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HELDER HENRIQUE LIMA DINIZ

Resilience in the Design of Critical Infrastructure: Applications in Power Grid and Logistic Systems

Recife

2017

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Resilience in the Design of Critical Infrastructure: Applications in Power Grid and Logistic Systems

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HELDER HENRIQUE LIMA DINIZ

“RESILIENCE IN THE DESIGN OF CRITICAL INFRASTRUCTURE: APPLICATIONS IN POWER GRID AND LOGISTIC SYSTEMS”

ÁREA DE CONCENTRAÇÃO: PESQUISA OPERACIONAL

A comissão examinadora, composta pelos professores abaixo, sob a presidência do(a) primeiro(a), considera o(a) candidato(a) **HELDER HENRIQUE LIMA DINIZ, APROVADO(A).**

Recife, 28 de Dezembro de 2017.

____
Prof. MÁRCIO JOSÉ DAS CHAGAS MOURA, Doutor (UFPE)

____
Prof. CRISTIANO ALEXANDRE VIRGÍNIO CAVALCANTE, Doutor (UFPE)

____
Prof. ADIEL TEIXEIRA DE ALMEIDA FILHO, Doutor (UFPE)

____
Prof. PAULI ADRIANO DE ALMADA GARCIA, Doutor (UFF)

____
Prof. LUIZ HENRIQUE ALVES DE MEDEIROS, Docteur (UFPE)

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ABSTRACT

Due to the great need to meet demand and remain competitive, companies are seeking to become more resilient, and thus systems must withstand, adapt to, and rapidly recover from the effects of undesired events. Resilience can be considered as the capacity of an entity to recover from a disruption, involving the ability to reduce effectively both magnitude and duration of the deviation from the nominal performance. This thesis proposes an optimization model, using Mixed-Integer Linear Programming (MILP), to support decisions related to making investments in the design of infrastructure critical systems that experience interruptions in supplying their customer demands due to disruptive events. In this approach, by considering the probabilities of the occurrence of a set of such disruptive events, the model minimizes the overall expected costs by determining an optimal strategy involving pre- and post-event actions. The pre-event actions, which are considered during the initial design phase, take into account the resilience capacity (absorption, adaptation and restoration). Although, according to the literature, pre-event resilience actions are faster in recovering the system, more useful and more cost-effective, especially when they are implemented during system design, most of research papers about resilience have focused on post-event policies. Therefore, in this work, in addition to post-event recovery actions, we corroborate with literature and consider pre-event actions so as to reduce recovery costs and increase recovery speed. The optimization model is thus developed and applied in two contexts: power grids serving industrial clients and a logistics distribution network. The results demonstrate that higher investments during the design phase, when optimally allocated, have the potential to improve infrastructure performance and still reduce overall costs.

Keywords: Resilience. Design. Pre-event decisions. Infrastructure critical. Power grid. Logistic.

RESUMO

Devido à grande necessidade de atender à demanda e permanecerem competitivas, as empresas estão buscando tornar-se mais resilientes e, portanto, os sistemas devem resistir, se adaptar e se recuperar rapidamente dos efeitos de eventos indesejados. Resiliência pode ser considerada como a capacidade de uma entidade se recuperar de uma interrupção, envolvendo a capacidade de reduzir efetivamente tanto a magnitude como a duração do desvio do desempenho nominal do sistema. Esta tese propõe um modelo de otimização, utilizando Programação Linear Inteira-Mista (PLIM), para apoiar decisões relacionadas à realização de investimentos em projeto de sistemas infraestrutura crítica que experimentam interrupções no fornecimento da demanda de seus clientes devido a eventos indesejados. Nesta abordagem, ao considerar as probabilidades da ocorrência de um conjunto desses eventos, o modelo minimiza os custos esperados totais ao determinar uma estratégia ótima envolvendo ações pré e pós-evento. As ações pré-evento, que são consideradas durante a fase inicial de projeto, levam em consideração a capacidade de resiliência (absorção, adaptação e restauração). Embora, conforme a literature, as ações de resiliência pré-eventos sejam mais rápidas na recuperação do sistema, mais útil e mais econômica, especialmente quando elas são implementadas durante a fase inicial nos projetos dos sistemas, a maioria dos trabalhos de pesquisa sobre resiliência se concentraram nas políticas pós-evento. Portanto, neste trabalho, além das ações de recuperação pós-evento, corroboramos com a literature e consideramos ações pré-evento, de modo a reduzir os custos de recuperação e aumentar a velocidade de recuperação. O modelo de otimização é, portanto, desenvolvido e aplicado em dois contextos: fornecimento de energia elétrica que atendem clientes industriais e uma rede de distribuição logística. Os resultados demonstram que altos investimentos durante a fase de projeto, quando alocados de forma otimizada, têm o potencial de melhorar o desempenho da infraestrutura e ainda reduzir os custos gerais.

Palavras-chave: Resiliência. Projeto. Decisões pré-evento. Infraestrutura crítica. Fornecimento de energia. Logística.

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LIST OF ACRONYMS

CI - Critical Infrastructure;

DC - Distribution Center;

EPSN - Electric Power Supply Network;

IDR - Investments in Design for Resilience;

ISE - Impact on System Expenditures;

IS - Impact on System;

MILP - Mixed-Integer Linear Programming;

NIAC- National Infrastructure Advisory Council

PCR - Post-interruption Cost of Recovery;

KPG - South Korean Power Grid;

SC - Supply Chain

SCM - Supply Chain Management

SL - Service Level

SS - Subtransmission Substations;

TS - Transmission Substations

CONTENTS

1 INTRODUCTION

1.1 Motivation for the Study

Systems such as those for the distribution of electricity, water, oil, material supplies, and electronic communications correspond to Critical Infrastructures (CIs) by providing fundamental services to the economy and the routine operation of society. Many elements of CIs take the form of networks (Turnquist & Vugrin, 2013), with dependency among nodes and links, which in turn are usually interconnected with other networks. The efficiency of an entire CI depends on the availability of each element (Cardoso et al. 2015); therefore, the occurrence of undesired and unexpected events, such as natural disasters, bad weather or a combination of other factors, can cause adverse and extended effects on the system, leading to social, environmental and economic impacts, although the probability of such events is usually low (Labaka et al. 2015; Sawik, 2013).

Disruption events can cause losses in different infrastructure systems: the August 2003 US blackout that caused transportation and economic network disruptions; 50 million people lost power for up to two days in the biggest blackout in North American history. The event contributed to at least 11 deaths and costs an estimated U$ 6 billion (JR, 2008). In 2011, a 9.0 magnitude earthquake and tsunami struck Japan, causing over 15,000 confirmed deaths and disrupting global supply chain networks (MacKenzie et al. 2012). Over the 2010-2011 summer, Australia's second largest state, Queensland, was affected by widespread flooding that resulted in significant damage to six zone substations and numerous poles, transformers and overhead wires. Approximately 150,000 customers experienced power disruptions (Panteli & Mancarella, 2015).

Besides that, a disruption event can cause losses not only to one system, but several infrastructure systems. Examples as Hurricane Sandy, which devastated New York in 2012, is among the more recent examples of a disruptive event that adversely impacted multiple networked systems. Months after the storm, power had not been restored to all communities in the New York area (Manuel, 2013) and one million cubic yards of debris impeded transportation networks (Lipton, 2013). In the Fukushima nuclear accident, several companies in Japan and over the world suffered disruptions in their supply chain (Zeiler, 2011). Companies such as Nissan and Toyota had to stop their production plants for several reasons: power cuts, oil shortage, lack of part and components supply due to the closure of suppliers (Zubieta, 2013).

These recent examples show that the lack of sufficient prevention and preparedness level in a CI could lead to detrimental effects on other CIs and society. Therefore, infrastructure networks must be resilient and sufficiently flexible to overcome the consequences of the occurrence of disruptive events as rapidly and economically as possible (Hosseini & Barker, 2016).

Although the resilience concept has become increasingly important, there remain a significant number of distinct definitions, demonstrating Da lack of standardization to evaluate resilience, both qualitatively and quantitatively (Filippini, 2014; Linkov,2014; Zubieta, 2015; Hosseini & Barker,2016; Levalle & Nof,2015;). This work understands the concept of resilience as the ability of the system to reduce both the magnitude and the duration of deviations from target performance levels, given the occurrence of undesired events (Tang, 2006; Vugrin et al. 2010; Filippini,2014; Swierczek, 2014).

According to Turnquist & Vugrin, (2013), models that focus on post-event strategies can frequently be time consuming, and they do not guarantee that one will identify an optimal or near-optimal set of actions that enable the most effective recovery for a variety of potential disruption scenarios. Thus, it is expected that pre-event strategies tend to be more efficient, useful, and profitable, especially when implemented during the design phase of a system. According to Linkov et al. (2014), strategies to build resilience during a system's design phase can either minimize performance loss or increase recovery speed through redundancy, modularity, flexibility and independency between elements.

Despite this finding, most of the research on resilience has focused on post-event policies, as seen in (Levalle & Nof 2015; Filippini & Silva 2014; Labaka et al. 2015; Świerczek 2014; Tang 2006; Mattsson & Jenelius 2015; Bode et al. 2011), and thus the design of resilient systems remains a topic with limited research (Bode et al. 2011). However, there has been a trend for decision makers to change from a reactive stance to a proactive one; consequently, the concept of resilience has been increasingly incorporated into systems' design phase (Mari et al. 2014). Moreover, there is a limited number of quantitative works focusing both on resilience and on the variables that affect system performance, such as cost of operation, customer service and investments in design (Mari et al. 2014; Cardoso et al. 2015). Therefore, designing a resilient infrastructure system is a prominent area for study because of its potential to enable improvements in network performance, and thus to provide benefits to customers by enhancing the service level, regularity and quality of the supply.

Furthermore, under disruptive events, through resources allocation, systems can either reduce the impacts from a disruption or improve recovery time. How much decision makers should allocate to one of those two factors depends to a large extent on how they believe resources affect those factors and on the level and type of uncertainty (MacKenzie & Zobel, 2016). In addition, optimal resource allocation among infrastructures at the system level is critical for resilience enhancement due to the budget limitations (Zhang et al. 2018).

Therefore, the present work aims to develop a quantitative model that determines the optimal allocation of financial resources to establish a resilience-based strategy. To this end, we consider the expected financial impacts of uncertain disruptive scenarios and confront them with a set of strategies of investment to support decisions related to enhancing infrastructure systems resilience. Thus, similar to Turnquist & Vugrin (2013), our problem is modelled using Mixed-Integer Linear Programming (MILP) with the overall expected costs as the objective function, including the costs of pre-event decisions, the expected costs arising from the financial impact of disruptive scenarios on the network and the expected costs of post-event actions.

We present two application examples of critical infrastructure systems to illustrate the applicability of the proposed models. First, in the context of power grid, four cases are analysed to explore the results for different situations regarding the probability of the occurrence of disruptive scenarios. The resilience-based strategy defined for each case minimizes the total expected costs and is analysed in terms of power grid overall performance, involving power grid configuration, demand satisfied and recovery time. Moreover, two individual scenarios are analysed, demonstrating how the model can be applied to propose an appropriate resilience-based strategy for a specific situation.

Secondly, this work proposes an optimization model for resilience through cost modelling on a project of a logistics distribution network. The optimization model is thus developed and applied in the context of the logistics network design and it minimizes the overall cost associated with the occurrence of disruption events, trading off the cost of promoting an improvement on system's design against the expected cost of the impact on the system and recovery efforts from such disruption events. Different disruption scenarios probabilities are analyzed in order to show how these changes will affect the investments required to achieve an optimal resilient design.

For both models, sensitivity analysis is also conducted to evaluate the impact of financial constraints for design investments compared to the overall performance of the infrastructure system and the overall cost. The results demonstrate that higher investments during the design phase, when optimally allocated, have the potential to improve infrastructure performance and still reduce overall costs.

1.2 Objectives of this Research

1.2.1 Main Objective

The main objective of this thesis is to develop a quantitative model involving the evaluation of the expected financial impacts of disruptive scenarios in infrastructure systems. The evaluation of the expected financial impacts of disruptive scenarios in system aims to establish a resilience-based strategy, which determines the optimal design and allocation of financial resources. Such strategy may avoid or at least reduce the negative impacts on network performance due to disruptions, considering a set of investment alternatives for resilience improvement.

1.2.2 Specific Objectives

- To develop a quantitative model to support decisions related to make investments in the design of critical infrastructure systems;
- To evaluate the resilience of infrastructure systems in meeting customer demand not only by designing a system in which resilience is increased but also by identifying how much resilience is improved when different possible ways to invest in the design of a system are considered;
- To apply a scenario planning approach, defining sets of outcomes of possible disruptive events, weighted by discrete probability values to evaluate infrastructure systems decisions;
- To show the applicability of the proposed models for two infrastructure critical cases: power grid serving clients industrial and logistics distribution network;
- To establish a "view of the grid" from the perspective of client and focusing analysis on ways to improve the resilience of the infrastructure systems;
- To provide a glimpse into the decisions that consumers can make that influence the resilience of the overall system;

1.3 Structure of the Thesis

This thesis is organized in five chapters as follows.

The second chapter presents the theoretical background and literature review on resilience, including different approaches, applications and comparisons with other concepts. Chapter 2 also introduces useful concepts about CIs and their state-of-the-art in the context of resilience.

The third chapter shows the characteristics of the Electric Power Supply Network (EPSN) considered and the formulation of the proposed optimization model. Chapter 3 also discusses examples to illustrate the applicability of the model. Four cases are analysed to explore the results for different probabilities of the occurrence of disruptions. Moreover, two severe scenarios, in which the probability of occurrence is lowest but the consequences are most serious, are selected to illustrate the model's applicability.

The fourth chapter presents a quantitative model that determines the optimal allocation of financial resources to establish a resilience-based strategy in the context of the logistics distribution network by minimizing the overall cost associated with the occurrence of disturbing events. Different disruption scenarios probabilities are analyzed to show how these changes will affect the investments required to achieve an optimal resilient design. Finally, an application example is discussed, where the impacts include the additional cost of not being able to meet the demand given the occurrence of a disruptive event and that the recovery resources are limited. Finally, chapter 5 concludes remarks, showing the limitations of this study and presenting suggestions for future work.

2 THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1 Critical infrastructures

CIs are networks, services and systems "comprising identifiable industries, institutions (including people and procedures) and distribution capabilities that provide a reliable flow of products and services essential to the defense and economic security of all countries" (Rinaldi 2001). Luiijf & Klaver (2005) define critical infrastructures as ''those physical and information technology facilities, networks, services and assets which, if disrupted or destroyed, have a serious impact on the health, safety, security or economic well-being of citizens or the effective functioning of governments". The American presidential policy directive on critical infrastructure security (Obama, 2013) identifies 16 critical infrastructure sectors: chemical, commercial facilities, communications, critical manufacturing, dams, defense industrial base, emergency services, energy, financial services, food and agriculture, government facilities, healthcare and public health, information technology, nuclear reactors, logistics systems, transportation systems, water and wastewater systems. Then, continuous supply of critical infrastructure services is essential for people, public and private organizations, and for the security and economy of the society as a whole (Bruijne & van Eeten 2007). Thus, CIs has become the central system of the economy in all countries because it is not possible to achieve the goals of energy sustainability, economic or social development if the operation of its infrastructure network are at risk or vulnerable (Yusta et al. 2011).

In recent years, the United States (US) Department of Homeland Security (DHS) and the European Commission (EC) have been concerned about the security of their country infrastructure because of new international threats. Examples of this policy include the Presidential Policy Directive 8 (PPD-8; Obama, 2011) (Obama, 2011) and the Directive 114/08/EC, adopted by the Council of the European Union (CEU): ''*on the identification and designation of European critical infrastructures and the assessment of the need to improve their protection''* (The Council of the European Union 2008), which gave rise to the European Programme for Critical Infrastructure Protection (EPCIP) (Yusta et al. 2011).

Within a CI network, there are several types of nodes such as: production nodes (e.g., factories, and power generation plant), storage/trans-shipment nodes (e.g., water supply reservoirs, warehouses, substations) and consumption nodes (end users). Regardless of the feedstock or product being considered, the network is characterized by a flow through links (roads, power transmission lines, water pipelines) from production to consumer, which form a connected network (Turnquist & Vugrin 2013). A set of costs associated with transporting materials, energy and products, and a set of constraints, such as production capacity, demand requirements and flow limits through links, typically determines the flow pattern within the network.

Nowadays, in order to provide this service to meet the demand and remain competitive in a global market, CIs have grown in size and complexity, becoming increasingly more interdependent locally, regionally and globally, constituting a system of systems (Eusgeld et al. 2011). However, as a result, they have also inadvertently increased their vulnerability, and the potential for disruptions events increases (Zubieta, 2013; Johansson et al. 2013).

Moreover, the increase in the number of current terrorist attacks and natural disasters that threaten the proper functioning of CIs have increased the concern and the preoccupation regarding the reliability and safety level of CIs (Bruijne & van Eeten 2007). It is because a partial or total disruption of elements of the network may cause a serious social, environmental, economic and political impact (Labaka et al. 2015). In this context, CIs must be highly reliable in performance to provide uninterrupted service. Thus, it is a must that infrastructure systems become more resilient, ensuring performance after unwanted events.

2.2 The Concept of Resilience

The word resilience has been originally originated from the Latin word "resiliere," which means to "bounce back" (Hosseini et al. 2016). Although there is a lack of standardization when defining resilience (Vugrin et al. 2010; Francis & Bekera 2014; Henry & Ramirez-Marquez 2012; Panteli & Mancarella 2015), it is important to highlight that the concept has considerably evolved since the first definition put forth by Hollings in 1973, which defined resilience as a measure of "*the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables*" (Holling 1973).

In recent decades, applications of resilience has widely been discussed and applied in numerous fields, such as economics (Rose & Liao 2005), organizational system (Reniers et al. 2014), safety management (Dinh et al. 2012), socio-ecological system (Chopra & Khanna 2014) and critical infrastructure (Hosseini et al. 2016; Panteli & Mancarella 2015). The common use of resilience implies the ability of an entity or system to return to "normal" condition after the occurrence of an event that disrupts its state.

Several definitions of resilience have been offered. Many are similar, though many overlap with a number of already existing concepts such as robustness, fault-tolerance, flexibility, survivability, and agility, among others. Some general definitions of resilience that span multiple disciplines have also been given. For example, Haimes (2009) defined resilience as the "*ability of a system to withstand a major disruption within acceptable degradation parameters and to recover with a suitable time and reasonable costs and risks*." The National Infrastructure Advisory Council (NIAC) defined resilience as the "*ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event*" (National Infrastructure Advisory Council (NIAC) 2010).

Table 2.1 includes a summary and key characteristic of each definition referenced, including critical infrastructure resilience; resilience as a safety management paradigm; organizational resilience; socio-ecological resilience and coupled ecological-engineered systems; and economic resilience.

Table 2.1 - A brief of resilience definitions from different perspectives

CATEGORIES OF RESILIENCE DEFINITIONS	DEFINITIONS	KEY PROPERTIES	REF.
Infrastructure systems	The effectiveness of a resilient infrastructure or enterprise depends upon its ability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event	-Ability to anticipate; -Ability to absorb -Ability to adapt	(NIAC,2010)
Safety Management system	Resilience engineering is distinguished from traditional safety management in that, instead of identifying and alleviating risk factors, it aims to build on strong dimensions of a system so as to compensate for poor design or management in case of unanticipated disruptions	-Strong dimensions -Unanticipated disruptions	(Furniss et al. 2011)
Organizational system	Capacity of an organization to recognize threats and hazards and make adjustments that will improve future protection efforts and risk reduction measures	-Capacity to recognize threats -Capacity to prepare for future protection efforts -Ability to reduce likely risks	(DHS, 2010)
Social system	defined social resilience as comprised of three dimensions: coping capacities, adaptive capacities, and transformative capacities.	-Coping capacities, -Adaptive capacities -Transformative capacities	(Keck & Sakdapolrak 2013)
Social-ecological system	Resilience is a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables	-Persistence to change -Ability to absorb change -Retain Relationships between people or state variables	(Holling 1973)
Economic system	Described economic resilience as the “inherent ability and adaptive response that enables firms and regions to avoid maximum potential losses.”	-Ability to recover Resourcefulness -Ability to adapt	(Rose & Liao 2005)

According to Hosseini et al. (2016), the review of resilience definitions indicates that there is no unique insight about how to define resilience. However, several similarities can be observed across these resilience definitions. Thus, according to Hosseini et al. (2016), the main highlights of resilience definitions reviewed above are summarized as follows:

- Some definitions do not specify mechanisms to achieve resilience; however, many of them focus on the capability of system to “absorb” and “adapt” to disruptive events, and “recovery” is considered as the critical part of resilience;

- For engineered systems, such as nuclear power systems, reliability is often considered to be an important feature to measure an ability to stave off disruption;

- Some definitions, such that of Sheffi & Rice Jr. (2005), emphasize that returning to steady state performance level is needed for resilience, while other definitions do not impose that the system (e.g., infrastructure, enterprise, community) return to pre-disaster state.

- Some definitions such as Allenby & Fink (2005) and Adger (2000) defined resilience in terms of preparedness (pre-disaster) activities, while the role of recovery (post-disaster) activities are discarded. Definitions presented by organizations such as National Infrastructure Advisory Council (NIAC) (NIAC, 2010) emphasized the role of both preparedness and recovery activities to achieve resilience.

According to the literature, there are several definitions of the concept of resilience, but the majority focuses on the ability to anticipate, absorb and rapidly recover from an external, high-impact low-probability shock (Panteli & Mancarella 2015). In this thesis, we embrace a similar concept as presented by Vugrin et al. (2010), who define system resilience as the "ability to reduce effectively both the magnitude and duration of the deviation from targeted system performance levels, given the occurrence of a particular disruptive event". This definition implicates that resilience is determined by a combination of the impact of the event on the system performance and the time and cost required for system recovery from this event.

