = 1 work shift, with $I_{168,1} < I_{336,1} < I_{504,1} < I_{672,1} << I_{1344,1}$. That is, the level of $I_{t,S}$ is randomly increased from $I_{168,1}$ to $I_{1344,1}$, and the number of work shifts S is kept fixed at the current level ($I_{t,1}$). This design is replicated two times for each $I_{t,S}$, for a total of 30 SC-configurations (from Cf_{31} to Cf_{60}) for each one of the three categories of risk (R_{1r}, R_{2r}, and R_3). Due to the nature of each category of risk considered, the simulation horizon for each Cf_i in Tables 6.17 and 6.18 is 10 years, while for the Cf_i in Table 6.15 it is 20 years.

Table 6.17 Design matrix with on-hand inventory buffers ($I_{t,S}$) and levels of R_{1r} increased (H_{2a})

Cf_i	$I_{t,S}$	Cf_i	$I_{t,S}$
Cf_{31}	$I_{504,1}$	Cf_{36}	$I_{1344,1}$
Cf_{32}	$I_{336,1}$	Cf_{37}	$I_{672,1}$
Cf_{33}	$I_{168,1}$	Cf_{38}	$I_{672,1}$
Cf_{34}	$I_{1344,1}$	Cf_{39}	$I_{168,1}$
Cf_{35}	$I_{336,1}$	Cf_{40}	$I_{504,1}$

Table 6.18 Design matrix with on-hand inventory buffers ($I_{t,S}$) and levels of R_{2r} increased (H_{2b})

Cf_i	$I_{t,S}$	Cf_i	$I_{t,S}$
Cf_{41}	$I_{1344,1}$	Cf_{46}	$I_{1344,1}$
Cf_{42}	$I_{336,1}$	Cf_{47}	$I_{168,1}$
Cf_{43}	$I_{504,1}$	Cf_{48}	$I_{336,1}$
Cf_{44}	$I_{168,1}$	Cf_{49}	$I_{672,1}$
Cf_{45}	$I_{504,1}$	Cf_{50}	$I_{672,1}$

Table 6.19 Design matrix with on-hand inventory buffers ($I_{t,S}$) and levels of R_3 increased (H_{2c})

Cf_i	$I_{t,S}$	Cf_i	$I_{t,S}$
Cf_{51}	$I_{672,1}$	Cf_{56}	$I_{504,1}$
Cf_{52}	$I_{1344,1}$	Cf_{57}	$I_{336,1}$
Cf_{53}	$I_{672,1}$	Cf_{58}	$I_{336,1}$
Cf_{54}	$I_{1344,1}$	Cf_{59}	$I_{168,1}$
Cf_{55}	$I_{504,1}$	Cf_{60}	$I_{168,1}$

This second scenario of simulation assumes that the MFSC starts with inventory buffers (raw material or rations) at positions Op_3, Op_5, and Op_9, as described in Table 6.16. These operations can be impacted by R_{21} in the case of Op_3; R_{11}, R_{21} and R_3 in the case of Op_5; and, R_{21} and R_3 in the case of Op_9 (see Figure 6.2). Thus, independently of the occurrence of the above risks, every $t = 168, 336, 504, 672$, or $1,344$ hours, and the level of $I_{t,S}$ is replenished in the quantities of raw material and rations indicated in Table 6.16. In general, the policy described for this second scenario of simulation fits the practices implemented by some armies after World War II as a vehicle for risk management and is known as *strategic inventory reserves* (NRC, 2008). In this regard, Sheffi (2001), and Chopra and Sodhi (2004) have suggested its use as alternative to buffer severe disruptions when holding cost and risk of obsolescence are low. More recently, Son and Orchard (2013) tested its cost-effectiveness ratio in mitigating SC-disruptions.

6.7.4 Scenario III: Increasing the levels of short-term manufacturing capacity

Similarly to the previous case, starting from configurations described in Tables 6.13, 6.14, and 6.15, the DSE for the third scenario consists of elevating the levels of short-term manufacturing capacity of the MFSC (S). The output data obtained are the input to calculate Re^T and to test the third set of hypotheses (H_{3a}, H_{3b}, and H_{3c}), which in general indicate that 'increases in the level of short-term manufacturing capacity moderate the relationship between risks and the level of SCRes.' To this end, Table 6.19 describes the three configurations of the MFSC according to the number of work shifts activated per day, i.e. $S = 1, 2,$ or 3. The differences between configurations relate to the quantities of raw material sent from WDC ($Op_{3,j}$) to AL ($Op_{5,j}$). Hence, with two work shifts activated, the quantity of raw material sent from $Op_{3,j}$ to $Op_{5,j}$ is double (31,000 units of each *rm*) that of operating with one work shift activated ($S = 1$), and triple (47,000 units for each *rm*) that of operating with three work shifts activated ($S = 3$). In addition, when MFSC operates full capacity ($S = 3$), the lot size of combat rations sent from AL ($Op_{7,j}$) to SB ($Op_{9,j}$) increases up to 7,000 rations/shipment. In the three mentioned configurations ($S = 1, 2,$ and 3), zero inventory stock is held at critical storage points ($Op_{3,j}$, $Op_{5,j}$, and $Op_{9,j}$), in order to isolate the effect of adding more manufacturing capacity to the MFSC.

Table 6.20 Short-term manufacturing capacity (S) of the MFSC

$Op_{k,j}$	PT	S = 1		S = 2		S = 3	
		Q	ROP	Q	ROP	Q	ROP
$Op_{1,j}$	672	12 contracts	4,032	12 contracts	4,032	12 contracts	4,032
$Op_{2,j}$	24	190,000 units of each rm	672	190,000 units of each rm	672	190,000 units of each rm	672
$Op_{3,j}$	24	15,500 units of each rm	168	31,000 units of each rm	168	47,000 units of each rm	168
$Op_{4,j}$	24	15,500 units of each rm	168	31,000 units of each rm	168	47,000 units of each rm	168
$Op_{5,j}$	0	1 pre-assembly	0	1 pre-assembly	0	1 pre-assembly	0
$Op_{6,j}$	0	1 pre-assembly	0	1 pre-assembly	0	1 pre-assembly	0
$Op_{7,j}$	0	5,000 rations	48	5,000 rations	24	7,000 rations	24
$Op_{8,j}$	24	5,000 rations	48	5,000 rations	24	7,000 rations	24
$Op_{9,j}$	24	2,000 to 2,500 rations	24	2,000 to 2,500 rations	24	2,000 to 2,500 rations	24
$Op_{10,j}$	24	2,000 to 2,500 rations	24	2,000 to 2.500 rations	24	2,000 to 2,500 rations	24
$Op_{11,j}$	0	2,000 to 2,500 rations	24	2,000 to 2,500 rations	24	2,000 to 2,500 rations	24
$Op_{12,j}$	24	2,000 to 2,500 rations	24	2,000 to 2,500 rations	24	2,000 to 2,500 rations	24

The number of S associated with each Cf_i described in Tables 6.21, 6.22 and 6.23 represents the number of work shifts activated according to the needs of contracts, raw materials, WIP, and rations detailed in Table 6.20. The level of S is increased randomly from S = 1 to full capacity or S = 3. This design is replicated up to three times for each S, for a total of 30 configurations (from Cf_{61} to Cf_{90}) for each one of the three categories of risk (R_{1r}, R_{2r}, and R_3). Due to the nature of the categories of risk considered, the simulation horizon for each Cf_i in Tables 6.21 and 6.22 is 10 years, while for the Cf_i in Table 6.23 it is 20 years.

Table 6.21 Design matrix with short-term manufacturing capacity (S) and levels of R_{1r} increased (H_{3a})

Cf_i	S	Cf_i	S
Cf_{61}	2	Cf_{66}	2
Cf_{62}	1	Cf_{67}	1
Cf_{63}	3	Cf_{68}	2
Cf_{64}	3	Cf_{69}	3
Cf_{65}	1	Cf_{70}	3

Table 6.22 Design matrix with short-term manufacturing capacity (S) and levels of R_{2r} increased (H_{3b})

Cf_i	S	Cf_i	S
Cf_{71}	1	Cf_{76}	3
Cf_{72}	3	Cf_{77}	2
Cf_{73}	2	Cf_{78}	1
Cf_{74}	3	Cf_{79}	2
Cf_{75}	2	Cf_{80}	1

Table 6.23 Design matrix with short-term manufacturing capacity (S) and levels of R_3 increased (H_{3c})

Cf_i	S	Cf_i	S
Cf_{81}	1	Cf_{86}	3
Cf_{82}	3	Cf_{87}	2
Cf_{83}	2	Cf_{88}	1
Cf_{84}	3	Cf_{89}	2
Cf_{85}	2	Cf_{90}	1

6.7.5 Evaluation of the efficiency of the simulation experiment design

As important as the experimental design itself, is the evaluation of its level of efficiency. For this purpose, three optimality criteria were applied to the nine design matrices described in Tables 6.13 to 6.15, Tables 6.17 to 6.19, and Tables 6.21 to 6.23, respectively: (1) *D-efficiency*, (2) *G-efficiency*, and (3) *A-efficiency*.

Table 6.24 Evaluation of the efficiency of the simulation experiment

Testing design matrix for hypothesis	Table #	Execution order	*D*-criteria	*G*-criteria	*A*-criteria
H_{1a}	6.14	Random	95.72	91.28	92.59
H_{1b}	6.15	Random	95.72	91.28	92.59
H_{1c}	6.16	Random	95.72	91.28	92.59
H_{2a}	6.18	Random	95.72	91.28	92.59
H_{2b}	6.19	Random	95.72	91.28	92.59
H_{2c}	6.20	Random	95.72	91.28	92.59
H_{3c}	6.22	Random	95.72	91.28	92.59
H_{3b}	6.23	Random	95.72	91.28	92.59
H_{3c}	6.24	Random	95.72	91.28	92.59

The calculations for the three optimality criteria are shown in Table 6.24 and were made based on Equations 6.1, 6.2, and 6.3, respectively:

$$\text{D-efficiency} = 100 \left(\frac{1}{n} \left| X'X \right|^{1/p} \right), \tag{6.1}$$

where X is the model matrix, n is the number of simulation runs, and p is the number of terms;

$$\text{G-efficiency} = 100p / n\text{Var}\left(\hat{y} \,|\, \dot{x}\right)_{\text{max}}, \tag{6.2}$$

where $n\text{Var}(\hat{y} \,|\, \dot{x})_{\text{max}}$ is the maximum relative prediction variance over the design region, and

$$\text{A-efficiency} = 100p / n\text{Trace}\left(X'X\right)^{-1}, \tag{6.3}$$

where $\text{Trace}(X'X)^{-1}$ is the sum of the squares of the entries in X.

Three key inferences can be made from the results described in Table 6.24: (1) the volume of the joint confidence region for the vector of regression coefficients was minimised, (2) the maximum prediction variance over the design region was minimised, and (3) the sum of the variances of the regression coefficients were minimised (Pukelsheim, 2006). In a nutshell, the results of the three-optimality criteria point to high efficiency in the experimental design for simulating the MFSC.

6.8 Simulation Output Data

6.8.1 Simulation run length

Several heuristic procedures have been proposed to ascertain the run length of a non-terminating simulation model (Chen & Kelton, 2003; Chen, 2016; Srikant & Whitt, 1995). The key to solving this problem is to find an appropriate balance between the accuracy of simulation output data and the amount of time available for making the simulation runs (Cheng, 2007). Accordingly, the execution time for the simulation model is determined via application of the *multiple of the number of events' criterion* (El-Haik & Al-Aomar, 2006; Garg & Wang, 1990). These authors suggested that the simulation run length is a function of the frequency and duration of the events considered within the analysis, especially those considered as 'the rarest events'. This definition leads us to *black-swan events*, the most uncertain category of risk of all considered in this research, and the one with the lowest frequency of occurrence. As was established in Table 6.11, 'one black-swan event occurs every 20 years'.

In this regard, El-Haik and Al-Aomar (2006) suggested that each type of event must be repeated at least five times per run, which would require consideration of a simulation run length of 100 years for analysing a black-swan event scenario. This period would be too long for evaluating the MFSC, especially if the model assumptions explained in Section 6.5 were taken into account.

Moreover, a 100-years simulation horizon would require a time period of 15.85 hours to run a single simulation, making the execution of the whole simulation model impractical. Thus, taking into consideration all of the above arguments, it makes sense to set the simulation run length at 20 years or 161,280 hours.

6.8.2 Warm-up period for the simulation model

For a non-terminating simulation with steady-state parameters as the present, the output data of the simulation model must converge to a *steady-state mean* before they can be analysed. This is in order to avoid erroneous inferences about the phenomenon studied. The above problem is known in the literature on simulation as an "initial transient period", "start-up period" or "warm-up period" (Lavenberg, 1981; Sandikci & Sabuncuoglu, 2006). In the specific case of the MFSC, the analysis of the problem of a warm-up period means that the simulation output data must be eliminated at the beginning of the simulation. This period is equivalent to the time elapsed before an order of size $Q = 5,000$ rations reach the *supply battalion* or Op_9, as shown in Figure 6.2. Due to the configuration of the MFSC, the availability of finished products at this point allows troops to be supplied within a pre-set lead-time of 48 hours.

Thus, if the nature of SC-operations 1 to 9 were deterministic, the warm-up period would be equal to the sum of its processing times, i.e., 838.8 hours. However, as has been mentioned, the processing times may be affected by stochastic events (risks), which make directly estimating the warm-up period complex. Although several methods have been proposed in the literature for solving the warm-up period problem in non-terminating simulations, e.g. see (Robinson, 2007), they are imprecise and there is always a latent risk of loss of valuable simulation data. To avoid these shortcomings, the robustness of the simulation tool (*Simulink®*) is used to determine the warm-up period in each simulation run accurately. Thus, within the framework of the flow diagram that simulates the behaviour of the *supply battalion* (Op_9), a *Boolean flag* is activated, i.e., it takes the value "true", when the first arrival of an order $Q = 5,000$ rations is verified. It is from this moment on that the output data of the simulation model is collected. This procedure ensures that the simulation data comes from a phase when the MFSC has reached a steady state.

6.8.3 Output data of the simulation model

Output data of the simulation model needed for calculating the measure of resilience (Re^T) and testing the research hypotheses are summarized in Table 6.25. The first column describes the configuration of the SC (Cf_i) with $i = 1…90$. The second column refers to the number of *j*-th order of combat ration packs on the simulation horizon, with $j = 1…6,000$. The third column (OPT_j) contains order-placement times for each order *j*. Similarly, the fourth column (OAT_j) contains order-arrival times for each order *j*. The fifth column (CT_j) indicates the time cycle for each order *j* (OAT_j minus OPT_j). The sixth column (LT_j) contains SC lead-times (fixed) for each order *j*. The seventh column (B_t) describes backorders accumulated for each period *t*. Likewise, the eighth column (U_t) describes unattended orders accumulated for each period *t*. The ninth, tenth, and eleventh columns represent the criteria formulated in Chapter 5, i.e., the autotomy period (AP_j), the recovery period (RP_j), and the disruption period (RP_j), respectively, for each

order j. Lastly, the twelfth column (R_{cr}) describes the type of risk r associated with the category of uncertainty c for each operation $Op_{k,j}$.

Table 6.25 Simulation output data by supply chain configuration, $Cf_{i=1\ldots90}$

Cf_i	j	OPT_j	OAT_j	CT_j	LT_j	$\sum B_t$	$\sum U_t$	AP_j	RP_j	DP_j	$R_{cr/Op}$
											R_{12}, none
											R_{13}, none
											R_{21}, none
											R_{22}, none
											R_{11}, R_{21}, R_3, none
$Cf_{1\ldots90}$	1	OPT_1	OAT_1	CT_1	LT_1	$\sum B_1$	$\sum U_1$	AP_1	RP_1	DP_1	R_{11}, R_{21}, R_3, none
											R_{14}, R_{21}, R_3, none
											R_{22}, none
											R_{21}, R_3, none
											R_{22}, none
											R_{23}, none
											R_{22}, none
											R_{24}, none
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	6,000	$OPT_{6,000}$	$OAT_{6,000}$	$CT_{6,000}$	$LT_{6,000}$	$\sum B_{6,000}$	$\sum U_{6,000}$	$AP_{6,000}$	$RP_{6,000}$	$DP_{6,000}$	R_{24}, none

6.9 Simulation Output Data

6.9.1 Simulation data matrix (SDM)

The purpose of the simulation model developed in this chapter is to provide the necessary data for calculation of the four sub-indicators that make up the measure of resilience (Re^T), as described in Figure 6.6. Each sub-indicator is calculated for each order j throughout a simulation horizon of up to 20 years. Hence, a total of ninety simulation runs were performed according to the experimental design proposed in Section 6.7 of this chapter. Each one of the ninety simulation runs describes a specific configuration of the MFSC ($Cf_{1\ldots90}$), as shown in the simulation data matrix (SDM) in Equation 6.4. In the SDM, each $Re^T(Cf_{1\ldots90})$ is a numerical univariate time series describing the measure of SCRes for MFSC. By way of example, Figure 6.7 shows the measure of SCRes for Cf_1, Cf_{47}, and Cf_{85} for $j = 1\ldots200$ graphically.

Figure 6.6 Data flow in the simulation model for MFSC
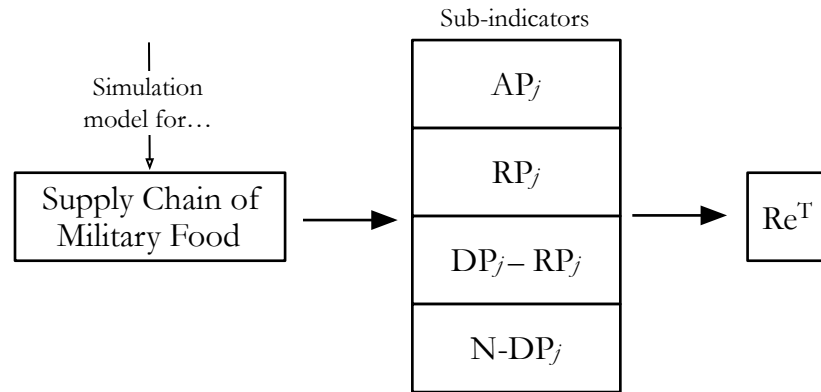
Figure 6.7 Measure of SCRes for Cf_1, Cf_{47}, and Cf_{85}
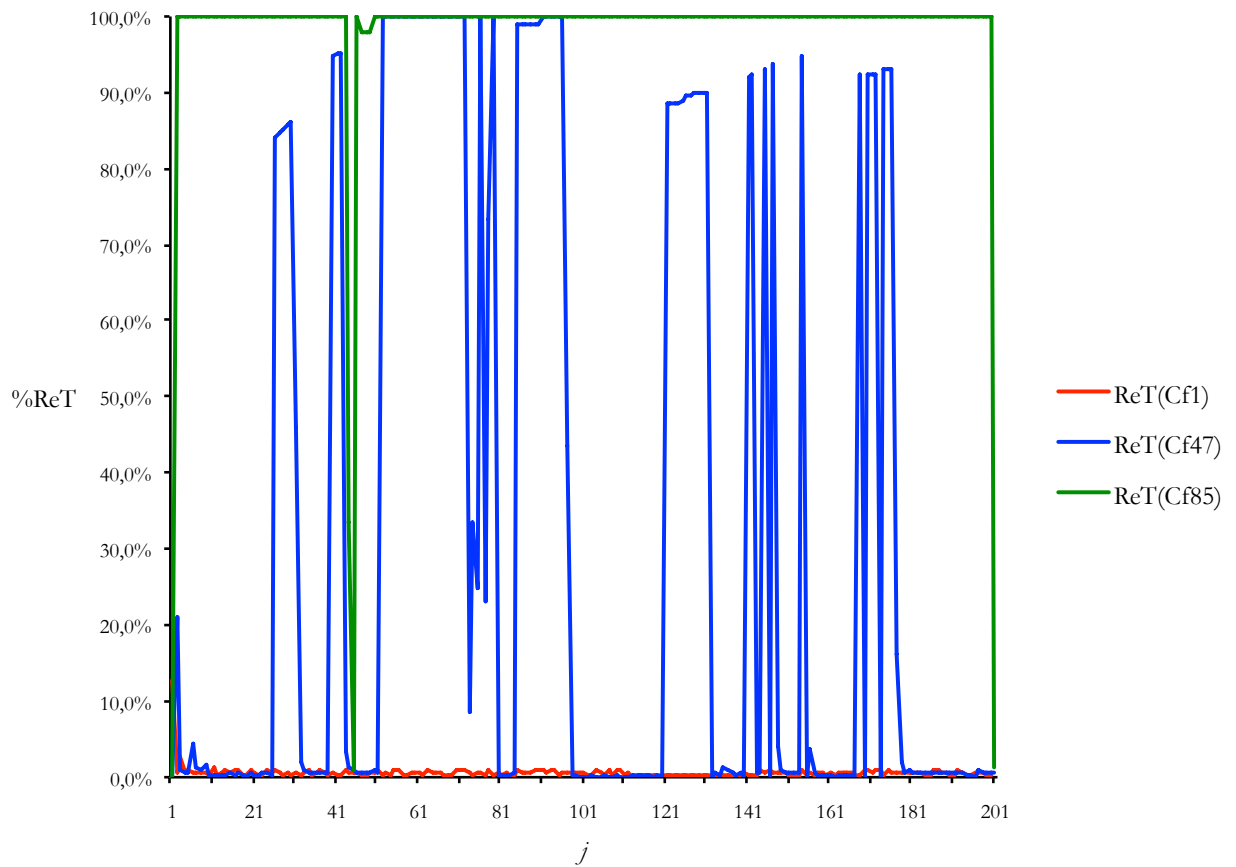
The first 10 simulation runs in Equation 6.4, or $Re^T(Cf_{1\ldots10})$, configure data sample 1 (DS_1) and underpin hypothesis 1a (H_{1a}). Similarly, data sample 2 (DS_2) is associated with hypothesis 1b (H_{1b}), data sample 3 (DS_3) with hypothesis 1c (H_{1c}), data sample 4 (DS_4) with hypothesis 2a (H_{2a}), data sample 5 (DS_5) with hypothesis 2b (H_{2b}), data sample 6 (DS_6) with hypothesis 2c (H_{2c}), data sample 7 (DS_7) with hypothesis 3a (H_{3a}), data sample 8 (DS_8) with hypothesis 3b (H_{3b}), and data sample 9 (DS_9) with hypothesis H3c (H_{3c}). It is worth noting that $DS_{1\ldots3}$ in the SDM include, in addition to $Re^T(Cf_{1\ldots30})$, the element R_{cr} or univariate time series denoting the frequency of occurrence of the three categories of risk. Lastly, the columns of the SDM represent the states 'initial configuration of the MFSC (Cf_0)', 'increased on-hand inventory buffers ($Cf_0 + I_{t,S}$)', and 'increased short-term manufacturing capacity ($Cf_0 + S$)'; the rows show the three categories of risk considered in this study (R_{1r}, R_{2r}, and R_3).

