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To
My wife Bayan
My daughter Lana
My father, my mother, and my brothers and sisters

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Abstract

Unexpected disruptive events have significant impacts on Supply Chain Networks (SCN), their capacity, and overall performance. Thus, it is critical to developing efficient techniques to improve their robustness and resilience while guaranteeing other constraints are met. This dissertation proposes four mathematical models that aim to improve the supply chain transportation network performance (SCTN). Chapter 2 proposes the first model, a bi-objective mixed integer programming (MIP) model that minimizes the impacts of disruptive events on the SCN while procuring a fairness-based distribution of commodities. To illustrate the proposed bi-objective MIP model, we present a realistic case study based on the transportation of commodities in Colombia. The case study considers a multi-commodity framework with 258 products and raw materials encompassing the country's six main economic sectors. The results show that seeking fairness within cost-effective distribution strategies reduces disruptions and helps maintain the required service levels at more demand points than when following distribution strategies that only focus on cost reduction.

Due to the high dependency on infrastructure networks, having an effective restoration plan to restore the network performance is essential. Chapter 3 proposes the second model, a multi-criteria nonlinear mixed integer programming (NMIP) model, to deal with disruptions in transportation networks. The model examines two restoration approaches to recover the transportation network performance, thus dependent networks, supply chain network (SCN), resilience improves. The model focuses on reducing the travel time of delivering the required demand in order to maintain a higher satisfaction rate. The model is designed to restore the transportation network during unpredicted events based

not only on the cost-effectiveness approach but also on fairness. The results show that the fair distribution helps to maintain and recover the satisfaction rate faster when comparing to the results of the restoration plan based on the cost-effectiveness approach only.

The SCN is highly interconnected within its network; thus, for any disruption in any part of the SCN, the economic impacts might be catastrophic on the SCN overall performance. Consequently, in Chapter 4, we propose the third model, a bi-objective mixed integer programming (MIP) model that aims to minimize the impacts of disruptive events and restore the SCN performance, considering the economic interdependencies among various SCNs. The results show that both restoration methods helped to restore and recover the disrupted components and economic performances of the SCN. In addition, however, the fairness-based distribution method helped to keep most of the demand nodes satisfied by maintaining the required Service Level (SL) for the majority during the restoration time until the system had been fully restored.

As a result of the strong reliance on infrastructure networks, having efficient mitigation plans to protect the road transportation networks and restore them during the post-disruption stage is critical; thus, the network functionality is recovered. In Chapter 4, the fourth model, two bi-objective models, are proposed. The first model is a bi-objective, robust, fair mitigation MIP model that aims to allocate the mitigation budget fairly to generate a robust solution against the worst-case scenario that might impact the SCN performance. The other model is a bi-objective, fairness-based distribution MIP model that aims to restore the disrupted components in the road network and restore SCN performance to normal status. The results show that mitigating the road network before disruptions occur and implementing a fairness-based distribution during the post-disruption help SCNs recover quickly and maintain a higher service level at most demand nodes for each commodity.

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND:

The concept of disruptive events and their effects on supply chains and infrastructure networks has been widely studied in recent years. Diverse studies that explore the impacts of the disruptions on the performance supply chain networks emphasize that supply chains are constantly seeking to meet customer demands and maintain high service levels at all times, while procuring a cost-efficient operation (Altay & Ramirez, 2010; and Ho et al., 2015). However, disruptive events, both natural and manmade, are constantly hampering the performance of supply chains and their operations. Those disruptions can cause significant losses to supply chain management and stakeholders in the short and long term by reducing the supply chain capabilities to produce and deliver the required demands to the customers (Ho et al., 2015). For example, just in 2011, a flood in Thailand resulted in 1.25 billion dollars of economic losses for Toyota Motor Corporation (Haraguchi, 2013). Similarly, the 2011 Japanese tsunami had a large negative impact over multiple financial and supply chain networks, including the aerospace sector, where three out of the five leading companies which were producing structural parts for the Boeing 777 and 787 aircrafts reduced their share of productions after the disruption took place (Reuters, 2011).