In addition, the concept of resilience is concerned with the resistance, flexibility and recovery of an entity (Francis & Bekera 2014), emphasizing that actions can be undertaken to mitigate of Impact on the System (IS). Thus, a resilient system is defined by the following capabilities:

(i) Absorptive capacity – Vugrin et al. (2010) define absorptive capacity "as the degree to which a system can absorb the impacts of system perturbations and minimize consequences with little effort. That is, the capacity to anticipate, minimize and withstand the consequences of disturbances;

(ii) Adaptive capacity – the capacity for reconfiguration in undesirable situations. Adaptive capacity is distinguished from absorptive capacity so that adaptive systems change in response to adverse impacts, especially if absorptive capacity has been exceeded. A system's adaptive capacity is enhanced by its ability to anticipate disruptive events, recognize unanticipated events, re-organize after occurrence of an adverse event, and general preparedness for adverse events (Francis & Bekera 2014).

(iii) Restorative capacity – the speed and ease with which the system returns to normal operation.

These three capacities make up the "resilience triangle" (Francis & Bekera, 2014) (Figure 2.1) and should ideally be considered during the design phase of a system to effectively mitigate IS.

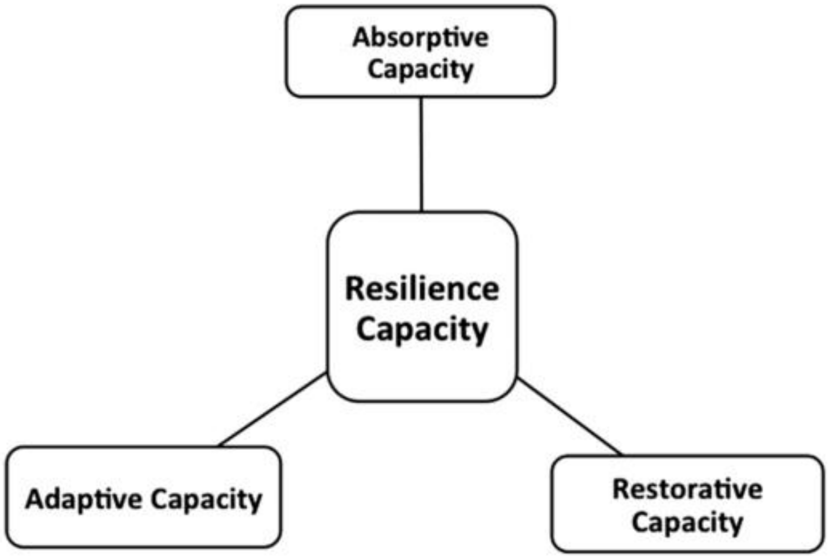

Figure 2.1.The resilience triangle showing three major capacities that make up the resilience capacity of a system. Francis (2014)

It has been realized that resilience as a concept involves several definitions. Although we introduced resilience as a function of absorptive, adaptive, and restorative capacities (Vugrin et al. 2010; Francis & Bekera, 2014; Hosseini et al. 2016), other concepts are also possible. For example, Lundberg & Johansson (2015) outline six "functions" in a systemic model, drawing primarily on resilience engineering, and disaster response: anticipation, monitoring, response, recovery, learning, and self-monitoring. The model consists of four areas: event-based constraints, functional dependencies, adaptive capacity, and strategy. Vlacheas et al. (2013) identified properties of resilience in the scope of telecommunication networks. They found that reliability, safety, availability, confidentiality, integrity, maintainability, and performance, along with their interactions, are most influential properties of networks resilience.

In addition, some authors define resilience in "dimensions" and "principles". The Multidisciplinary Center for Earthquake Engineering Research (MCEER, 2008) and Bruneau et al. (2003) break resilience down into four dimensions:

- Robustness: refers to the strength or the capacity of a system or an element to resist the impact of a triggering event in terms of magnitude of the impact or loss of functionality;
- Redundancy: refers to the extent to which components of the system are substitutable, or able to be replaced when functionality has been lost or reduced;
- Resourcefulness: refers to the capacity to efficiently respond to a crisis, identifying problems, establishing solutions, and mobilizing the required resources;

- Rapidity: refers to the rate or speed at which a system is able to bounce back to the normal situation, and achieve goals in order to reduce the magnitude of losses and avoid future disruptions.

Other conceptual framework for analyzing resilience, as well as some guiding principles and characteristics of resilient systems, can be found in (Abreu, 2012; Thomas et al. 2013; Hosseini et al. 2016; Ribeiro & Barbosa-Povoa, 2018).

2.3 Resilience Assessment Framework for Infrastructure Systems

Resilience assessment requires information about the disruptive events which an entity might be exposed to, such as their likelihood and their expected Impact on the System (IS), enabling the estimation of the resources necessary to bring the system back into operation. IS corresponds to the reduction of the system's ability to perform an assigned function after the occurrence of disruptive events. Given this information, the system's performance should return to its targeted level over time, incurring a Post-interruption Recovery Cost (PCR). In this thesis, both IS and PCR are measured as expected costs, weighted with the likelihoods of the disruptive events considered.

This work focuses on setting a resilience-based strategy that determines the appropriate pre-event actions that have the potential to minimize IS by considering the capacities for resilience previously presented. The investments associated with these three capacities can be defined as Investments in Design for Resilience (IDR), comprising actions undertaken during the system's design phase that seek to reduce both the impact and the system recovery time, as represented by Figure 2.2

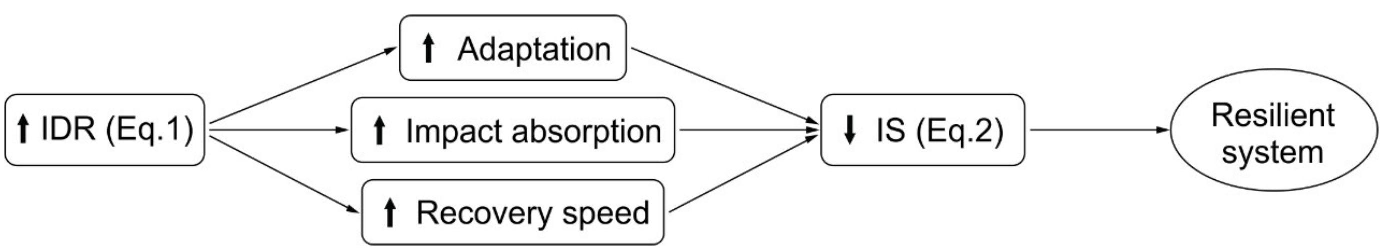

Figure 2.2 Relationship among IDR, IS, and the three resilience capacities.

As seen in the arrows in Figure 2.2, the system designed to absorb and anticipate the impact of an unwanted event and to adapt to new conditions might have a low IS, and thus should be more resilient. In addition, the recovery speed is influenced by the investments to return the system to operation quickly. Thus, this thesis aims to demonstrate the important interactions between IDR and IS decisions, in which IDR could positively influence system resilience by increasing absorption and adaption capacities, shortening recovery time and consequently reducing IS.

2.3.1. Investments in Design for Resilience

The pre-event decisions are defined as resilience strategies, which can be accomplished with the inclusion of absorptive, adaptive, and restorative capacities (Turnquist & Vugrin, 2013; Francis & Bekera, 2014; Levalle & Nof, 2015; Hosseini et al. 2016). Each scenario represents how an interruption may occur and has an associated probability. In this context, the possibilities for design decisions related to IDR are:

- Investment in absorptive capacity: expanding the capacity of each node, allowing it to more easily weather the loss of one or more nodes;
- Investment in adaptive capacity:
    a. Defining backup connections in the event that its primary node is inoperable or runs out of capacity (supplying client demand, for example, by the closest node). This investment allows the system to adapt to the loss of node operation by reconfiguring the material distribution network (e.g. products, energy and water);
    b. Establishing redundant lines between consumption nodes and the corresponding storage/trans-shipment nodes;
    c. Establishing temporary operating systems for operation, such as allocating diesel generators to keep manufacturing at least in partial operation during periods of power outage;
- Investment in restorative capacity: investment in resources to allow faster recovery after a disruption, improving the node recovery rate by increasing resources reserved for hiring crews and buying spares.

2.3.2 Impact on the System and Recovery Cost

Post-event expected costs are associated with the financial impact IS caused by a disruptive scenario on the system performance and the efforts (PCR) to restore the system nominal capacity. The Impact on the System (IS) is the first quantity to be observed. In fact, the IS results in deviation from the desired performance, such as loss or reduction of capability to perform the designated function, losses in the volume and quality of production and contractual penalties for not meeting customer demand. As the system is designed to absorb these events, the lower the IS, the more resilient the system. After the reduction or loss of efficiency, the post-event actions include the efforts the system has to return to its nominal performance over time through Post-interruption Recovery Cost (PCR).

2.4 Evaluation of Critical Infrastructures: Resilience vs Other Concepts

Under uncertainty, a CI can be assessed by different approaches, e.g., resilience (Francis & Bekera 2014; Vugrin et al. 2010; Barker et al. 2013), reliability (Salami et al. 2011; Johansson et al. 2013), risk (Kjølle et al. 2012; Utne et al. 2011; Garg et al. 2015; Rokstad & Ugarelli, 2015), robustness (Cuadra et al. 2015; Shukla et al. 2011) and vulnerability (Ramirez-Marquez & Rocco, 2012; Gedik et al. 2014). According to Hokstad et al. (2012), reliability is measured in terms of the probability that a system or a component can perform its required function at a given point of time under a given set of conditions. Traditional risk assessment in turn focuses on the likelihood and consequences of disruptive events, by understanding the nature of potential disturbances, characterizing their negative consequences and mitigating the level of risk which the system is exposed to (e.g., Kjølle et al. 2012; Garg et al. 2015). Robustness or vulnerability are often used to measure the extent to which a power grid has high or low reliability (Cuadra et al. 2015). According to Linkov et al. (2014), "resilience is not a substitute for principled system design or risk management. Instead, resilience is a complementary attribute that uses strategies of adaptation and mitigation to improve traditional risk management".

According to Hokstad et al. (2012), the scope of risk analysis is to calculate the probability and consequences of interruptions to certain parts of the network. On the other hand, resilience assessment emphasizes an evaluation of the system's ability to anticipate potential disturbances; accommodate internal or external changes to the system and establish response behaviours towards building the capacity to withstand the disruption or recover as quickly as possible (Francis & Bekera, 2014). In addition, another important aspect, which diverges resilience from a traditional risk assessment, consists of evaluating the performance of the critical infrastructure over time, where a resilience assessment must explicitly incorporate time into the analysis (Francis & Bekera, 2014), considering the evolution of the impact of an event on the system and its recovery. In this point, according to Linkov et al. (2016), "resilience analysis differs in a temporal sense from traditional risk analysis by also considering recovery of the system once damage is done. Thus, in addition to considering system decline immediately after an event (i.e. risk), resilience adds consideration of longer term horizons that include system recovery and adaptation."

Panteli & Mancarella (2015) in turn argued that the resilience concept encompasses all of the aforementioned concepts. Indeed, because risk assessment results in an understanding and mitigation of the potential disturbances, and robustness/vulnerability evaluation can help to identify weaknesses and candidates for the implementation of actions of resilience enhancement, these two approaches can serve as inputs to resilience analysis during the CI's design phase. In contrast, reliability assessment can measure the effectiveness of a resilience-based strategy over time.

2.5 Literature Review

The literature review for this thesis was exploratory, because the main objective was to look for and identify previous studies that could be drawn on with a view to proposing a model based on resilience design of critical infrastructure systems. Concepts of resilience have been studied regarding infrastructure networks in the areas of supply chain (Cardoso et al. 2015; Ambulkar et al. 2015; Brusset & Teller 2017; Lim-Camacho et al. 2017; Mancheri et al. 2018), hub-and-spoke network design (Chen et al. 2017; Zhalechian et al. 2018), transportation systems (Miller-Hooks et al. 2012; Faturechi & Miller-Hooks 2014; Faturechi et al. 2014; Zhang et al. 2015; Chen & Miller-Hooks 2012; Bhatia et al. 2015; Zhang & Wang 2016), natural gas networks (Carvalho et al. 2014; Feofilovs & Romagnoli, 2017), telecommunications (Omer et al. 2009; Brown et al. 2017), water supply networks (Chopra & Khanna, 2014; Baños et al. 2011; Diao et al. 2016) and designs for infrastructure (Ganin et al. 2016; Turnquist & Vugrin, 2013; Tran et al. 2017).

Ganin et al. (2016) presented an approach that evaluates the effect of design parameters on the overall resilience of a network. The results showed that the desired levels of resilience are achievable by trading off different design parameters such as redundancy, available backup supply and node recovery time. Miller-Hooks et al. (2012) propose a method for assessing and maximizing the resilience of an intermodal freight transportation network by incorporating preparedness decisions and recovery options given possible future disruptions.

Diao et al. (2016) proposes a method of resilience analysis which is designed to assess the resilience of water distribution systems. This study proposes a approach that shifts the objective from analysing multiple and unknown threats to analysing the more identifiable and measurable system responses to extreme conditions, i.e. potential failure modes. The work aims to evaluate a system's resilience to a possible failure mode regardless of the causal threat(s) (known or unknown, external or internal). The method is applied to test the resilience of four water distribution systems with various features to three typical failure modes (pipe failure, excess demand, and substance intrusion). The results provide an overview of a water system's resilience to various failure modes. It is also shown that increased resilience to one failure mode may decrease resilience to another and increasing system capacity may delay the system's recovery in some situations. For a comprehensive review of the existing literature on definitions and measures on resilience of several systems, the interested reader can consult Hosseini et al. (2016). In this thesis, the literature review is focused on two main contexts which address supply chain and power grid resilience.

2.5.1 Resilient in Power Grid Systems

In the field of EPSN resilience, there have been papers in the literature with both qualitative (Roege et al. 2014; Mendonça & Wallace 2015; Mathaios Panteli & Mancarella 2015; Ghanem et al. 2016) and quantitative (Francis & Bekera 2014; Reed et al. 2009; Ouyang 2014; Kim et al. 2017; Fang & Sansavini 2017; Dewenter & Hartmann 2015; Nezamoddini et al. 2017) approaches. For example, Panteli & Mancarella (2015) evaluated the impact of weather changes on the reliability, operation and resilience of an electric power network by observing the intensity, frequency and duration of severe weather events and proposing plans to increase EPSN resilience. Ouyang et al. (2014) used a probabilistic modelling approach to quantify electrical system resilience and economic losses, given the occurrence of hurricanes, assessing (i) hurricane risk, (ii) fragility, (iii) performance and (iv) restoration.

Kim et al. (2017) investigated the topological properties of the South Korean Power Grid (KPG), including its resilience. Their study considered node-based and network-based measures to characterize the structural dimensions of a network and to understand its topology and resilience. The results obtained concerning the KPG were compared with random and scale-free reference networks. Finally, several suggestions were made to improve its resilience. Nezamoddini et al. (2017) discussed the power grid resilience against physical attacks. This paper addressed the problem of the transmission system security and develop an optimization model to determine the optimal investment decision for the resilient design of the transmission systems against physical attacks. The results showed that to extend power grid resiliency, it is necessary to develop comprehensive protection models that address cyber and physical attacks together and determine a more inclusive protection plan.

Fang & Sansavini (2017) considered investments in capacity expansion and backup to evaluate the performance of electrical transmission networks under nominal operations and after deliberate attacks. Dewenter & Hartmann (2015) studied the resilience of power-flow models to the failure of a transmission line, with resilience characterized in terms of the “backup capacity”, defined as the additional capacity of the links that must be supplied to secure stable operation of the link with the greatest load in case of an attack or a failure in that link.

Münzberg et al. (2017) introduced an indicator-based spatial-temporal vulnerability assessment to enable crisis management groups and CI providers to enhance their understanding of the initial impacts of a power outage. The assessment results provide insights into the resilience of certain CIs and districts, and, hence, allow for simulating the effectiveness of considered preparation and response. The implementation of the assessment was demonstrated for the CIs of the health sector in the city of Mannheim in Germany.

According to Cuadra et al. (2015), there are two different approaches to evaluating power grid resilience. The first is solely based on topological concepts, using metrics such as the mean path length, clustering coefficients, efficiency and betweenness centrality (Wei et al. 2012; Prieto et al. 2014). The second, a hybrid approach, introduces some electrical engineering concepts in an effort to enhance the topological approach, using metrics such as electrical betweenness and net-ability (Guohua et al. 2008; Wang et al. 2015; Koç et al. 2014; Pepyne 2007; Dewenter & Hartmann 2015). For example, Guohua et al. (2008) presented an assessment of the North China power grid based on complex network theory to investigate the tolerance of the power grid to attacks. Pepyne et al. (2007) evaluated the resilience of a synthetic Watts-Strogatz network with 200 nodes and 400 links in terms of link attack schemes, disruption of the network and overhead lines.

2.5.2 Resilient in Supply Chain

Preparing for adverse events as if they are inevitable requires that regular evaluation of operational procedures, safety procedures, policy guidelines, risk assessment methods and countermeasures, which are key aspects of resilience assessment (Ivanov et al., 2016). Supply chain decisions can be distinguished into: (i) strategic: corresponding to investment decisions; (ii) tactical: according to short and long term goals, such as inventory policies; and (iii) operational: associated with everyday decisions, such as truck load (Diabat & Al-Salem, 2015). Building a resilient enterprise should be a strategic initiative that changes the way a company operates and that increases its competitiveness (Sheffi & Rice Jr., 2005).

According to Sheffi & Rice Jr. (2005), market power coupled with responsiveness have the potential to create opportunities to solidify a leadership position, as the case of Nokia and Ericsson illustrates in (Heckmann et al. 2015), what exemplifies how the degree of awareness and preparedness may lead to different outcomes. Still according to Sheffi & Rice Jr. (2005), reducing vulnerability means reducing the likelihood of a disruption, while resilience relates to responsiveness to disruptions and can be achieved by either creating redundancy or increasing flexibility. Examples of redundancy are: safety stock, multiple suppliers and low capacity utilization rates. It is important to note that companies need to be careful about inventory management, as low inventory holding may limit immediate response capacity while extra inventory has proven to be detrimental to product quality and to lean operation. In contrast, flexibility relates to inherent capabilities of the system to sense and respond quickly to disruptive events.

The design of such networks should incorporate the ecological principles of diversity, adaptability, interconnection and flexibility in order to increase emphasis on “safe-fail” rather than “fail-safe” (Francis & Bekera, 2014). Therefore, the definition of a resilience strategy must consider the costs of implementing these actions and their impact on mitigating the effects of certain disruptions. The occurrence of supply chain disruptions emphasizes that efficiency and effectiveness are conflicting objectives, as supply chain efficiency is related to the minimization of operational cost while supply chain effectiveness refers to the satisfaction of customers' demand (Heckmann, Comes, & Nickel, 2015). Focusing only on efficiency, for example, may prevent investments on flexibility to enable continuity or recovery of the network.

Measuring resilience is still a questionable task, thus comparing the supply chains' resilience is almost unfeasible. Cimellaro et al.(2010) developed a framework to quantify system's resilience to disasters, based on the level of system operation (robustness) and on the recovery time (rapidity). Azevedo et al. (2013) proposes an integrated Ecosilient index to reflect the resilience and greenness of companies and the corresponding supply chain. The proposed index is produced by the aggregation of a set of SCM practices related to green and resilient paradigms. Zhang et al. (2014) proposed a multi-objective optimization framework to support decisions related to supply chain planning, expansion and design, considering three objectives: total cost, Greenhouse Gas emissions and lead time.

Cardoso et al. (2015), on the other hand, selected eleven indicators from the literature to apply in several network structures with different levels of flexibility, under different types of disruption. The aim of this paper was to identify which indicators are more suitable when comparing supply chains' resilience. The eleven indicators address network design (node complexity, flow complexity, density and node criticality), network centralization (out- and in-degree centrality, based on the actual number of arcs and based on the actual amounts of flow circulating in those arcs) and operational performance (expected net present value, expected customer service level and investment).

Lim-Camacho et al. (2017) used a network-based simulation approach to estimate the resilience of supply chains, particularly to disruption experienced during climate related extreme events. The work considers supply chain examples from three Australian resource industries – fisheries, agriculture and mining – that have experienced climate shocks in recent years. The results highlight the importance of considering the broader economic benefits of diversified chains, related to risk reduction, business continuity and improved system design in the post-disruption recovery phase.

Zhalechian et al. (2018) developed a framework to design a resilient hub network under operational and disruption risks. The work proposed a novel bi-objective two-stage stochastic programming model which is able to account for both operational risks and disruption risks by considering several resilience strategies (i.e., improving network design characteristics, multiple allocation of hub nodes to spokes and fortifying hub nodes).

Mancheri et al. (2018) presented a study on resilience in the tantalum supply chain. The paper traced the entire value chain of the tantalum industry from mining to the intermediate and the downstream industries. The work aim was to see how dependent the tantalum supply chain is on specific countries, how exposed primary production is to disruptions, and what mechanism counteracts disruption. This study analyzed several resilience-promoting mechanisms such as: (i) diversity of supply, (ii) material substitution, (iii) recycling and (iv) stockpiling. Each of these mechanisms was evaluated, and find that even though diversity of supply and stockpiling mechanisms have been decreasing for years, the tantalum supply chain has been flexible in its response to disruption.

The creation of a resilient supply chain can be achieved through the design of a network capable of absorbing the impacts of disruptive events by improving flexibility or building up redundancies. Thus, the incorporation of resilience into the system can be accomplished through pre-event investments, which correspond to the inclusion of three different capacities: absorption (anticipate and absorb disturbances to withstand and minimize its consequences), adaptation (rearrange network structure) and recovery (speed and ease by which the system returns to normal operation). Almost all definitions of resilience can be characterized by these three capacities, which correspond to the resilience pillars (Turnquist & Vugrin, 2013; Labaka, Hernantes & Sarriegi, 2015; Francis and Bekera, 2014).

The impact of disruptions on the SC performance depends on the characteristics of both the incident and SCD (Thun & Hoenig, 2011). Most research work on resilience has focused on establishing post-event policies (Ambular, 2015), although pre-event actions are expected to increase system recovery speed and greater cost effectiveness, especially when they are implemented during the design phase of the system.