$$
SDM = \begin{pmatrix}
 & Cf_0 & Cf_0+I_{t,S} & Cf_0+S \\
R_{1r} & DS_1 = \begin{bmatrix} [R_{1r}, Re^T(Cf_1)] \\ \vdots \\ [R_{1r}, Re^T(Cf_{10})] \end{bmatrix} & DS_4 = \begin{bmatrix} Re^T(Cf_{31}) \\ \vdots \\ Re^T(Cf_{40}) \end{bmatrix} & DS_7 = \begin{bmatrix} Re^T(Cf_{61}) \\ \vdots \\ Re^T(Cf_{70}) \end{bmatrix} \\
R_{2r} & DS_2 = \begin{bmatrix} [R_{2r}, Re^T(Cf_{11})] \\ \vdots \\ [R_{2r}, Re^T(Cf_{20})] \end{bmatrix} & DS_5 = \begin{bmatrix} Re^T(Cf_{41}) \\ \vdots \\ Re^T(Cf_{50}) \end{bmatrix} & DS_8 = \begin{bmatrix} Re^T(Cf_{71}) \\ \vdots \\ Re^T(Cf_{80}) \end{bmatrix} \\
R_3 & DS_3 = \begin{bmatrix} [R_3, Re^T(Cf_{21})] \\ \vdots \\ [R_3, Re^T(Cf_{30})] \end{bmatrix} & DS_6 = \begin{bmatrix} Re^T(Cf_{51}) \\ \vdots \\ Re^T(Cf_{60}) \end{bmatrix} & DS_9 = \begin{bmatrix} Re^T(Cf_{81}) \\ \vdots \\ Re^T(Cf_{90}) \end{bmatrix}
\end{pmatrix} \tag{6.4}
$$

The DSs shown in Equation 6.4 share another common feature. To obtain the $DS_{1\ldots3}$, 30 different seeds were used, one for each $Re^T(Cf_{1\ldots30})$. These same seeds were 're-used' to obtain $DS_{4\ldots6}$ and $DS_{7\ldots9}$. For example, the seed used for $Re^T(Cf_7)$ is the same for $Re^T(Cf_{37})$ and $Re^T(Cf_{67})$. This commonality allows comparison of MFSC performance under identical conditions of risk, though using different configurations or parameters. This property of simulation-based models is key for 'isolating the underlying cause' that produces variations in the MFSC, particularly for testing the set of hypotheses H_2 and H_3 of this study. Law (2015) called this property of simulation models *comparison of system configurations*.

6.9.2 Assessing normality of SDM

Before performing subsequent statistical analysis, it is necessary to determine whether the main output variable of the simulation model, or $Re^T(Cf_i)$, follows a normal distribution. As known, if statistical analyses are applied to data that do not fit the normality assumption, the results of the analysis may be biased (Kennedy & Bush, 1985). Therefore, three standard statistical criteria are applied to the first thirty $Re^T(Cf_i)$ series contained in $DS_{1\ldots3}$ of SDM: (1) *Histogram*, (2) *Q-Q plot*, and, (3) *Kolmogorov-Smirnov* and *Shapiro-Wilk* tests. For the remaining data samples ($DS_{4\ldots9}$), it is plausible to assume monotonic results since each $Re^T(Cf_{31\ldots90})$ series was run with the same seed per row, as explained in the previous section.

By way of example, Figure 6.8 shows histogram and Q-Q plot for $Re^T(Cf_1)$. One observes in Figure 6.8a that the data do not fit the theoretical quartile of a normal distribution. Similarly, in Figure 6.8b, if the series were normal, the quartiles observed would be similar to the kernel (straight line)—another indication that the data do not come from a normal distribution. Similar results were obtained for the remaining DSs. Hence, the Kolmogorov-Smirnov (KS) and Shapiro-Wilk (SW) tests were applied to confirm or deny this result. Thus, the null and alternative hypotheses can be posited as:

H_0:   'Data follow a normal distribution'

H_a: 'Data do not follow a normal distribution'

Table 6.26 Test of normality for $Re^T(Cf_1)$

Kolmogorov-Smirnov*			Shapiro-Wilk		
KS	df	p-value	SW	df	p-value
0.429	4,241	0.000	0.054	4,241	0.000

* Lilliefors significance correction

Figure 6.8 Histogram and Normal Q-Q plot for $Re^T(Cf_1)$

(a)   (b)
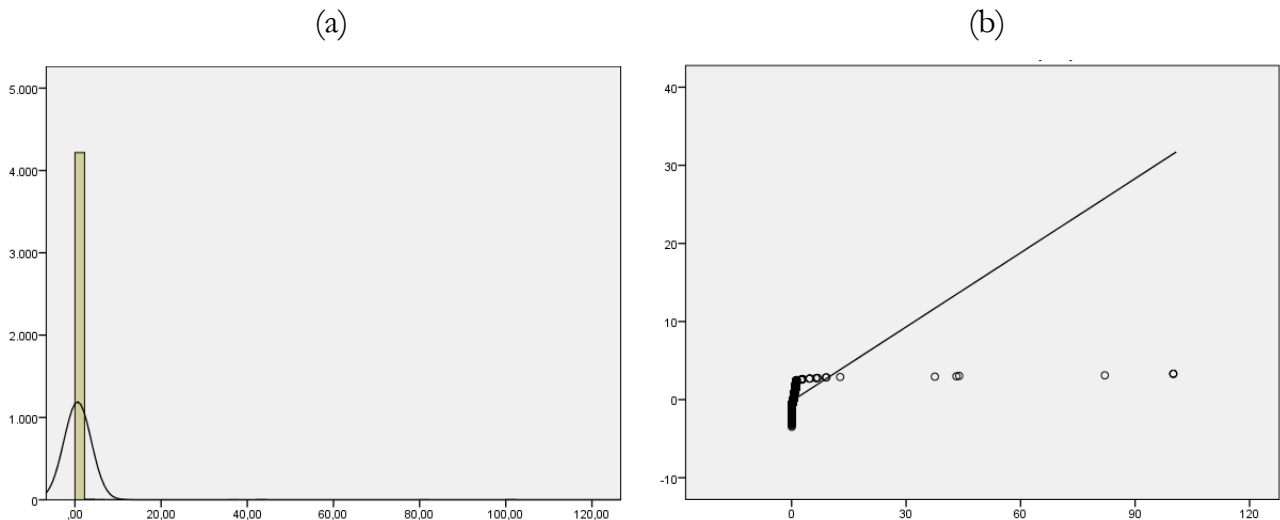
The results of both statistics tests are shown in Table 6.26. Thus, since the p-value for the observed KS = 0.429 and SW = 0.054 are both lower than 2.2×10^{-16} with 4,241 degrees of freedom (df) and a level of significance $\alpha = 0.01$, therefore H_0 can be rejected with 99% confidence, i.e., $Re^T(Cf_1)$ do not follow a normal distribution. The same analysis is replied to the remaining 29 univariate time series, as shown is Table 6.27. In all cases, results are equivalent to $Re^T(Cf_1)$; namely, $Re^T(Cf_{2...30})$ do not follow a normal distribution. The blank spaces in $Re^T(Cf_{21...30})$ for the SW-test cannot be calculated because the data series are saturated and there

are not enough degrees of freedom per error; in other words, the nature of the simulated risk (R_3) produces relatively few impacts on SCRes compared to the total number of instances. However, the KS-test provides sufficient evidence itself to confirm that the data examined is non-normal.

Table 6.27 Test of normality for $Re^T(Cf_{2\ldots30})$

	Kolmogorov-Smirnov*			Shapiro-Wilk		
	KS	df	p-value	SW	df	p-value
$Re^T(Cf_2)$	0.429	4,420	0.000	0.045	4,420	0.000
$Re^T(Cf_3)$	0.439	2,151	0.000	0.057	2,151	0.000
$Re^T(Cf_4)$	0.410	2,186	0.000	0.051	2,186	0.000
$Re^T(Cf_5)$	0.436	2,279	0.000	0.051	2,279	0.000
$Re^T(Cf_6)$	0.432	2,061	0.000	0.045	2,061	0.000
$Re^T(Cf_7)$	0.427	2,115	0.000	0.056	2,115	0.000
$Re^T(Cf_8)$	0.456	2,278	0.000	0.053	2,278	0.000
$Re^T(Cf_9)$	0.367	2,061	0.000	0.110	2,061	0.000
$Re^T(Cf_{10})$	0.433	2,061	0.000	0.046	2,061	0.000
$Re^T(Cf_{11})$	0.438	2,165	0.000	0.531	2,165	0.000
$Re^T(Cf_{12})$	0.454	2,186	0.000	0.030	2,186	0.000
$Re^T(Cf_{13})$	0.459	1,956	0.000	0.486	1,956	0.000
$Re^T(Cf_{14})$	0.410	2,186	0.000	0.051	2,186	0.000
$Re^T(Cf_{15})$	0.437	2,203	0.000	0.527	2,186	0.000
$Re^T(Cf_{16})$	0.417	2,218	0.000	0.550	2,218	0.000
$Re^T(Cf_{17})$	0.448	2,227	0.000	0.521	2,227	0.000
$Re^T(Cf_{18})$	0.410	2,277	0.000	0.599	2,277	0.000
$Re^T(Cf_{19})$	0.459	2,120	0.000	0.473	2,120	0.000
$Re^T(Cf_{20})$	0.474	2,168	0.000	0.051	2,168	0.000
$Re^T(Cf_{21})$	0.487	5,709	0.000	n.d.	n.d.	n.d.
$Re^T(Cf_{22})$	0.491	5,695	0.000	n.d.	n.d.	n.d.
$Re^T(Cf_{23})$	0.461	5,697	0.000	n.d.	n.d.	n.d.
$Re^T(Cf_{24})$	0.476	5,689	0.000	n.d.	n.d.	n.d.
$Re^T(Cf_{25})$	0.483	5,698	0.000	n.d.	n.d.	n.d.
$Re^T(Cf_{26})$	0.482	5,710	0.000	n.d.	n.d.	n.d.
$Re^T(Cf_{27})$	0.472	5,710	0.000	n.d.	n.d.	n.d.
$Re^T(Cf_{28})$	0.471	5,709	0.000	n.d.	n.d.	n.d.
$Re^T(Cf_{29})$	0.456	5,698	0.000	n.d.	n.d.	n.d.
$Re^T(Cf_{30})$	0.485	5,710	0.000	n.d.	n.d.	n.d.

* Lilliefors significance correction
n.d.: not defined

6.10 Case Study Survey Research (CSSR)

Compared to the previous works analysed in Section 2.2 or *Topical Research and Gaps*—which are mainly based on the use of a single methodology for gathering data—, the implications of the findings of this research have to a certain extent greater scientific validity, since the

methodological shortcomings attributed to discrete simulation models—discussed in Section 4.2—are alleviated by the inclusion of a *case study survey research* or CSSR (Chmiliar, 2010). By virtue of the above, the present research can be catalogued as a *mixed study*, i.e. the combination of positivist and interpretative approaches (Johnson et al., 2007). Figure 6.9 describes the integration of both methodologies for the collection of data.

Figure 6.9 Research design for the collection of data
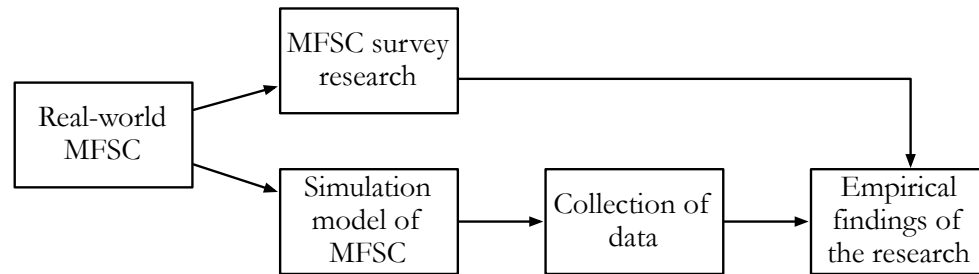
6.10.1 Purpose of the CSSR

Before proceeding further, it is convenient to clarify the specific role that the CSSR plays in this research. The CSSR herein applied is an open-ended questionnaire of eleven questions via paper-and-pencil, administered only to the staff of MFSC under study in a single session, to examine their individual beliefs or preferences regarding 'what is the most effective way to prevent the occurrence of disruptions into the MFSC.' Thereby, CSSR is intended to be used as a *supplement* to the output data of simulation model by adding a more realistic perspective, rather than to explain the relationships of the variables considered in the conceptual framework in Chapter 3. Information from the CSSR allows having a more holistic view of the research problem by directly contrasting the results of the simulation model with real data. In this sense, Chmiliar (2010) pointed out that although a CSSR can be used for describing how the answers respondents distribute and relate regarding the questionnaire-answer options, it cannot explain the cause-and-effect relationship among them.

6.10.2 Validity, sample size, and administering of the CSSR

Chmiliar (Ibid, 2010) underlined that the validity of a CSSR is contingent to the honesty degree and willingness to participate of respondents. For this reason, the validation process of the questionnaire consisted of two main parts. Firstly, the initial versions of the questionnaire were drafted and discussed with the CEO of the MFSC and his team of advisors. This process of internal validation of the questionnaire took no less than three weeks and was definite not only to ensure its suitability, but also to allow the selected staff members could answer it without fear of reprisal or prejudice. Secondly, from these meetings, several suggestions were incorporated and, as result, a first completed version of the questionnaire was sent to the Biomedical and Scientific Research Ethics Committee of the University of Warwick (BSREC) to be reviewed. The BSREC follows a strict protocol established for these cases. Thus, substantial queries about

different aspects of the study and related documentation were raised by the BSREC. After this new round of queries and issues, a second completed version of the questionnaire was sent back to the BSREC. Counting from when the first questionnaire was designed, to fully approved by the BSREC (REGO-2017-1919) and administered to MFSC staff members, the whole process required a period of eight months.

Regarding the size of the sample, the questionnaire was administered to a group of twelve people from a total of sixteen that make up the staff of the MFSC under study, which represents a very significant sample size close to 70% of the total population, though the selection of the respondents was the responsibility of the MFSC's CEO. Lastly, it should be noted that the application of the questionnaire was preceded by the presentation of the scope and objectives of the research to the group of interest, and each of the eleven questions was carefully explained to avoid misinterpretations among respondents.

6.10.3 Results of the CSSR

The questionnaire in discussion is detailed in Annex C and consists of eleven questions in total, as is explained in Figure 6.10. The first two are contextual questions, and the remaining nine are questions related to the risk events considered in the simulation analysis. Within these 'hypothetical scenarios', respondents were asked to indicate what alternative they would consider the most effective for preventing the occurrence of disruptions in the MFSC (vignette). The response options available were a choice between 'to increase the on-hand inventory buffers along different locations of the MFSC', or, alternatively, 'to increase the number of working-shifts per day'.

Figure 6.10 Questionnary design
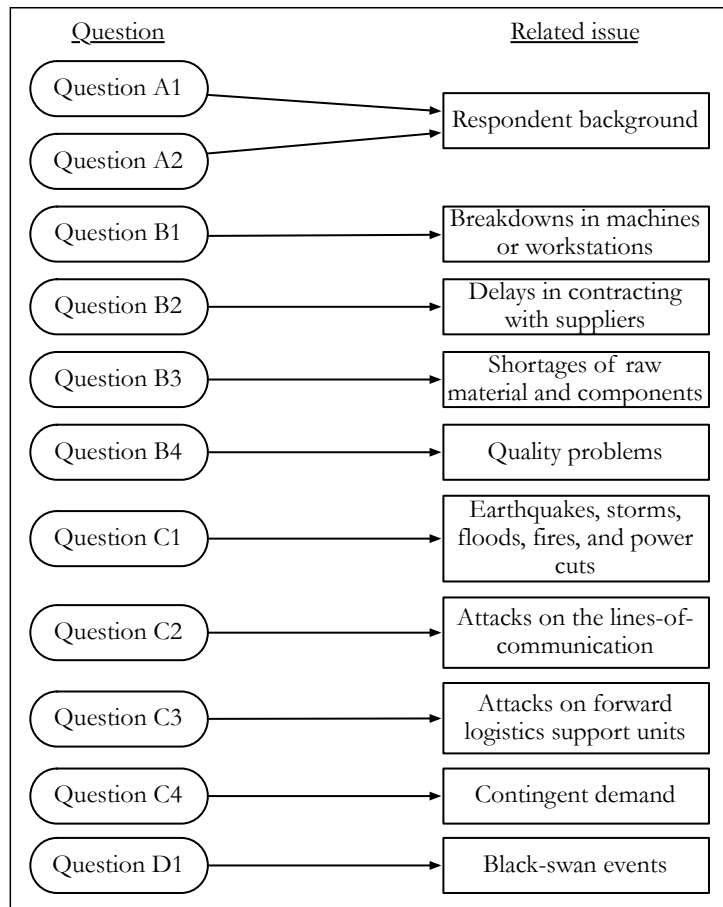
The use of hypothetical scenarios to elicit information about beliefs, intentions, or attitudes from participants regarding a particular phenomenon is part of what is called *experimental vignette studies* (Atzmüller & Steiner, 2010). Aguinis and Bradley (2014) argued in this sense that this experimental approach is appropriate for contrasting causal inferences derived from quantitative methods in which the researcher can manipulate and control independent variables. In this same sense, the reason of using this approach in the questionnaire was to measure in practice what the MFSC staff would do if they faced risk events as described in each question. Although the questions raised implicitly suggest a relation of causality between the implementation of the two practices mentioned (inventory and capacity) and a reduction of disruptions in the MFSC, they only serve to contrast the results of the simulation model in the terms mentioned. The results of the questionnaire are summarized in Table 6.28.

Table 6.28 Questionnaire data matrix (QDM)

Inquiry of questionnaire (risk considered) — Respondent	B1 (R_{11})		B2 (R_{12})		B3 (R_{13})		B4 (R_{14})		C1 (R_{21})		C2 (R_{22})		C3 (R_{23})		C4 (R_{24})		D1 (R_3)	
	$I_{t,S}$	S	$I_{t,S}$	S	$I_{t,S}$	S	$I_{t,S}$	S	$I_{t,S}$	S	$I_{t,S}$	S	$I_{t,S}$	S	$I_{t,S}$	S	$I_{t,S}$	S
1. Chief Executive Officer		•	•			•	•			•	•		•		•			•
2. Distribution Manager	•		•		•		•		•		•		•			•	•	
3. Business Manager	•			•	•			•	•		•		•			•	•	
4. Operations Manager 1	•		•		•		•		•		•		•		•		•	
5. Operations Manager 2	•		•		•		•		•		•			•	•			•
6. Senior Engineer 1		•	•		•			•		•	•		•			•	•	
7. Senior Engineer 2	•		•		•		•		•		•		•		•		•	
8. Senior Engineer 3		•	•			•	•		•		•		•			•		•
9. Industrial Engineer 1		•		•	•			•		•	•		•			•	•	
10. Industrial Engineer 2	•		•		•		•		•			•	•			•		•
11. Industrial Engineer 3	•			•	•			•		•	•		•			•	•	
12. Industrial Engineer 4	•			•		•	•			•	•		•			•	•	
Total answers	8	4	8	4	9	3	8	4	7	5	11	1	11	1	4	8	8	4
%	67	33	67	33	75	25	67	33	58	42	92	8	92	8	33	67	67	33

The results of the questionnaire data matrix (QDM) in Table 6.28 point to a clear preference—with the single exception of question C4 for R_{24} or contingent orders—for the use of on-hand inventory buffers ($I_{t,S}$) instead of short-term manufacturing capacity (S). Of the total of respondents' answers (108), 74 of them favour using on-hand inventory buffers (68.5%) over short-term manufacturing capacity (31.5%). This perspective about 'what SC managers would do for preventing the occurrence of disruptions' serves as a baseline for the output data of the simulation model, and will be discussed in detail in the following chapter.