It is to be noted that due to the high dependency of supply chain networks (SCN) on the transportation infrastructure, supply chain performance can be affected directly by disruptive events involving the transportation networks. Among the processes involved in supply chain operations, transportation of commodities represents one of the highest costs, as well as one of the most affected by natural and manmade disruptive events. In particular, it is estimated that the cost of transportation in supply chains can be over 50% of the total costs (Daehy et al., 2019). Moreover, unexpected disruptive events disturb the normal flow of products and commodities through supply chain networks and are considered potential threats for organizations, both operationally and financially (Stauffer, 2003; Kleindorfer & Saad, 2005; Craighead et al. 2007). The disruptions are challenging to be forecasted and identified due to their uncertain nature. Thus, their negative impacts are hard to be measured in the short-term when it comes to different dependent networks (Dolgui et al., 2018; and He et al., 2018). Several disasters in the last decades have highlighted the importance of preventing critical infrastructure networks. For instance, Hurricane Sandy has caused massive disasters to several networks, including power, metro tunnels, fuel supply chain, and the road transportation network (Kunz et al., 2013). The flood almost stopped the transportation system, and the water covered the metro tunnels. The flood damaged the fuel pipelines, and the fuel supply chain was damaged as well (The City of New York, 2013). Another example of the impacts of disruption on other dependent networks is the disruption where the tsunami and earthquake took place in Japan in 2011 and had significant impacts on multiple supply chain networks. Toyota was incapable of distributing and delivering the required demand on time; thus, their production was stopped for days. Furthermore, the impacts of the disruption on Nissan's company were so significant that they led the company to stop production on one of its plants. Such a plant was highly depended on raw materials supplied from Japanese facilities, where large disruptions took place (BBC News 2011).

Thus, in general, it is evident that dependent networks become more vulnerable and need to be efficiently protected with regard to such uncertain events.

Moreover, the reliance on transportation networks to move freight has increased rapidly in the last years. Thus, disruptions in any of the transportation networks hinder the performance of supply chain networks (SCN). Statistics show that U.S. products transported through air, trucks, and railroad increased by 28.5% in 11 years (1996-2007) (Bureau of Transportation Statistics. 2010). Furthermore, this percentage is expected to triple to 65% by 2035 (Federal Highway Administration, 2006). The road transportation network is also considered the most used network among other transport networks to transfer freight and goods. According to the Federal Highway Administration, in the U.S., a daily average flow of freight of more than 50 million tons (valued at 48 billion dollars) was distributed through the transportation system in 2012 (Strocko et al., 2014), and 70 percent of the freight was distributed by trucks (Margreta, Ford, and Grube 2014; and Government Accountability Office 2013). To reduce the impact of disruptive events, the U.S. government emphasized the need to increase the preparedness of the critical infrastructure systems, one of which is the transportation network (Yusta, Correa, & Lacal-Arántegui, 2011). Considering these, disruptions in the road transportation network, which are critical for the efficient transportation and distribution of raw materials and finalize products, would increase traffic congestion and the delivery time it takes to move commodities between the suppliers and the demand nodes. It is to be noted that diverse properties of the disrupted road transportation networks play a critical role in resisting such disruptions, such as their level of redundancy and connectedness. Developing countries where most commodities flow through the road transportation network face increased difficulties with withstanding disruptive events considering that the networks tend to be less redundant, leading to increased travel time and road congestion (Mitsakis et al., 2014). As a result, the road transportation networks need to be expanded, and efficient restoration strategies need to be in place. Considering this, it is vital to develop efficient mathematical and computational models to design cost-effective distribution strategies for supply chain transportation networks (SCTN), particularly after being affected by a disruptive event.

During disruptive events, one of the main challenges that decision-makers face is ensuring that the demand of commodities is adequately satisfied. Unmet demands can affect the reputation of companies, and by extension, may lead to losing customers to competitors (Ni, Howell, & Sharkey, 2018). In this regard, Ni, Howell, and Sharkey (2018) studied the effects of the unmet demand in supply chain resilience and measured customers' behaviors when their demands were not properly met. The authors found that the impact of losing customers to competitors included not only the cost of current orders lost but also cancellation costs and penalties for breaking contracts. Thus, it is critical to developing efficient disaster management and mitigation strategies to reduce the impacts of disruptive events, such that demands are adequately serviced, and customers maintain high levels of satisfaction.

Transportation and SCN are interdependent networks. As such, the impacts of these disruptions and uncertainties can cascade across networks and become catastrophic. The interdependency between networks is not only physical but can also be economical. Thus, a disruption in one network can also affect other networks' physical performance and significantly affect other dependent networks' economic performance. An example of such a catastrophic impact is the 2008 snowstorm in China. The storm affected the power network that led to the failure of the rail network. Thus, several plants shut down due to the lack of raw materials arriving from different sectors (Wei, Dong, & Sun 2010). As a result of this supply chain disruption, these firms' productivity and economic performance were adversely impacted.