Recent literature indicates more efforts on the development of pre-event strategies, in contrast to the adoption of a reactive posture (Bode & Wagner, 2015). Examples of these strategies are: (i) definition of back-up suppliers, (ii) definition of back-up depots, (iii) definition of alternative transportation channels and modes, (iv) capacity expansion, (v) inventory buffer and (vi) facility fortification (Ivanov, Pavlov, et al. 2016).

2.5.3 State of the art and Contribution of the work

Due to the increased focus on structural dimensions of resilience, a limited number of quantitative studies focusing on resilience and the variables that affect system performance, such as the cost of post-disruption operation, customer service and investments in design (Dixit et al. 2016). Therefore, the present work aims to fill this gap by assessing the resilience of infrastructure systems in meeting customer demand, not only by designing a system with increased resilience, but also by identifying how much resilience is improved when considering different possible methods to invest in the design of a system.

In this context, the main contribution of our work is to propose an optimization model using MILP to make decisions related to investments in the design of CI resilience with a focus on the customer perspective. Our work evaluates how costs associated with investments in the design phase can reduce both the impact and recovery efforts over time, given the occurrence of an undesired event. In other words, we can now determine how financial resources should be spent to design a resilient CI.

Furthermore, even with the variety of applications of resilience, to the best of the authors' knowledge, the aforementioned articles do not consider the impact of disruptions to the electricity supply on industrial clients. Indeed, most of the resilience literature has overlooked differences among customers and their needs. Thus, our goal is to assess power grids' resilience with a focus on the industrial client perspective (Kwasinski 2016). Therefore, the proposed framework is intended to establish a "view of the grid" from the perspective of an industrial client; thus, our focus is not to address different types of failures in the main electrical power grid but to improve the resilience of the power supplies connected to industrial clients. In this manner, we provide a glimpse into the decisions that consumers of electric power can make that influence the resilience of the overall system.

Additionally, in contrast to (Fang & Sansavini 2017; Kim et al. 2017; Ouyang 2014; Chen & Miller-Hooks 2012; Pepyne 2007; Dewenter & Hartmann 2015; Prieto et al. 2014; Wei et al. 2012; Guohua et al. 2008; Wang et al. 2015; Koç et al. 2014; Cuadra et al. 2015; Kwasinski 2016), this work evaluates the performance of the electricity supply over time by examining the evolution of the impact of disruptive events on the system and its response. Despite the importance of considering this factor, the vast majority of work on power grids has not included the time dimension in its analyses of resilience (Haimes 2009; Henry & Ramirez-Marquez 2012; Francis & Bekera 2014).

3 EMBEDDING RESILIENCE IN THE DESIGN OF THE ELECTRICITY SUPPLY FOR INDUSTRIAL CLIENTS

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3.1 Problem statement

Critical infrastructures have undergone and are currently undergoing large changes. They are becoming more dependent on each other (Ghorbani & Bagheri, 2008). In addition, they are increasingly connected across geographical borders, and thus become more large-scale. These trends make the critical infrastructures more efficient, but at the same time more complex and more vulnerable, and the potential for large-scale disruptions increases (Johansson et al. 2013). As such, improving the structural and functional resilience of critical infrastructure systems to various natural and man-made hazards has always been an important problem to public and research disciplines (Chang, 2009).

Among critical infrastructure systems, Electric Power Supply Networks (EPSNs) are especially critical because other CIs rely on electricity to manage and operate their processes (Francis & Bekera, 2014; Kim et al. 2017). Despite the importance, regulatory authorities have noted a disconcerting increase in the frequency and severity of electrical grid disruptions (Summaries, 2014). Data from several studies estimate that the annual costs to the U.S. economy due to blackouts are between US$ 20 billion and US$ 55 billion (Campbell 2012). Moreover, although the increasing number of disruptions may be attributed primarily to changing environmental and climactic conditions, the grid's increasing technological complexity and operational “interconnectedness” have significantly exacerbated the severity, geographic distribution, and societal ramifications of those outages (Roege et al. 2014). For example, the impact of power outages on the manufacturing industry involves losses of output volume and quality, inventory and asset damage, and production delays and inconveniences (U.S. Department of Energy, 2013). A survey conducted by the Brazilian National Confederation of Industry (CNI- National Confederation of Industry, 2016) showed that electrical energy is the primary power source of nearly 80% of factories located in Brazil, of which 67% stated that power supply interruptions significantly increase production costs. For instance, in 2012, a set of factories in Midwest Brazil suffered a total loss of US$ 20 million due to disruptions in the power supply (Correio Brazilience 2012). Therefore, it is a necessity to develop techniques for assessing the impact of disruption events in a comprehensive and systematic way, which will enable the resilience enhancement of these events (Espinoza et al. 2016).

In the context, this chapter proposes an optimization model by using mixed linear programming to make decisions related to investments in the design of resilient electric power grid to industrial clients. We minimize the overall expected cost as objective function, which includes the cost of pre-event decisions, the expected cost of the financial impact of disruptive scenarios on the network and the expected cost of post-event actions. To that end, we evaluate how costs associated with investments in the design phase may reduce both the impact and the recovery efforts over time, given the occurrence of an undesired event.

3.2 Scope of the analysis

In this section, we first describe the main characteristics of an electrical grid to contextualize the scope of our analysis. A power network can be made up of the following subsystems: transmission, subtransmission and distribution (Kundur, 1994). The transmission interconnects all the major generating units and main load centers in the system. It forms the backbone of the electric power network and operates at the highest voltage levels (typically 230 kV or above). On the other hand, the subtransmission system provides power at relatively lower voltages (e.g., 69 kV or 13.8 kV), connecting the electric grid from the transmission level substations to distribution substations. In some cases, large industrial clients can be directly supplied by a subtransmission system. Finally, distribution is the last stage of the power transmission system for customers, usually connected to lower voltage levels, such as 69 kV, 13.8 kV, 220V and 110V.

The bulk power system is generally designed in accordance with the N-1 security criterion, requiring the system is able to bear the loss of one major component (mainly transmission lines and power transformers) without interrupting the electricity supply (Hokstad et al. 2012). Another example is an electric distribution system in which the feeders are designed in loop (Willis, 1997). As the name implies, the feeders form a loop through the service area and returns to the original point. By placing switches in strategic locations, the utility can supply power to the customer from either direction. Moreover, typical distribution networks usually have interconnected feeders that can be automatically and/or manually switched on in case of failures. If one source of power fails, switches are thrown, and power can be fed to customers from the other source. This type of configuration is more expensive because more switches and conductors are required to provide flexibility to the system.

In contrast, the electric power supply to industrial clients is usually provided by a single connection line and a step-down substation, and failures in this infrastructure can cause power supply interruptions and therefore additional production costs. Given this fact, the scope of our analysis is highlighted in Figure 3.1, representing our focus on the user perspective. Thus, disruptions of the system are analysed in terms of interruptions of the electricity supply to industrial clients that, for instance, serve critical societal functions.

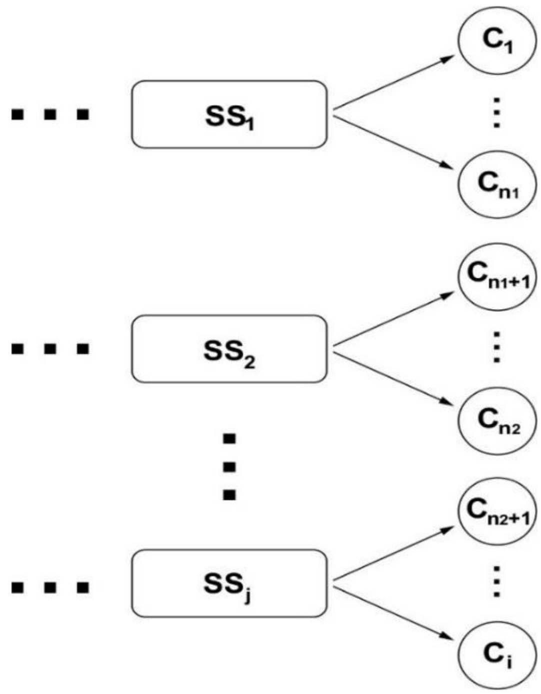


Figure 3.1 Representation of the electrical connections for industrial clients (C1, …, Ci);

Figure 3.1 contains a set of Subtransmission Substations (SSs) denoted by SS_j, which are responsible for ensuring energy supply to industrial clients, denoted by C_i, where $i > n_2 + 1 > \dots n_1 > 1$, through subtransmission lines. Under normal conditions, each client has a demand Q_i, which is served by a specific SS_j (primary assignment) with capacity K_j to accommodate the demand assigned to it. The electrical connection of industrial clients shown in Figure 3.1 could be generalized to other configurations. For example, it could involve a different number of SSs or industrial clients, which would only require modifying the allocation of clients per SS.

In this manner, the proposed model provides some alternatives to improve the resilience of the electric power supply for industrial plants, including normally open backup power lines, active parallel lines, purchasing of diesel generators, or increases in restorative capacity. However, the implementation of these reinforcements, in practice, depends on the costs of expanding the electrical connection and the expenditures arising from interruptions to the energy supply. Thus, based on some input data regarding a set of industrial plants, the solution proposed by the model indicates whether these alternatives should be implemented.

3.3 Modelling Assumptions

This thesis proposes an optimization model to minimize the total expected costs by means of implementing resilience-based alternatives that are useful in case of stoppages of the supply of electrical energy to industrial clients due to disruptions in the configuration analysed in Figure 3.1.

The uncertainty of potential disruptions makes the use of scenarios important. The stochastic characteristic of the proposed model relies on considering different disruptive scenarios (each with its own probability of occurrence) in the electrical connections to industrial clients; the probabilities of occurrence are used in the calculation of the total expected cost. The similar stochastic characteristic for the proposed model can be seen in Cardoso, (2015); Mari et al. (2014) and Turnquist & Vugrin, (2013).

However, there are myriad events that might cause disruptions in the electricity supply, for example, climate change (Bartos et al. 2016), natural disasters (Ghanem et al. 2016; Espinoza et al. 2016), physical attacks (Nezamoddini et al. 2017) and terrorism (Mendonça & Wallace 2015). Nevertheless, this paper does not intend to consider every possible contingency or to model the causes of the disruptive events that affect power supplies to industrial clients. To evaluate different scenarios of disruption, we consider the following assumptions for the power grid in Figure 3.1.

- *SSj* can be affected by an event that will partially or fully impact its capacity, thereby influencing the supply of the set of customers C_i assigned to it. This capacity will be recovered over time in accordance with the recovery rate of the system;
- The subtransmission line between *SSj* and a connected C_i can be affected, thus halting only the supply of C_i;
- Multiple failures can occur, affecting SS_1 and SS_2, two subtransmission lines, SS_j and a subtransmission line not connected to it, or a subtransmission line and its corresponding *SSj*.

Thus, we consider the system might be exposed to internal or external factors that may affect its nodes and/or links. Each scenario represents how an interruption may occur and has an associated probability. In this context, the possibilities for design decisions related to IDR are:

- Investment in absorptive capacity: expanding the capacity of each SS_j;
- Investment in adaptive capacity: defining backup connections (supplying client C_i's demand, for example, by the closest SS_j); or establishing redundant lines between C_i and the corresponding SS_j; or allocating diesel generators to keep C_i at least in partial operation;
- Investment in restorative capacity: improving the SS recovery rate. The restoration capacity includes the number of repair crews, available equipment and replacement components.

It is important to mention that this thesis aims to increase the resilience of the system, and it is out of scope determining who is responsible for carrying out the investment: either the managers of the energy supply or the industrial clients. Indeed, the idea is to design a power supply system for industry clients with optimal cost, resulting in a win-win partnership, co-responsibility, and knowledge sharing to make the entire chain more competitive.

Thus, the method will determine the optimal allocation of resources to minimize the overall expected costs for designing this power grid, assuming that an undesirable scenario could occur. In addition to the post-event response (i.e., efforts to restore the supply of energy to industrial plants), we consider pre-event decisions related to investments in improving resilience, which can be accomplished by including absorptive, adaptive and restorative capacities (Francis & Bekera 2014; Turnquist & Vugrin 2013; Levalle & Nof 2015) in the phase of designing the electrical connections to industrial customers. The idea is to incorporate the concept of resilience into the design of the system, thereby considering different possibilities of IDR and the respective IS and PCR.

This problem gives rise to an MILP approach, for which the parameters and variables are described in Tables 3.1 and 3.2, respectively. The binary variables are set so that 1 indicates the existence or operation of some SS or link of the system and 0 otherwise.

Table 3.1 -Description of the parameters

Parameter	Description	Range or unit
T	Time period	Hours
d	Deadline to restore system to nominal performance threshold	Hours
ℓ	Recovery rate of subtransmission lines	Line/hour
Q_i	Demand of C_i per period	MVA/hour
r	Recovery rate of SS capacity	MVA/hour
G	Capacity of diesel generator	MVA
K_i	Initial capacity of SS_j	MVA
p_c	Probability of occurrence of scenario c	[0,1]
V_{ic}	Portion of SS_j capacity affected in scenario c	[0,1]
F_{ijc}	Occurrence of an event in the subtransmission line between SS_j and C_i in scenario c	0 or 1
L_{ij}	Predefined connections between SS_j and C_i	0 or 1
α_i	Cost of adding K_j units to SS_j capacity	$
λ_{ij}	Cost of establishing a backup (SS_j for C_i)	$
φ_{ij}	Cost of adding a redundant line between SS_j and C_i	$
γ	Cost of siting a generator	$
μ	Cost of adding resources to accelerate SS recovery	$
ρ	Cost of supplying demand	$
θ	Cost of supplying demand by means of a generator	$
ϕ_i	Penalty for unmet demand of C_i	$
δ_i	Penalty for unmet demand of C_i after a deadline d	$
ω_i	Penalty for unmet demand of C_i when C_i has diesel generators	$
π	Cost of recovering SS capacity	$
σ	Cost of recovering subtransmission lines	$

Parameter	Description	Range or unit
M	Budget available for costs incurred for IDR and PCR	$

Table 3.2 - Description of the variables

Variable	Description	Range or unit
A_i	Addition of K_j units to the capacity of SS_j	units
W	Additional resources for SS recovery	MVA/period
n_i	Quantity of generators added to C_i	units
B_{ij}	Backup connection between C_i and SS_j	0 or 1
H_{ij}	Redundant line between C_i and SS_j	0 or 1
g_{itc}	Operation of C_i generators in period t for scenario c	0 or 1
S_{ijtc}	Operation of the subtransmission system from SS_j to C_i in period t for scenario c	0 or 1
O_{ijtc}	Operation of the subtransmission line between SS_j and C_i in period t for scenario c	0 or 1
U_{itc}	Capacity of SS_j in period t for scenario c	MVA
R_{itc}	Capacity of SS_j recovered in period t for scenario c	MVA
x_{ijtc}	Portion of C_i demand supplied by SS_j in period t for scenario c	[0,1]
z_{itc}	Portion of C_i demand supplied by generators in period t for scenario c	[0,1]
D_{itc}	Portion of C_i demand supplied in period t for scenario c	[0,1]
y_{itc}	Portion of C_i demand that is not met in period t for scenario c when C_i does not have a generator	[0,1]
h_{itc}	Portion of C_i demand that is not met in period t for scenario c when this client uses its diesel generator	[0,1]
N_{itc}	Portion of C_i demand that is not met in period t for scenario c	[0,1]
a_{ijtc}	Portion of the subtransmission line between SS_j and C_i recovered in period t of scenario c	[0,1]

3.4 Design Phase: Pre-event Costs

The alternatives available for pre-event investments are translated into costs defined as IDR, and they are divided into three types of capacity: adaptation, absorption and restoration. Considering possible system interruptions and according to the adaptive concepts presented in (Francis & Bekera 2014; Turnquist & Vugrin 2013), the possibilities for increasing the adaptive capacity are the following.

- To establish a backup line between SS_k and C_i so that the impact on the industrial plant operation will be reduced. Indeed, if SS_j is affected, its demand can be supplied by SS_k, with $k \neq j$. Determining which SS_k would work as a backup for C_i will be based on the cost to establish the new connection. Backup lines are deemed to operate in hot standby mode.

- To build a redundant line that shares a load with the main line (active parallel) to ensure the supply of C_i from its corresponding SS_j. The model will determine the existence (or not) of this line so that, if the main line is affected, the redundant one will be able to support the full load.
- To invest in diesel generators to keep the plant at partial or full operation until the main power supply returns. Failures on demand of the diesel generators are not considered here.

Investments in absorptive capacity can be made by expanding the capacity of SS_j so that the system will be able to better respond to an event that could affect subtransmission substations or links. The opportunity to invest and expand the capacity of each SS_k allows the system to more easily bear the loss of one or more SS_j $(k \neq j)$ because the system will have additional capacity to manage the additional demand of SS_j, and consequently will continue to meet demands (partially or totally). The investments in restorative capacity will be spent on deploying additional maintenance crews and buying spares to increase the recovery rate. Considering the available alternatives and using the parameters and variables mentioned in tables 3.2 and 3.4, the IDR can be expressed as shown in Equation (3.1):

$$IDR = \sum_j \alpha_j A_j + \gamma \sum_i n_i + \sum_i \sum_j \lambda_{ij} B_{ij} + \varphi \sum_i \sum_j H_{ij} + \mu w \tag{3.1}$$

The first part of Equation (1) corresponds to investing in absorption, which is the possibility of adding capacity to each SS_j. The next three terms correspond to possible investments in adaptive capacity: installing generators for C_i, establishing backups for clients so their demands can be met by another SS (besides their primary supplier) and the possibility of setting a redundant line between C_i and SS_j, respectively. The last term corresponds to the investment in increasing the recovery rate.

3.5 Post-event Costs

Post-event expected costs are associated with the financial impact of IS caused by a disruptive scenario on system performance and the efforts (PCR) to restore the system supply capacity. In this thesis consider that the losses of industries are a step-change function of the demand that is not met in period t for scenario c and for each type of client. However, there is a monetary penalty for each unmet MVA.

It also considers that industrial plants manufacture products, which have different added values; thus, the penalty depends on the specific industrial sector. Therefore, IS can be specified as the impact on the demand supply, and it is expressed in Equation (3.2):

$$IS = \sum_c p_c \left[\rho \sum_i Q_i \sum_j \sum_t x_{ijtc} + \theta \sum_i Q_i \sum_t z_{itc} + \sum_i \phi_i Q_i \sum_t y_{itc} + \sum_i \delta_i Q_i \sum_{\tau=d}^{T} y_{i\tau c} + \sum_i \omega_i Q_i \sum_t h_{itc} + \sum_i \delta_i Q_i \sum_{\tau=d}^{T} h_{i\tau c}\right], \tag{3.2}$$

where p_c is the probability of each scenario c, which corresponds to a disturbing event that causes an interruption to the energy supply. The first and second terms of Equation (3.2) represent the cost of supplying power from SS_j and diesel generators, respectively. The third part reflects the penalty incurred because the main SS did not meet some portion of clients' demands. The fourth portion represents an additional fee for unmet demand beyond deadline d, which is usually established in the contract signed with the client. In this manner, if the supplier fails to meet such a time limit, there will be additional costs in addition to the existing penalties. Despite its importance, this penalty structure is not considered in the other works mentioned above.

The fifth term corresponds to the penalty for not meeting some portion of clients' demands when these clients have diesel generators. However, as before, there is a possible sixth term, which is an additional fee that is charged if the non-supply of power extends beyond d. We considered the fifth and sixth parts of Equation (3.2) because of the specific characteristics of the production processes. Usually, industries suffer great losses due to failures in the power supply even if interruptions are short. Equipment such as reactors, homogenizers, blast furnaces and other critical items do not simply return to their operational state when the power supply is re-established, related to the inputs not being processed by the equipment (work-in-process) due to interruptions in the supply of power, which cannot usually be made to the full specifications set. This failure indicates that there has been a lack of control in the process. Moreover, even when the energy returns, there are production losses until the process returns to the default condition.

Therefore, the possibility of using a diesel generator can reduce the impacts caused by this problem and keep the equipment in operation to remove, for example, the material in process until power is restored, thus reducing the costs incurred by this interruption. In this case, the plant would be penalized only with the loss of production during this period and would no longer suffer losses due to the time spent on re-establishing process control. Therefore, the penalties that might be associated with the lead time when the power supply is cut and the generators are started will not be considered. Note that this approximation is reasonable given that the generators are equipped with automatic start, which usually takes 10 to 30 seconds to become operational.

PCR, in turn, includes the costs associated with the resources required to recover the system due to disturbances, i.e., the cost of restoring the performance of the system after an interruption c. The expected PCR is shown in Equation (3.3):

$$PCR = \sum_c p_c \left[\pi \sum_j \sum_t R_{jtc} + \sigma \sum_i \sum_j \sum_t a_{ijtc}\right], \tag{3.3}$$

where the first part indicates the costs associated with the use of recovery resources, if the recovery actions are directed to SS_j, and the second term represents the cost associated with recovering a subtransmission line between SS_j and C_i.