6.11 Summary of Chapter 6

This chapter is the backbone of the research of this thesis. It provides the output data of the simulation model required to calculate the measure of resilience (Re^T) and to test the three sets of research hypotheses, but also how Re^T was calculated. To this end, by applying well-known procedures for non-terminal simulation, it described and developed a thorough simulation model for the supply chain of military food (MFSC) by using Simulink® tool by MATLAB. The development of the simulation model required an in-depth characterization of the MFSC subject of study, including the identification of raw materials used, the determination of effective and theoretical assembly capacity, the operations needed for the assembly of combat rations, and a description of patterns of demand. Second, it identified and characterized the three categories of risk that might affect the MFSC. Third, it specified the assumptions utilised for the simulation model of the MFSC, as well as mechanisms for its verification and validation. Fourth, it designed an efficient simulation experiment for three scenarios of simulation, one for each set of research hypotheses. Fifth, it described the output data of the simulation model. Sixth, it explained how Re^T was calculated from output data of the simulation model (four sub-

indicators). Graphical descriptions of Re^T were also provided. Seventh, it detailed the relationship between the samples of data of the SDM and the research hypotheses. Eighth, it corroborated with several statistical tests the non-normality of Re^T, which implies that non-parametric tests should be conducted for further analyses. Lastly, it explained the protocol through which an open-ended questionnaire was administered to the staff of the MFSC. Finally, the consolidated results of the questionnaire were presented and analysed. In the following chapter, the output data from the simulation model will be used for testing the nine hypotheses of research, and outcomes from the questionnaire, to contrast the previous results.

Chapter 7
DISCUSSION OF RESULTS OF
SIMULATION MODEL AND
QUESTIONNAIRE

Chapter 7. Discussion of Results of Simulation Model and Questionnaire

7.1 Introduction

This chapter is closely integrated with Chapter 3—Hypotheses Development and Conceptual Framework—and Chapter 6—Simulation Model Output Data and Questionnaire—of this study and comprises three main sections. The first section relates to the testing of the set of hypotheses 1 (H_1) and includes the extraction of the rules of association between the categories of risk (R_{cr}) and the measure of SCRes (Re^T), as well as the determination of causality between them. The second section relates to the testing whether 'increases in on-hand inventory buffers (I_t,S) moderate the relationship between R_{cr} and Re^{T}' or the second set of hypotheses (H_2). Lastly, the third section relates to the testing whether 'increases in short-term manufacturing capacity (S) moderate the relationship between R_{cr} and Re^{T}' or the third set of hypotheses (H_2). The two previous sections are based on Mill's method of concomitant variation, the conjoint application of the Kruskal-Wallis rank sum test and Wilcoxon rank sum test with continuity correction, and the Binomial distribution test.

7.2 Examining the Direct Effect of Increases in the Frequency of Occurrence of Risks (R_{cr}) on the Measure of Resilience in Supply Chains (Re^T): Hypotheses H_{1a}, H_{1b}, and H_{1c}

Section 7.2 sets up the link between risk and resilience, which was raised through the set of hypotheses 1 (H_{1abc}) in Chapter 3. For this purpose, the first subsection establishes the *degree of association* between the three categories of risk considered in the analysis (R_{cr}) and the proposed resilience measure (Re^T). The second subsection establishes the *degree of causality* between R_{cr} and Re^T, based on the analysis of the previous subsection.

7.2.1 Extracting rules of association between R_{cr} and Re^T

The set of hypotheses 1 (H_1) raised in Chapter 3 of this research indicates in general that, 'ceteris paribus, increases in the frequency of occurrence of risks (R_{cr}) reduce the measure of resilience in supply chains (Re^T).' In this hypothetical relationship, R_{cr} represent the *predictor variables*, and Re^T, the *response variable*, together configuring a *frequent item set* (Borgelt, 2012). Testing this relationship is necessary condition for examining the set of hypotheses H_2 and H_3 since in the proposed simulation model the occurrence of risks is the only possible cause of disruptions in the MFSC under analysis. For this purpose, in Equation 6.4, the $DS_{1...3}$ were examined independently. Thus, for example, the analysis of the element 'R_{1r}, Re^T (Cf_1)' that belongs to DS_1 is a tuple of 5 variables (columns) and 4,240 instances (rows). Four of these variables describe the frequency of occurrence of operational risks and their respective location in the MFSC (R_{11} in Op_5, R_{11} in Op_6, R_{12} in Op_1, and R_{14} in Op_7); the fifth variable describes the numerical value of Re^T for Cf_1. The remaining 29 elements that make up column 1 of the simulation data matrix are organized in tuples in an equivalent way. It is important to note that

by 'frequency of occurrence of risk' in this context is meant the probability distribution that governs the relation between the available information and the decision process (Heckman et al., 2015).

The methodology selected to analyse such a volume of data is *association rule mining* or ARM (Agrawal et al., 1993; Agrawal et al., 1996). ARM is considered one of the most well-studied techniques in data mining (Witten et al., 2017), as well as an area of growing interest in LSCM given its demonstrated efficacy for the analysis of large datasets (Chen et al., 2005; Jain et al., 2007; Vinodh et al., 2011). ARM is selected to capture relations of the form 'when variable X adopts value $\bar{x}$ then variable Y adopts value $\bar{y}$', symbolically '$X = \bar{x} \Rightarrow Y = \bar{y}$', with both X and Y being a frequent item set. The application of ARM requires three conditions: (1) X and Y must be non-empty sets, (2) any variable must appears at least once in X and Y, and (3) Y must be a categorical variable (van der Aalst, 2016).

Thus, taking into consideration the mentioned conditions, two algorithms in language R (see Annexes D and E) were elaborated to be applied on $DS_{1...3}$. The first algorithm was used to categorize R_{cr} and Re^T, as shown in Equation 7.1; and the second algorithm, to extract the interesting association rules based on a 'minimum support' or *minsup* and a 'minimum confidence' or *minconf*. The application of this approach is a condition necessary 'to prune' the large number of association rules that are obtained by utilising *a priori* algorithms (Agrawal & Srikant, 1994; Tan et al., 2004).

$$R_{cr} = \begin{cases} R_{cr} = 0 & \underline{N}\text{on-occurrence} \\ R_{cr} = 1 & \underline{O}\text{ccurrence} \\ R_{cr} > 1 & \underline{F}\text{requent occurrence} \end{cases} \qquad Re^T = \begin{cases} 0.0 \le Re^T \le 0.3 & \underline{L}\text{ow} \\ 0.3 < Re^T \le 0.5 & \underline{M}\text{edium} \\ 0.5 < Re^T \le 1.0 & \underline{H}\text{igh} \end{cases} \qquad (7.1)$$

Thereby, considering the categorization proposed in Equation 7.1, 'support' and 'confident' measures are defined as

$$supp(R_{cr} = \text{'O'} \vee \text{'F'} \Rightarrow Re^T = \text{'L'}) = P(R_{cr} = \text{'O'} \vee \text{'F'} \cup Re^T = \text{'L'}) \qquad (7.2)$$

$$conf(R_{cr} = \text{'O'} \vee \text{'F'} \Rightarrow Re^T = \text{'L'}) = P(Re^T = \text{'L'} \,|\, R_{cr} = \text{'O'} \vee \text{'F'}) \qquad (7.3)$$

The values selected for Equations 7.2 and 7.3 were a *minsup* ≥ 0.1 and a *minconf* ≥ 0.9. *Minsup*'s value represents the percentage of transactions from $D_{1...3}$ that contains both 'R_{cr} = O or F' and 'Re^T = L'; while *minconf*'s value is the conditional probability that a transaction from $D_{1...3}$ that contains 'R_{cr} = O or F' also contains 'Re^T = L'. In this way, the result of applying the *a-priori* algorithm on $D_{1...3}$ with the mentioned values of minsup and minconf allowed the extraction of 755 association rules or *strong rules* (Lenca et al., 2008). Bearing in mind that the total number of risks occurring by operation in the MFSC is equal to 20, 755 strong rules still represent a large number of data to be analysed. Therefore, as Bayardo and colleagues (2000) suggested, the 755 strong rules are filtered out by applying a criterion of redundancy. These authors pointed out that an association rule could be considered redundant if other association rules with the same

or a higher confidence value also exist. Applying this criterion to the above analysis, the rule 'R_{cr} = O or F $\Rightarrow Re^T$ = L' is *redundant* if

$$conf(R^{\bullet}_{cr} = \text{'O'} \vee \text{'F'} \Rightarrow Re^T = \text{'L'}) \geq conf(R_{cr} = \text{'O'} \vee \text{'F'} \Rightarrow Re^T = \text{'L'}) \qquad (7.4)$$

The result of applying the criterion of redundancy described in Equation 7.4 considerably reduced the number of strong rules, from 755 to 79. Thereafter, the association rules of this sub-set with any $R_{cr} = 0$ (N) were discarded. Thereby, the final selection of association rules for $DS_{1\ldots3}$ and their measures of interestingness is shown in Table 7.1.

Table 7.1 Interesting association rules of the form $R_{cr}=$'O' $\vee$ 'F'$=>Re^T(Cf_i)=$'L' extracted from $DS_{1\ldots3}$

#	Cf_i	Association rules	Supp	Conf	Lift[*]
2	5	R_{11_2}=F, R_{13}=O=> Re^T=L	0.11	1.00	2.98
5	9	R_{11_2}=F, R_{14}=F=> Re^T=L	0.23	0.98	2.60
6	9	R_{11_1}=F, R_{14}=F=> Re^T=L	0.24	0.98	2.60
1	13	R_{22_4}=O, R_{24}=F=> Re^T=L	0.11	1.00	2.36
3	13	R_{22_1}=O, R_{24}=F=> Re^T=L	0.13	1.00	2.37
4	13	R_{22_3}=O, R_{24}=F=> Re^T=L	0.14	1.00	2.37
5	13	R_{24}=F=>Re^T=L=> Re^T=L	0.27	0.98	2.33
1	15	R_{23}=O, R_{24}=F=> Re^T=L	0.11	1.00	2.52
2	15	R_{22_2}=O, R_{24}=F=> Re^T=L	0.12	0.99	2.51
1	27	R_{3_2}=O=> Re^T=L	0.10	0.96	9.15
2	27	R_{3_3}=O=> Re^T=L	0.10	0.96	9.15
3	27	R_{3_4}=O=> Re^T=L	0.10	0.96	9.15
4	27	R_{3_1}=O=> Re^T=L	0.10	0.96	9.15

*Lift = Supp/$P(R_{cr} =$'O' $\vee$ 'F')$P(Re^T=$'L')

7.2.2 Determining causality for interestingness rules of association between R_{cr} and Re^T

The confirmation of the set of hypotheses H_1 is a condition necessary but not sufficient to prove the interaction effect of on-hand inventory buffers (set of hypotheses H_2) and/or short-term manufacturing capacity (set of hypotheses H_3) that make up the conceptual framework of this research. Thus, once the set of thirteen interesting association rules described in Table 7.1 have been mined from $DS_{1\ldots3}$, the following step is to establish their relation of causality if any. In this regard, Houtsma and Swami (1995) pointed out that rules of association of the form '$X = \bar{x} \Rightarrow Y = \bar{y}$'—as described in Table 7.1—do not imply a causal relationship per se. Accordingly, three criteria were applied: (1) Chi-squared test or χ^2, (2) Phi-coefficient or φ, and (3) Causal rule based on odds-ratio (ω).

Chi-squared test (χ^2) and *Phi coefficient* (φ)

Regarding the first two criteria, χ^2 is used as a measure of the *significance* of the association between R_{cr} and Re^T; and φ, as a measure of their *degree* of association (Fleiss et al., 2003). It is noteworthy that neither χ^2 nor φ are decisive statistical criteria of the purported causal relationship between R_{cr} and Re^T, though a high level of significance or degree of association of these variables supports this proposition. Thus, based on Fleiss and colleagues (2003) and Álvarez (2003), the general form of the contingency table is described in Table 7.2, and the formulas for χ^2 and φ are described in Equations 7.5 and 7.6, respectively:

Table 7.2 The 2×2 contingency table for association rules of the form R_{cr}='O' ∨ 'F'=>$Re^T(Cf_i)$='L'

R_{cr}= 'O' ∨ 'F'	$Re^T(Cf_j) = $'L'		Total
	1	0	
1	n_{11}	n_{10}	$n_{1.}$
0	n_{01}	n_{00}	$n_{0.}$
Total	$n_{.1}$	$n_{.0}$	$n_{..}$

$$\chi^2 = n_{..}(\text{lift} - 1)^2 \frac{\text{supp} * \text{conf}}{(\text{conf} - \text{supp})(\text{lift} - \text{conf})} \tag{7.5}$$

and

$$\varphi = \sqrt{\frac{\chi^2}{n_{..}}} \tag{7.6}$$

With the above elements, null and alternative tests of hypothesis of the level of significance and degree of association for rules described in Table 7.1 are formulated as follows:

H_0: 'R_{cr} and Re^T are *not* related/associated or they are independent variables of each other.'

H_a: 'R_{cr} and Re^T are related/associated or they are dependent variables of each other.'

In this manner, as general rule, if the *p*-values of χ^2 or φ obtained from Equation 7.5 or 7.6 are lower than a specific level of significance, the inference is made that R_{cr} and Re^T are associated/related of each other; otherwise, the null hypothesis cannot be rejected. Fleiss and colleagues (2003) suggested that φ values above 0.35 point to a positive association of the variables considered.

Causal rule based on odds-ratio (ω)

Regarding the third criterion, Li and colleagues (2013, 2015) proposed using the values of the contingency table to estimate the lower (ω_-) and the upper (ω_+) confidence intervals of the odds ratio for rules of association of the form '$X = \bar{x} \Rightarrow Y = \bar{y}$', as is described in Table 7.2, and Equations 7.7, 7.8 and 7.9. The odds-ratio is defined as

$$\omega = \frac{n_{11}n_{00}}{n_{01}n_{10}}, \tag{7.7}$$

the lower confidence interval is defined as

$$\omega_- = exp\left(\ln \omega - z' \sqrt{\frac{1}{n_{11}} + \frac{1}{n_{10}} + \frac{1}{n_{01}} + \frac{1}{n_{00}}} \right), \tag{7.8}$$

and the upper confidence interval is defined as

$$\omega_+ = exp\left(\ln \omega + z' \sqrt{\frac{1}{n_{11}} + \frac{1}{n_{10}} + \frac{1}{n_{01}} + \frac{1}{n_{00}}} \right), \tag{7.9}$$

where z' corresponds to the tabulated value of the standard Normal distribution chosen according to the desired confidence level for the critical region. Formally, the hypotheses testing can be written as:

H$_0$:   'R_{cr} is not the cause of Re^T'

H$_a$:   'R_{cr} is the cause of Re^T'

In this way, the rule of decision is given by 'if ω_- is higher than 1, the value of ω is significantly higher than 1, and therefore it can be inferred that R_{cr} is the cause of Re^T, or, in other words, H$_0$ is rejected.'

Results of the statistical hypothesis tests

Table 7.3 summarizes the interestingness measures for χ^2, φ, and ω, as well as the values of contingency tables required to calculate the observed values of ω_- and ω_+. By way of example, from data in Table 7.3, the rule of association # 1 of the configuration 13—'when risk R$_{22}$ *occurs at least one time* or risk R$_{24}$ *occurs frequently*, the level of Re^T is low'—is examined through the Chi-square test, the Phi-coefficient, and the Causal rule based on odds-ratio, respectively. Since the p-value for the observed value of χ^2 = 329.53 obtained from Equation 7.5 and one degree of freedom (df = 1) is lower than a significance level of 2.2×10^{-16}, there are sufficient arguments to

reject H_0; thereby the inference is made that R_{22} or R_{24} and Re^T are related/associated with each other. Equivalently, since the *p*-value for the observed value of $\varphi = 0.40$ obtained from Equation 7.6 is higher than the chosen reference value (0.35), there are sufficient arguments to reject H_0; thereby the inference is made that a positive association between R_{22} or R_{24} and Re^T exists. Lastly, since the observed value for $\omega_- = 52.72$ obtained from Equation 7.8 is higher than 1 and the value of $\omega = 377$ is significantly higher than 1, there are sufficient arguments to reject H_0; thereby the inference is made that increases in the frequency of R_{22} or R_{24} reduce the level of Re^T. By and large, given that the observed values for $\chi^2 = 329.53$, $\varphi = 0.40$, and $\omega_- = 52.72$ are the lowest ones for χ^2, φ, and ω_- in Table 7.3, and that larger values of χ^2, φ, and ω_- provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining twelve rules of association are also rejected.

Table 7.3 Interestingness measures, contingency tables, and odds-ratio confidence intervals for interesting association rules[*]

#	Cf_i	R_{cr}='O' ∨ 'F'=>$Re^T(Cf_i)$='L'	Interestingness measures			Contingency tables				Confidence intervals	
			χ^2	φ	ω	n_{11}	n_{10}	n_{01}	n_{00}	ω_-	ω_+
2	5	R_{11_2}=F, R_{13}=O=>Re^T=L	576.92	0.50	772.47	258	1	506	1,515	108.11	5,519.07
5	9	R_{11_2}=F, R_{14}=F=>Re^T=L	959.79	0.68	192.69	467	10	309	1,275	101.74	364.93
6	9	R_{11_1}=F, R_{14}=F=>Re^T=L	1014.55	0.70	196.25	488	11	288	1,274	106.51	361.58
1	13	R_{22_4}=O, R_{24}=F=>Re^T=L	<u>329.53</u>	<u>0.40</u>	377.00	206	1	618	1,131	<u>52.72</u>	2,695.77
3	13	R_{22_1}=O, R_{24}=F=>Re^T=L	401.02	0.45	504.44	254	1	570	1,132	70.59	3,604.26
4	13	R_{22_3}=O, R_{24}=F=>Re^T=L	426.68	0.47	551.21	270	1	554	1,131	77.15	3,937.76
5	13	R_{24}=F=>Re^T=L	962.80	0.70	203.34	531	10	293	1,122	107.35	385.12
1	15	R_{23}=O, R_{24}=F=>Re^T=L	397.08	0.44	531.09	248	1	622	1,332	74.34	3,794.00
2	15	R_{22_2}=O, R_{24}=F=>Re^T=L	438.30	0.45	279.01	257	2	613	1,331	69.17	1,125.34
1	27	R_{3_2}=O=>Re^T=L	5,444.25	0.98	116,978.00	598	26	1	5,086	15,844.98	863,608.04
2	27	R_{3_3}=O=>Re^T=L	5,444.25	0.98	116,978.00	598	26	1	5,086	15,844.98	863,608.04
3	27	R_{3_4}=O=>Re^T=L	5,444.25	0.98	116,978.00	598	26	1	5,086	15,844.98	863,608.04
4	27	R_{3_1}=O=>Re^T=L	5,444.25	0.98	116,978.00	598	26	1	5,086	15,844.98	863,608.04

[*] Zero values in contingency tables were replaced by 1 to avoid infinite ω as Li et al (2015) indicated.

The above results mostly confirm hypotheses H_{1a}, H_{1b}, and H_{1c}. As derived from the rules of association shown in Table 7.1, not all types of risk initially considered as 'potentially disruptive' were included—e.g. see Tables 6.6a-b-c and 6.7a-b-c. For example, for the categories of risk R_{1r} and R_{2r}, increases in the frequency of occurrence of risk R_{12}—'delays in contracting with suppliers'—and R_{21}—'earthquakes, storms, floods, fires and power cuts'—turned out not to be associated with reductions in Re^T. Although it cannot be ruled out that in the simulation model the occurrence of such types of risk do not disrupt the MFSC under study, the most plausible explanation for this 'counter-intuitive' result seems to be related to the use of 'minsup-minconf's approach' for the extraction of the 'strong rules'. In this regard, it is known that during the process of pruning several interesting association rules may not be included (Brijs & Vanhoof, 2003), which inevitably leads to a loss of valuable information. Hence, despite this result, the sample of the thirteen causal association rules described in Table 7.1 still provides

sufficient basis for testing the sets of hypothesis H_2 and H_3, as described in the following section.

7.3 Examining the Moderating Effect of On-Hand Inventory Buffers ($I_{i,s}$) in the Relationship between the Frequency of Occurrence of Three Categories of Risks (R_{cr}) and the Measure of Resilience in Supply Chains (Re^T): Hypotheses H_{2a}, H_{2b}, and H_{2c}

Testing of hypotheses H_{2a}, H_{2b}, and H_{2c} is based on the comparison of levels of $Re^T(Cf_i)$ in datasets DS_4, DS_5, and DS6 with respect to datasets DS_1, DS_2, and DS_3, as is pointed out in Equation 6.4. The reasoning here employed is grounded on *Mill's method of concomitant variation* or MCV (2012). In this respect, Mill stated "Whatever phenomenon varies in any manner whenever another phenomenon varies in some particular manner, is either a cause or an effect of that phenomenon, or is connected with it through some fact of causation." (p.387). Mill's ideas are the basis of mostly experimental and quasi-experimental designs for generalized causal inference (Shadish & Cook, 2002).

Comparison of system configurations, a key property in simulation-based models, perfectly matches the above description of MCV since (1) the presumed cause of increases/decreases in the level of SCRes, i.e. inventory buffers or manufacturing capacity, is known and manipulable; (2) the consequent output in the simulation model can be objectively measured, i.e. Re^T; and, (3) there is no other attributable cause apart from the two mentioned variables—inventory and capacity—that explain increases/decreases in the level of SCRes, bearing in mind that the simulation runs per row described in Equation 6.4 were performed using the same seed (see discussion in Sub-section 6.9.1). Therefore, by applying MCV to the scenarios described by the set of hypotheses 2, if statistical evidence is found indicating that increases in the levels of on-hand inventory buffers elevate Re^T, then it can be inferred that the first causes the second, or, in other words, on-hand inventory buffers moderate the relationship between risks and resilience. This same reasoning is also applied to examine the set of hypotheses 3 in Section 7.4.