Another example is the 9/11 attack that led to the closure of the border between the U.S. and Canada. The Ford Motor Company experienced disruptions, as their plant operations relied on supplies from Canada (Wei, Dong, & Sun, 2010). As such, any disruption to any of the components of the network (e.g., the nodes of the SC, and transportation links) can affect the performance of several SCNs' components, that may not necessarily be physically disrupted but rather indirectly impacted by the economic interdependencies existing across the SCN. These examples show the importance of protecting the infrastructure networks, having response strategy to reduce the propagation of the impact due to the physical and economical interdependencies between networks and sectors, and ensuring that a resilient SCN can withstand this kind of disruption by restoring the disruptive components while implementing a fair distribution method.

Considering the adverse effects associated with disruptive events over service levels and customer satisfaction, *fairness-based mitigation strategies* may help to reduce the propagation of negative impacts by balancing the effects and loads among all entities in the SCN. Several studies have applied the *fairness* concept to maximize the customers' satisfaction in the SC networks. Gershoff, Kivetz, and Keinan (2011) highlighted the importance of using *fairness* by the retailers due to the growing of unfair and unethical treatment among business entities in the network. By applying *fairness-based distribution* *strategies* among retailers, companies could gain a better reputation, and thus their system could expand and grasp the attention of other retailers. On the other hand, according to Brady, Voorhees, and Brusco (2012), treating consumers unfairly results in negative behaviors against the firm, with customers demanding equal treatment (especially those who are not favorably treated). The implementation of *fairness-based distribution strategies* would result in (i) making the market outcome more desirable, (ii) improving the retailers' reputation, and (iii) increasing the loyalty of customers. Campbell (1999) emphasizes that *fairness* could be the main source of those positive outcomes, while unfairness could lead to several negative consequences for some or even all retailers. For example, a lack of *fairness-based distribution strategies* could cause customers' dissatisfaction that may result in a reduced reputation and distrust between entire branch retailers and suppliers, which could result in a shift to supplemental goods and a demand reduction (Lo et al. 2007; White et al. 2012). Thus, by applying *fairness-based strategies*, SC decision-makers can maintain a superior reputation and ensure high customer satisfaction.

1.2 RESEARCH OBJECTIVES & CONTRIBUTIONS:

In this dissertation, four main components are studied to develop an integrated framework that assists the SC management in handling more efficiently the impacts of disruptive events in the road transportation network as well as on the satisfaction rate at each demand node for various commodities. To address each component, a research question needs to be addressed. The four research components that represent the objective components are as follows:

- How do disruptions in the transportation network affect the SCN performance, and how do we develop adequate response strategies to reduce the impacts of such disruptions?

In Chapter 2, we focus on the implementation of *fairness-based strategies* in the SCN downstream stage from the perspective of the customers and how to distribute goods among them fairly. The contribution of this chapter centers on the development of a novel mathematical framework that helps to reduce the effects of disruptions on the SCTN performance while following *a fairness-based distribution strategy*, such that not only the SCTN aggregate demand being satisfied is maximized, but also the number of customers without adequate service levels is minimized.

- How to optimize the *restoration* of disrupted transportation networks such that SCN performance is recovered efficiently?

In Chapter 3, we extend the outcomes of Chapter 2 by including the restoration processes and the road congestion regarding the disruptive events. The contribution of this chapter focuses on designing a mathematical model for optimal restoration that reduces the impacts of unpredicted events that disturb the performance of the road transportation network and propagate to other dependent networks such as SCNs, while considering a fair distribution of commodities between demand nodes and economic sectors.

- How to optimize the restoration of the SCN economic performance considering interdependencies between commodities?

In Chapter 4, we propose a bi-objective mixed integer programming (MIP) model that aims to reduce the economic impacts of road transportation disruption on the performance of the SCN while applying the *fairness-based distribution*. In particular, the impact is evaluated based on the ability of the SCN to fulfill the demand requirements and maintain the service level (SL) at the demand nodes. The model measures each sector's performance that depends on the transportation network both post-disruption and during the restoration processes. We consider the economic interdependencies between the SCN's sectors and the required material that each sector requires from other sectors to produce and meet the demands needed while implementing a *fairness-based distribution* method to distribute commodities and reduce the unmet demand percentage the majority of the demand nodes. The model considers a complex system of multi-suppliers, demanders, and multi-commodities.

- How to retrofit the transportation network to improve the robustness of SCN performance?