3.6 Formulation of the Model

The stochastic optimization model proposed is defined as an MILP problem with an objective function that combines the cost of investing in resilience-based actions in the network design phase (IDR) and the expected costs related to system performance and recovery (IS plus PCR). Thus, the objective function (Equation (3.4)) is the sum of IDR, IS and PCR, which are presented in Equations (3.1), (3.2) and (3.3), respectively.

$$\begin{aligned} \mathrm{Min\ IDR + IS + PCR} = {} & \sum_j \alpha_j A_j + \gamma \sum_i n_i + \sum_i \sum_j \lambda_{ij} B_{ij} + \varphi \sum_i \sum_j H_{ij} + \mu w + \\ & \sum_c p_c \Big[\rho \sum_i Q_i \sum_j \sum_t x_{ijtc} + \theta \sum_i Q_i \sum_t z_{itc} + \sum_i \phi_i Q_i \sum_t y_{itc} + \sum_i \delta_i Q_i \sum_{\tau=d}^{T} y_{i\tau c} + \\ & \sum_i \omega_i Q_i \sum_t h_{itc} + \sum_i \delta_i Q_i \sum_{\tau=d}^{T} h_{i\tau c} + \pi \sum_j \sum_t R_{jtc} + \sigma \sum_i \sum_j \sum_t a_{ijtc}\Big] \end{aligned} \tag{3.4}$$

subject to:

$$\sum_j B_{ij} \leq 1 \qquad \forall i, \tag{3.5}$$

$$D_{itc} = \sum_j x_{ijtc} + z_{itc} \qquad \forall i,t,c \tag{3.6}$$

$$S_{ijtc} - x_{ijtc} \geq 0 \qquad \forall i,j,t,c \tag{3.7}$$

$$g_{itc} - z_{itc} \geq 0 \qquad \forall i,t,c \tag{3.8}$$

$$z_{itc} Q_i \leq n_i G \qquad \forall i,t,c \tag{3.9}$$

$$\sum_i x_{ijtc} Q_i \leq U_{jtc} \qquad \forall j,t,c \tag{3.10}$$

$$N_{itc} = y_{itc} + h_{itc} \qquad \forall i,t,c \tag{3.11}$$

$$g_{itc} - h_{itc} \geq 0 \qquad \forall i,t,c \tag{3.12}$$

$$g_{itc} + y_{itc} \leq 1 \qquad \forall i,t,c \tag{3.13}$$

$$D_{itc} + N_{itc} = 1 \qquad \forall i,t,c \tag{3.14}$$

$$g_{itc} \leq n_i \qquad \forall i,t,c \tag{3.15}$$

$$S_{ijtc} \leq L_{ij}H_{ij} + O_{ijtc} + B_{ij} \qquad \forall i, j, t, c \tag{3.16}$$

$$U_{jtc} - K_j\, S_{ijtc} \geq 0 \qquad \forall i, j, t, c \tag{3.17}$$

$$O_{ijtc} \leq (1 - F_{ijc})L_{ij} + \sum_{\tau=1}^{t-1} a_{ij\tau c} \qquad \forall i, j, t, c \tag{3.18}$$

$$O_{ijTc} \leq L_{ij} \qquad \forall\, i, j, c \tag{3.19}$$

$$O_{ijTc} = L_{ij} \qquad \forall\, i, j, c \tag{3.20}$$

$$U_{jtc} = (1 - V_{jc})(K_j + K_jA_j) + \sum_{\tau=1}^{t-1} R_{j\tau c} \quad \forall j, t, c \tag{3.21}$$

$$U_{jtc} \leq K_j + K_jA_j \qquad \forall j, t, c \tag{3.22}$$

$$U_{jTc} = K_j + K_jA_j \qquad \forall j, c \tag{3.23}$$

$$\sum_j R_{jtc} \leq r + w \qquad \forall t, c \tag{3.24}$$

$$\sum_i \sum_j a_{ijtc} \leq \ell \qquad \forall t, c \tag{3.25}$$

$$\alpha \sum_j A_j + \gamma \sum_i n_i + \sum_i \sum_j \lambda_{ij} B_{ij} + \varphi \sum_i \sum_j H_{ij} + \mu w + \sum_c p_c \left[\pi \sum_j \sum_t R_{jtc} + \sigma \sum_i \sum_j \sum_t a_{ijtc}\right] \leq M \tag{3.26}$$

$$A_j, n_i, w, \qquad R_{jtc}, U_{jtc} \geq 0 \tag{3.27}$$

$$x_{ijtc}, z_{itc}, y_{itc}, h_{itc}, a_{ijtc}, D_{itc}, M_{itc}, O_{ijtc} \geq 0 \tag{3.28}$$

$$B_{ij}, H_{ij}, S_{ijtc}, g_{itc} \in \{0,1\} \tag{3.29}$$

Constraint 3.5 is related to the limit of connections per client, assuming that each client can have only one backup connection at most. We assume this limit because (i) the cost of implementation of a backup power line is higher than that of a diesel generator; (ii) multiple backup lines would require increased space, which is not always feasible, mainly near urban areas; and (iii) finally, provided that the substation is operational, a single line would provide all of the energy needed to supply the industrial plant, while it would require multiple generators to have the same outcome.

Constraints 3.6-3.14 are associated with meeting the clients' demand. The demand of each client can be served by the corresponding SS_j and its diesel generators (Constraint 3.6) so that the demand of C_i can only be served by SSj, assuming this link exists and is operational (Constraint 3.7). Therefore, the portion of C_i demand served by generators can only exist if generators have been installed in C_i (Constraint 3.8), and this amount cannot exceed the capacity of the generators (Constraint 3.9). In addition, the whole demand that

SSj is expected to meet cannot exceed its capacity (Constraint 3.10). Constraint 11 represents the portion of C_i demand that is not supplied in each period, which can occur if either SS or the generators do not have sufficient capacity. If C_i generator is activated, information represented by g_{itc}, the unmet portion of C_i demand is represented by h_{itc} (Constraint 3.12); otherwise, it will be represented by y_{itc} (Constraint 3.13). Consequently, the portion of each client's demand that is met and the portion that is not met in each period are complementary factors (Constraint 3.14).

Generators can only be activated if the subtransmission system for C_i has been affected, given that the investment in their acquisition has been made (Constraint 3.15). In this context, the predefined subtransmission system operates in series such that, if any component that provides energy for C_i is affected, the power does not reach C_i. Therefore, Constraints 3.16 and 3.17 correspond to the connection between SS_j and C_i in accordance with the operational condition of each component of this system. The connection is operational if and only if at least K_j of the capacity of SS_j has been recovered (Constraint 3.17). Moreover, Constraint 16 represents the operation of the connection between SS_j and C_i, considering that the following:

i. If C_i is primarily connected to SS_j, this connection might or might not be operational (O_{ijtc});

ii. If C_i is primarily connected to SS_j, this connection could be ensured by a redundant line (H_{ij}); and

iii. If C_i is not primarily connected to SS_j, SS_j might be its backup (B_{ij}).

Constraints 3.18-3.20 register the state (whether operational or not) of the subtransmission line between SS_j and C_i, given that it is a primary connection (Constraint 3.19), and this line is subject to the occurrence of events that can affect its performance. A portion of each line (a_{ijtc}) can be recovered in each period and for a given scenario using the recovery rate ℓ and these lines must be fully recovered over time (Constraints 3.18 and 20) using the available resources (Constraint 3.25), which are shared among all subtransmission lines.

Constraints 3.21-3.23 represent the determination of the capacity of SS_j, given that an event affects its operation, and its capacity must be recovered over time. Immediately after the occurrence of the disruptive event, SS_j has reduced capacity or no capacity at all. Thus, restoration efforts can be undertaken by increasing capacity by *r* (the recovery rate parameter in MVA/hour). This process continues, with recovery efforts being made hourly so that the entire capacity is recovered until T is reached. In the model, the SS recovery rate can be increased using additional resources (variable *w*), which should be devoted to hiring maintenance crews and buying spares.

Constraint 3.24 corresponds to the total resources available to recover SS and must be shared among all SSs. In addition, the costs associated with IDR and PCR cannot exceed the limit M, as shown in Constraint 3.26, which represents financial constraints. Constraints 3.27-3.29 specify the variation ranges of the variables as being non-negative integer, non-negative real and binary, respectively.

We demonstrate the applicability of the proposed model. Our aim is to evaluate how the strategies for improving resilience vary for a wide range of scenarios and for different investment alternatives , assessing the corresponding impacts over time. In addition, the example is useful for discussing the validation and verification of the model.

3.7 Application Example

3.7.1 Description of the Problem

This section discusses the application of the proposed model to an example involving an EPSN with industrial clients from the chemical/petrochemical, food and manufacturing sectors. As mentioned above, this paper does not aim to consider every possible contingency over the whole power supply network. In fact, our aim is to improve the resilience of the power supply with regard to industrial clients' connections to the electrical power grid. This situation is of practical application for medium to large industries that have very high costs (and thus very low tolerance) when interruptions to the power supply occur in their production plants. Therefore, alternatives that improve the resilience of industrial clients' connections to the EPSN are provided. Figure 3.2 shows the original power grid that will be addressed in this section. In Figure 3.2, clients are represented according to their sectors.

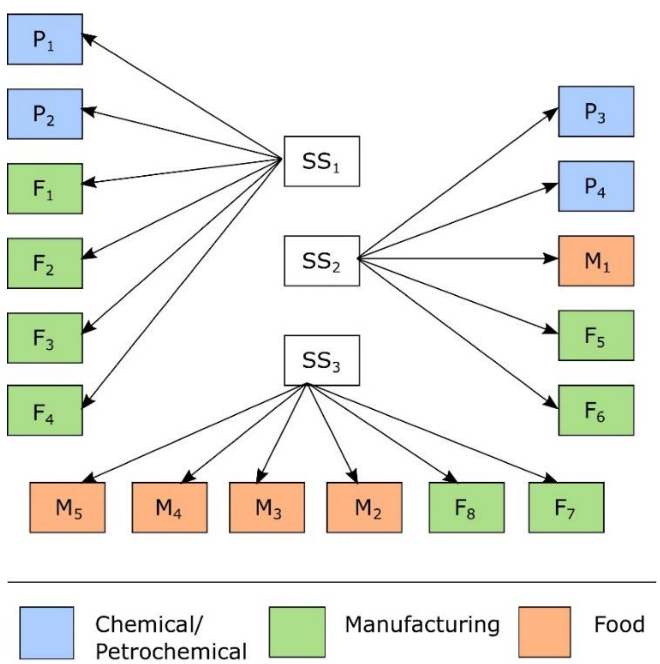


Figure 3.2 Representation of power grid supply to industrial clients

In this example, the power grid consists of 3 substations that together supply 150 MVA (Table 3.3) to industrial customers such that the capacity of each SS is given by the total demand assigned to it. Having both the added value of the products and the eventual loss of production as criteria, the chemical/petrochemical, manufacturing and food industries are ranked in this order, according to their level of importance to local economic activity. Thus, the energy supplier incurs different penalties for demand not supplied because of a disruption in the performance of the system.

Table 3.3 - Client data

Client	Industrial segment	Demand (MVA)
P_k, with k = 1, 2, 3, 4.	Petrochemical/chemical	15
M_m, with m = 1, 2, 3, 4, 5.	Manufacturing	10
F_r, with r = 1, 2, 3, 4, 5, 6, 7, 8.	Food	5

To show how disruptions in the network can affect the investments necessary to achieve an optimal, resilient design, we defined a set of scenarios and their associated probability p_c. These scenarios are used to specify the loss of SS supply capacity and the loss of subtransmission lines between SS and its clients.

As discussed above, interruptions can occur due to internal or external factors, including various natural factors. For example, in Brazil, atmospheric discharges and torrential rains, combined with falling trees, can interrupt the power supply to industrial clients. According to (Shukla et al. 2011), the disaster probabilities are difficult to quantify. However, for this example, we are not concerned with identifying and analysing specific causes of events that could affect the network. In fact, our aim is to quantify several ways by which the system might become unavailable.

In this context, the proposed method for defining p_c considers the observation of the network as a random experiment, for which three possible situations can arise: (i) no occurrence of a disruptive event; (ii) a single failure; or (iii) multiple failures. A single failure is understood as the loss of a node (SS) or a link (subtransmission lines). Multiple failures can be observed in (i) simultaneous failures: SS_1 and SS_2, two subtransmission lines and SS and a subtransmission line not connected to it; or (ii) cascading failures since failures in both the line and its respective SS are a sort of cascading failure and cannot be considered independent events. Thus, the costs related to their recovery should also be considered. Observations of three or more simultaneous failures are not considered because they are very unlikely to occur.

We also consider simultaneous failures in both SS_1 and SS_2 because they are assumed to be connected to the same step-down Transmission Substation (TS). Thus, this failure could be related to a common cause, such as the loss of TS supply. However, we do not consider other joint failures of SS because they are very unlikely to occur, especially if they are connected to independent TSs. Table 3.4 shows that each element of the sample space (Ω) is related to a scenario, which represents how an undesired event can impact the supply of electricity to industrial clients; all scenarios are assumed to be mutually exclusive.

Furthermore, scenario $\{S_1S_2\}$ (related to a TS failure) is considered less likely than joint failures $\{S_jLP_k\}$, $\{S_jLM_m\}$ and $\{S_jLF_r\}$ with k, m and r connected to j, which in turn are considered as probable as $\{S_j\}$. Additionally, $\{S_j\}$ is less likely than scenarios $\{LP_k\}$, $\{LM_m\}$ and $\{LF_r\}$, which represent the disconnection of single lines. Such an assumption is based on the practice that a TS is designed with a more robust bus or better switching schemes, compared to an SS (McDonald, 2007).

Given this assumption, we can establish relationships among the probabilities of occurrences of these scenarios. More specifically, if x is the probability of the scenario $\{S_1S_2\}$, then $P(\{S_jLP_k\}) = P(\{S_jLM_m\}) = P(\{S_jLF_r\}) = P(\{S_j\}) = c_1x$ for k, m and r connected to j; and $P(\{LP_j\}) = P(\{LM_m\}) = P(\{LF_r\}) = c_2x$, where c_1 and c_2 are positive constants such that $c_1 < c_2$.

Moreover, the probabilities of the scenarios with simultaneous failures (except $\{S_1S_2\}$, $\{S_jLP_k\}$, $\{S_jLM_m\}$ and $\{S_jLF_r\}$ with k, m and r connected to j and with the corresponding probabilities defined above) are given by multiplying the probabilities of their respective single scenarios. For example, if c_2x is the probability of $\{LP_k\}$, then the probability of $\{LP_kLP_{q\neq k}\}$ is $c_2^2x^2$. In this manner, Table 3.4 shows the scenarios and their respective probabilities. Note that scenarios $\{S_1\}$, $\{S_2\}$ and $\{S_3\}$ are equally likely. Thus, scenario type $\{S_j\}$, *j* = 1, 2, 3, represents three different scenarios with similar definitions and likelihoods (each corresponding to the failure of one SS). The number of similar scenarios is also indicated in Table 3.4, which shows a total of 209 possible scenarios. Then, the event "no occurrence of a disruptive event (no failure)" is considered complementary to the other failure scenarios.

Table 3.4 - Description of the scenarios

Type of event	Description	p_c	Number of similar
Single failures	$\{S_j\}$: failure of the j-th SS with j = 1, 2, 3;	c_1x	3
	$\{LP_k\}$ failure of the line between the k-th chemical/petrochemical and the corresponding SS;	c_2x	4
	$\{LM_m\}$: failure of the line between the m-th manufacturer and its SS	c_2x	5
	$\{LF_r\}$: failure of the line between the r-th food and its SS.	c_2x	8
Multiple failures	$\{S_1S_2\}$	x	1
	$\{S_jLP_k\}$, k not connected to j	$c_1c_2x^2$	8
	$\{S_jLM_m\}$, m not connected to j	$c_1c_2x^2$	10
	$\{S_jLF_r\}$, r not connected to j	$c_1c_2x^2$	16
	$\{S_jLP_k\}$, k connected to j	c_1x	4

Type of event	Description	p_c	Number of similar
	$\{S_jLM_m\}$, m connected to j	c_1x	5
	$\{S_jLF_r\}$, r connected to j	c_1x	8
	$\{LP_kLP_{q\neq k}\}$	$c_2^2x^2$	6
	$\{LM_mLM_{q\neq m}\}$	$c_2^2x^2$	10
	$\{LF_rLF_{q\neq r}\}$	$c_2^2x^2$	28
	$\{LP_kLM_m\}$	$c_2^2x^2$	20
	$\{LP_kLF_r\}$	$c_2^2x^2$	32
	$\{LM_mLF_r\}$	$c_2^2x^2$	40
{No failure}	No occurrence of a disruptive event	$1 - x(1 + 20c_1 + 17c_2) - x^2(34c_1c_2 + 136c_2^2)$	1

The consequences of each of these scenarios are different; for example, scenarios $\{LP_1LP_2\}$ and $\{LP_2LP_3\}$ are equally likely, but their effects can differ because P_1 and P_2 are connected to SS_1, whereas P_3 is connected to SS_2. Thus, all scenarios should be incorporated into the optimization problem.

In this context, we analysed four cases, for each of which all of the scenarios shown in Table 3.4 were considered. The different cases were defined based on the probability of the scenario {no failure}. Thus, x is estimated by the definition of the probability of {no failure} and using the property that the sum of probabilities of all scenarios equals 1. For the positive constants c_1 and c_2 with $0 < c_1 < c_2$, the computation of x is always possible. Therefore, having obtained x, the probability of the other scenarios can be estimated using the relations given in Table 3.4.

We cannot predict exactly which adverse events will occur or when and with what intensity. Nevertheless, given that our approach anticipates the resilience pre- and post-event actions that should be considered, using the probabilities of disruptive events is a method to represent their intrinsically uncertain nature, and doing so also permits the calculation of the expected cost, which is a measure that can guide how resources should be allocated to enhance resilience. In the next section, we present examples of applying the proposed model, which was solved using IBM ILOG CPLEX software, which applies the exact Branch-and-Cut technique (Hillier and Lieberman) (Hillier & Lieberman 2015).

3.7.2 Results and Discussion

The probability of scenario {no failure} and the corresponding x for each of the 4 cases are shown in Table 3.5. Note that we consider P{No failure} = 0.9, 0.7, 0.3, 0.0 for cases 1, 2, 3 and 4, respectively. In other words, we assume that the probability of a disruptive event is low in case 1. Next, we increase this probability in cases 2 and 3. Finally, we analyse in case 4 a situation in which a disruption will occur for certain. These cases were defined to evaluate the behaviour of the system over T = 8 hours and the response of the model to different possibilities. However, we considered $c_1 = 10$ and $c_2 = 100$, i.e., the failure of a subtransmission line is ten times more likely than the failure of an SS or of a line and its respective SS.

Table 3.5 - Probability of cases 1, 2, 3 and 4

	Probabilities of Cases			
	1	2	3	4
{No failure}	0.9	0.7	0.3	0
x	5.10E-05	1.43E-04	3.02E-04	4.05E-04

The results presented in this section were obtained disregarding financial resource constraints. In fact, we disregard Constraint 26 to achieve an optimal resilience strategy with unconstrained financial resources. We also perform sensitivity analysis to assess the impact of limited budgets on the optimal resilience strategy and hence on system performance (see next section). The parameter values for the proposed model shown in Table 3.6 are fictitious for the sake of confidentiality. However, they were carefully estimated to represent reality.

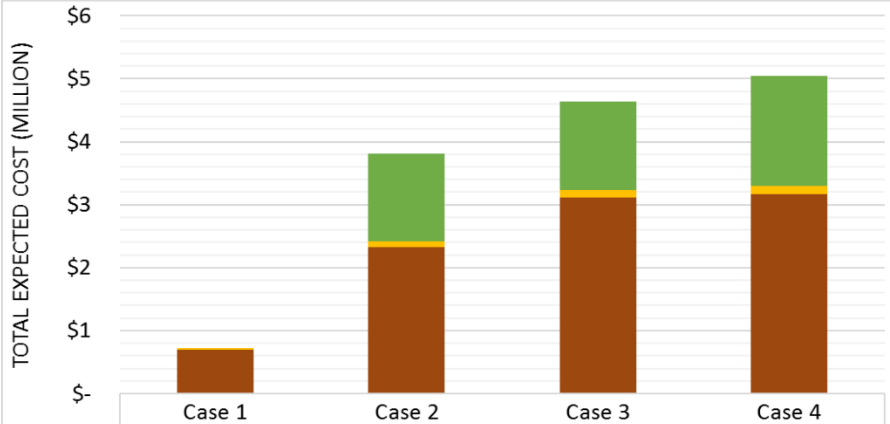
Table 3.6 - Values of the parameters used for all 4 cases

Parameter	Description	Value
α_j	Cost of adding K_j MVA of capacity to SS	\$ 3 million
λ_{ij}	Cost of establishing backup (SSj for C_i)	k\$ 480
φ	Cost of adding a redundant subtransmission line (SSj for C_i)	k\$ 350
γ	Cost of installing a diesel generator	k\$ 260
μ	Cost of adding resources to accelerate SS recovery	k\$ 100 /MVA
ρ	Cost of meeting the demand for supply (from the main power supply system)	\$ 0.5 /MVA
θ	Cost of meeting the demand for supply from the diesel generator	\$ 0.8 /MVA

Parameter	Description	Value
ϕ_i	Penalty for unmet demand of C_i	k$ 200 / MVA
δ_i	Penalty for unmet demand of C_i after a certain deadline d	k$ 200 / MVA
ω_i	Penalty for unmet demand of C_i , when C_i has generators	k$ 100 /MVA
π	Cost of recovering SS capacity	k$ 15 /MVA
σ	Cost of recovering subtransmission lines (between SSj and C_i)	k$ 50
T	Time period	8 hours
d	Deadline for return of subtransmission to normal operation	3 hours
r	Recovery rate for SS capacities	20 MVA/hour
G	Capacity of a diesel generator	2 MVA
ℓ	Recovery rate for subtransmission lines	0.5 line/hour

The comparison between the results in terms of IS, IDR and PCR obtained for each of the four cases is shown in Figure 4, where the total expected costs are presented. Figure 4 illustrates that in case 1, which has a low probability of occurrence of any disruptive event, no investments in resilience are necessary. In fact, one can state that, when the probability of scenario {no failure} is high, the model does not suggest investments in resilience.

Moreover, in analysing Figure 3.3, we observe that, as the probability of scenario {no failure} decreases, the total expected cost considerably increases. In fact, comparing cases 1 and 2, the expected total cost was approximately 5 times greater in case 2 than in case 1. Additionally, compared to case 1, the total expected cost of case 4 increased drastically from $ 716,370 to $ 5,049,530. This significant increase is justified by the increases in IS, PCR and IDR values as the probability of {no failure} decreases. For case 1, the highest penalties (related to unmet demand) are observed in scenarios {LP1}, {LP2}, {LP3} and {LP4}, comprising 17% of the total expected penalty. For case 2, there was an investment of $ 1,400,000 in IDR.



	Case 1	Case 2	Case 3	Case 4
IDR	-	1,400,000.00	1,400,000.00	1,750,000.00
PCR	17,960.00	93,374.00	123,400.00	138,730.00
IS	698,410.00	2,319,800.00	3,114,000.00	3,160,800.00
TOTAL	716,370.00	3,813,174.00	4,637,400.00	5,049,530.00

Figure 3.3.Total expected costs of the 4 different cases.