Due to the non-normality feature of the $Re^T(Cf_{1...90})$ time series discussed in Subsection 6.9.2, two analogous non-parametric methods were selected to obtain the aforesaid statistical evidence: (1) the Kruskal-Wallis rank sum test or KW (Kruskal & Wallis, 1952), and (2) the Wilcoxon rank sum test with continuity correction or W (Wilcoxon, 1945). The first test (KW) is the equivalent of an F test for one-way ANOVA and is used in this analysis to be sensitive to differences among means in the $Re^T(Cf_i)$ time series, as long as both time series are random samples of their respective populations, independent of each other and mutually independent among $Re^T(Cf_i)$, and their scale of measurement is expressed in ordinal terms. Similarly, the second test (W) is an unbiased and consistent yardstick equivalent to the two-sample t test, and is used in this analysis to determine if one of the two time series of $Re^T(Cf_i)$ is lower than the other—one-sided test, as long as both time series are symmetric, independent of each other, and their scale of measurement is at least an interval. For the proposed analysis, it is reasonable to consider that the two time series $Re^T(Cf_i)$ to be compared are random samples, exhibit

mutual statistical independence, and can be paired as "before" and "after" observations (Conover, 1999). Therefore, the hypotheses testing for the KW-test can be set up as follows:

H_0: 'Both $Re^T(Cf_i)$ and $Re^T(Cf_{i+30})$ or $Re^T(Cf_i)$ and $Re^T(Cf_{i+60})$ come from identical populations and their differences are due to randomness'

H_a: "Either $Re^T(Cf_i)$ and $Re^T(Cf_{i+30})$ or $Re^T(Cf_i)$ and $Re^T(Cf_{i+60})$ come from different populations'

The null distribution for the KW-test is the T probability distribution as described in Equation 7.10:

$$T = \frac{12}{N(N+1)} \sum \frac{R_l^2}{n_l} - 3(N+1), \tag{7.10}$$

where $N = \sum_{l=1}^{m} n_l$ denotes the total number of observations in each $Re^T(Cf_i)$, and R_l represents the sum of the ranks assigned to the l-th sample. However, due to the fact that the mathematical form of Equation 7.10 is too cumbersome to work with, Chi-square distribution (χ^2) with $k - 1 = 1$ degree of freedom (df) is recommended as an approximation to null distribution T (Conover, 1999). Thus, the hypothesis testing for the W-test can be written as follows:

H_0: 'Both $Re^T(Cf_i)$ and $Re^T(Cf_{i+30})$ or $Re^T(Cf_i)$ and $Re^T(Cf_{i+60})$ come from identical populations and their differences are due to randomness'

H_a: 'Values of $Re^T(Cf_i)$ are systematically lower than $Re^T(Cf_{i+30})$ or $Re^T(Cf_{i+60})$',

with $i = 1\ldots30$.

The observed rank sum W of the W-test is given by the sum of the dominant rank where

$$W = \sum R_l, \tag{7.11}$$

where the expressions

$$\mu_W = \frac{n_1(N+1)}{2}, \tag{7.12}$$

and

$$\sigma_W = \sqrt{\dfrac{n_1 n_2 (N+1)}{12}}, \tag{7.13}$$

are the mean and the standard deviation, with n_1 and n_2 the number of observations for $\mathrm{Re}^T(Cf_i)$ and $\mathrm{Re}^T(Cf_{i+30})$ or $\mathrm{Re}^T(Cf_i)$ and $\mathrm{Re}^T(Cf_{i+60})$, respectively. In the cases in which the sizes of n_1 and n_2 increase, the null distribution for the WMW-test suggested is the Normal probability distribution (Z). The z statistic by standardizing W is described in Equation 7.14:

$$z = \dfrac{W - \mu_W}{\sigma_W} \tag{7.14}$$

where z is the quartile of the standard Normal random variable Z with $P(Z \leq z) = p$ and $P(Z > z) = 1 - p$.

7.3.1 Testing hypothesis 2a (H$_{2a}$): 'Increases in I$_{t,s}$ moderate the relationship between R$_{1r}$ and Re^T'

The results of all pairwise comparisons between $\mathrm{Re}^T(Cf_{1\ldots10})$ or DS_1 and $\mathrm{Re}^T(Cf_{31\ldots40})$ or DS_4 of using KW and W tests are summarized in Table 7.4.

Table 7.4 Results of the application of Kruskal-Wallis and Wilcoxon rank sum tests for comparison of DS$_1$ to DS$_4$

DS$_1$	DS$_4$	Kruskal-Wallis			Wilcoxon	
		χ^2	df	p-value	W	p-value
$\mathrm{Re}^T(Cf_1)$	$\mathrm{Re}^T(Cf_{31})$	5,655.600	1	0.000	518,580.000	0.000
$\mathrm{Re}^T(Cf_2)$	$\mathrm{Re}^T(Cf_{32})$	5,597.800	1	0.000	895,530.000	0.000
$\mathrm{Re}^T(Cf_3)$	$\mathrm{Re}^T(Cf_{33})$	2,890.100	1	0.000	124,580.000	0.000
$\mathrm{Re}^T(Cf_4)$	$\mathrm{Re}^T(Cf_{34})$	2,775.000	1	0.000	215,900.000	0.000
$\mathrm{Re}^T(Cf_5)$	$\mathrm{Re}^T(Cf_{35})$	2,772.500	1	0.000	259,000.000	0.000
$\mathrm{Re}^T(Cf_6)$	$\mathrm{Re}^T(Cf_{36})$	<u>2,771.000</u>	1	0.000	114,130.000	0.000
$\mathrm{Re}^T(Cf_7)$	$\mathrm{Re}^T(Cf_{37})$	2,864.900	1	0.000	112,280.000	0.000
$\mathrm{Re}^T(Cf_8)$	$\mathrm{Re}^T(Cf_{38})$	2,943.600	1	0.000	187,020.000	0.000
$\mathrm{Re}^T(Cf_9)$	$\mathrm{Re}^T(Cf_{39})$	2,817.400	1	0.000	<u>97,736.000</u>	0.000
$\mathrm{Re}^T(Cf_{10})$	$\mathrm{Re}^T(Cf_{40})$	2,806.500	1	0.000	101,370.000	0.000

By way of example, from data shown in Table 7.4, the KW-test is used to compare whether time series $\mathrm{Re}^T(Cf_6)$ and $\mathrm{Re}^T(Cf_{36})$ come from identical populations. Since the p-value for the observed $\chi^2 = 2,771$ and one degree of freedom (df $= k - 1 = 1$) is lower than 2.2×10^{-16} with a level of significance $\alpha = 0.01$, there are sufficient arguments to reject H$_0$; thereby the inference is made that the values of the time series $\mathrm{Re}^T(Cf_6)$ and $\mathrm{Re}^T(Cf_{36})$ are statistically different from each other. By and large, given that the observed value of $\chi^2 = 2,771$ is the lowest one for χ^2 in

Table 7.4, and that larger values of χ^2 provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining nine pairwise comparisons are also rejected.

Similarly, from data shown in Table 7.4, the W-test is used to assess whether the time series $Re^T(Cf_9)$ has systematically lower values than $Re^T(Cf_{39})$. Since the p-value for the observed rank sum $W = 97736$ and a level of significance $\alpha = 0.01$ is lower than 2.2×10^{-16}, there are sufficient arguments to reject H_0; thereby the inference is made that the values of the time series $Re^T(Cf_9)$ are systematically lower than the values of the time series $Re^T(Cf_{40})$. Overall, given that the observed rank sum $W = 97,736$ is the lowest one for W in Table 7.4, and that larger values of W provide more convincing evidence to reject H_0; the corresponding null hypotheses for the remaining nine pairwise comparisons are also rejected. To sum up, the results of the KW and W tests indicate that the hypothesis H_{2a} is statistically supported with 99% confidence. The statistics verification of H_{2a} also confirms the presumption of the MFSC staff on its effectiveness as inhibitor of disruptions caused by operational risks (R_{1r}). Indeed, as can be seen from Table 6.28 on this category, respondents' answers widely favoured the use of inventory rather than capacity to prevent disruptions caused by risks R_{11}—'breakdowns in machines or workstations'—and R_{14}—'quality problems' by a percentage of 67% to 33%, and for disruptions caused by risk R_{13}—'shortages of raw material and components', by a percentage of 75% to 25%.

7.3.2 Testing hypothesis 2b (H_{2b}): 'Increases in $I_{t,s}$ moderate the relationship between R_{2r} and Re^T'

The results of all pairwise comparisons between $Re^T(Cf_{11...20})$ or DS_2 and $Re^T(Cf_{41...50})$ or DS_5 using both the KW and W tests are summarized in Table 7.5.

Table 7.5 Results of the application of Kruskal-Wallis and Wilcoxon rank sum tests for comparison of DS_2 to DS_5

DS_2	DS_5	Kruskal-Wallis			Wilcoxon	
		χ^2	df	p-value	W	p-value
$Re^T(Cf_{11})$	$Re^T(Cf_{41})$	419.690	1	0.000	1,501,300.000	0.000
$Re^T(Cf_{12})$	$Re^T(Cf_{42})$	1,886.900	1	0.000	<u>595,550.000</u>	0.000
$Re^T(Cf_{13})$	$Re^T(Cf_{43})$	1,274.800	1	0.000	657,310.000	0.000
$Re^T(Cf_{14})$	$Re^T(Cf_{44})$	<u>129.860</u>	1	0.000	1,889,700.000	0.000
$Re^T(Cf_{15})$	$Re^T(Cf_{45})$	520.420	1	0.000	1,464,100.000	0.000
$Re^T(Cf_{16})$	$Re^T(Cf_{46})$	1,447.800	1	0.000	842,810.000	0.000
$Re^T(Cf_{17})$	$Re^T(Cf_{47})$	250.360	1	0.000	1,800,900.000	0.000
$Re^T(Cf_{18})$	$Re^T(Cf_{48})$	549.880	1	0.000	1,553,100.000	0.000
$Re^T(Cf_{19})$	$Re^T(Cf_{49})$	1,127.400	1	0.000	910,590.000	0.000
$Re^T(Cf_{20})$	$Re^T(Cf_{50})$	297.600	1	0.000	1,639,200.000	0.000

By way of example, from data shown in Table 7.5, the KW-test is used to compare whether time series $Re^T(Cf_{14})$ and $Re^T(Cf_{44})$ come from identical populations. Since the p-value for the

observed $\chi^2 = 129.86$ and df $= 1$ is lower than 2.2×10^{-16} with a level of significance $\alpha = 0.01$, there are sufficient arguments to reject H_0; thereby the inference is made that the values of the time series $Re^T(Cf_{14})$ and $Re^T(Cf_{44})$ are statistically different from each other. By and large, given that the observed value of $\chi^2 = 129.86$ is the lowest one for χ^2 in Table 7.5, and that larger values of χ^2 provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining nine pairwise comparisons are also rejected.

Similarly, from data shown in Table 7.5, the W-test is used to assess whether the time series $Re^T(Cf_{12})$ has systematically lower values than $Re^T(Cf_{42})$. Since the p-value for the observed rank sum $W = 595{,}550$ and a level of significance $\alpha = 0.01$ is lower than 2.2×10^{-16}, there are sufficient arguments to reject H_0, thereby the inference is made that the values of the time series $Re^T(Cf_{12})$ are systematically lower than the values of the time series $Re^T(Cf_{42})$. By and large, given that the observed rank sum $W = 595{,}550$ is the lowest one for W in Table 7.5, and that larger values of W provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining nine pairwise comparisons are also rejected.

To sum up, the results of the KW and W tests indicate that the hypothesis H_{2b} is statistically supported with 99% confidence. However, the statistical verification of H_{2b} only confirms the presumption of the MFSC staff on its effectiveness as inhibitor of disruptions in two of the three risks considered: R_{22} or 'attacks on the lines-of-communication' and R_{23} or 'attacks on forward logistics-support units' in percentages of 92% to 8% and 67% to 33%, respectively.

7.3.3 Testing hypothesis 2c (H_{2c}): "Increases in $I_{t,s}$ moderate the relationship between R_3 and Re^T"

The results of all pairwise comparisons between $Re^T(Cf_{21\ldots30})$ or DS_3 and $Re^T(Cf_{51\ldots60})$ or DS_6 of using both the KW and the W tests are summarized in Table 7.6.

Table 7.6 Results of the application of Kruskal-Wallis and Wilcoxon rank sum tests for comparison of DS_3 to DS_6

DS_3	DS_6	Kruskal-Wallis			Wilcoxon	
		χ^2	df	p-value	W	p-value
$Re^T(Cf_{21})$	$Re^T(Cf_{51})$	394.270	1	0.000	15,151,000.000	0.000
$Re^T(Cf_{22})$	$Re^T(Cf_{52})$	749.380	1	0.000	14,107,000.000	0.000
$Re^T(Cf_{23})$	$Re^T(Cf_{53})$	725.430	1	0.000	14,224,000.000	0.000
$Re^T(Cf_{24})$	$Re^T(Cf_{54})$	777.810	1	0.000	14,041,000.000	0.000
$Re^T(Cf_{25})$	$Re^T(Cf_{55})$	744.310	1	0.000	14,199,000.000	0.000
$Re^T(Cf_{26})$	$Re^T(Cf_{56})$	251.160	1	0.000	15,563,000.000	0.000
$Re^T(Cf_{27})$	$Re^T(Cf_{57})$	389.250	1	0.000	15,190,000.000	0.000
$Re^T(Cf_{28})$	$Re^T(Cf_{58})$	355.970	1	0.000	15,284,000.000	0.000
$Re^T(Cf_{29})$	$Re^T(Cf_{59})$	677.880	1	0.000	14,368,000.000	0.000
$Re^T(Cf_{30})$	$Re^T(Cf_{60})$	375.980	1	0.000	15,246,000.000	0.000

By way of example, from data shown in Table 7.6, the KW-test is used to compare whether time series $Re^T(Cf_{26})$ and $Re^T(Cf_{56})$ come from identical populations. Since the p-value for the observed $\chi^2 = 251.16$ and $df = 1$ is lower than 2.2×10^{-16} with a level of significance $\alpha = 0.01$, there are sufficient arguments to reject H_0. Thereby the inference is made that the values of the time series $Re^T(Cf_{26})$ and $Re^T(Cf_{56})$ are statistically different from each other. By and large, given that the observed value of $\chi^2 = 251.16$ is the lowest one for χ^2 in Table 7.6, and that larger values of χ^2 provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining nine pairwise comparisons are also rejected.

Similarly, from data shown in Table 7.6, the W test is used to assess whether the time series $Re^T(Cf_{24})$ has systematically lower values than $Re^T(Cf_{54})$. Since the p-value for the observed rank sum $W = 14,041,000$ and a level of significance $\alpha = 0.01$ is lower than 2.2×10^{-16}, there are sufficient arguments to reject H_0. Thereby the inference is made that the values of the time series $Re^T(Cf_{24})$ are systematically lower than the values of the time series $Re^T(Cf_{54})$. By and large, given that the observed rank sum $W = 14,041,000$ is the lowest one for W in Table 7.6, and that larger values of W provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining nine pairwise comparisons are also rejected.

To sum up, the results of the KW and W tests indicate that the hypothesis H_{2c} is statistically supported with a 99% confidence. It is noteworthy that the statistical verification of H_{2c} totally confirms the presumption that the MFSC staff has on its effectiveness as inhibitor of disruptions caused by R_3 or 'black swan events' in a percentage of 67% to 33%.

7.4 Examining the Moderating Effect of Short-Term Manufacturing Capacity (S) in the Relationship between the Frequency of Occurrence of Three Categories of Risks (R_{cr}) and the Measure of Resilience in Supply Chains (Re^T): Hypotheses H_{3a}, H_{3b}, and H_{3c}

The set of hypotheses H_3 is tested in the following sub-sections by utilising the same reasoning and statistical approach as in the previous section.

7.4.1 Testing hypothesis 3a (H_{3a}): 'Increases in S moderate the relationship between R_{1r} and Re^T'

The results of all pairwise comparisons between $Re^T(Cf_{1...10})$ or DS_1 and $Re^T(Cf_{61...70})$ or DS_7 using both KW and W tests are summarized in Table 7.7.

Table 7.7 Results of the application of Kruskal-Wallis and Wilcoxon rank sum tests for comparison of DS_1 to DS_7

DS_1	DS_7	Kruskal-Wallis			Wilcoxon	
		χ^2	df	p-value	W	p-value
$Re^T(Cf_1)$	$Re^T(Cf_{61})$	5,509.610	1	0.000	709,713.000	0.000
$Re^T(Cf_2)$	$Re^T(Cf_{62})$	165.640	1	0.000	8,224,947.000	0.000
$Re^T(Cf_3)$	$Re^T(Cf_{63})$	2,833.620	1	0.000	167,260.500	0.000
$Re^T(Cf_4)$	$Re^T(Cf_{64})$	2,900.800	1	0.000	143,101.000	0.000
$Re^T(Cf_5)$	$Re^T(Cf_{65})$	0.000	1	0.000	2,596,921.000	0.000
$Re^T(Cf_6)$	$Re^T(Cf_{66})$	2,795.780	1	0.000	104,789.500	0.000
$Re^T(Cf_7)$	$Re^T(Cf_{67})$	23.760	1	0.000	2,068,911.000	0.000
$Re^T(Cf_8)$	$Re^T(Cf_{68})$	3,003.400	1	0.000	186,471.000	0.000
$Re^T(Cf_9)$	$Re^T(Cf_{69})$	2,757.560	1	0.000	138,219.500	0.000
$Re^T(Cf_{10})$	$Re^T(Cf_{70})$	2,842.930	1	0.000	87,905.500	0.000

Unlike in the previous analysis, the results of the application of the KW-test in Table 7.7 shows an χ^2 atypical-value in one of the ten pairwise comparisons: $Re^T(Cf_5)$ and $Re^T(Cf_{65})$. As can be seen, an observed value of $\chi^2 = 0.00$ and df $= 1$ produces a p-value $= 1$, a result that is not statistically significant at $\alpha = 0.01$, implying that the mean of the two populations is equal to the mean of the other. In other words, H_0 has failed to be rejected for this pairwise comparison. In contrast to this result, the remaining nine comparisons show KW-test values above zero. Thus, the time series $Re^T(Cf_7)$ and $Re^T(Cf_{67})$ are compared to each other to see whether they come from identical populations. Since the p-value for the observed $\chi^2 = 23.76$ and df $= 1$ is lower than 1.091×10^{-6} with a level of significance $\alpha = 0.01$, there are sufficient arguments to reject H_0. Thereby the inference is made that the values of the time series $Re^T(Cf_7)$ and $Re^T(Cf_{67})$ are statistically different of each other. Given that the observed value of $\chi^2 = 23.76$ is the lowest one for χ^2 in Table 7.7—not including the mentioned atypical value, and that larger values of χ^2 provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining eight pairwise comparisons are also rejected.

So, what statistical inference can be made if both results are considered at the same time, i.e. *one* observed value of χ^2 that is not statistically significant and *nine* observed values of χ^2 that are? To answer this question, an additional hypothesis testing based on the *binomial distribution* is applied. This probability distribution fits to the above-mentioned question since there are a fixed 'number of pairwise comparisons using KW test (*n*)'; each KW-test has two possible outcomes—'statistically significant' or 'not statistically significant'; the probability that a KW test is statistically significant (*p*) is the same for each KW test; and the KW tests are independent of each other. Thus, from the data described in Table 7.7, the null and alternative hypotheses can be set up as follows:

H₀:	'Probability (p) that the proportion of the number of KW-tests in which the null hypothesis is rejected is 0.9 or higher'

Hₐ:	'Probability (p) that the proportion of the number of KW-tests in which the null hypothesis is rejected is lower than 0.9"

With $n = 10$ and $p = 0.9$, an observed value of the binomial distribution x such that $B(X = x, 10, 0.9) \leq 0.05$ is required. The value found that satisfies this condition is $x = 6$ at a significance level $\alpha = 0.05$; thereby, the rejection region corresponds to the values of $x \leq 6$ and H₀ has failed to be rejected.

Similarly, from data shown in Table 7.7, the W-test is used to assess whether the time series $Re^T(Cf_{10})$ has systematically lower values than $Re^T(Cf_{70})$. Since the p-value for the observed rank sum $W = 87,905.5$ and a level of significance $\alpha = 0.01$ is lower than 2.2×10^{-16}, there are sufficient arguments to reject H₀, thereby the inference is made that the values of the time series $Re^T(Cf_{10})$ are systematically lower than the values of the time series $Re^T(Cf_{70})$. By and large, given that the observed rank sum $W = 87,905.5$ is the lowest one for W in Table 7.7, and that larger values of W provide more convincing evidence to reject H₀, the corresponding null hypotheses for the remaining nine pairwise comparisons are also rejected.

To sum up, the results of KW, Binomial distribution, and W tests confirm that the hypothesis H₃ₐ is statistically supported with a 95% of confidence. However, this statistics verification of H₃ₐ contradicts the presumption that MFSC staff has on its effectiveness as inhibitor of disruptions caused by operational risks (R_{1r}). As pointed in the Subsection 6.2.8, respondents' answers supported in all cases the use of on-hand-inventory buffers rather than short-term manufacturing capacity.

7.4.2 Testing hypothesis 3b (H₃ᵦ): 'Increases in S moderate the relationship between R_{2r} and Re^T'

The results of all pairwise comparisons between $Re^T(Cf_{11\dots20})$ or DS_2 and $Re^T(Cf_{71\dots80})$ or DS_8 using both the KW and W tests are summarized in Table 7.8.

Table 7.8 Results of the application of Kruskal-Wallis and Wilcoxon rank sum tests for comparison of DS_2 to DS_8

DS_2	DS_8	Kruskal-Wallis			Wilcoxon	
		χ^2	df	p-value	W	p-value
$Re^T(Cf_{11})$	$Re^T(Cf_{71})$	142.550	1	0.000	2,174,721.000	0.000
$Re^T(Cf_{12})$	$Re^T(Cf_{72})$	1,874.390	1	0.000	<u>597,565.000</u>	0.000
$Re^T(Cf_{13})$	$Re^T(Cf_{73})$	864.830	1	0.000	1,585,366.000	0.000
$Re^T(Cf_{14})$	$Re^T(Cf_{74})$	154.690	1	0.000	1,834,199.000	0.000
$Re^T(Cf_{15})$	$Re^T(Cf_{75})$	509.600	1	0.000	1,417,720.000	0.000
$Re^T(Cf_{16})$	$Re^T(Cf_{76})$	1,424.330	1	0.000	801,059.000	0.000
$Re^T(Cf_{17})$	$Re^T(Cf_{77})$	1,427.640	1	0.000	797,669.000	0.000
$Re^T(Cf_{18})$	$Re^T(Cf_{78})$	<u>68.170</u>	1	0.000	1,795,998.000	0.000
$Re^T(Cf_9)$	$Re^T(Cf_{79})$	1,129.920	1	0.000	912,433.500	0.000
$Re^T(Cf_{10})$	$Re^T(Cf_{80})$	72.220	1	0.000	1,532,981.000	0.000

By way of example, from data shown in Table 7.8, the KW test is used to compare whether time series $Re^T(Cf_{18})$ and $Re^T(Cf_{78})$ come from identical populations. Since the p-value for the observed $\chi^2 = 68.17$ and df = 1 is lower than 2.2×10^{-16} with a level of significance $\alpha = 0.01$, there are sufficient arguments to reject H_0; thereby the inference is made that the values of the time series $Re^T(Cf_{18})$ and $Re^T(Cf_{78})$ are statistically different from each other. By and large, given that the observed value of $\chi^2 = 68.17$ is the lowest one for χ^2 in Table 7.8, and that larger values of χ^2 provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining nine pairwise comparisons are also rejected.

Similarly, from data shown in Table 7.8, the W test is used to assess whether the time series $Re^T(Cf_{12})$ has systematically lower values than $Re^T(Cf_{72})$. Since the p-value for the observed rank sum W = 597565 and a level of significance $\alpha = 0.01$ is lower than 2.2×10^{-16}, there are sufficient arguments to reject H_0; thereby the inference is made that the values of the time series $Re^T(Cf_{12})$ are systematically lower than the values of the time series $Re^T(Cf_{72})$. By and large, given that the observed rank sum W = 597,565 is the lowest one for W in Table 7.8, and that larger values of W provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining nine pairwise comparisons are also rejected.

To sum up, the results of the KW and W tests indicate that the hypothesis H_{3b} is statistically supported with a 99% confidence. However, the statistics verification of H_{3b} only confirms the presumption that the MFSC staff has on its effectiveness as inhibitor of disruptions in one of the three risks considered: R24 or 'contingent demand', at a percentage of 67% to 33%. As pointed out in Subsection 6.2.8, respondents' answers mostly support the use of on-hand inventory buffers over short-term manufacturing capacity.

7.4.3 Testing hypothesis 3c (H₃c): 'Increases in S moderate the relationship between R₃ and Reᵀᵀ'

7.4.3 Testing hypothesis 3c (H_{3c}): 'Increases in S moderate the relationship between R_3 and Re^T'

The results of all pairwise comparisons between $Re^T(Cf_{21\ldots30})$ or DS_3 and $Re^T(Cf_{81\ldots90})$ or DS_9 of using both KW and W tests are summarized in Table 7.9.

Table 7.9 Results of the application of Kruskal-Wallis and Wilcoxon rank sum tests for comparison of DS_3 to DS_9

DS_3	DS_9	Kruskal-Wallis			Wilcoxon	
		χ^2	df	p-value	W	p-value
$Re^T(Cf_{21})$	$Re^T(Cf_{81})$	6,333.570	1	0.000	14,755,996.00	0.000
$Re^T(Cf_{22})$	$Re^T(Cf_{82})$	797.280	1	0.000	14,061,608.00	0.000
$Re^T(Cf_{23})$	$Re^T(Cf_{83})$	749.530	1	0.000	14,201,009.00	0.000
$Re^T(Cf_{24})$	$Re^T(Cf_{84})$	807.560	1	0.000	14,013,353.00	0.000
$Re^T(Cf_{25})$	$Re^T(Cf_{85})$	747.570	1	0.000	14,195,900.00	0.000
$Re^T(Cf_{26})$	$Re^T(Cf_{86})$	266.080	1	0.000	15,548,548.00	0.000
$Re^T(Cf_{27})$	$Re^T(Cf_{87})$	345.070	1	0.000	15,334,500.00	0.000
$Re^T(Cf_{28})$	$Re^T(Cf_{88})$	5,920.180	1	0.000	14,656,195.00	0.000
$Re^T(Cf_{29})$	$Re^T(Cf_{89})$	0.000	1	0.000	16,233,602.00	0.000
$Re^T(Cf_{30})$	$Re^T(Cf_{90})$	0.000	1	0.000	163,02,050.00	0.000

The results of the application of the KW test in Table 7.9 show χ^2 atypical-values in two of the ten pairwise comparisons: $Re^T(Cf_{29})$-$Re^T(Cf_{89})$ and $Re^T(Cf_{30})$-$Re^T(Cf_{90})$. As mentioned before, an observed value of $\chi^2 = 0.00$ and df = 1 produces a p-value = 1—a result which is not statistically significant at $\alpha = 0.01$, implying that the mean of each of the two populations is equal to the other. In other words, H_0 has failed to be rejected for these pairwise comparisons. In contrast to these results, the remaining eight comparisons show KW-test values above zero. Thus, the time series $Re^T(Cf_{26})$ and $Re^T(Cf_{86})$ are compared to each other to see whether they come from identical populations. Since the p-value for the observed $\chi^2 = 266.08$ and df = 1 is lower than 2.2×10^{-16} with a level of significance $\alpha = 0.01$, there are sufficient arguments to reject H_0. Thereby the inference is made that the values of the time series $Re^T(Cf_{26})$ and $Re^T(Cf_{86})$ are statistically different from each other. By and large, given that the observed value of $\chi^2 = 266.08$ is the lowest one for χ^2 in Table 7.9, no including the two atypical values, and that larger values of χ^2 provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining seven pairwise comparisons are also rejected. However, similar to the case described in Subsection 7.4.1, there are *two* observed values of χ^2 that are not statistically significant and *eight* observed values of χ^2 that are. By applying the same form of the null and alternative hypotheses, an observed value of the binomial distribution x such that $B(X = x, 10, 0.8) \leq 0.05$ is required. Thus, with $n = 10$ and $p = 0.8$, the value found that satisfies this condition is $x = 5$ at a significance level $\alpha = 0.05$; thereby the rejection region corresponds to the values of $x \leq 5$ and H_0 has failed to be rejected.

Likewise, from data shown in Table 7.9, the W test is used to assess whether the time series $Re^T(Cf_{22})$ has systematically lower values than $Re^T(Cf_{82})$. Since the *p*-value for the observed rank sum W = 140,61,608 and a level of significance $\alpha = 0.01$ is lower than 2.2×10^{-16}, there are sufficient arguments to reject H_0; thereby the inference is made that the values of the time series $Re^T(Cf_{22})$ are systematically lower than the values of the time series $Re^T(Cf_{82})$. By and large, given that the observed rank sum W = 14,061,608 is the lowest one for W in Table 7.9 and that larger values of W provide more convincing evidence to reject H_0, the corresponding null hypotheses for the remaining nine pairwise comparisons are also rejected.

To sum up, although the results of the KW and W tests indicate that hypothesis H_{3c} is statistically supported at 95% confidence, the verification of H_{3c} is not supported by the presumption that MFSC staff has on its effectiveness as inhibitor of disruptions caused by R_3 or 'black-swan events'. As pointed out in Subsection 6.2.8, respondents' answers give no credibility to the use of short-term manufacturing capacity for this purpose.

7.5 Summary of Chapter 7

This chapter statistically tested the three sets of hypotheses that make up the conceptual framework constructed in Chapter 3 of this study. The output data of the simulation model were the main input for the process of hypotheses testing, though the data from the questionnaire were used as a baseline to compare overall results. Thus, for the analysis and testing of the first set of hypotheses (H_{1a}, H_{1b}, and H_{1c}), four techniques were used: Association rule mining, Chi-squared test, Phi-coefficient, and Causal rule based on odds-ratio. The result of the hypothesis tests partially supported H_{1a}, H_{1b}, and H_{1c}, that is, these included solid statistical evidence of the adverse effects that seven of the nine risk events considered (R_{11}, R_{13}, R_{14}, R_{22}, R_{23}, and R_3) have on the level of SCRes of the MFSC when their frequency of occurrence is increased. The two remaining risk events (R_{12} and R_{21}) were discarded during the process of pruning the interesting rules of association. Similarly, for the analysis and testing of the set of hypotheses 2 (H_{2a}, H_{2b}, and H_{2c}) and the set of hypotheses 3 (H_{3a}, H_{3b}, and H_{3c}), Mill's method of concomitant variation, two non-parametric tests—Kruskal-Wallis rank sum test and Wilcoxon rank sum test with continuity correction, and the Binomial distribution were utilised conjointly. In this regard, the application of the aforementioned tests totally confirmed the set of hypotheses 2 (H_2) and the hypothesis H_{3b} with 99% confidence, while the hypotheses H_{3a} and H_{3c} were confirmed with 95% confidence. The following chapter discusses in depth the above findings in terms of their theoretical and practical contributions and limitations, as well as avenues for future studies.

Chapter 8
CONCLUSIONS AND FUTURE RESEARCH

Chapter 8. Conclusions and Future Research

8.1 Introduction

This study set out to examine the theoretical effectiveness of a buffering strategy, founded on increases in on-hand inventory buffers and short-term manufacturing capacity, to elevate the level of resilience of a real-world supply chain of military food (MFSC) highly exposed to the occurrence of various types of risk due to its very nature. The central research question that was formulated for this purpose is restated as follows:

How is the resilience level—dynamic and inherent—of a military food supply chain in a risky environment affected by increases in on-hand inventory buffers/short-term manufacturing capacity?

The importance of this topical research lies in the positive effects that the application of a buffering strategy as described could have on the performance of military-SCs. As demonstrated in the results of the simulation modeling, when the buffering strategy was applied on the MFSC, the *period of autotomy* increased, or the *period of recovery* decreased, or the *period of disruption* decreased, or a combination of the three. In short, the MFSC became more resilient, which translates into a lower risk of loss of human lives.

Prior to the completion of this study, there was controversy prevalent in the literature regarding the effectiveness of using on-hand inventory buffers and/or short-term manufacturing capacity to prevent the occurrence of disruptions and/or to create SCRes. Aspects such as the relatively low number of empirical works and the abundance of anecdotal evidence on the subject, the inadequacy of the methodologies used to measure SCRes, the gap between theoretical and practical issues on this concept, and the little interest of researchers on topics related to defence logistics, among others, fueled this controversy. I argue that the results and findings provided in this study greatly clarify this debate, as well as enable new research to be developed.

This chapter has been structured in six main sections. The second section synthesizes the empirical findings derived from the analysis of the nine research hypotheses and the open-ended questionnaire. The third section discusses the implications of the results of the study with respect to the current debate in the literature on the effectiveness of a buffering strategy based on on-hand inventory buffers and short-term manufacturing capacity. The fourth section gives some practical suggestions on how to apply the mentioned buffering strategy. The fifth section points out the limitations of the study, particularly those related to the assumptions of the simulation model, the non-inclusion of the factor cost, and the utilisation of a single unit of analysis. And lastly, the sixth section delineates an agenda for future research.

8.2 Empirical Findings

Based on the central research question mentioned above, this study formulated nine research hypotheses for analysis organized into three sets (H_1, H_2, and H_3), and an open-ended

questionnaire initially introduced in Chapters 6 and further discussed in Chapter 7. The synthesis of the discussion of results for each one is stated as follows:

8.2.1 From the research hypotheses

Hypothesis 1a (H_{1a}): '*Ceteris paribus, increases in the frequency of occurrence of operational risks* (R_{1r}) *reduce the measure of resilience in supply chains* (Re^T)'

In the proposed analysis, this category of risk comprises 'breakdown in machines or workstations (R_{11})', 'delays in contracting with supplies (R_{12})', 'shortages of raw material and components (R_{13})', and 'quality problems (R_{14})'. These risks were modelled as 'highly frequent and low impact stochastic events', whilst the initial configuration of the MFSC—one work shift activated and zero-inventory level at operations 3, 5, and 9—was kept unaltered during the time of the simulation or *ceteris paribus* condition. Therefore, the three statistical criteria employed— Chi-squared test, Phi-coefficient, and Causal Rule based on Odds-ratio—confirmed with a degree of confidence equal to 99% that when the frequency of occurrence of R_{11}, R_{13}, and R_{14} was increased, MFSC's measure of resilience (Re^T) was reduced. This result is not, however, extensible to R_{12} since this type of risk was discarded during the process of extraction of rules of association between R_{cr} and Re^T.

Hypothesis 1b (H_{1b}): '*Ceteris paribus, increases in the frequency of occurrence of natural-disasters-and-intentional-attacks* (R_{2r}) *reduce the measure of resilience in supply chains* (Re^T)'

This category of risk comprises 'earthquakes, storms, floods, fires, and power cuts (R_{21})', 'attacks on the lines-of-communication (R_{22})', 'attacks on forward logistics-support units (R_{23})', and 'contingent demand (R_{24})'. These risks were modelled as rare and high-impact stochastic events, whilst the initial configuration of the MFSC—one work shift activated and zero-inventory level at operations 3, 5, and 9—was kept unaltered during the time of the simulation. Therefore, the three statistical criteria employed—Chi-squared test, Phi-coefficient, and Causal Rule based on Odds-ratio—confirmed with a degree of confidence equal to 99% that when the frequency of occurrence of R_{22}, R_{23}, and R_{24} was increased, MFSC's measure of resilience (Re^T) was reduced. This result is not, however, extensible to R_{21} since this type of risk was discarded during the process of extraction of rules of association between R_{cr} and Re^T.

Hypothesis 1c (H_{1c}): '*Ceteris paribus, increases in the frequency of occurrence of black-swan events* (R_3) *reduce the measure of resilience in supply chains* (Re^T)'

This category of risk (R_3) was modelled as stochastic events with the 'lowest frequency and highest impact' within the analysis—'one time every twenty years', whilst the initial configuration of the MFSC—one work shift activated and zero-inventory level at operations 3, 5, and 9—was kept unaltered during the time of the simulation. Therefore, the three statistical criteria employed—Chi-squared test, Phi-coefficient, and Causal Rule based on Odds-ratio— confirmed with a degree of confidence equal to 99% that when the frequency of occurrence of R_3 was increased, MFSC's measure of resilience (Re^T) was also reduced.

Hypothesis 2a (H$_{2a}$): '*On-hand inventory buffers* (I$_{t,S}$) *moderate the relationship between the frequency of occurrence of operational risks* (R$_{1r}$) *and the measure of resilience in supply chains* (Re^T), *with the relationship being enhanced by increases in the levels of* I$_{t,S}$'

For the analysis of this hypothesis, MFSC's on-hand inventory buffers at three critical points—operations 3, 5, and 9—were randomly increased from five pre-determined levels—on-hand inventory buffers for one, two, three, four, and up to eight weeks—following an efficient simulation experiment, while the four risks of the category R$_{1r}$ were enabled. Therefore, the results of the two hypothesis tests utilised—the Kruskal-Wallis sum rank test and the Wilcoxon sum rank test with continuity correction—confirmed with a degree of confidence equal to 99% that when on-hand inventory buffers were increased by the indicated levels, the MFSC's measure of resilience (Re^T) increased in the presence of R$_{1r}$.

Hypothesis 2b (H$_{2b}$): '*On-hand inventory buffers* (I$_{t,S}$) *moderate the relationship between the frequency of occurrence of natural-disasters-and-intentional-attacks* (R$_{2r}$) *and the measure of resilience in supply chains* (Re^T), *with the relationship being enhanced by increases in the levels of* I$_{t,S}$'

For the analysis of this hypothesis, MFSC's on-hand inventory buffers at three critical points—operations 3, 5, and 9—were randomly increased from five pre-determined levels—on-hand inventory buffers for one, two, three, four, and up to eight weeks—following an efficient simulation experiment, while the four risks of the category R$_{2r}$ were enabled. Therefore, the results of the two hypothesis tests utilised—the Kruskal-Wallis sum rank test and the Wilcoxon sum rank test with continuity correction—confirmed with a degree of confidence equal to 99% that when on-hand inventory buffers were increased by the indicated levels, the MFSC's measure of resilience (Re^T) increased in the presence of R$_{2r}$.

Hypothesis 2c (H$_{2c}$): '*On-hand inventory buffers* (I$_{t,S}$) *moderate the relationship between the frequency of occurrence of black-swan events* (R$_3$) *and the measure of resilience in supply chains* (Re^T), *with the relationship being enhanced by increases in the levels of* I$_{t,S}$'

For the analysis of this hypothesis, MFSC's on-hand inventory buffers at three critical points—operations 3, 5, and 9—were randomly increased from five pre-determined levels—on-hand inventory buffers for one, two, three, four, and up to eight weeks—following an efficient simulation experiment, while the category of risk R$_3$ was enabled. Therefore, the results of the two hypothesis tests utilised—the Kruskal-Wallis sum rank test and the Wilcoxon sum rank test with continuity correction—confirmed with a degree of confidence equal to 99% that when on-hand inventory buffers were increased by the indicated levels, the MFSC's measure of resilience (Re^T) increased in the presence of R$_3$. .

Hypothesis 3a (H_{3a}): '*Short-term manufacturing capacity* (S) *moderates the relationship between the frequency of occurrence of operational risks* (R_{1r}) *and the measure of resilience in supply chains* (Re^T), *with the relationship being enhanced by increases in the levels of* S'

For the analysis of this hypothesis, MFSC's short-term manufacturing capacity was increased randomly from the two available levels—two or three work shifts activated—following an efficient simulation experiment, while the four risks of the category R_{1r} were enabled. Therefore, the results of the three hypothesis tests utilised—the Kruskal-Wallis sum rank test and Binomial distribution test, and the Wilcoxon sum rank test with continuity correction—confirmed with a degree of confidence equal to 95% that when short-term manufacturing capacity was increased by the indicated levels, the MFSC's measure of resilience (Re^T) increased in the presence of R_{1r}.

Hypothesis 3b (H_{3b}): "*Short-term manufacturing capacity* (S) *moderates the relationship between the frequency of occurrence of natural-disasters-and-intentional attacks* (R_{2r}) *and the measure of resilience in supply chains* (Re^T), *with the relationship being enhanced by increases in the levels of* S"

For the analysis of this hypothesis, MFSC's short-term manufacturing capacity was increased randomly from the two available levels—two or three work shifts activated—following an efficient simulation experiment, while the four risks of the category R_{2r} were enabled. Therefore, the results of the two hypothesis tests utilised—the Kruskal-Wallis sum rank test and the Wilcoxon sum rank test with continuity correction—confirmed with a degree of confidence equal to 99% that when short-term manufacturing capacity was increased by the indicated levels, the MFSC's measure of resilience (Re^T) increased in the presence of R_{2r}.

Hypothesis 3c (H_{3c}): '*Short-term manufacturing capacity* (S) *moderates the relationship between the frequency of occurrence of black-swan events* (R_3) *and the measure of resilience in supply chains* (Re^T), *with the relationship being enhanced by increases in the levels of* S'

Lastly, for the analysis of this hypothesis, MFSC's short-term manufacturing capacity was increased randomly from the two available levels—two or three work shifts activated—following an efficient simulation experiment, while the category of risk R_3 was enabled. Therefore, the results of the three hypothesis tests utilised—the Kruskal-Wallis sum rank test and binomial distribution tests, and the Wilcoxon sum rank test with continuity correction—confirmed with a degree of confidence equal to 95% that when short-term manufacturing capacity was increased by the indicated levels, the MFSC's measure of resilience (Re^T) increased in the presence of R_3.

8.2.2 From the open-ended questionnaire

The analysis of the results of the open-ended questionnaire administered to twelve staff members of the MFSC showed respondents' strong preference for the use of on-hand inventory buffers to prevent the occurrence of disruptions over short-term manufacturing capacity. Thus, in eight of the nine questions of the questionnaire posited—one for each type of risk, the alternative selected as the most effective to prevent the risk of disruption was 'to

increase the inventory buffers at different locations in the supply chain.' The only exception to this was for the risk R_{24} or 'contingent demand.' In this regard, when the respondents were consulted about this pattern, the answer was unanimous: "The needs of the troops do not wait, so what better than to use the on-hand inventory buffers?"