Figure 3.4 shows for case 3 that an active parallel subtransmission line (dashed line) should be added for client P_4, which is the highest penalty related to unmet demand (chemical/petrochemical sector), as shown in Table 3.6. The investment in this resilience-based alternative assures that P_4 has its demand fully met when its main subtransmission line is affected. Consequently, the penalty for the $\{LP_4\}$ scenario decreased from $86,000 in case 2 to zero in case 3. In addition, this design feature, while maintaining the operation of the system, is also used to share the workload with the main subtransmission line. It is important to note that, in practice, the design and installation of redundant lines connected to the same SS consider a distance criterion to avoid one tower falling onto an adjacent line.

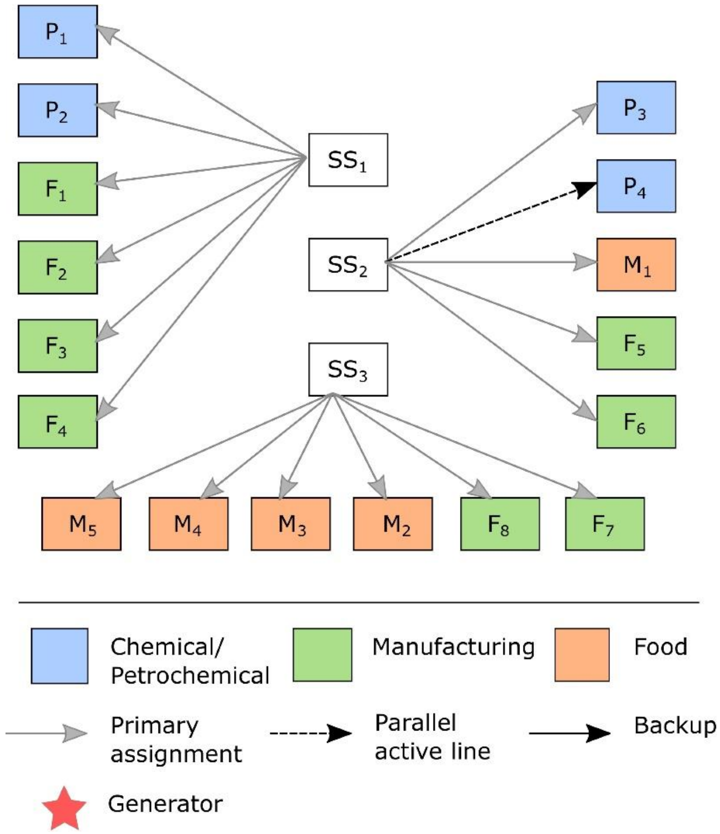


Figure 3.4 - Resilience enhancement actions defined for case 3

In case 4, the solution of the model suggested active parallel subtransmission lines for clients P_1 and P_2 (Figure 3.5). Comparing cases 3 and 4, after investing in redundant subtransmission lines, the penalty related to unmet demand for the $\{LP_1\}$ and $\{LP_2\}$ scenarios decreased from k$ 362 in case 3 to zero in case 4. As in case 2, there was also a recommendation to invest in restorative capacity for cases 3 and 4, causing an increase in the SS recovery rate of 5 MVA/hour; i.e., it increased from 20 MVA/hour to 25 MVA/hour.

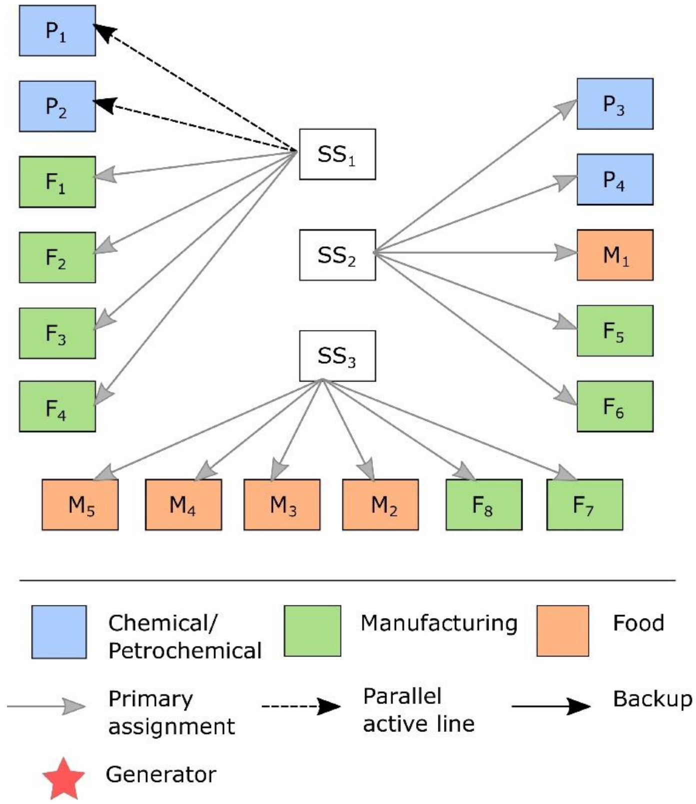
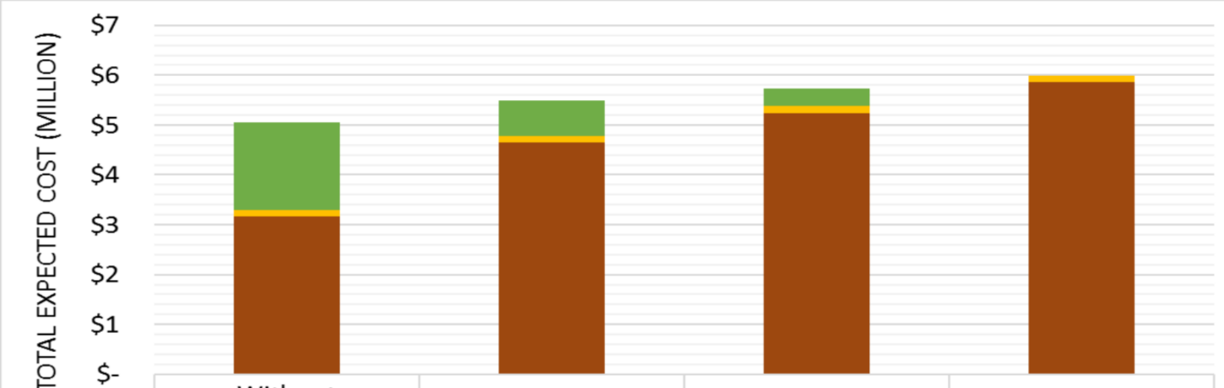


Figure 3.5 - Resilience enhancement actions defined for case 4

Investment in active parallel subtransmission lines and in restorative capacity seems reasonable since the probability of each scenario remains low, although the probability that an event could impact a subtransmission line is considered to be ten times greater than the probability of an event that could affect an SS. However, although the cost of adding a single 2 MVA diesel generators is approximately 25% less, this action would not be as efficient as the parallel active subtransmission line in cases 3 and 4 because it would not enable the system to supply the client's entire demand. For example, a petrochemical client would have to invest in eight generators to ensure that its demand supply was met during disruption, and the cost of this action would be approximately six times greater than that of investing in an active parallel subtransmission line.

3.7.3 Assessment of the Constraint on Financial Resources

In this section, we evaluate the impact of budget constraints on defining the optimal resilience-based strategy and hence on system performance. In the proposed model, the financial constraint is represented by the parameter M, which limits the investments in resilience enhancement actions (pre-event actions) and the costs associated with post-event recovery (see Constraint 26). Thus, we analyse case 4 for three different new possibilities: (i) M = $ 1 million; (ii) M = $ 0.5 million; and (iii) no investment in actions to enhance resilience ("without IDR"); the results are shown in Figure 3.6.



	Without Restriction	$1,000,000.00	$500,000.00	Without IDR
IDR	1,750,000.00	700,000.00	350,000.00	-
PCR	138,730.00	138,730.00	138,730.00	138,730.00
IS	3,160,800.00	4,645,700.00	5,240,100.00	5,856,700.00
TOTAL	5,049,530.00	5,484,430.00	5,728,830.00	5,995,430.00

Figure 3.6-Total expected costs for case 4 for different constraints on financial resources.

As shown in Figure 3.6, as M decreases, the cost associated with the impact on the system (IS) increases. For example, from the "without restriction" case to M = $ 1 million and M= $ 0.5 million, IS increases by approximately 15% and 44%, respectively. Consequently, the total expected cost also increases. Therefore, the reduction in M directly impacts the decisions on drawing up a resilience-based strategy and hence on the system performance to meet demands.

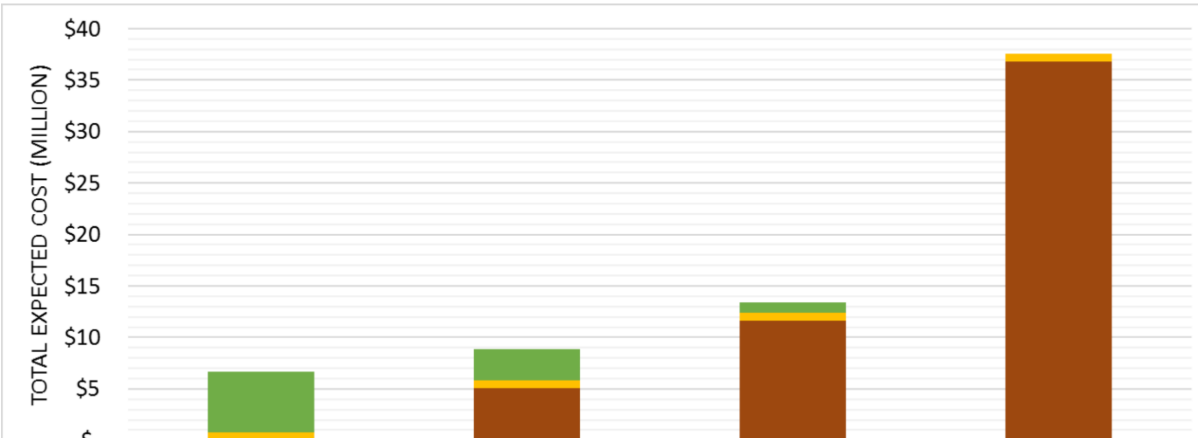
Note also that PCR does not change in the situations presented in Figure 3.6 because (i) all of them represent the same case 4, with all 209 scenarios and their respective likelihoods, and (ii) the system must fully recover over the time period of 8 hours (see Constraints 20 and 23). Thus, it is important to note that increasing IDR does not indicate that the PCR will be reduced because a certain total amount of resources will always be needed to perform the recovery actions associated with the disruptive event, regardless of IDR.

3.7.4 Further Assessments: Evaluating Specific Scenarios

It is also important to emphasize the flexibility that the model offers to propose solutions for a given particular event. Thus, we analyse two different scenarios to identify the optimal resilience-based strategy considering the occurrence of (i) failure of SS_1 (scenario $\{S_1\}$) and (ii) simultaneous failure of SS_1SS_2 (scenario $\{S_1S_2\}$). We believe that these disruptions are related to severe consequences; thus, we analyse the resilience actions that are appropriate for each of them. To this end, for each scenario, we consider its probability of occurrence equalling 1; thus, the other events in Table 3.4 will not occur.

3.7.4.1 Assessment of Failure of Substation SS1

We evaluate this scenario for 4 investment possibilities. First, we disregard financial resource constraints (the “without restriction” case). Next, we consider M = $ 4 and M = $ 2 million. Finally, we consider the worst-case situation with no investments in resilience enhancement actions (the “without IDR” case); the results are shown in Figure 3.7.



	Without restriction	$4,000,000	$2,000,000	Without IDR
IDR	5,880,000.00	3,100,000.00	1,020,000.00	-
PCR	750,000.00	750,000.00	750,000.00	750,000.00
IS	-	5,040,600.00	11,601,000.00	36,801,000.00
Total	6,630,000.00	8,890,600.00	13,371,000.00	37,551,000.00

Figure 3.7-Total expected costs for scenario {S1} for different constraints on financial resources.

As in the previous case, Figure 3.7 also shows that, when M is reduced, the costs associated with the system impact IS, and expected total cost increases, affecting the decisions in the elaboration of the strategy based on resilience. Thus, the expected total cost for the "without IDR" case is almost six times greater than that for the "without restriction" case.

Figure 3.8 shows the investments that should be made to enhance power grid resilience for each budget. These investments are assessed according to the performance of the SS recovery and the extent to which the supply of electricity meets the client’s demand, which is directly affected by the resilience actions undertaken during the downtime of the corresponding SS. We evaluate the impacts on clients P_1 and F_1, considering the portion of their demands supplied in scenario $\{S_1\}$; these clients were selected to evaluate performance in supplying power to the industrial sector. The recovery speed of SS_1 and the costs associated with PCR and IS are also illustrated in Figure 3.8.

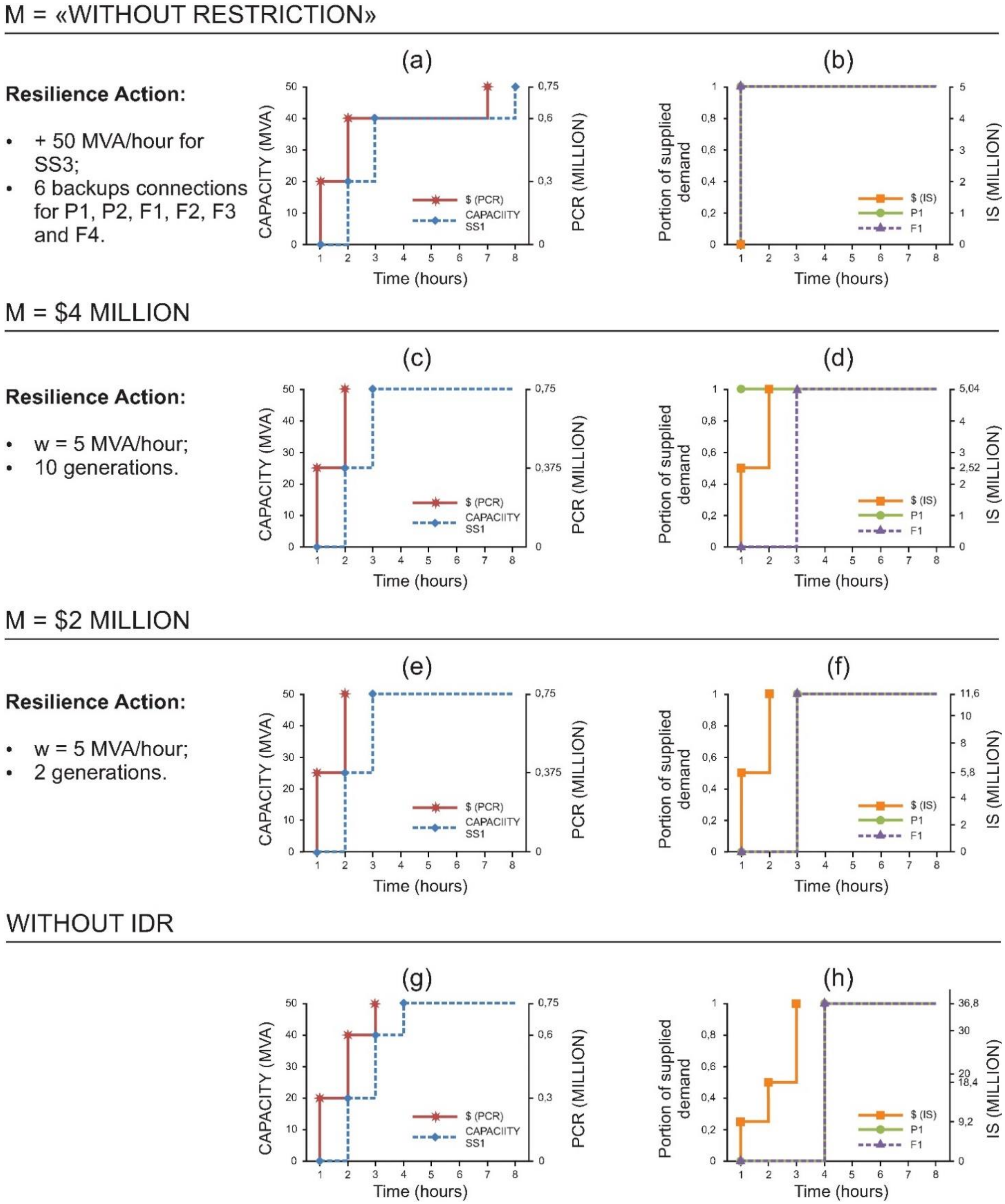


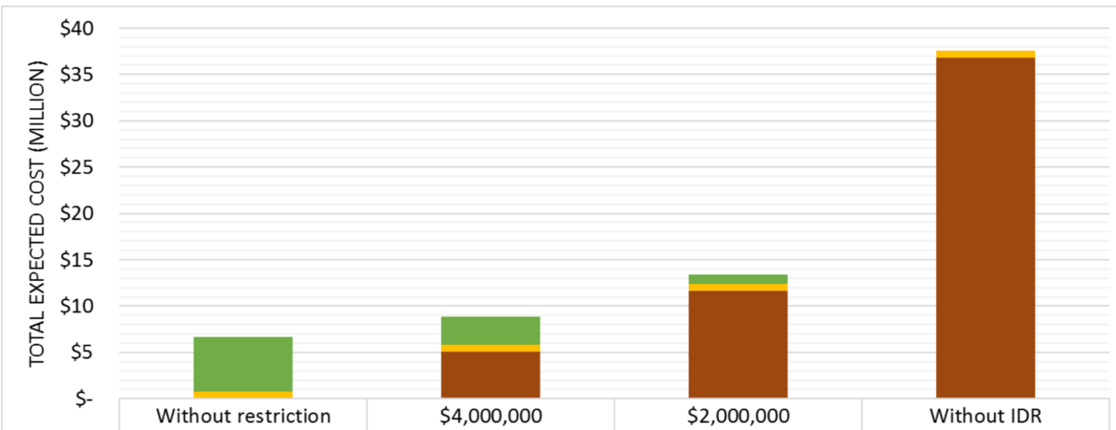
Figure 3.8 - Assessment of different budgets for scenario {S1} over time.

Figure 3.8 (a, c, e, g) show the capacity recovery of SS1 and post-interruption cost recovery (PCR) for M = "Without restriction", $ 4 and $ 2 million and "without IDR". Figure 3.8 (b, d, f, h) present the supply portion that meets the demand of customers P1 and F1 and IS for M = "Without restriction", $ 4 and $ 2 million and "without IDR". In addition, for each M, there is a list of resilience strategies employed on the left side of each figure. According to Figure 3.8, higher budgets (M) emphasize investment to minimize the portion of unmet demand, while lower budgets show increased IS. In contrast to the previous cases, note that, when we consider the unavailability of SS_1, the investments for the "without restriction" case yield improvement in the absorptive and adaptive capacities. Indeed, we can see in Figure 9 that the model suggests that (i) 6 backups connections should be established (P_1, P_2, F_1, F_2, F_3 and F_4) so that the clients can be supplied by SS_3 and (ii) additional capacity should be added to SS_3 so that it will be able to supply the additional demand.

Because SS_1 clients would be fully supplied by SS_3 (Figure 3.8b), recovery of SS_1 would only be completed in T = 8 h (Figure 3.8a), as Constraint 23 requires. However, note that in Figure 3.8c (M = $4 million) the recovery of SS_1 is faster (T = 3 h) than in Figure 3.8a because, in this case, we would have neither the additional capacity of SS_3 nor the backup connections. We can also see in Figure 3.8 that, as the financial resources decrease, the investment focuses on improving restorative and adaptive capacities so that generators can be allocated to help addressing the most important clients, while SS_1 is still in the process of recovering.

3.7.4.2 Assessment of the Simultaneous Failure of Substations SS1 and SS2

Although the probability of scenario $\{S_1S_2\}$ is usually very low, if it occurs, it would have great impact on the performance of the system. Figure 3.9 shows the total cost of this event for different budget constraints. First, as in the previous section, we do not consider financial resource constraints (the "without restriction" case), and then M = $ 10, 7 and 3 million. Finally, we also consider the worst-case situation with no investments in resilience enhancement actions (the "without IDR" case).



	Without restriction	$4,000,000	$2,000,000	Without IDR
IDR	5,880,000.00	3,100,000.00	1,020,000.00	-
PCR	750,000.00	750,000.00	750,000.00	750,000.00
IS	-	5,040,600.00	11,601,000.00	36,801,000.00
Total	6,630,000.00	8,890,600.00	13,371,000.00	37,551,000.00

Figure 3.9 - Total expected cost for scenario {S1S2} and for different financial resource constraints.

Therefore, the optimal strategy for scenario $\{S_1S_2\}$ has a total cost of $13,500,600: approximately 88% less than the case in which no investments in resilience are made. In fact, IS represents 16% of total expected costs for the "without restriction" case and 98% for the "without IDR" case. This finding emphasizes that investments in pre-event actions to enhance resilience (including investments in adaptive, absorptive and restorative capacities) have the potential to enable better allocation of the available financial resources to improve the efficiency of the response if disruptive events occur.

Note that, as explained for case 4, PCR remains constant for all situations presented in Figure 3.9 since all of them represent the occurrence of scenario $\{S_1S_2\}$, and the system must fully recover over the time period of 8 hours (see Constraints 20 and 23). However, PCR is much greater for scenario $\{S_1S_2\}$ than for case 4 because we would then have more severe consequences.

For the "without restriction" case, according to Figure 3.10, the resilience actions are (i) acquiring 17 diesel generators; (ii) establishing 4 backup connections from SS_3 to P_1, P_2, P_3 and P_4 (Figure 3.11); (iii) investing in additional capacity to SS_3 (50 MVA) to accommodate the backup connections; and (iv) investing in increasing the recovery rate (w = 5 MVA/hour). Note that (i) and (ii) are related to adaptive actions, whereas (iii) and (iv) concern absorption and restoration actions, respectively.

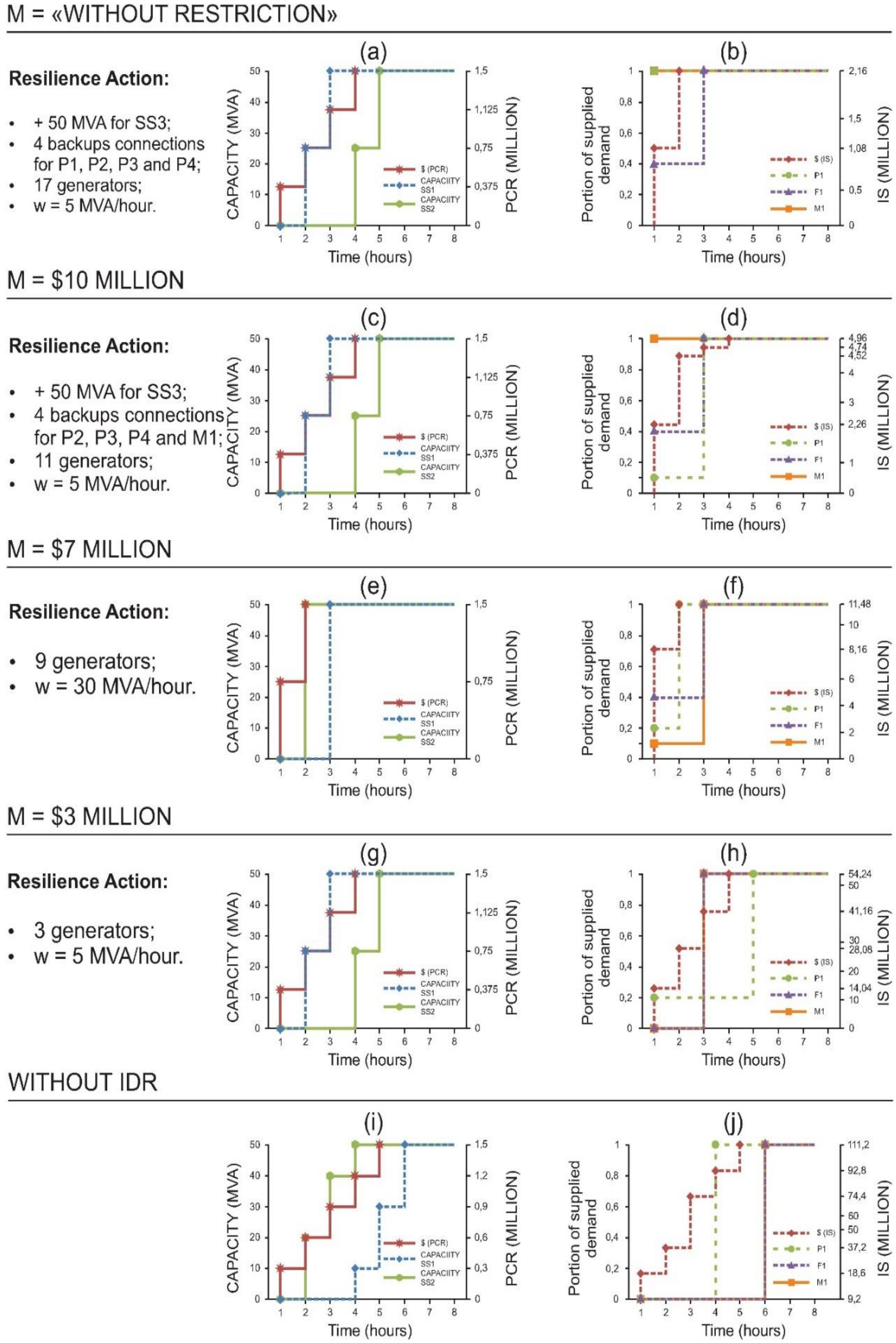


Figure 3.10 - Assessment of different budgets for scenario {S1S2} over time.

Figure 3.10 (a, c, e, g, i) show the capacity recovery of SS1 and PCR for M = "without restriction", $ 10, 7 and 3 million and "without IDR". Figures 3.10 (b, d, f, h, j) present the supply portion that meets the demand of customers P1, M1 and F1 and the cost of IS for M = "without restriction", $ 10, 7 and 3 million and "without IDR". In addition, for each M, there is a list of resilience strategies employed on the left side of each figure.

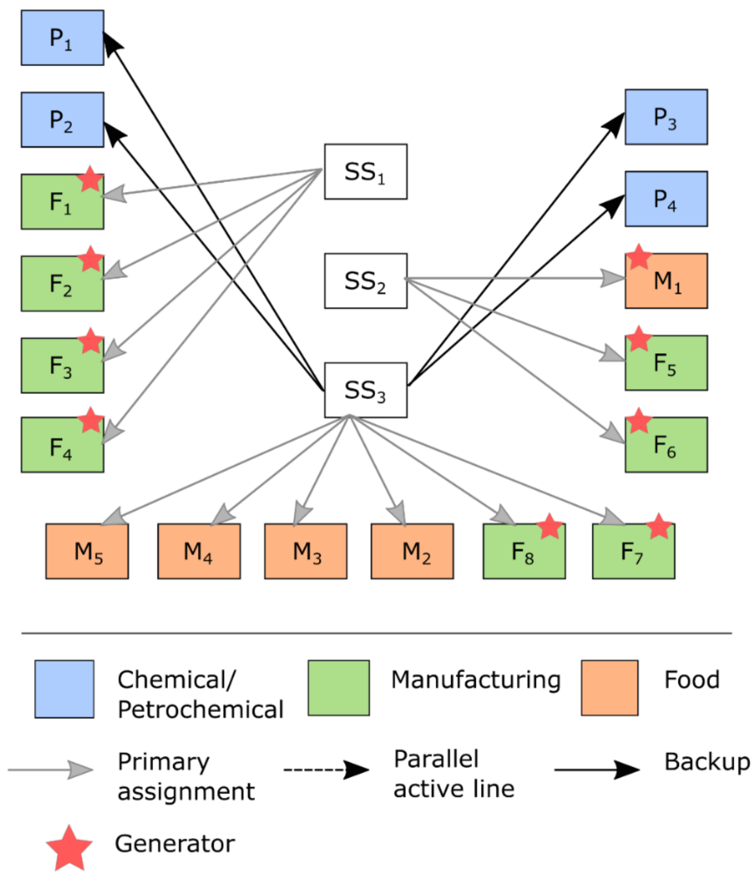


Figure 3.11 - Resilience enhancement actions defined for scenario {S1S2} for M = "without restriction"

Although the investment in the recovery rate seems small, note that each SS can only be stated as operational when at least K_j of its capacity (50 MVA in this case) is fully recovered. Thus, this investment allows for the recovery of SS_1 to be completed in d = 3 hours (see Figure 3.10a). Although SS_1 and SS_2 have the same demand in MVA, note that SS_2 has more clients, which are ranked higher in importance than SS_1 (see Figure 3.2). Thus, the penalties would be higher if the clients of SS_2 are not rapidly supplied. In this manner, the model prioritizes pre-event (adaptive and absorptive) actions to enhance resilience for SS_2 clients, and it determines recovery strategies for SS_1.

However, the sum of the clients' demands would be allocated as backup to SS_3 (P_1, P_2, P_3, P_4), exceeding its additional capacity by 10 MVA and thus indirectly affecting the supply of its own clients. In fact, clients P_1, P_2, P_3, and P_4 are prioritized because they have greater importance than the clients of SS_3. To reduce this consequence, generators could be added to some clients of SS_3, such as F_7 and F_8. In this case, after an interruption, because P_1 is connected to SS_3 by means of a backup connection, its demand is not affected (Figure 3.10 b).

Table 3.7 shows the allocation of generators to each client; for the "without restriction" case, we also show the portion of their demand supplied by generators during SS_1 and SS_2 downtime. For instance, even during SS_2 downtime, M_1 will have 100% of its demand supplied because 5 diesel generators have been added (Figure 3.10b). In contrast, only 1 generator was allocated to F_1. Because the supply capacity of the diesel generator is 2 MVA/hour, the supply of 40% of its demand is ensured until SS_1 is fully recovered by period d = 3 (Figure 3.10b). Therefore, this allocation actually reduces the overall expected penalties incurred due to unmet demand. Thus, by adopting this strategy, only 5% of the total demand originally allocated to SS_3 would not be supplied during concomitant SS_1 and SS_2 downtime.

Table 3.7 - Allocation of diesel generators for scenario {S1S2}. Financial constraints (in millions).

Client	Without restriction		$ 10	$ 7	$ 4	$ 3	Without IDR
	No. of generators	Portion of demand supplied (%)	No. of generators				
P1	-	-	1	1	1	-	-
P2	-	-	-	1	-	-	-
F1	1	40	1	1	-	-	-
F2	1	40	1	1	-	-	-
F3	1	40	1	1	-	-	-
F4	1	40	1	1	-	-	-
P3	-	-	-	1	1	1	-
P4	-	-	-	1	1	1	-
M1	5	100	-	1	1	1	-
F5	3	100	3	-	-	-	-
F6	3	100	2	-	-	-	-
F7	1	40	1	-	-	-	-
F8	1	40	-	-	-	-	-

Client	Without restriction		$ 10	$ 7	$ 4	$ 3	Without IDR
	No. of generators	Portion of demand supplied (%)	No. of generators				
M2	-	-	-	-	-	-	-
M3	-	-	-	-	-	-	-
M4	-	-	-	-	-	-	-
M5	-	-	-	-	-	-	-
Total	17	-	11	9	4	3	-

For M = $10 million, the number of diesel generators was reduced by 35% (Table 3.7), and the 4 backup connections were now from SS_3 to P_2, P_3, P_4 and M_1. In the "without restriction" case, the backup allocation to SS_3 affected the supply of its own clients (F_7 and F_8), which no longer occurs. However, in this case, supplying the demand of P_1 is greatly affected, as shown in Figure 3.10b, since only one generator is allocated to P_1 (Table 3.7). For client M_1, because it has SS_3 by means of a backup connection, its demand is not affected. Conversely, F_1 remains with one generator, thus ensuring the supply of 40% of its demand until SS_1 is fully recovered. In this case, three clients of SS_2 are also connected through backup to SS_3 (P_3, P_4 and M_1). Thus, to minimize the impact, SS_1 should be recovered before SS_2 (Figure 3.10c), and the demand of their clients (P_1 being one of them) is supplied normally from period 3 (Figure 3.10d).

For M = $ 7 million, the total number of diesel generators decreases to 9, and the resilience strategy adopted for this case is more reactive because the highest amount of investment is directed to accelerating the recovery rate, which increases from 20 MVA/hour to 50 MVA/hour (w = 30 MVA/hour). Thus, the resources for SS recovery are shared between SS_1 and SS_2 so that both return to normal operation by the deadline d = 3 (Figure 3.10 e). Another important point is that the fastest recovery speed was achieved for M = $ 7 million, even when compared to the case "without restriction" and M = $ 10 million.

For M = $ 3 million, investment is still made in (i) accelerating the recovery rate (w = 5 MVA/hour) and (ii) one generator each for clients P3, P4 and M1. The recovery speed is similar to what was presented for the "without restriction" case and M = $ 10 million, the recovery of SS1 being completed in three hours and that of SS2 in five hours (Figure 3.10g). However, the results for the supply meeting the demand in this case are worse than those presented for M = $ 10 million (Figure 3.10b). Figure 3.10i and Figure 3.10j also illustrate the worst situations ("without IDR" case), in which no resilience enhancement actions are implemented during the design phase.

Briefly, we can note that when the budget reduces, the cheapest strategy is to invest in (i) acquiring diesel generators and (ii) accelerating recovery. As mentioned before, using generators can reduce the impact of an event on the system because doing so can keep critical, industrial equipment in minimal operating condition until the power supply returns to normal. For petrochemical clients, for example, the generators can be used to remove the work in process and to allow the system to restart without any further delays when the power supply returns.

However, Figure 3.12 illustrates the portion of the overall demand supplied in each situation, considering the performance for all clients over the 8-hour period. Figure 3.12 indicates that actions towards incorporating the absorption and adaptation capacities enable the response to be more effective than actions that focus on recovery. Moreover, our model reflects that it is economically unfeasible to ensure that 100% of the demand will be met should disruptive events occur. However, we can minimize the impact on the system (IS) by adopting pre-event resilient actions.

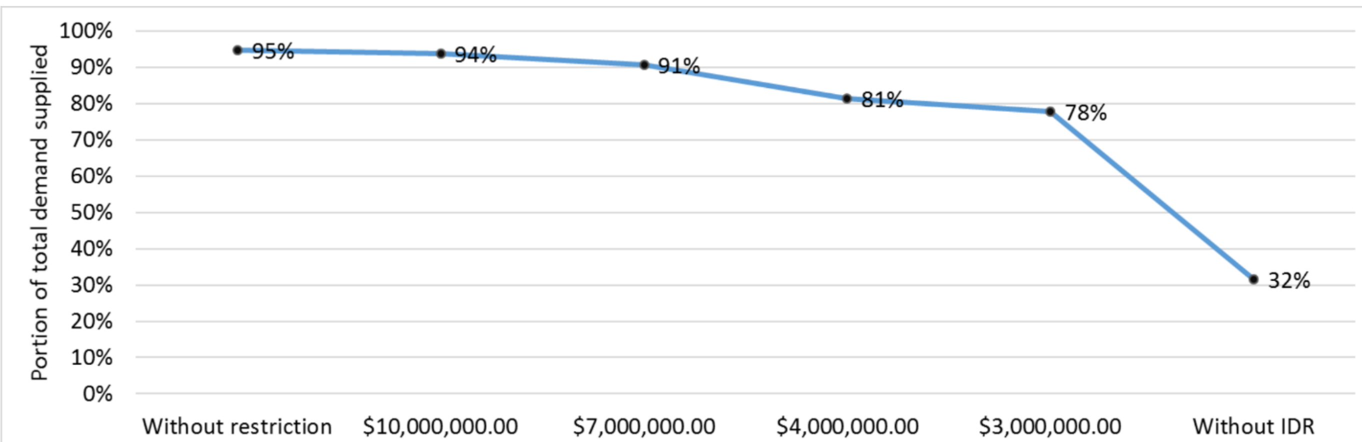


Figure 3.12 - Assessment of the total demand for supply met over the period of 8 hours for different financial resource constraints.

3.8 Final Comments

We have developed a stochastic optimization model using Mixed-Integer Linear Programming to support decisions related to investments in the design of resilient power grids serving to industrial clients. We minimize the overall expected cost by means of an optimal strategy involving pre- and post-event actions.

The model was validated by two types of sensitivity analysis. First, we increased the probability of the occurrence of an undesired event. From the results, we can see that our model indicated that the decision maker should also increase investments to design a more resilient system. In contrast, by reducing the probability of occurrence, no investment should be made. Thereafter, we also evaluated how the model behaves for different budgets. As expected, as we decreased the budget, the IS increased rapidly, indicating the usefulness of investing in resilience during the design phase. Note that the proposed model also indicated how the resources should be spent for each case.

The results obtained enabled the optimal solution to be analysed in terms of IS, IDR and PCR. Moreover, detailed IDR actions (e.g., redundant or backup lines, diesel generators) are real-world suggestions to improve the resilience of EPSN related to industrial clients. Thus, the impacts on EPSN clients due to disruptions were reduced, as evidenced in the sensitivity analysis, in which IS increased by reducing the investments in resilience strategies. This analysis also showed that the lower the investment in IDR, the greater the level of unmet demand, which can yield financial losses for the entire system.

Another important contribution is to draw attention to a paradigm change in how a power grid is viewed: the traditional stance is that the grid is system centred on electric power utilities. However, the new paradigm is that the grid is not only system centred but is also a customer-focused system, which is the reasoning followed by other authors, such as (Kwasinski 2016). Therefore, our model includes strategies that can be applied both to electric power grids and by industrial customers. For example, such strategies include considering redundant or backup systems and diesel generators, thus allowing customers to make decisions about managing electric power, which has a strong influence on enhancing the overall resilience of the entire grid.

4 DETERMINATION OF DESIGN CHARACTERISTICS FOR A RESILIENT LOGISTIC NETWORK CONSIDERING CLIENT SERVICE LEVEL

A part of this chapter was based on a research article published at the European Conference on Safety and Reliability (ESREL) (Diniz et al. 2015). In addition, in the date or publication of the thesis, this chapter was considered as an original research article for publication in the journal PLOS ONE.

4.1 Problem statement

In the context of intense transformations driven by technological advances, commercial and financial integrations and increasingly global competition, efficient logistics has become a decisive factor to ensure the survivability of organizations. This recognition derives from the potential of logistics to aggregate values of both time and space for consumers and to create competitive advantages for organizations. The internationalization of industries increasingly extends the importance of logistics, as logistic costs represent a significant share of the total cost of goods. It is through the logistics processes that the inputs arrive to the factories and the products are distributed to the consumers.

Moreover, for the current competitive market, it is not enough for companies to have attractive products, competitive prices and creative ads, because the trend of customers requiring new levels of services is increasing. In addition to quality and performance, customers have been requiring the products to be in the desired location and at the planned time (Christopher & Peck 2004).

In this scenario, companies tend to be increasingly demanded in terms of the level of resilience they encounter after an unwanted event. According to Francis et al. (Francis & Bekera 2014), the term resilience is generally understood as an entity's ability to recover from an external disturbance such as threats, shocks, disasters, and anomalies. In this way, the system must successfully withstand, absorb and recover from the effects of these disturbing events, adapting to adversity or a change in normal operating conditions. In other words, resilience involves reducing both the magnitude and duration of the effects of an event under the normal performance of the system.

As a way to prevent or minimize the impacts after the occurrence of disruption events, companies are seeking to develop a tool to support decisions related to investment in the resilience strategy. Thus, the objective of this chapter is to develop a quantitative model that determines the optimal allocation of financial resources to establish a resilience-based strategy in the context of the system design of a logistics network by minimizing the overall cost associated with the occurrence of disturbing events.

The design of a supply chain involves strategic decisions regarding the number and capacity of distribution centers, their locations and their mission, in order to meet the needs of final consumers. Thus, the decisions regarding the network design are long term and therefore need to anticipate the future levels of network activity (Klibi et al. 2010). To this end, it is necessary to evaluate the exposure of the network to disturbing events to promote improvements in system resilience by controlling some variables such as: inventory level, alternative supply sources, outsourced activities and level of information shared among network partners (Carvalho et al. 2012).

According to the concepts previously presented, this work will evaluate the possibilities of investments in the design of a logistic network, with the purpose of improving network resilience and, with this, attendance of the service level specified to the client considering that the network is exposed to disruption events. The objective is to promote improvements to an existing network, according to the probability of occurrence of disruptive events in the network, making a trade-off between how much to invest in the network and the expected costs of the occurrence of these events.

4.2 Supply Chain Disruptions

A disruptive event is an event (or set of events) that causes a disturbance in the normal operating condition of a system (Francis & Bekera 2014), leading to a degradation of its performance. Uncertainty, inherent in the study of potential interruptions, makes consideration of scenarios important to cover a wide range of potential situations (Turnquist & Vugrin 2013), encouraging effective decisions regarding the allocation of investments with the porpoise of minimizing the degradation of system's performance.

Some authors have suggested that these rare but catastrophic disruptions are different from frequent, smaller disruptions and, thus, should be managed accordingly (Bradley 2014). Many companies use comprehensive scenario planning to model the dynamics and consequences of high-impact risks in order to recognize the direct effects as well as secondary effects of disruptions, such as the public fear and resource hoarding (Sheffi & Rice Jr. 2005).

In the context of Supply Chain Management (SCM), in addition to the increase of supply chain disruptions' frequency (Bradley 2014; Schmitt et al. 2015), the adoption of lean concepts into Supply Chain (SC) performance, like single sourcing and low inventories, achieved by close collaboration between customers and suppliers, leads to high vulnerability (Thun & Hoenig 2011; Ivanov, Dolgui, et al. 2016). Furthermore, with the increased specialization and geographical concentration of manufactures, disruptions in one node may affect the whole SC (Ivanov, Dolgui, et al. 2016).

According to Mensah & Merkuryev (2014), research shows that supply chains are at greater risks than their managers recognize. A research conducted by Thun & Hoenig (2011), comprising data of 67 companies in the automotive segment of German's industry, where most of them are first tier suppliers, identified seven key developments driving supply chain risks: globalization, product variants, outsourcing, limited number of suppliers, focus on efficiency, central distribution and centralized production.

Therefore, factors that increase the complexity of the SC and actions that seek to build up a lean SC, are the main drivers of supply chain risks. Risks can be identified at a focal firm, at its supply chain or at its supply chain environment (Heckmann et al. 2015; Yu & Goh 2014). In fact, new risks may emerge from the dependency and integration between companies in the supply chain (Thun & Hoenig, 2011).

According to Tang & Nurmaya Musa (2011), supply chain risk should refer to events with low probability but substantial negative consequences to the entire network. In fact, disruptive events that affect one supply chain entity or process have the potential to interrupt the operations of other supply chain members either directly or indirectly (Kim et al. 2014; Ivanov, Dolgui, et al. 2016). For example, Ford and Toyota had to interrupt their production in US due the terrorist attacks of September 11, 2001 (Sheffi 2001), that caused significant delays in the delivery of parts coming from foreign countries.

Naturally, after the terrorist attack of September 11, 2001, the U.S. government closed the country's borders and shut down all incoming and outgoing flights, causing shipments across the U.S.-Canada border to be slowed for at least a week and, therefore, many auto assembly plants were intermittent closed (Bradley 2014).

According to Ivanov et al. (Ivanov, Dolgui, et al. 2016), the main types of reactions to disruptions for SC are parametrical and structural adaptation. Parametrical adaptation permits an adjustment on critical parameters, such as lead time and inventory, to stabilize and recover network performance, while structural adaptation considers rearrangements on network structure in order to maintain network performance for critical parameters.