In conclusion, taking into account both results of the analysis of the simulation model and of the open-ended questionnaire with respect to the above-mentioned research question, it can be said that in all cases considered, higher levels of on-hand inventory buffers or short-term manufacturing capacity led to a higher level of resilience in military-SCs faced with operational risks, or intentional attacks, or black-swan events with at least a 95% confidence; though if military logisticians had to decide between the use of on-hand inventory buffers or short-term manufacturing capacity, they would choose the first alternative over the second in all cases except to prevent the risk of disruption due to contingent demand.

8.3 Theoretical Implications

As mentioned throughout this study and discussed in detail in Chapter 3, a theoretical conflict regarding the effectiveness of using inventory and/or capacity to reduce the incidence of SC-disruptions and/or to create SCs more resilient has been prevalent in the literature on SC-disruptions/SCRes.

Regarding the supportive arguments, three points of view can be identified: (1) Authors as Rice and Caniato (2003), Colicchia et al (2010), Schmitt and Singh (2012), Lee and Wolfe (2003), Christopher and Peck (2004), Sheffi (2002), Jüttner et al (2003), Sheffi and Rice (2005), Stecke and Kumar (2009), and Bradley et al (2015) emphasise in general that '*the more…the better*'—i.e. increases in the level of inventories or in the manufacturing capacity is an effective strategy to make SCs more resilient with little or none undesired effect; (2) In an intermediate position, other authors as Chopra and Sodhi (2004), Lockamy and McCormack (2010), Boone et al (2013), Son and Orchard (2013), Brandon-Jones et al (2015), and Hoffman et al (2013) advocate that '*the more…the better, but…*'—i.e. although increases in the level of inventories or in the manufacturing capacity may be an effective strategy to make SCs more resilient, this is not exempt of adverse effects. Lastly, (3) there is a group of authors as Tomlin (2006), Hopp et al (2012), Zsidisin and Wagner (2010), Zsidisin et al (2005), Tomlin and Wang (2012), Faden (2014), Tang (2006), Pickett (2006), and Bode et al (2011) argue that '*the more…the better only for…*'—i.e. to increase the level of inventories or the manufacturing capacity could be an effective strategy to make SCs more resilient, but only under certain circumstances.

On the opposite side, there is a line of authors who have a diverging standpoint with respect to the use of inventory or manufacturing capacity to inhibit SC-disruptions or to make SCs more resilient, on which two points of view can be identified: (4) authors as Kim et al (2015) and Brusset and Teller (2017) argue in general that '*the more…the same*'—i.e. increases in the levels of inventories or in the manufacturing capacity have no effect on SCs to make them more resilient. And (5) authors as Marley et al (2014), Christopher and Lee (2004), Bandaly et al (2012), and Park et al (2016) posit that '*the more…the worse*'—i.e. increases in the levels of inventories or in

the manufacturing capacity not only is an innocuous strategy to make SCs more resilient, but also their performance can be negatively affected.

Regarding the above supportive arguments, the results of this research contradict to some extent the authors' position (1)—'*the more…the better*'—and give support to the authors' position (2)—'*the more…the better, but…*' That is, although this research did not include the 'cost factor' due to the nature of the unit of analysis—see discussion in this regard in Section 3.2—, it is undeniable that increases in the level of on-hand inventory buffers or short-term manufacturing capacity carry higher costs and make SCs prone to the incidence of some risks. Likewise, the results of the study confirm that both on-hand inventory buffers/short-term manufacturing capacity are efficient inhibitors in the short term of disruptions caused by a broad range of risks—nine in total, or up to twenty if the place of occurrence of the risk is considered as a differential element, which contradicts to some extent the authors' position (3)—'*the more…the better only for…*' Lastly, concerning the non-supportive arguments —author's position (4) and (5) —, the results of the study directly contradict the two authors' position discussed.

Last, but not least, this research confirms the observations made by Lapide (2008) and Waters (2007) in the sense of the relative ease for implementing a buffering strategy as described to prevent the occurrence of SC disruptions and/or increase the level of resilience. This aspect is of paramount importance for military-SCs, especially when the rigidities they face are taken into account, as discussed in Section 3.2.

8.4 Practical Implications

As emphasized in Chapter 3, the choice of the aforesaid buffering strategy as a central research topic was motivated by its advantages and ease of use for application in military-SCs. This type of strategy represents in practice not only the first line of defense available to military logisticians to deal with the occurrence of disruptions, but also the easiest strategy to implement. In this sense, it is worth mentioning that the results obtained cover not only military-SCs but also commercial-SCs. Thus, the results of the study indicate that a buffering strategy based on on-hand inventory buffers or short term manufacturing capacity as simulated can effectively hedge against the risks and high uncertainty that, for the most part, characterizes military operations. Technical details on how to implement and evaluate such a strategy in practice were described in Chapter 6 of this study. Hence, for its correct application, a careful monitoring of the holding/replenishment/obsolescence inventory costs, for the first case, and the labour cost, for the second, has to be implemented conjointly. Lastly, any change detected in the long-term pattern of demand affecting its steadiness must be quickly incorporated into the buffering strategy, which implies that the SC should have a fine-tuned cross-functional forecasting process in advance.

8.5 Limitations of the Study

The limitations of the present study are explained as follows:

8.5.1 From the assumptions of the simulation model

The simulation model that represents the behaviour of the MFSC incorporates a number of simplifying assumptions (eight). The output data of the simulation model are the main input of the results of the study; thereby the results and findings of this study must be seen in light of such assumptions. Of all of them, one in particular strongly influences the results of this study: the assumption related to the stationarity of the SC-parameters over time—see Subsection 6.58. Thus, although it is reasonable to suppose that assembly of rations 'hunts' the demand in a push-based SC—the behaviour of the MFSC up to operation 9 or *supply battalion*, to assume in general that demand is stable throughout the simulation period—up to 20 years—is a strong assumption within the model. This factor is decisive since it delimits the effectiveness of the buffering strategy studied. In other words, the effectiveness of the buffering strategy is guaranteed as long as the demand for items is steady over time; otherwise, as pointed out by Christopher and Lee (2004), the outcome can be higher financial risks. However, this assumption—steady-state demand function—is not entirely implausible, at least for military-SCs, since the total number of combat rations demanded in a period t is function of the number of troops in period t, and this latter, in turn, is restricted by the installed capacity of military garrisons and the assigned budget.

8.5.2 From the non-inclusion of the cost factor

Cost factor was not considered in the analysis as a critical variable mainly for the reasons explained in Section 3.2 of this study, which can be summarized in the following proposition: 'For military-SCs only, in conditions of war, the cost of shortages of troops is always higher than the result of adding, holding, replenishing, or obsolescence inventory costs and/or labour cost.' This proposition encompasses the premise that failures in the timeliness of supply order deliveries entail the risk of loss of life. In addition, neither the seminal concept of resilience proposed by Holling (1973) nor the SCRes definitions introduced in Table 5 include the cost factor, except for in the work of Tukamuhabwa and colleagues (2015). However, for the sake of discussion, if the military-SCs operated in peace mode, their operating conditions would be quite similar to commercial-SCs, therefore further research should include the cost factor.

8.5.3 From utilising of a single unit of analysis

This study is based on the analysis of a single military-SC responsible for supplying a broad range of subsistence items, in particular, combat ration packs. Hence, the utilisation of a single unit of analysis limits to some extent the generalization of the results to other similar SCs. This is attributable not only to the difficulties in accessing information on this typology of SCs—due to their strategic nature for the armed forces of a country, but also because of their small number. For example, in the country in which the MFSC under analysis is located, only a total of six SCs currently operate. To overcome this limitation, the simulation model considered 90

different SC configurations within the experimental design, which is in practice equivalent to having the same number of units of analysis.

8.6 Agenda for Further Studies

The following subsections present the agenda for further research.

8.6.1 Between on-hand inventory buffers and short-term manufacturing capacity, is there any synergistic effect, and is one more effective at preventing SC-disruptions/creating SCRes than the other? Is there any other factor to consider?

As previously stated, the empirical findings of this study indicated with a high degree of confidence that both on-hand inventory buffers and short-term manufacturing capacity positively moderate the measure of SCRes or Re^T. Moreover, respondents' preference clearly favoured the use of the first over the second. In fact, the results of the non-parametric tests appear to be more significant for on-hand inventory buffers than for short-term manufacturing capacity. However, the results of the present study are not conclusive for this aspect and more research needs to be completed to answer the two header questions. Finally, the SC lead-time could be an additional factor to include within the analysis of buffer-related strategies.

8.6.2 In search of an optimum level of SCRes

As mentioned before, the empirical evidence found in the simulation model indicates with a high degree of confidence that both on-hand inventory buffers and short-term manufacturing capacity positively moderates the level of SCRes. In the case of the MFSC under analysis, as outlined above, the cost factor was not included in the study as a critical variable. However, if the same studied buffering strategy was to be implemented in commercial-SCs, this critical factor (cost) should be included into the analysis. In this sense, the idea of finding 'an optimum level of resilience in supply chains' that also could integrate the four sub-indicators described in Equation 5.5 might be a good starting point for a new promising research avenue. The above would require, however, re-considering the use of a simulation-based tool as the primary research method to gather (generate) data.

8.6.3 Applying the measure of SCRes (Re^T) to management of projects

This study developed a robust theoretical framework in Chapter 5 to assess resilience in military-SCs by using the *tail autonomy effect*. As was explained, this novel perspective offers an alternative way of understanding SC-disruptions. However, this theoretical framework might be also be used in a discipline allied with logistics and supply chain management (LSCM): project management (PM). The LSCM and PM disciplines are intrinsically coupled, to extent that the design and enhancement of SCs can be seen as a set of interrelated projects (Ayers, 2010). Therefore, the application of concepts such as an 'autotomy period', 'recovery period', 'disruption period', and 'filled rate' may help to respond to the research question: How do we make more resilient projects?

8.7 Summary of Chapter 8

The chapter explained in detail how the study fulfilled the research problem introduced in Chapter 1. In doing so, it synthesized the empirical findings from the research hypotheses and the open-ended questionnaire. Second, it pinpointed the theoretical implications for the open debate on the effectiveness of a buffering strategy based on on-hand inventory buffers and short-term manufacturing capacity. Third, it highlighted the practical implications for military logisticians and stakeholders on how to implement a buffering strategy as mentioned. Fourth, it pointed out the three main aspects that limit the generalization of the results of the study. Lastly, it delineated an agenda for future research.

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Annexes

Annex A. Algorithm for Text Mining Applications in *R*

Software 1: Text mining package (tm)

Version: 0.7-1
Authors: Feinerer, I. and Hornik, K.
Year: 2017
Repository: https://cran.r-project.org/web/packages/tm/index.html

Step 1: Load the packages

```
library("tm")
library("wordcloud")
library("RColorBrewer")
```

Step 2: Load the text

```
text <- readLines(file.choose())
```

Step 3: Load the data as a corpus

```
docs <- Corpus(VectorSource(text))
```

Step 4: Text transformation

Replace some characters with space:

```
toSpace <- content_transformer(function (x , pattern ) gsub(pattern, " ", x))
docs <- tm_map(docs, toSpace, "/")
docs <- tm_map(docs, toSpace, "@")
docs <- tm_map(docs, toSpace, "\\|")
```

Step 5: Cleaning the text

Convert the text to lower case:

```
docs <- tm_map(docs, content_transformer(tolower))
```

Step 6: Remove numbers, common stop-words, punctuations and unnecessary white space

```
docs <- tm_map(docs, removeNumbers)
docs <- tm_map(docs, removeWords, stopwords("english"))
docs <- tm_map(docs, removePunctuation)
docs <- tm_map(docs, stripWhitespace)
```

Step 7: Build a document matrix that contains the frequency of the words

```
dtm <- TermDocumentMatrix(docs)
m <- as.matrix(dtm)
v <- sort(rowSums(m),decreasing=TRUE)
d <- data.frame(word = names(v),freq=v)
```

Software 2: Word clouds

Version: 2.5
Author: Fellows, I.
Year: 2014
Repository: https://cran.r-project.org/web/packages/wordcloud/index.html

Step 8: Generate the word cloud

```
set.seed(1234)
wordcloud(words = d$word, freq = d$freq, min.freq = 1,
        max.words=200, random.order=FALSE, rot.per=0.35,
        colors=brewer.pal(8, "Dark2"))
```

Arguments of the word-cloud generator function:

words: the words to be plotted.
freq: their frequencies.
min.freq: words with frequency below min.freq will not be plotted.
max.words: maximum number of words to be plotted.
random.order: plot words in random order. If false, they will be plotted in decreasing frequency.
rot.per: proportion words with 90-degree rotation (vertical text).
colors : color words from least to most frequent.

Annex B. Simulink program code

The software *Simulink*® [v.8.6.0] of MATLAB was used for modeling a supply chain of military food (MFSC) subjected to the stepwise occurrence of three categories of risk—operational risks, R_{1r}; natural disasters and intentional attacks R_{2r}; and black-swan events, R_3—while on-hand inventory buffers and short-term manufacturing capacity—the buffering strategy—were gradually increased following an efficient experimental design. All Simulink models work based on the discrete time specified in each configuration. In the case analysed, the reference was 0.00312 real-time seconds, which describes the lowest processing time of the MFSC that occurred in operations 5, 6, and 7 or *assembly-line*.

In order to ensure that all simulation runs generate different data from each other, that is, the quantity of rations required and times of occurrence of risks in each case, it was necessary to specify within the function of uniform distribution of pseudorandom numbers embedded in MATLAB, a seed or initial value that would guarantee the generation of different data in the variables mentioned in each configuration. Likewise, to simulate the occurrence of the risks, MATLAB code functions were used, independent and distinct in each case, as described in Tables 6.6, 6.7, and 6.8. These functions have as their only input-parameter a seed that generates different time-values in each execution, while inside they have an output that throws a vector containing both the time of occurrence of the risk and the recovery time of the operation, for those cases in which operations would require these.

Each of the 13 operations of the simulation model is represented by a block containing two main components: one *buffer*, which is responsible for storing the rations that arrive at the operation as the SC 'pushes' each order; and a *flowchart*, coded within a flowchart-block in charge of controlling the inputs, time, and output of each of the operations. In each of the 13 operations of the MFSC, the buffer is modelled through a reading-function that verifies whether the immediately preceding operation sends supplies. If the buffer detects the entry of new rations, it adds the amount received to the amount stored in its memory; otherwise it overwrites the value stored in its memory. Regarding the flowchart, this is represented differently in each of the operations.

Because the simulation model considers the delays caused by the risks that occurred during the execution of each configuration, it was necessary to program a block that would act as a barrier of the data on each of the parameters associated with each request generated. The parameters that were specified within this matrix were: the quantity of rations required by the order, the number of the associated order, the time in which the order was generated, and the total amount of accumulated orders and lost orders. This matrix is sent as an input variable to operation 9 or the *supply battalion*, which is responsible for processing and ordering, from lowest to highest value (SPT-rule), and then the attended order is removed from the queue.
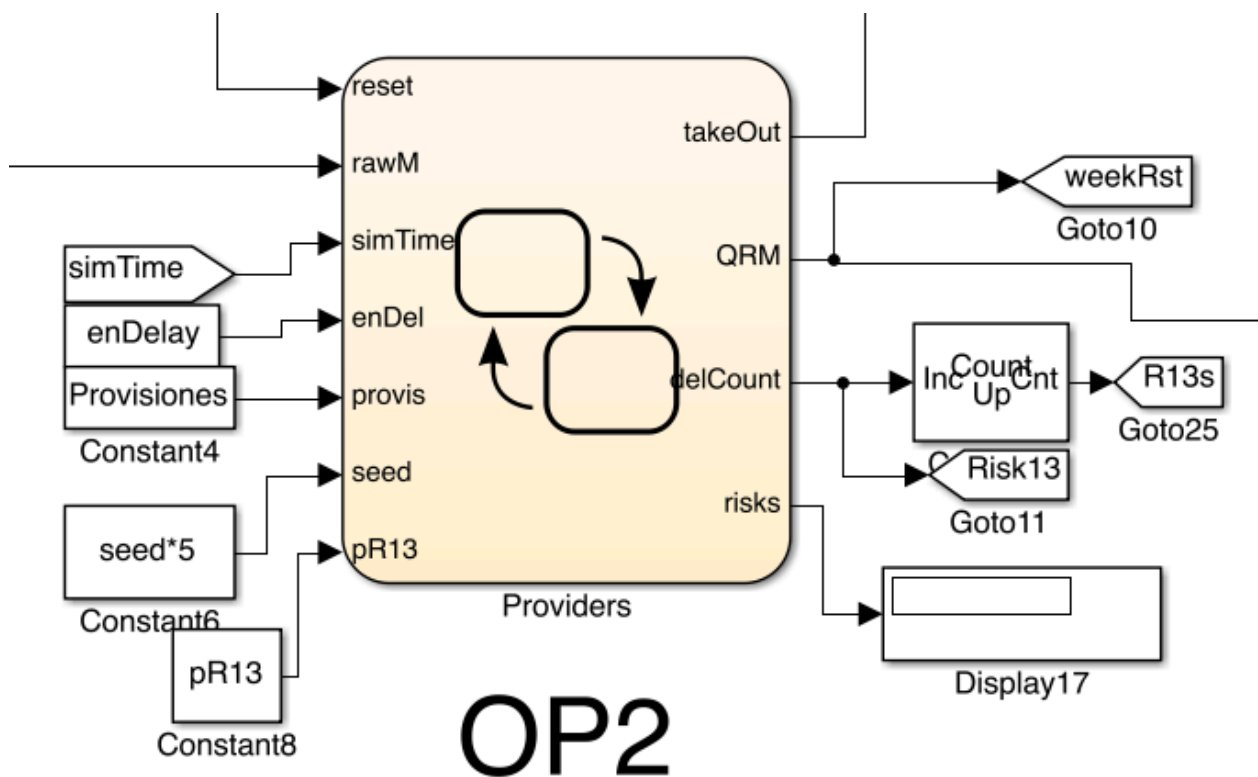
Thereby, from a macro-perspective, the simulation model of the MFSC is visualized as follows:
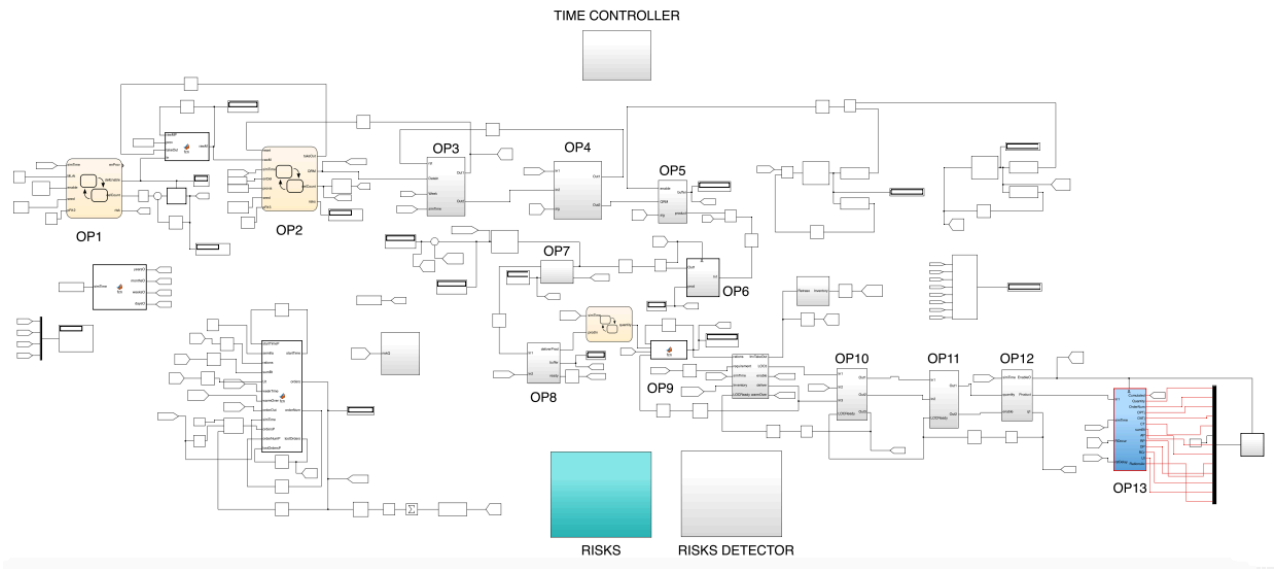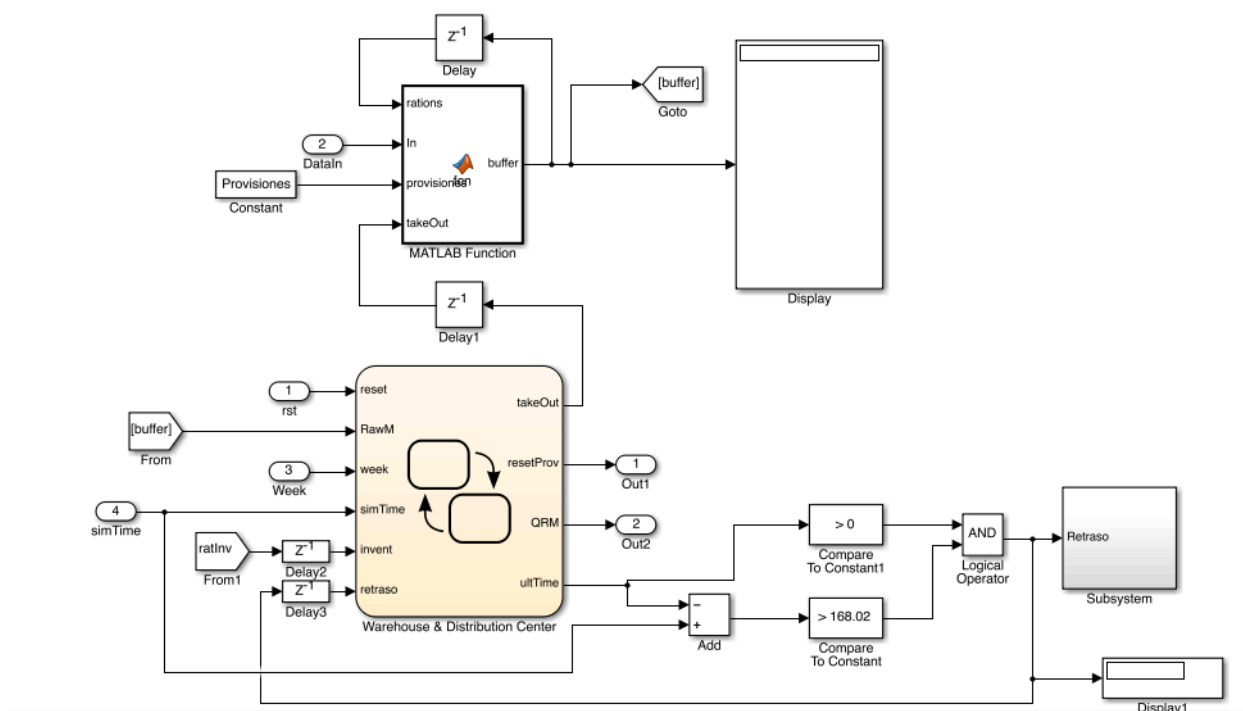
The operation 1 ('Military logistics agency') as follows:

OP1
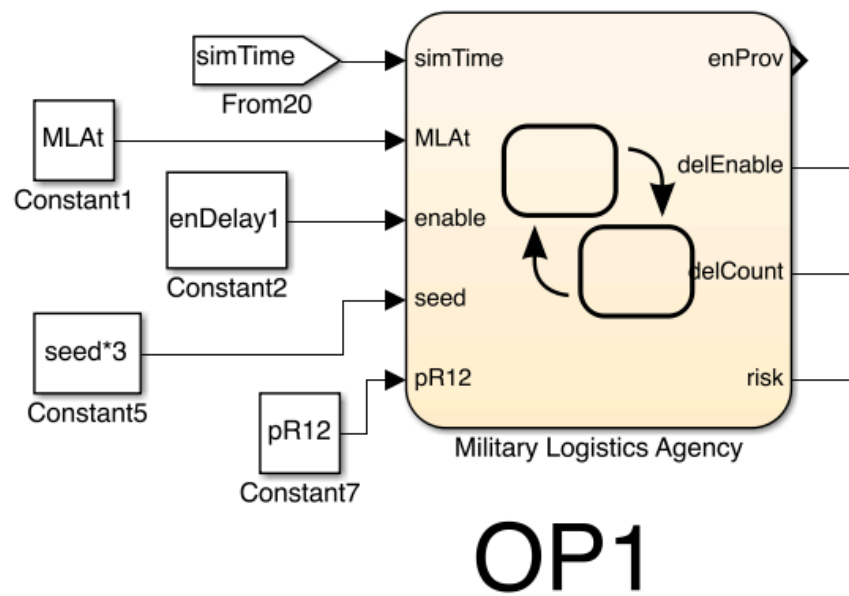
The operation 2 ('Suppliers') as follows:
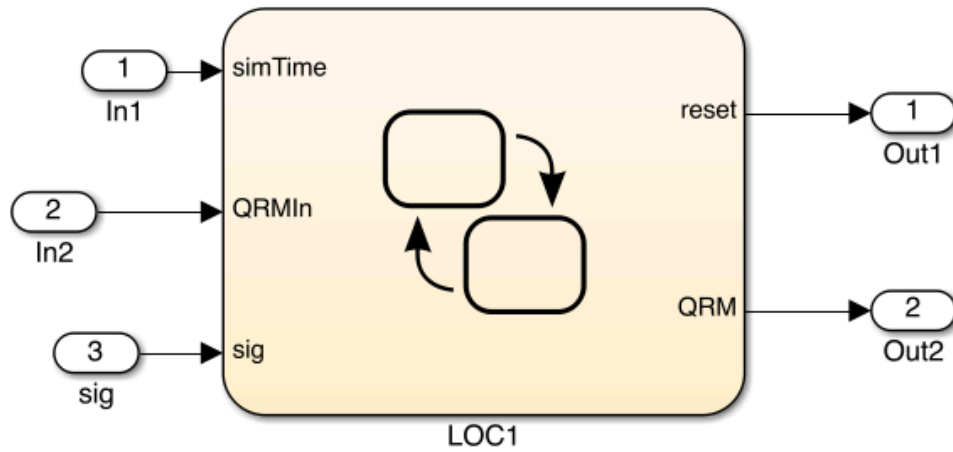

The operation 3 ('Warehouse & Distribution Centre') as follows:

The operation 4 ('Line-of-Communication') as follows:

The operation 5 ('Assembly-Line') as follows:
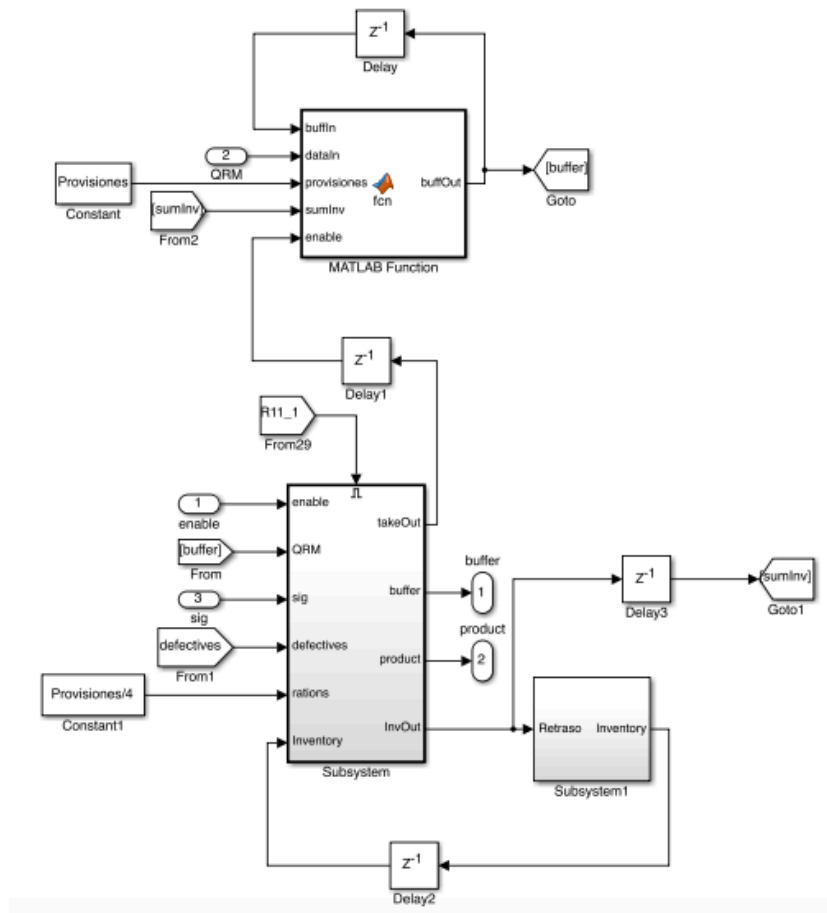
The operation 6 ('Assembly-Line') as follows:
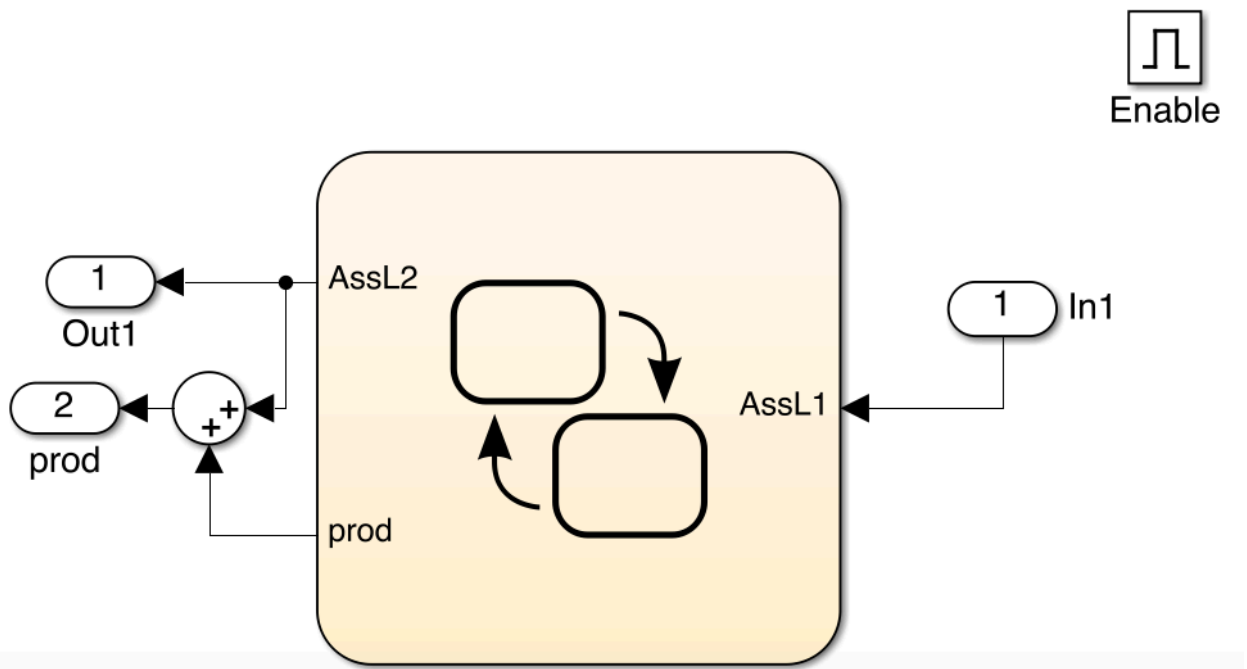
The operation 7 ('Assembly-Line') as follows:
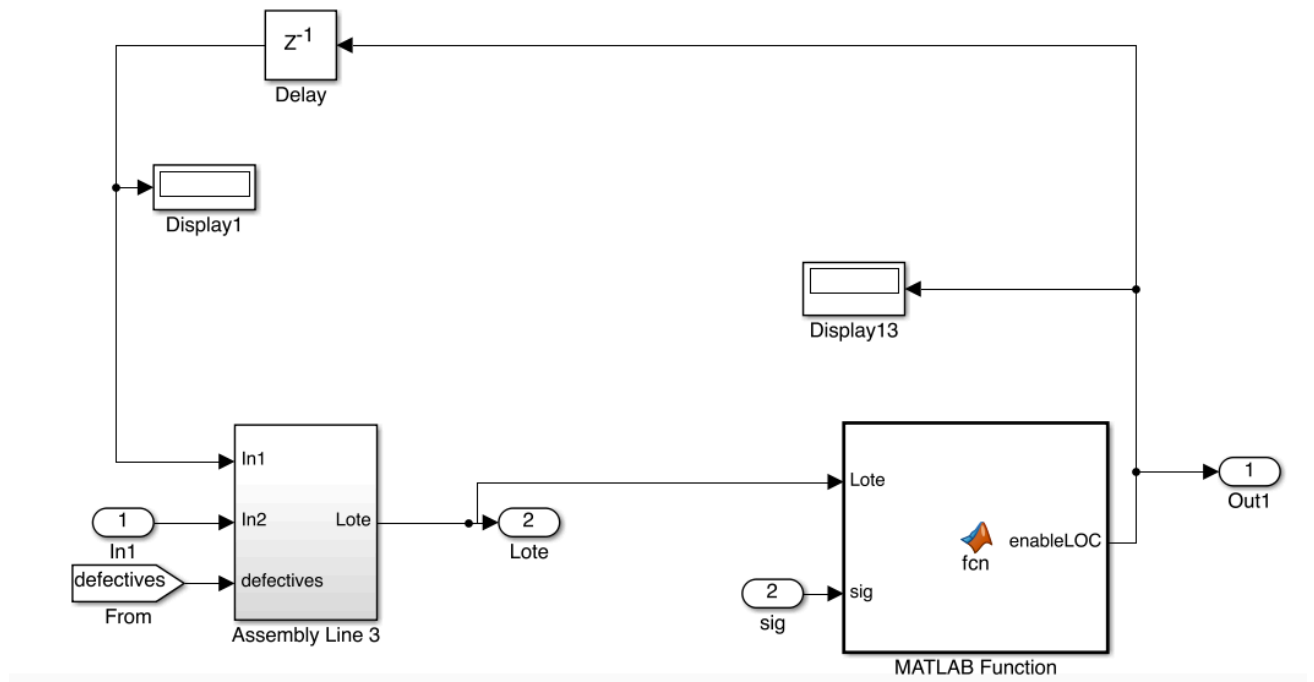
The operation 8 ('Line-of-Communication') as follows:

LOC2
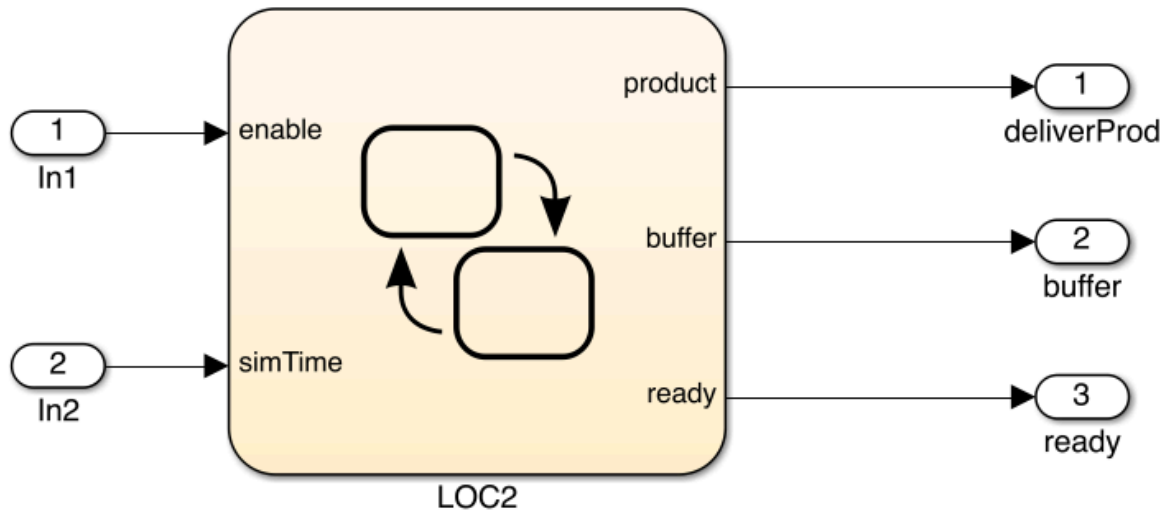
The operation 9 ('Supply Battalion') as follows:

OP9

The operation 10 ('Line-of-Communication') as follows:

The operation 11 ('Combat Service Support Units') as follows:
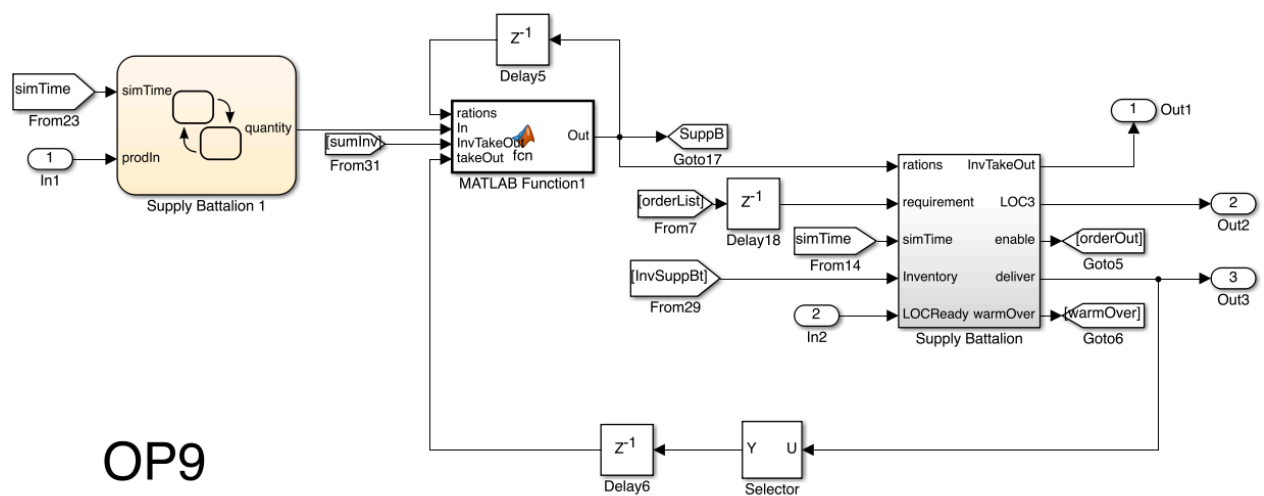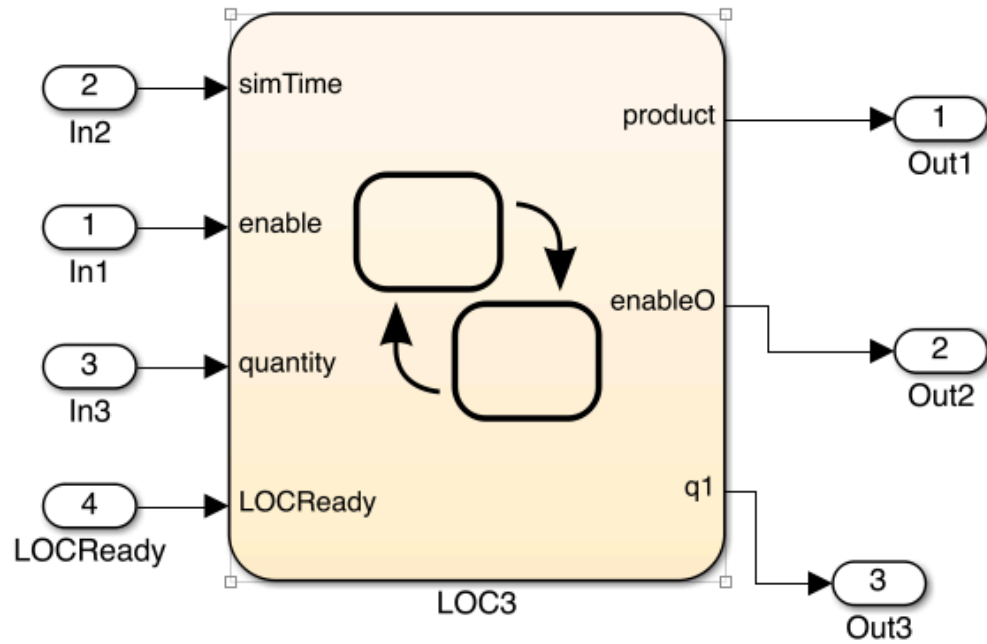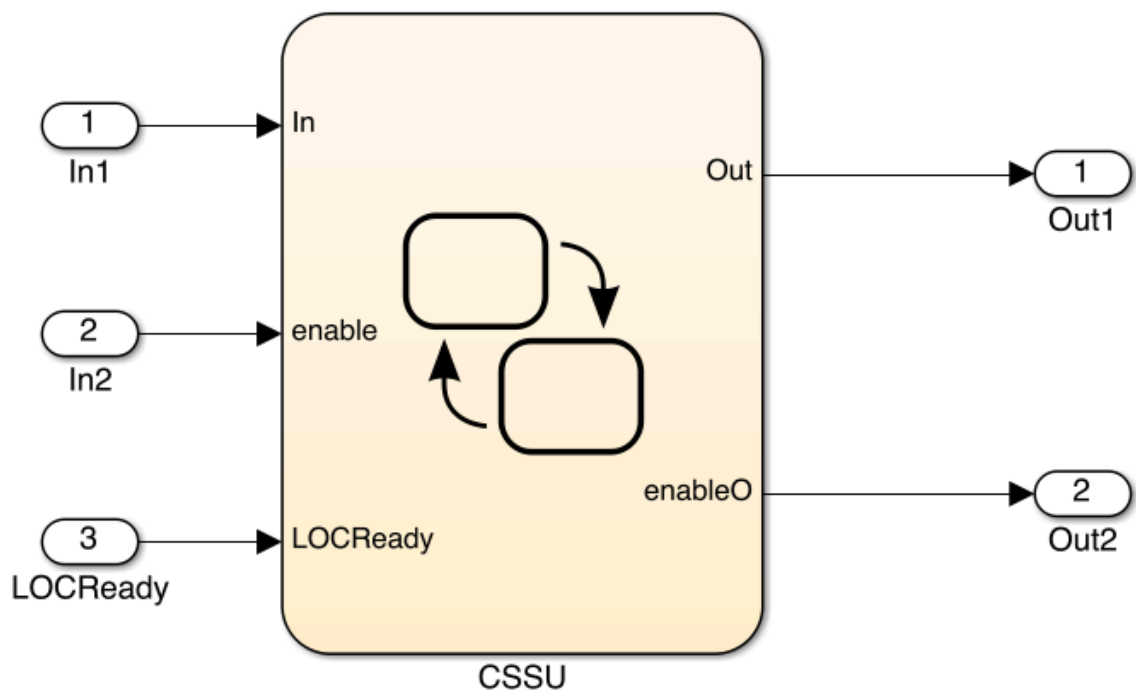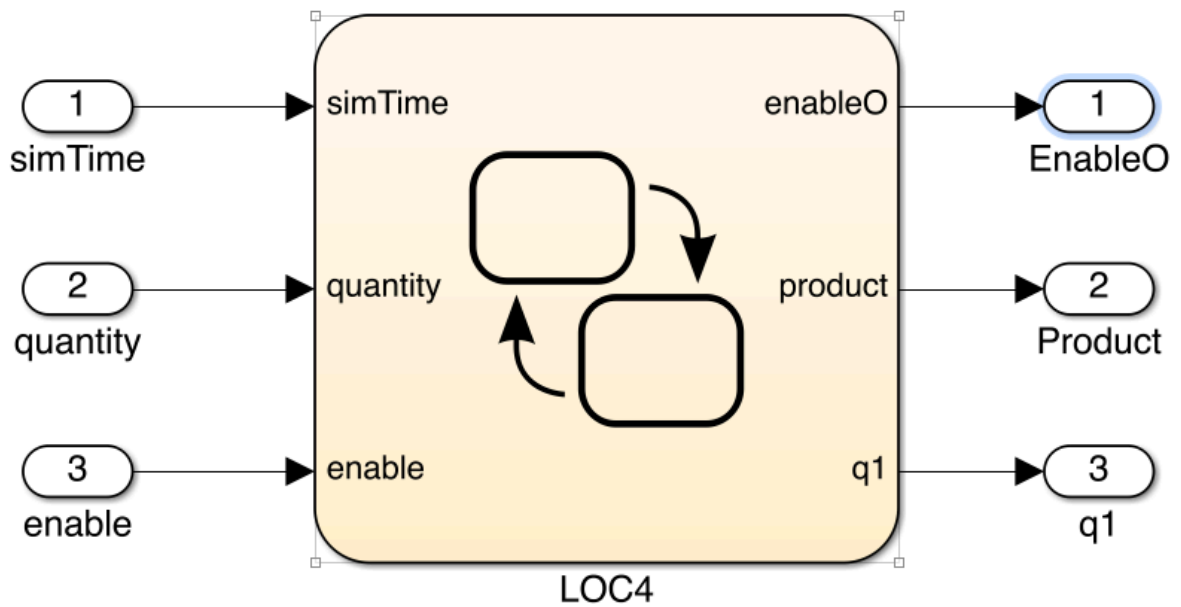
The operation 12 ('Line-of-Communication') as follows:

An lastly, the operation 13 ('Theatre of Operations') as follows:
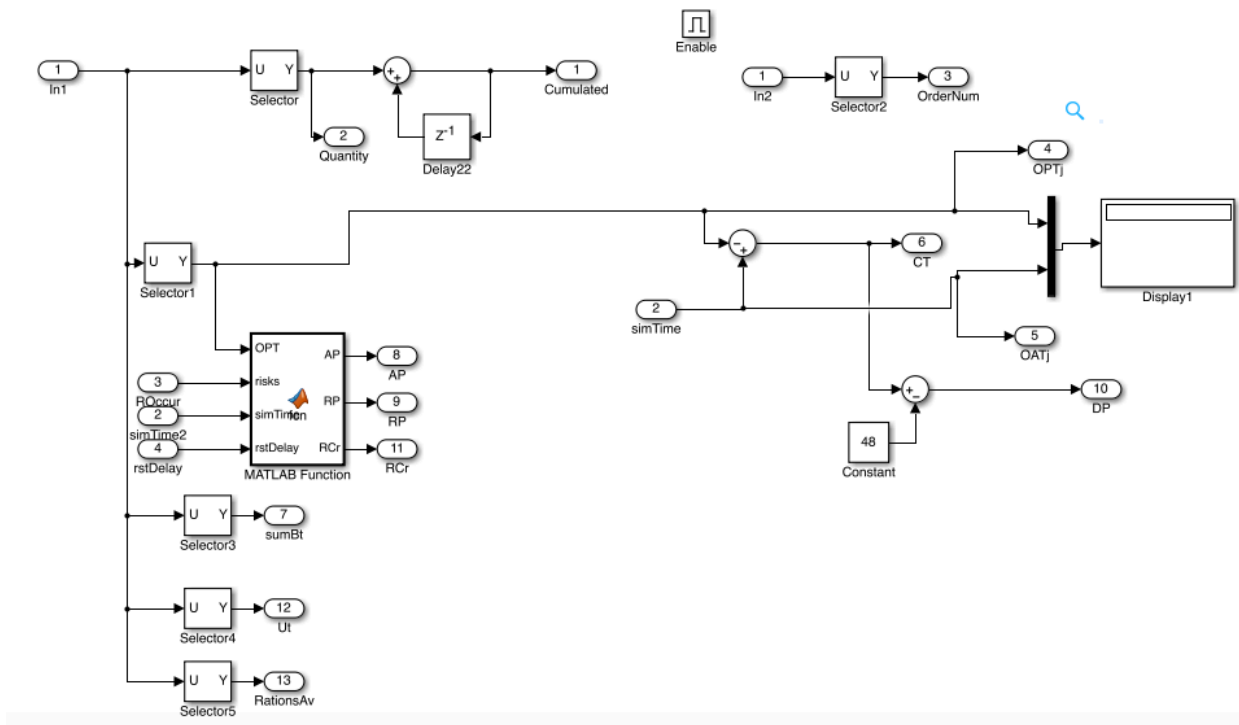
Annex C. The Open-Ended Questionnaire

Thank you for agreeing to take part in this important questionnaire whose main purpose is to contrast the output results of the simulation modeling regarding the effectiveness of buffering strategies in the relationship between risks and resilience. This questionnaire contains 11 questions organized in 4 sections, and an estimated time of 15-20 minutes to be completed. With the exception of the Section A, the Sections B, C and D are of the type "What do you think of…?". Assume in the questions in Sections B, C and D that you are able to decide on the implementation of any of the available alternatives. Remember that your answers will be kept strictly confidential.

Section A – Respondents Background (number of questions: 2)

Respondent's full name:

_____

A1. What is your position in the organization?

A2. Describe briefly the main functions of your position
-
-
-
-

Section B – Analysis of Operational Risks (number of questions: 4)

B1. Consider the following hypothetical situation: <u>A machine in one of the working stations in the assembly process suffers a breakdown</u>. The potential risk is that the flow of rations to the military personnel might be interrupted/impacted by this event. Of the following two alternatives choose the option (☑) that you consider is the most effective to prevent the risk of disruption (before the hypothetical situation occurs):

a. Increase the inventory buffers along different locations in the supply chain
b. Increase the number of working-shifts per day

B2. Consider the following hypothetical situation: <u>The contracting process of any of the raw materials required for the assembly of rations is delayed from the initial schedule</u>. The potential risk is that the flow of rations to the military personnel might be interrupted/impacted by this event. Of the following two alternatives choose the option (☑) that you consider is the most effective to prevent the risk of disruption (before the hypothetical situation occurs):

a. Increase the inventory buffers along different locations in the supply chain
b. Increase the number of working-shifts per day

B3. Consider the following hypothetical situation: <u>Planned deliveries of raw materials/components required for the assembly of rations are delayed from the initial schedule</u>. The potential risk is that the flow of rations to the military personnel might be interrupted/impacted by this event. Of the following two alternatives choose the option (☑) that you consider is the most effective to prevent the risk of disruption (before the hypothetical situation occurs):

a. Increase the inventory buffers along different locations in the supply chain
b. Increase the number of working-shifts per day

B4. Consider the following hypothetical situation: <u>A number of defective items or non-conforming are detected during the assembly process.</u> The potential risk is that the flow of rations to the military personnel might be interrupted/impacted by this event. Of the following two alternatives choose the option (☑) that you consider is the most effective to prevent the risk of disruption (before the hypothetical situation occurs):

a. Increase the inventory buffers along different locations in the supply chain
b. Increase the number of working-shifts per day

Section C – Analysis of Natural Disasters & Intentional Attacks (number of questions: 4)

C1. Consider the following hypothetical situation: <u>A natural disaster[1] affects the assembly plant taking out of operation for several days</u>. The potential risk is that the flow of rations to the military personnel might be interrupted/impacted by this event. Of the following two alternatives choose the option (☑) that you consider is the most effective to prevent the risk of disruption (before the hypothetical situation occurs):

a. Increase the inventory buffers along different locations in the supply chain
b. Increase the number of working-shifts per day

---

[1] Earthquake, storm, flood, fires, or power cuts.

C2. Consider the following hypothetical situation: <u>A ration shipment and its mean of transport are destroyed in a terrorist attack causing operation delays</u>. The potential risk is that the flow of rations to the military personnel might be interrupted/impacted by this event. Of the following two alternatives choose the option (☑) that you consider is the most effective to prevent the risk of disruption (before the hypothetical situation occurs):

a. Increase the inventory buffers along different locations in the supply chain
b. Increase the number of working-shifts per day

C3. Consider the following hypothetical situation: <u>A centre of warehousing of rations is affected by a terrorist attack causing operation delays</u>. The potential risk is that the flow of rations to the military personnel might be interrupted/impacted by this event. Of the following two alternatives choose the option (☑) that you consider is the most effective to prevent the risk of disruption (before the hypothetical situation occurs):

a. Increase the inventory buffers along different locations in the supply chain
b. Increase the number of working-shifts per day

C4. Consider the following hypothetical situation: <u>An unexpected increase in the demand of rations occurs</u>. The potential risk is that the contingent order will not be served on time. Of the following two alternatives choose the option (☑) that you consider is the most effective to prevent the risk of disruption (before the hypothetical situation occurs):

a. Increase the inventory buffers along different locations in the supply chain
b. Increase the number of working-shifts per day

Section D – Black-Swan Events (number of questions: 1)

D1. Consider the following hypothetical situation: <u>An air-attack from a neighbour country is launched taking the assembly plant out of operation for several weeks</u>. The potential risk is that the flow of rations to the military personnel might be interrupted/impacted by this event. Of the following two alternatives choose the option (☑) that you consider is the most effective to prevent the risk of disruption (before the hypothetical situation occurs):

a. Increase the inventory buffers along different locations in the supply chain
b. Increase the number of working-shifts per day

End of the questionnaire (*Fin del cuestionario*)---

Annex D. Algorithms for Categorizing R_{cr} and Re^T in R

```
library(Matrix)
library(arules)
library(xlsx)

i <- 1

for(i in c(1:30)){

  CF <- read.xlsx(paste("D:/Project/Input_Continuo/Cf", i, ".xlsx", sep = ""), sheetIndex = 1)

  name.column <- colnames(CF)
  columns <- ncol(CF)
  risks <- ncol(CF) - 1

  CF.1 <- CF
  x <- 1

  for(x in c(1:riesgos)){

    a <- CF[,x]

    b <- cut(a,
          breaks = c(-Inf,0,1,Inf),
          labels = c("N", "O", "F"))

    assign(paste("r", x, sep = ""), b)
    CF.1[ , paste("r", x, sep = "")] <- b

    x <- x+1

  }

  c <- CF[, columns]
  d <- cut(c,
        breaks = c(-Inf, 0.003, 0.0051, Inf),
        labels = c("L", "M", "H"))

  assign("ReT1", d)
  CF.1[ , "ReT1"] <- d

  CF.1[1:columns] <- list(NULL)
```

```r
  names(CF.1) <- name.column

  write.csv(CF.1, file = paste("D:/Project/Catego_Continuo/Cat_Con_Cf_", i, ".csv", sep =
  ""), row.names=FALSE)

  i <- i+1

}
```

Annex E. A Priori Algorithm for Mining Rules of Type 'R$_{cr}$ = O ∨ F ⇒Re^T = L' (E)

```
library(Matrix)
library(arules)
library(xlsx)

i <- 1

for(i in c(1:30)){

  CF <- read.csv(file= paste("D:/Project/Catego_Continuo/Cat_Con_Cf_",i, ".csv", sep = ""),
header=TRUE, sep = ",")

 #  View(CF)

 rules.CF  <-  apriori(CF,  parameter  =  list(maxtime=20, maxlen=20, minlen=2, supp=0.1,
conf=0.9, target="rules"), control = list(verbose=F))

 #  inspect(rules.CF)

 ## rules.CF <- subset(rules.CF, subset = rhs %pin% "ReT=")

 #  inspect(rules.CF)
 #                 Rules According to Experimental Design
 #                 ********************************

 switch( i,

      #  CF 1
      rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R13=O" | lhs %ain% "R13=F" |
                  lhs %ain% "R14=O" | lhs %ain% "R14=F" ),

      #  CF 2
      rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R12=O"| lhs %ain% "R12=F" ),

      #  CF 3
      rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R11_1=O" | lhs %ain% "R11_1=F"
|
                  lhs %ain% "R11_2=O" | lhs %ain% "R11_2=F" |
                  lhs %ain% "R13=O" | lhs %ain% "R13=F" |
                  lhs %ain% "R14=O" | lhs %ain% "R14=F" ),
      #  CF 4
```

```
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R11_1=O" | lhs %ain% "R11_1=F"
|
              lhs %ain% "R11_2=O" | lhs %ain% "R11_2=F" |
              lhs %ain% "R12=O" | lhs %ain% "R12=F" |
              lhs %ain% "R13=O" | lhs %ain% "R13=F" ),

# CF 5
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R13=O"| lhs %ain% "R13=F" ),

# CF 6
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R11_1=O" | lhs %ain% "R11_1=F"
|
              lhs %ain% "R11_2=O" | lhs %ain% "R11_2=F" |
              lhs %ain% "R12=O" | lhs %ain% "R12=F" |
              lhs %ain% "R14=O" | lhs %ain% "R14=F" ),

# CF 7
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R11_1=O" | lhs %ain% "R11_1=F"
|
              lhs %ain% "R11_2=O" | lhs %ain% "R11_2=F" |
              lhs %ain% "R14=O" | lhs %ain% "R14=F" ),
# CF 8
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R11_1=O" | lhs %ain% "R11_1=F"
|
              lhs %ain% "R11_2=O" | lhs %ain% "R11_2=F" ),

# CF 9
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R12=O" | lhs %ain% "R12=F" |
              lhs %ain% "R13=O" | lhs %ain% "R13=F" |
              lhs %ain% "R14=O" | lhs %ain% "R14=F" ),

# CF 10
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R12=O" | lhs %ain% "R12=F" |
              lhs %ain% "R14=O" | lhs %ain% "R14=F" ),

# CF 11
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R21_1=O" | lhs %ain% "R21_1=F"
|
              lhs %ain% "R21_2=O" | lhs %ain% "R21_2=F" |
              lhs %ain% "R21_3=O" | lhs %ain% "R21_3=F" |
              lhs %ain% "R21_4=O" | lhs %ain% "R21_4=F" |
              lhs %ain% "R21_5=O" | lhs %ain% "R21_5=F" |
              lhs %ain% "R23=O" | lhs %ain% "R23=F" |
              lhs %ain% "R24=O" | lhs %ain% "R24=F" ),
```

```
# CF 12
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R21_1=O" | lhs %ain% "R21_1=F"
|
                    lhs %ain% "R21_2=O" | lhs %ain% "R21_2=F" |
                    lhs %ain% "R21_3=O" | lhs %ain% "R21_3=F" |
                    lhs %ain% "R21_4=O" | lhs %ain% "R21_4=F" |
                    lhs %ain% "R21_5=O" | lhs %ain% "R21_5=F" ),

# CF 13
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R21_1=O" | lhs %ain% "R21_1=F"
|
                    lhs %ain% "R21_2=O" | lhs %ain% "R21_2=F" |
                    lhs %ain% "R21_3=O" | lhs %ain% "R21_3=F" |
                    lhs %ain% "R21_4=O" | lhs %ain% "R21_4=F" |
                    lhs %ain% "R21_5=O" | lhs %ain% "R21_5=F" |
                    lhs %ain% "R22_1=O" | lhs %ain% "R22_1=F" |
                    lhs %ain% "R22_2=O" | lhs %ain% "R22_2=F" |
                    lhs %ain% "R22_3=O" | lhs %ain% "R22_3=F" |
                    lhs %ain% "R22_4=O" | lhs %ain% "R22_4=F" |
                    lhs %ain% "R24=O" | lhs %ain% "R24=F" ),

# CF 14
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R21_1=O" | lhs %ain% "R21_1=F"
|
                    lhs %ain% "R21_2=O" | lhs %ain% "R21_2=F" |
                    lhs %ain% "R21_3=O" | lhs %ain% "R21_3=F" |
                    lhs %ain% "R21_4=O" | lhs %ain% "R21_4=F" |
                    lhs %ain% "R21_5=O" | lhs %ain% "R21_5=F" |
                    lhs %ain% "R22_1=O" | lhs %ain% "R22_1=F" |
                    lhs %ain% "R22_2=O" | lhs %ain% "R22_2=F" |
                    lhs %ain% "R22_3=O" | lhs %ain% "R22_3=F" |
                    lhs %ain% "R22_4=O" | lhs %ain% "R22_4=F" |
                    lhs %ain% "R23=O" | lhs %ain% "R23=F" ),

# CF 15
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R23=O" | lhs %ain% "R23=F" |
                    lhs %ain% "R24=O" | lhs %ain% "R24=F" ),

# CF 16
rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R22_1=O" | lhs %ain% "R22_1=F"
|
                    lhs %ain% "R22_2=O" | lhs %ain% "R22_2=F" |
                    lhs %ain% "R22_3=O" | lhs %ain% "R22_3=F" |
```

```
                              lhs %ain% "R22_4=O" | lhs %ain% "R22_4=F" ),

          # CF 17
          rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R22_1=O" | lhs %ain% "R22_1=F"
|
                              lhs %ain% "R22_2=O" | lhs %ain% "R22_2=F" |
                              lhs %ain% "R22_3=O" | lhs %ain% "R22_3=F" |
                              lhs %ain% "R22_4=O" | lhs %ain% "R22_4=F" |
                              lhs %ain% "R23=O" | lhs %ain% "R23=F" ),

          # CF 18
          rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R23=O" | lhs %ain% "R23=F" ),

          # CF 19
          rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R22_1=O" | lhs %ain% "R22_1=F"
|
                              lhs %ain% "R22_2=O" | lhs %ain% "R22_2=F" |
                              lhs %ain% "R22_3=O" | lhs %ain% "R22_3=F" |
                              lhs %ain% "R22_4=O" | lhs %ain% "R22_4=F" |
                              lhs %ain% "R24=O" | lhs %ain% "R24=F" ),

          # CF 20
          rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R21_1=O" |
                              lhs %ain% "R21_2=O" | lhs %ain% "R21_2=F" |
                              lhs %ain% "R21_3=O" | lhs %ain% "R21_3=F" |
                              lhs %ain% "R21_4=O" | lhs %ain% "R21_4=F" |
                              lhs %ain% "R21_5=O" |
                              lhs %ain% "R22_1=O" | lhs %ain% "R22_1=F" |
                              lhs %ain% "R22_2=O" | lhs %ain% "R22_2=F" |
                              lhs %ain% "R22_3=O" | lhs %ain% "R22_3=F" |
                              lhs %ain% "R22_4=O" | lhs %ain% "R22_4=F" |
                              lhs %ain% "R23=O" | lhs %ain% "R23=F" |
                              lhs %ain% "R24=O" | lhs %ain% "R24=F" ),

          # CF 21
          # CF 22
          # CF 23
          # CF 24
          # CF 25
          # CF 26
          # CF 27
          # CF 28
          # CF 29
          # CF 30
```

```
    rules.CF.S <- subset(rules.CF, subset = lhs %ain% "R3_1=O" |
                  lhs %ain% "R3_2=O" |
                  lhs %ain% "R3_3=O" |
                  lhs %ain% "R3_4=O" )

)

#  inspect(rules.CF.S)

rules.CF.S <- sort(rules.CF.S, by="confidence")

quality(rules.CF.S) <- cbind(quality(rules.CF.S), chiSquared = interestMeasure(rules.CF.S,
measure = "chiSquared", transactions = CF))
quality(rules.CF.S) <- cbind(quality(rules.CF.S), phi = interestMeasure(rules.CF.S, measure =
"phi", transactions = CF))
quality(rules.CF.S) <- cbind(quality(rules.CF.S), oddsRatio = interestMeasure(rules.CF.S,
measure = "oddsRatio", transactions = CF))
quality(rules.CF.S) <- cbind(quality(rules.CF.S), redundant = is.redundant(rules.CF.S))

rules.CF.S <- as(rules.CF.S, "data.frame")

write.xlsx(rules.CF.S,file=paste("D:/Project/Output_Continuo/Rules  _Con_CF_",i,  ".xlsx",
sep = ""), sheetName = paste("Rules CF_",i, ".xlsx", sep = ""), col.names=TRUE,
row.names=FALSE, append=FALSE, showNA=TRUE)

i <- i+1

}
```