4.3 Model Description

In this section, the formulation of the optimization model, using Mixed-Integer Linear Programming (MILP), to support decisions related to investments in the design of a resilient logistic network is presented. The objective is to minimize the total expected cost, taking into account the possible investments in network design and the costs associated with the impact of disruptive events on network performance. To this end, a set of scenarios will be defined, corresponding to the ways by which the network can be affected by external events, each with an associated probability. According to these scenarios, the model considers the possibilities of investments in the network design (pre-event decisions) as a way to complement the efficient recovery post-event, determining the optimal allocation of resources and minimizing the total expected impact on the network. As discussed in chapter 2, investments in resilience during network's design phase correspond to the promotion of absorption, adaptation and recovery capacities, with the aim of maintaining a specified network's level of service.

Distribution networks can be considered part of the broader definition of supply chains. Then, the SC network studied is represented by a set of distribution centers (DCs) denoted by *j*, who deliver a product to retail customers in the region, denoted by *i* (Figure 4.1). Initially, it is considered the existence of a pre-project for the network in which each customer has a demand q_i (uniform for all periods), which is attended by a specified DC (primary supplier), each with capacity *Kj* equal to the demand assigned to it.

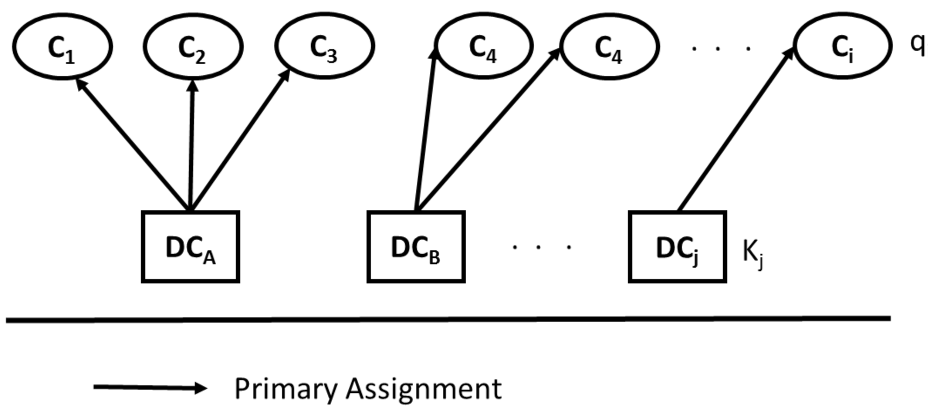


Figure 4.1 – Representation of the system considered

Before the presentation of the mathematical model formulation, the notation of variables and parameters are described in Tables 4.1 and 4.2, respectively.

Table 4.1 - Description of model's variables

Variable	**Description**
w_j	Additional capacity for DC_j
U_{jts}	Available capacity in DC_j in period t of the scenario c
z_{ij}	Back-up connections between DCs and clients
R	Additional resources for DC recovery

Variable	Description
a_{mits} *and* b_{nits}	Associated variables to Special Ordered Sets-Type 2 (SOS2)
x_{ijts}	Portion of customer demand *i* served by DC_j in period *t* of the scenario *c*
y_{its}	Portion of customer demand *i* which is not served in period *t* of the scenario *c*
O_{jts}	Outsourced DC_j capacity in period *t* of the scenario *c*
r_{jts}	Resources used for recovery of DC_j in period *t* of the scenario *c*

Table 4.2 - Description of model's parameters

Parameter	Description
F	Cost of adding 1 unit of capacity to DCs
θ_{ij}	Cost for establishing a connection between DC_j and client *i*
h	Cost to add resources for DC recovery
ϕ_i	Penalty for not serving the specified service level
q_i	Customer *i* demand
ρ_i	Penalty for not serving the demand after the determined period
η	Cost of outsourcing 1 unit capacity
K_j	DC_j initial capacity
μ	Cost of using recovery resources
ε	Penalty for unrecovered capacity
L_{ij}	Connections between pre-defined clients and DCs
SL	Service level
l	Deadline to restore system to nominal performance threshold

4.3.1 Pre-event investments alternatives

The pre-event investment alternatives available for improvements on network design are defined as the Investments in Design for Resilience (IDR) and can be divided into investments in three types of capacity:

- Absorption: investment in additional capacity for DCs. For instance, it includes: increasing the capacity of each DC to accommodate the loss of any of the others, expanding the physical space of each DC and expanding transporting capacity (e.g. increase the number of forklifts, lecturers, stored fuel, supervisors, invest in insurance). It is worth noting that the cost with idle capacity is expected to be lower than the prejudice of not meeting demand and losing customer credibility.

- Adaptation: investment in back-up connections between DCs and customers. It can be archived by reconfiguration of connections between DCs and costumers for the movement of material through the definition of a back-up (secondary assignment), in case of primary assignment rendered non-functional given the occurrence of a disruptive event. The definition of a back-up considers the costs associated with distance between DCs and costumers.

- Restoration: investment in additional resources for DC's recovery. It can be done through investments in resources that make the recovery faster given the occurrence of the event.

Although inventory costs are high, maintaining inventories can be an important strategy to minimize the effects of demand fluctuations and problems with interruptions. In addition, according to (Ratick et al. 2008), there are enough facts in history that prove the benefits of using emergency backup, even with low probability of occurrence of disruptive events. Hence, the expected cost of IDR can be written as follows:

$$\text{IDR} = F\sum_{j} w_j + \theta \sum_{i}\sum_{j} z_{ij} + hR \tag{4.1}$$

The first term of Equation 4.1 corresponds to investing in absorption, which is the possibility of adding capacity to each DC_j. The next two terms correspond to possible investments in adaptive capacity (establishing backups for clients so their demands can be met by another DC) and investment in increasing the recovery rate, respectively.

4.3.2 Post-event Costs

On the other hand, post-event costs associated with the occurrence of disruptive event involves both Impact on System Expenditures (ISE) and Post-interruption Cost of Recovery (PCR). The ISE is the cost associated with the impact of the event in the system due to performance degradation. It includes the impact on relevant performance metrics, such as additional cost for moving material through a degraded network, penalty costs related to the system's inability to meet the demand, extra penalty cost if the system is not able to meet demand within a given period. Therefore, ISE can be specified as the expected impact on the demand supply considering all possible scenarios, and it is expressed in Equation (4.2):

$$ISE = \sum_{s} p_s \left[\sum_{i} \phi_i \sum_{t} \alpha_{3its} + \sum_{i} \rho_i \sum_{t>l} q_i y_{its} + \eta \sum_{j} \sum_{t} O_{jtc} + \varepsilon \sum_{j} \sum_{t} \left(K_j + w_j - U_{jts} \right) \right. \tag{4.2}$$

Because it is an expected cost, all terms need to be weighted by the probability of occurrence of each scenario (p_s). The first term corresponds to penalty for not reaching the specified Service Level (SL). The second term represents an additional fee for unmet demand beyond deadline l, which is usually established in the contract signed with the client. In this manner, if the supplier fails to meet such a time limit, there will be additional costs. The third term reflects the cost of outsourcing part of the capacity of a DC. This work considers the possibility of manpower outsourcing as a way to compensate the capacity affected by some disruptive event. The fourth term represents penalty for incomplete recovery of DCs. That term penalizes the difference between the final restored capacity ($K + w$) and the currently available capacity in period t.

PCR includes costs associated with the necessary resources to promote system recovery due to the event, i.e., to recover the damaged capacity after the disruption in each scenario. Therefore, the expected PCR is shown in Equation 4.3.

$$PCR = \sum_{s} p_s [\mu \sum_{j} \sum_{t} r_{jts}] \tag{4.3}$$

4.3.3 Model formulation

The stochastic optimization model proposed is defined as an MILP problem with an objective function that combines the cost of investing in resilience-based actions in the network design phase (IDR) and the expected costs related to system performance and recovery (ISE plus PCR). A set of scenarios is defined, each with an associated probability, exemplifying the ways by which the network can be affected by external events. Different cases are analyzed, varying the scenarios' probabilities, in order to show how these changes will affect the investment required to achieve an optimal resilient design. The objective function (Equation (4.4)) is the sum of IDR, ISE and PCR, which are presented in Equations (4.1), (4.2) and (4.3), respectively.

$$Min \quad F\sum_j w_j + \theta\sum_i\sum_j z_{ij} + hR + \sum_s p_s\left[\sum_i \phi_i \sum_t \alpha_{3its} + \sum_i \rho_i \sum_{t>l} q_i y_{its}\right.$$
$$\left. + \eta\sum_j\sum_t O_{jtc} + \varepsilon\sum_j\sum_t \left(K_j + w_j - U_{jts}\right) + \mu\sum_j\sum_t r_{jts}\right] \tag{4.4}$$

Subject to

$$x_{ijts} - L_{ij} \le 0 \quad \forall i, j, t, s \tag{4.5}$$
$$x_{ijts} - z_{ij} \le 0 \quad \forall i, j, t, s \tag{4.6}$$
$$\sum_j z_{ij} \le 1 \quad \forall i \tag{4.7}$$
$$\sum_j x_{ijts} + y_{its} = 1 \quad \forall i, t, s \tag{4.8}$$
$$\sum_i x_{ijts} q_i \le U_{jts} + O_{jts} \quad \forall j, t, s \tag{4.9}$$
$$O_{jts} \le K_j + w_j \quad \forall j, t, s \tag{4.10}$$
$$U_{jts} \le \gamma_{js}\left(K_j + w_j\right) + \sum_{\tau=1}^{t-1} r_{j\tau s} \quad \forall j, s \tag{4.11}$$
$$U_{jts} \le K_j + w_j \quad \forall j, t, s \tag{4.12}$$
$$U_{jts} = K_j + w_j \quad \forall j, s \tag{4.13}$$
$$\sum_j r_{jts} \le B + R \quad \forall t, s \tag{4.14}$$
$$F\sum_j w_j + \theta\sum_i\sum_j z_{ij} + hR + \eta\sum_j\sum_t O_{jtc} + \mu\sum_j\sum_t r_{jts} \le M \tag{4.15}$$
$$y_{its} = \alpha_{2its}\left(1 - SL\right) + \alpha_{3its} \quad \forall i, t, s \tag{4.16}$$
$$\alpha_{1its} \le c_{1itc} \quad \forall i, t, s \tag{4.17}$$
$$\alpha_{2its} \le c_{1itc} + c_{2its} \quad \forall i, t, s \tag{4.18}$$
$$\alpha_{3its} \le c_{2its} \quad \forall i, t, s \tag{4.19}$$
$$\sum_{n=1}^{2} c_{nits} = 1 \quad \forall i, t, s \tag{4.20}$$
$$\sum_{m=1}^{3} \alpha_{mits} = 1 \quad \forall i, t, s \tag{4.21}$$
$$z_{ij}, c_{nits} \in \{0,1\} \quad \forall i, j \tag{4.22}$$
$$w_j, x_{ijts}, y_{its}, r_{jts}, U_{jts}, \alpha_{mits} \ge 0 \quad \forall i, j, t, s \tag{4.23}$$

Constraints (4.5) and (4.6) indicate that the demand of client *i* can only be satisfied by D_j if both are connected, either through a primary connection (L_{ij}) or a back up (z_{ij}). In addition, it is considered that each client can only have at most one DC as backup (constraint 4.7).

For each client, the portion of their demand served and the unmet portion are complementary factors (constraint 4.8). According to constraint (4.9), the demand of all customers served by DC_j cannot exceed its available capacity. We consider the possibility of manpower outsourcing as a way to compensate the capacity affected by some disturbing event (constraint 4.10).

Constraints (4.11) to (4.13) are related to the available capacity of the DCs, which may be affected by an event in scenario *s* that will compromise a portion γ_{js} of its capacity. This portion will be recovered over time (constraint 4.11) in a way that at the end of the time horizon considered the capacity of all DCs will be fully recovered (constraint 4.13).

It is worth mentioning that the recovery efforts carried out in a given period are only available in the following period and that the resources used for recovery cannot exceed what is available for each period (constraint 4.14). According to constraint (4.12), recovery efforts cannot increase the capacity of DCs above their rated capacity ($K_j + w_j$). In addition, investments are subjected to a specified amount of money (constraint 4.15). Constraints (4.22) and (4.23) refer to the boundary conditions of the problem.

Constraints (4.16) to (4.21) are associated with the use of the Special Ordered Sets-Type 2 artifact to represent the penalty for not meeting customer demand. The function representing this penalty is a piecewise linear function, shown in Figure 4.2, where SL represents the desired Service Level.

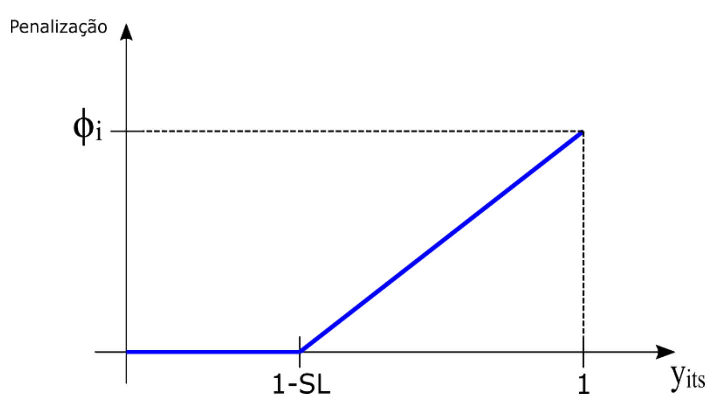


Figure 4.2 Representation of the penalty associated with non-compliance with demand

In this case, the following conditions are true:

- $a_1 = 0$, $a_2 = (1\text{-}SL)$ e $a_3 = 1$;

- $b_1 = 0$, $b_2 = 0$, $b_3 = \phi_i$.

Thus, the portion of customer demand *i* that is not met (for each *t* of each *s*) and the penalty for that non-fulfillment can be represented by a linear combination of a_n and b_n respectively, where n = 1, 2 and 3, as shown in equations (4.24) and (4.25).

$$y_{its} = \alpha_{1its} a_1 + \alpha_{2its} a_2 + \alpha_{3its} a_3 \tag{4.24}$$

$$penalization = \alpha_{1its} b_1 + \alpha_{2its} b_2 + \alpha_{3its} b_3 \tag{4.25}$$

In this context, constraints (4.16) to (4.21) are applied. In addition, it is worth noting that c_{nits} is a binary variable (constraint 4.22) and $\alpha_{mits} \geq 0$ (constraint 4.23).

4.4 Application Example

In this section, we show the applicability of our proposed model for an application example, represented in Figure 4.3, in order to evaluate the impact of disruptions over time and how the strategies for improving resilience vary for a wide range of scenarios with different possibilities of investment. In this example, the system consists of 4 DCs that together supply 97061 units to 19 clients such that the capacity of each DC is given by the total demand assigned to it. The client demand, the capacity of each DC and the other parameters, are presented respectively in tables 4.3, 4.4, 4.5 and 4.6.

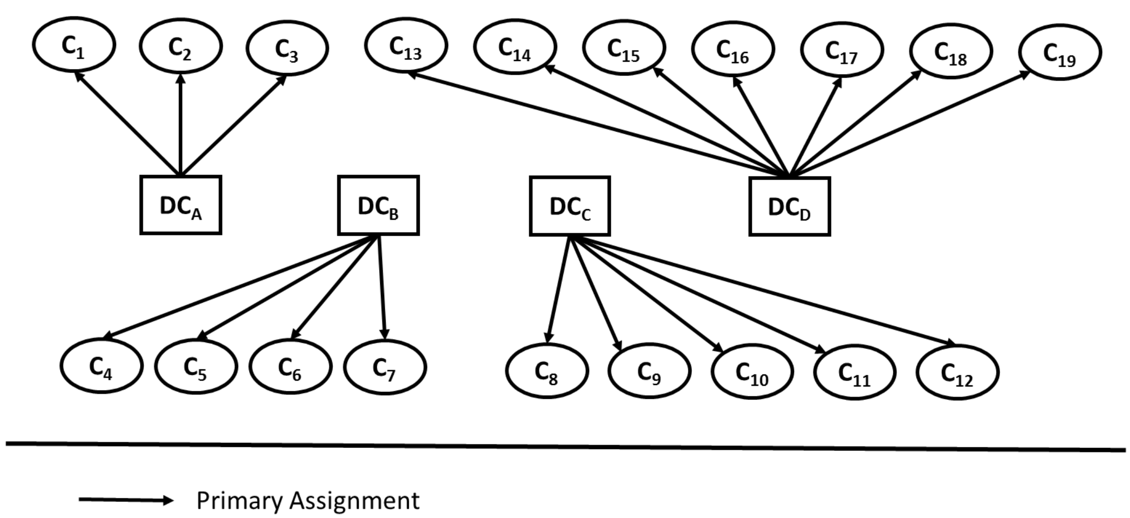


Figure 4.3 - Representation of the network considered

Table 4.3 - Client demand

Client	Demand	Primary supplier
1	5.783	A
2	8.075	A
3	14.362	A
4	13.570	B
5	6.121	B
6	2.258	B
7	4.344	B
8	3.730	C
9	1.650	C
10	2.271	C
11	1.404	C
12	10.429	C
13	1.079	D
14	2.484	D
15	1.451	D
16	5.249	D
17	3.507	D
18	8.844	D
19	1.350	D

Table 4.4 - DCs capacities

DC	Capacity
A	28220
B	26293
C	19484
D	23964

In order to show how disruptions may affect the investments necessary to achieve an optimal network resilient design, 3 cases were carried out, each composed of 11 scenarios representing the possible interruptions that the considered network may suffer due to external events. That is, each case includes all possible combinations of DC's supply capacity loss, considering scenarios where only one DC fails and simultaneous failures of two DCs. Scenarios with simultaneous failure of three or more DCs were not considered because their probabilities are very low.

First, we disregard constraint 4.15 in order to achieve an optimal resilience strategy with unconstrained financial resources. Then, we also carry out a sensitivity analysis to assess the impact of limited budgets on the optimal resilience strategy and, hence, on system performance. The probabilities associated with the cases are presented in Table 4.5 and the other parameters are shown in Table 4.6. The parameters values used in the application example are fictitious for the sake of confidentiality. However, they were carefully estimated to better represent reality.

Table 4.5 - Description of the cases performed

Scenarios	**Affected DCs**	**Probabilities of the cases**		
		1	**2**	**3**
1	A	0.0175	0.175	0.117
2	B	0.0175	0.175	0.117
3	C	0.0175	0.175	0.233
4	D	0.0175	0.175	0.233
5	A, B	0.005	0.05	0.046
6	A, C	0.005	0.05	0.046
7	A, D	0.005	0.05	0.046
8	B, C	0.005	0.05	0.046
9	B, D	0.005	0.05	0.046
10	C, D	0.005	0.05	0.093
11	None	0.9	0	0

Table 4.6 - Parameters used in the application example

Parameter	Description
F	100 (R$/un)
θ_{ij}	4000 (R$/ link) – except for primary connections
h	400 (R$/un)
ϕ_i	250 (R$/un of unmet demand)
ρ_i	500 (R$/un)
η	500 (R$/un)
μ	50 (R$/un)
ε	10 (R$/un)
SL	80%

The total cost of each of the cases is broken down into Figure 4.4 and the main results are discussed. As it can be seen in Figure 4.4, due to the low probability of the system being affected, no investment was made in the network design in case 1. In fact, one can state that when the probability of no DC being affected is high, the model will not suggest investments in resilience as an alternative. However, for some scenarios in which the simultaneous failure of two DCs occurred, the use of the outsourcing strategy for $t \geq l$ can be interesting. This action aims to meet part of the demand so that extra penalties are not incurred. In this case, some DCs cannot complete their recovery until the established deadline because of the lack of investment in recovery resources, for scenarios in which the combined failure of two DCs occurs, for example.

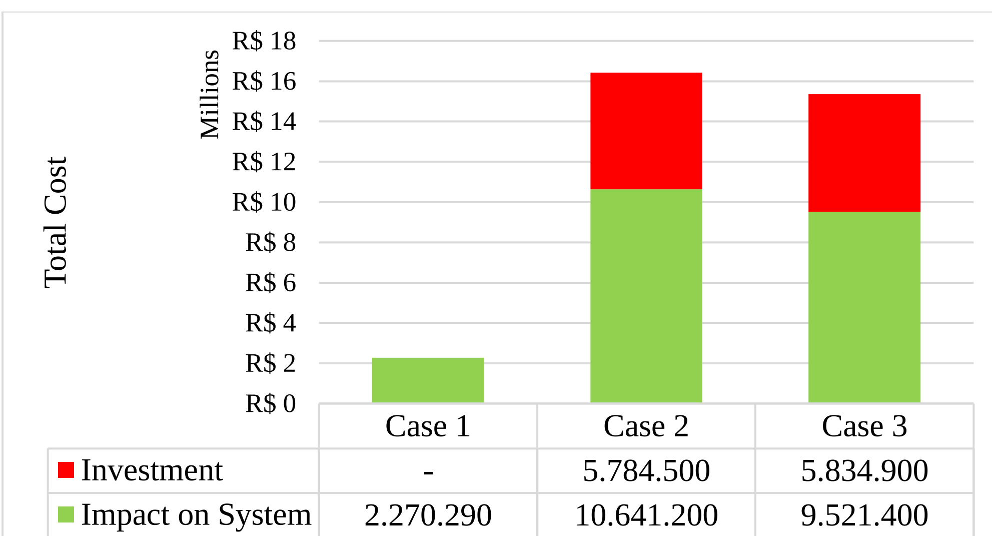


Figure 4.4 - Total expected cost of each case

In case 2, due to the higher probability of occurrence of some event, R$ 5,784,500.00 was invested in system's resilience. Figure 4.5 shows that the investments in additional capacity were made in a way that balanced the capacities of the DCs. In addition, the defined back-up connections are represented in Figure 4.6. This investment also includes the addition of 5,162 units of resources directed to the recovery of the DCs. The addition of these features was sufficient to ensure that in all scenarios the DCs were recovered before the established deadline (l), and thus the desired customer service level is maintained.

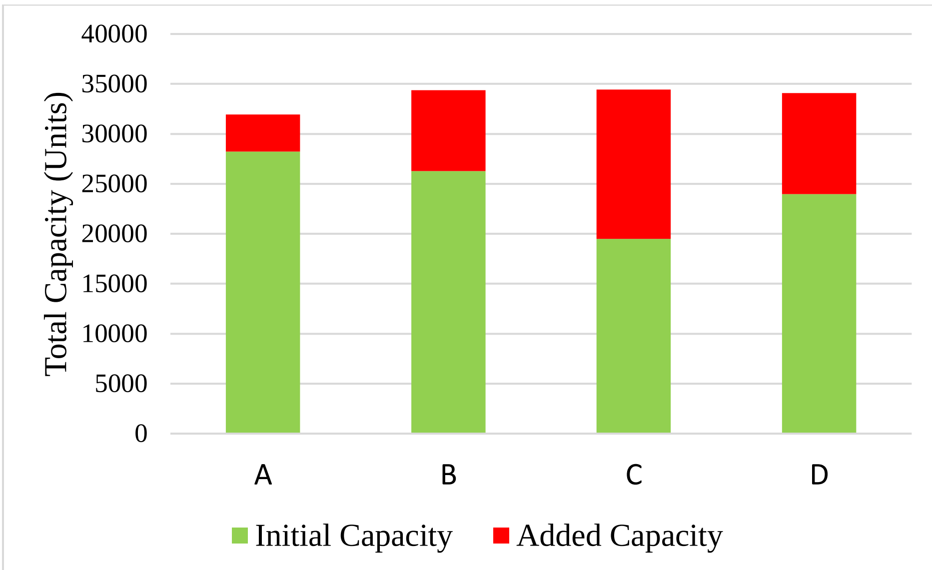


Figure 4.5 - Capacity of each DC according to case 2

For this case, there was no need for outsourcing to meet demand. This may be due to two facts: first, recovery is completed on time in all scenarios; secondly, additional capacity and backups allow the level of customer service to be maintained at almost all periods.

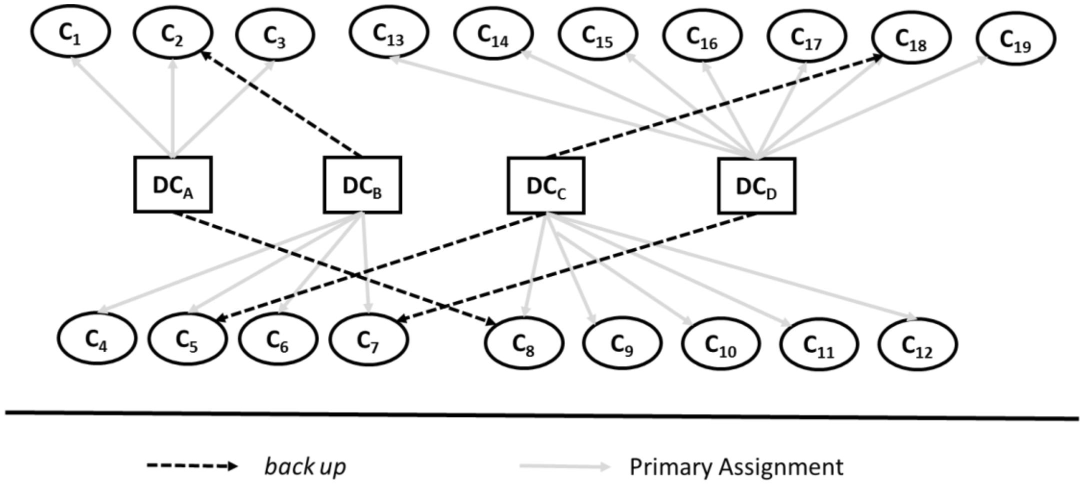


Figure 4.6 - Representation of the backup links established by the case 2

Case 3 presents a slightly higher probability that some event will affect C or D (or its combination) in relation to the other possibilities. In this way, A and B are expected to support them. In fact, as can be seen in Figure 4.7, A and B serve as backup for 3 clients of D and 2 clients of C. In addition, client 3 also ends up having a backup connection (with B), which can be due to the fact that it is the customer with the greatest demand.

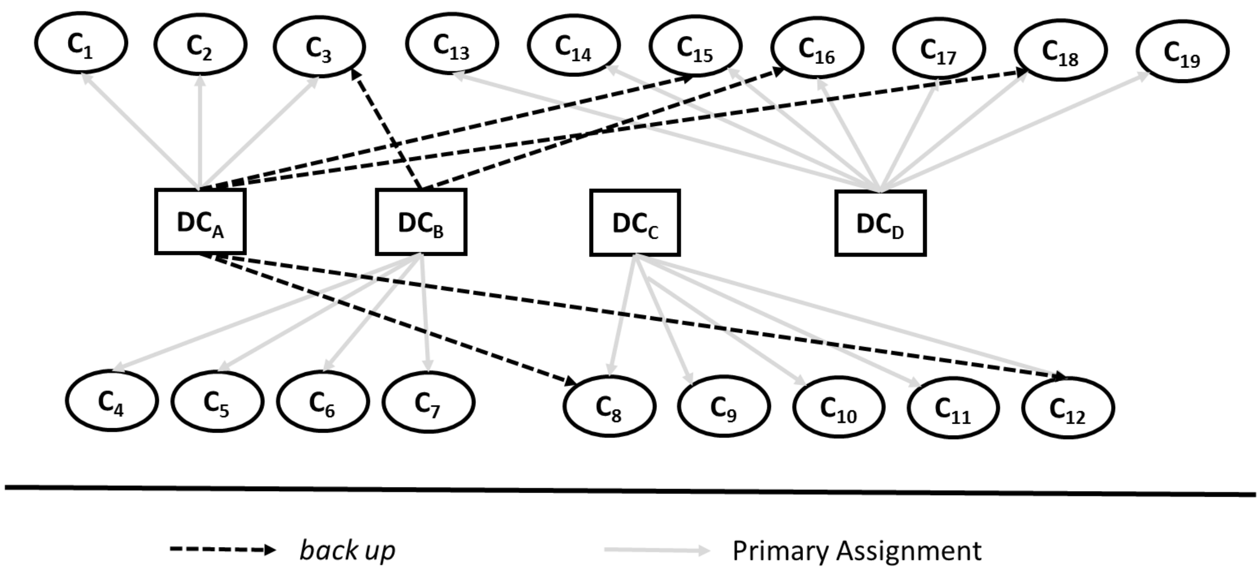


Figure 4.7 - Representation of backup connections established by the case 3

It was necessary to add 24,454 and 19,611 capacity units to A and B, respectively (Figure 4.8) so that the configuration shown in Figure 4.7 is feasible. In addition, 3,496 units of recovery resources were added. These features are not sufficient for recovery to be completed on time for all scenarios. In fact, the most critical scenario is 5 (A and B), in which the recovery is only completed in period 9. Therefore, the results of this case indeed favor C and D, which are able to maintain the service level to their customers.

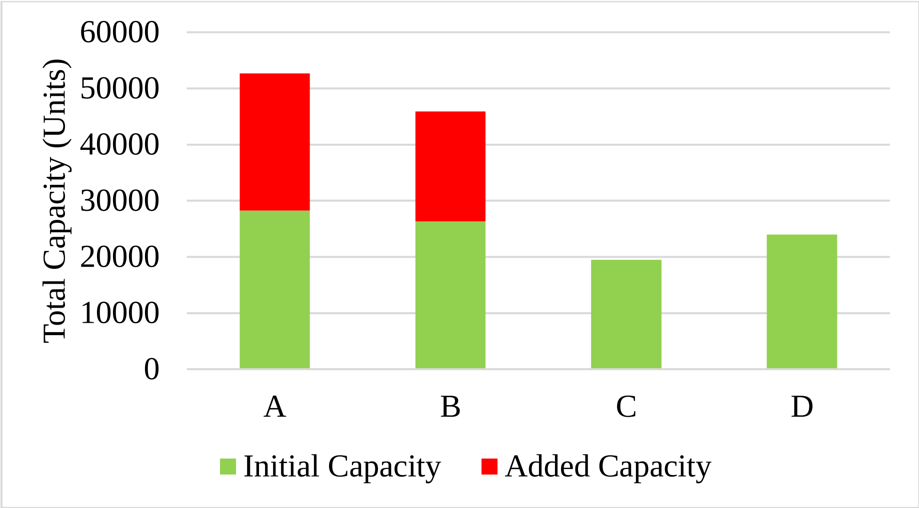


Figure 4.8 - Capacity of each DC according to case 3

4.4.1 Sensitivity analysis

According to what has been analyzed, outsourcing investments seem to be more advantageous in situations where the probability of occurrence is small. Still, there is a need to evaluate the tradeoff between the amount for investment and the expected costs associated with the occurrence of disruptive events, specially when there are limited financial resources available. This evaluation is performed considering case 2 and a service level of 80%. In the "without restriction" case, the optimization model is applied without investment restriction, as presented in Section 4.4, and then the restriction is gradually imposed. Thus, we analyse four different new possibilities for case 2 (Figure 4.9): (i) M = \$ 4 million; (ii) M = \$ 2 million; (iii) M= \$ 1 million and (iv) no investment in actions to enhance resilience ("without IDR"). These situations may represent the impact on system resilience in times of economic crisis, with consequent cost cutting.

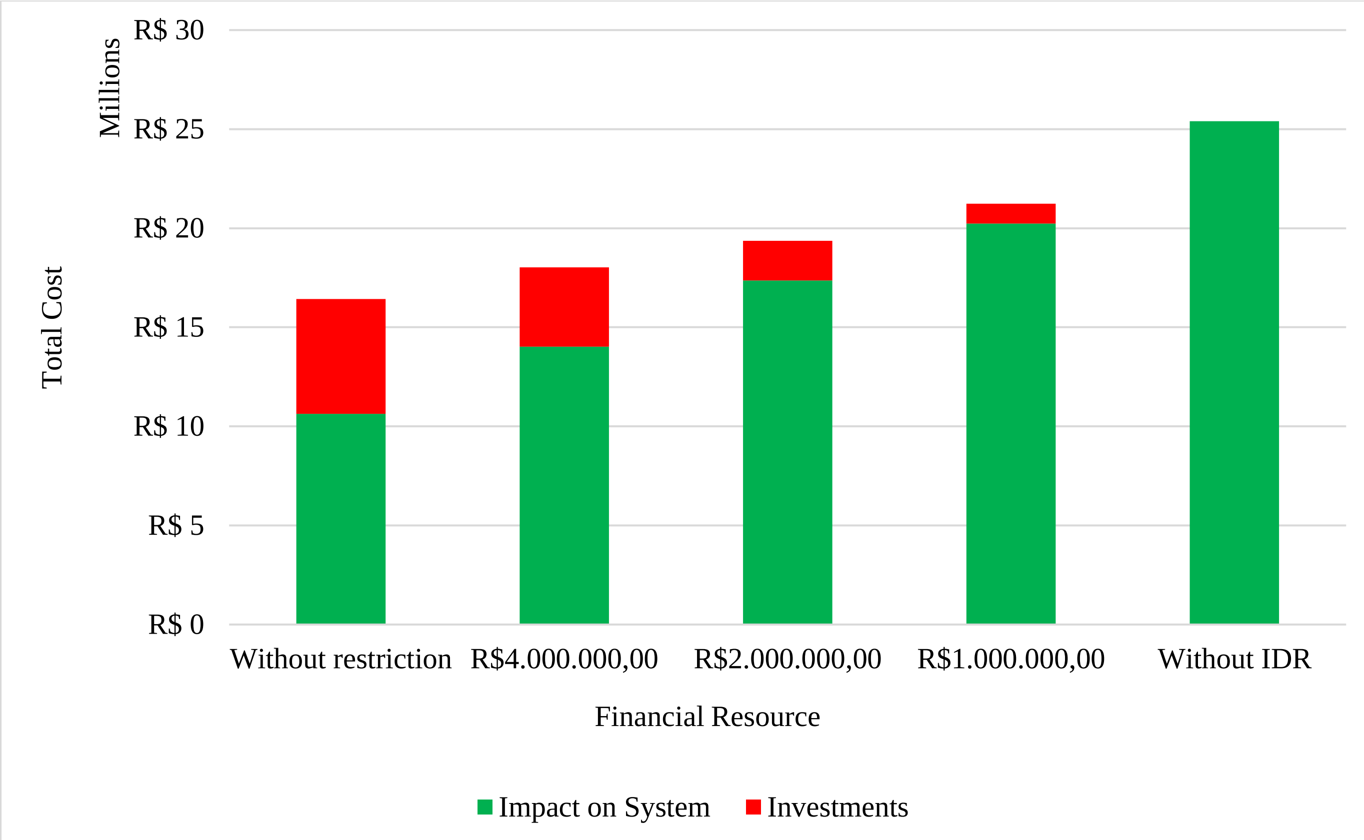
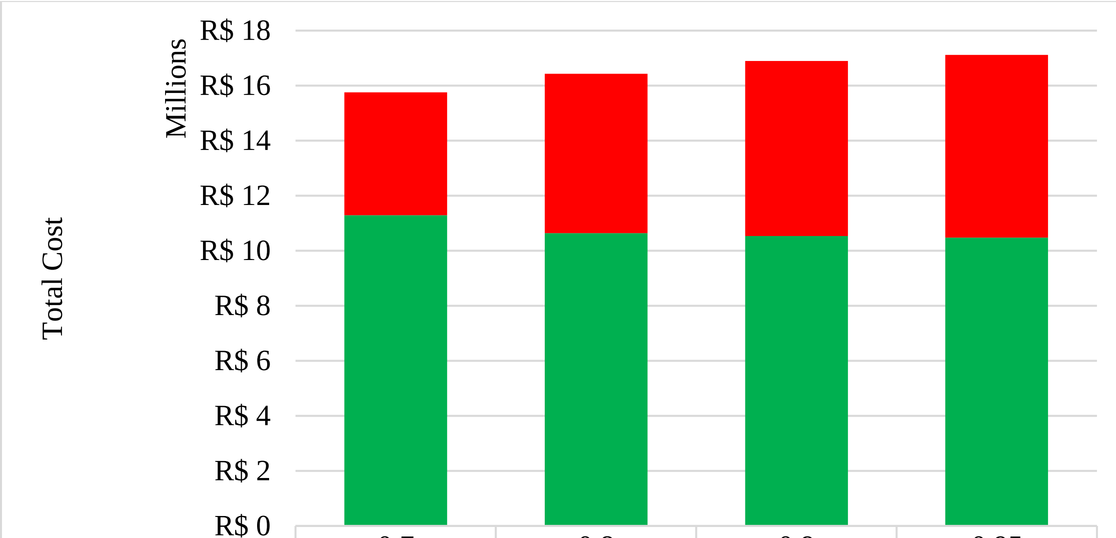


Figure 4.9 - Evaluation of investment in impact reduction

Figure 4.9 demonstrates that pre-event actions may in fact promote greater agility for system recovery and greater cost effectiveness, especially when implemented in the network design phase. As evidence of this, the situation in which no investment is made has a total cost approximately 55% higher than the case in which the investment is not restricted.

Figure 4.10 presents a comparative analysis between the model responses for different service levels, considering the situation "without restriction" for case 2. It is possible to observe that as the desired service level increases, there is a tendency to invest more in the design of the system, increasing total cost but decreasing the impact on the system. However, when the desired service level goes from 80% to 90%, the expected total cost is only increased by 3%. Similarly, from 90% to 95%, the expected total cost increases by only 1%. In this sense, there is a need to evaluate the benefit of providing a higher level of service, but also having to make more investments in the network, with the return that the company can have with the provision of a higher service quality.



	0,7	0,8	0,9	0,95
Investments	4.463.400	5.784.500	6.356.800	6.646.400
Impact on System	11.294.000	10.641.200	10.535.300	10.474.500

Figure 4.10 - Total expected cost versus service level

4.5 Final Comments

Although efficient logistics operations have the potential to add time and space value to customers, as well as generating competitive advantages for companies, it represents a significant portion of final products cost. Due to the increasing demand of consumers regarding the service level, the impact of logistics on company performance, the benefits promoted by the efficiency of the logistics network and their vulnerability, companies are increasingly abandoning the reactive stance towards adopting a preventive approach for network management.

In this context, the objective of this chapter was to propose a tool to help the decision makers to define an effective resilience strategy for the design of a logistics network, considering its exposure to external disruptive events. This strategy must take into account the probability of the events, the impact that these events would have on the performance of the network, guaranteeing the level of service specified to the client, and the minimization of the total costs.

The results show that decisions taken during the design phase (*a priori* of the event) can in fact promote greater agility for response and for system recovery, greater absorption (minimizing consequences) of impacts and greater effectiveness in terms of costs. For a service level of 80%, as shown in Figure 4.9 for example, the total cost becomes 55% higher without the investment in resilience.

5 CONCLUSIONS AND FUTURE RESEARCH

5.1 Concluding Remarks

This thesis proposed a model to optimize costs in the design phase of infrastructure critical systems when resilience-based actions are considered. Our main goal was to provide a systematic way to determine how financial resources should be spent to design a resilient critical infrastructure. This tends to make a distribution system less susceptible to the impacts caused by the occurrence of a disruptive event and effectively reduce both the duration and the costs associated.

The MILP model developed was able to incorporate (i) several disruptions with their respective probabilities of occurrence and (ii) worst-case scenarios, in which a specific event with severe consequences is considered. In the first situation, the probabilities of occurrence of each of the mutually exclusive scenarios are considered, and the output of the model is the optimal strategy involving pre- and post-event actions that minimize the expected total cost.

We presented two application examples to illustrate the applicability of the proposed models. The first example, in the context of power grid, we use MILP to find the ideal infrastructure investments that improve the resilience of industrial facilities to disruptions in electric power supply. Four cases were analysed to explore the results for different situations regarding the probability of the occurrence of disruptive scenarios. We review resilience, critical infrastructure, and electric power literature establishing a need to better understand how different industrial clients are impacted by power grid disruptions. We demonstrate the efficacy of model via a technical case study that includes three kinds of industrial facilities linked to various power grid subtransmission stations. Ideal resilience investment strategies vary depending upon the total budget allotted to the system of industrial facilities. Figure 3.8 demonstrates that the number of backup generators and their location among industrial facilities changes with increasing budgets. Moreover, budgets increasing from $4 to $7M focus investments on increasing the rate of system recovery, where larger budgets emphasize increased substation capacities, redundant power lines, and a large number of backup diesel generators. As power grid users are the individuals that actually experience failures when blackouts occur, it is surprising that the majority of resilience literature overlook differences among customers and their needs. We provide a comprehensive overview of resilience literature as it applies to power grids justifying the need for studies that consider different industrial facilities. Finally, this work is significant by establishing a “view of the grid” from the perspective of an industrial client and focusing analysis on ways to improve power availability outside the ownership and management of utilities. Therefore, this work provides a glimpse into the decisions electric power customers can make that influence resilience of the greater system.

In the second example, in the context of the logistics network design and it minimizes the overall cost associated with the occurrence of disruption events. This example aimed at proposing a model to optimize the resilience of a distribution network by investing in absorption, adaptation and restoration capacities (pre-event decisions) as a complement to effective post-event recovery strategies. The optimization model contains both continuous and discrete decision variables, then it is defined as a mixed-integer linear programming problem. Moreover, it involves scenarios whose occurrence is uncertain, and contains both variables determined before the scenario outcome is known and variables determined specifically in each scenario.

Through the application example, one can evaluate how the strategies for improving resilience vary for a wide range of scenarios and with different investment options, evaluating the corresponding impact over time. In addition, the example presented was useful to discuss validation and verification of the model. In fact, we performed two types of analysis (by varying input values) to verify if the outcomes of our model are reasonable for different situations. First, we varied the probability of occurrence of an undesired event in Section "3.7.2 Results and discussion". By increasing the value of this parameter, we can see from the results our model indicates that the decision maker should also increase the investments to design a more resilient system (see case 4). On the other hand, by reducing the probability of occurrence, no investment should be made (see case 1). Moreover, in Sections "3.7.3 Assessment of the constraint on financial resources" and "3.7.4 Further Assessments: Evaluating Specific Scenarios", we also evaluate how our model behaves for different budgets. As it was expected, as we decrease the budget, the IS (Impact on System) increases rapidly, which indicates the usefulness in investing in resilience in the design phase of a plant; note that the proposed model also indicates how the resources should be spent for each case.

In both cases, the results demonstrated that when optimally allocated, higher investments during the design phase have the potential to improve infrastructure performance and still reduce overall costs. In addition, this thesis demonstrated the important interactions between investments in design for resilience and impact on systems decisions, in which investments in design positively influenced system resilience by increasing absorption and adaption capacities, shortening recovery time and consequently reducing impact on systems after disruption events. For the application examples, each one of them had its specific conclusion sections (see sections 3.8 and 4.4).

5.2 Limitations

We point out some limitations of this work. First, we focused on adopting the “resilience triangle” concept. However, other capacities or strategies for resilience do exist and they can be the focus of future research. For example, Lundberg & Johansson (2015) suggests considering the “learning” capacity to monitor and anticipate a disaster. Another possibility is to deem structural changes to increase the absorptive capacity of the system against shock (Raby et al. 2015).

Moreover, we have considered the objective function as a weighted average of the costs of a set of possible interruption events, each with its respective probability. This could be thought of a limitation because, for example, low-probability high-consequence and high-probability low-consequence events are considered similar for resource allocation purposes. Despite that, the model allowed us to investigate specifically high-consequence events such as the failure of SS_1 and the simultaneous loss of SS_1 and SS_2.

5.3 Future Research

Finally, developing a multi-objective optimization model is an issue of our ongoing research. In fact, we aim at minimizing the total costs related to the three resilience capacities (absorption, adaptation and recovery), as well as maximizing the level of service to industrial customers. Other topics of ongoing research involve (i) analysing how local energy storage can contribute to rendering the electric service at an industrial plant more resilient to disruptions and (ii) for more fine-grained networks, although the proposed MILP is still valid, investigating a method that uses a metaheuristic solution (e.g., genetic algorithms) is an alternative due to the greater number of system nodes and links.

Additionally, many works consider multiple sources of uncertainty, increasing problem complexity. In future research, we can consider uncertainty in other parameters, e.g.in demand, supply, delivery lead times, with demand uncertainty being the most common, justified by the often present market volatilities (Cardoso et al. 2015).

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