In Chapter 5, two bi-objective mixed-integer programming models are proposed to address the pre-disruption stage and post-disruptions' stage in which we examine the impacts on the performance of the SCN. The pre-disruption model considers the mitigation and retrofitting processes of enhancing the road transportation network resiliency towards disruptions by implementing *fairness-based budget allocation* to ensure maximum fairness among the demand nodes (cities). The pre-disruption model aims to provide a robust solution that protects the SCTN against the worst-case disruption scenario that might disturb the flows of the commodities in the SCTN. The second model, the post-disruption model, addresses the performance of the SCN after the disruptions while restoring the disruptive components in the road transportation network and maintaining the required SL at most of the demand nodes by fairly distributing the available resources among demand nodes. The SCN resilience is achieved by maintaining the required service level at most of the demand nodes foe all commodities until the SL is fully maintained. The integration of both models ensures the SCN resiliency and robustness against unpredicted events.

This dissertation is organized as follows. Chapter 2 answers the first research component by designing a response strategy to reduce the impacts of disruption on the SCN performance. Chapter 3 addresses the second research component. Chapter 4 addresses the third research component, while Chapter 5 demonstrates the final research components. Chapter 6 represents the conclusion and remarks of this dissertation and the recommendation for potential extension and applications.

CHAPTER 2: RESPONSE STRATEGY TO MITIGATE THE IMPACTS OF DISRUPTION ON SUPPLY CHAIN NETWORKS USING FAIR DISTRIBUTION[1]

2.1 INTRODUCTION

In this chapter, we consider disruptions in the SCTN associated with reductions in the supply capacity of provider nodes (e.g., if production capacity is reduced to a fraction of what it was before the disruptive event) and reductions in the flow capacities (e.g., if roads can be used only partially). The proposed model considers a complex SCN that consists of a multi-commodity system with multiple supply and demand nodes. The proposed strategy provides an immediate post-disaster plan to allocate and distribute all the commodities throughout the system considering a *fairness-based distribution strategy*, such that the fraction of unmet demand is balanced among all demanders for each commodity. The motivation for conducting this study is to build a multi-criteria optimization model that helps to mitigate disruption impacts on the SCTN performance by fairly distributing commodities among customers, and to increase their satisfaction and trust. Furthermore, we consider how to fairly distribute the commodities during disruptive events to avoid the isolation of certain locations that otherwise may not receive enough goods, which may lead to exacerbated distress of individuals and communities.

Considering the adverse effects associated with disruptive events, *fairness*-based mitigation strategies may help to reduce the propagation of negative impacts by balancing the effects and loads among all entities in the SCN. Several studies have applied *fairness*

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concepts to maximize the customers' satisfaction. Gershoff, Kivetz, and Keinan (2011) highlighted the importance of using *fairness* by the retailers due to the growing of unfair and unethical treatment among business entities in the network. By applying *fairness*-based distribution strategies among retailers, companies could gain a better reputation and thus their system could expand and grasp the attention of other retailers. According to Brady, Voorhees, and Brusco (2012), treating consumers unfairly results in a negative behavior against the firm demanding equal treatments, especially from those who are not favorably treated. The implementation of *fairness* would result in (i) making the market outcome more desirable, (ii) improving the company's reputation, and (iii) increasing the loyalty of retailers and customers. Campbell (1999) emphasizes that *fairness* could be the main source of those practices, and unfairness could lead to several negative consequences for some or all retailers. Some of the negative consequences include customers' dissatisfaction, which may result in a reduced reputation, distrust between retailers and suppliers, and eventual switching to other companies (Lo et al. 2007; White et al. 2012). Thus, by applying *fairness*, companies can ensure to meet the minimum requirements of their customers during disruptive events.

The contribution of this chapter centers in developing a mathematical framework that helps to reduce the effects of disruptions on the SCN performance. In this chapter, we consider the disruption in the transportation network and how such events affect the SCN performance and customers satisfactions. The proposed model considers a complex SCN that consists of a multi-commodity, multi-supplier and multi-demand set of nodes. The proposed mitigation strategy provides an immediate plan to allocate the available resources and distribute them among the demanders considering *fair distribution* of each commodity shares in the shipment. Thus, the unmet demand percentage is balanced among all demanders for each commodity. The motivation for conducting this study is to build a multi-criteria optimization model that helps to fairly distribute commodities among customers, to increase their satisfaction and trust. Furthermore, we consider how to fairly distribute the commodities during disruptive events to avoid the isolation of some cities where they may not receive any goods. Most of the *fairness* studies focus mostly on the coordination strategies among the SC entities, and how fairly entities are sharing all expenses. We focus on the SCN downstream stage and how to fairly distribute goods among all retailers during disruptive events and ensure that all retailers have satisfied (at least partially) their demand.

The chapter is organized as follows. Section 2, composed of two subsections, presents the literature review. The first subsection covers the studies that focus on the impact of disruptive events on the performance of the supply chain networks and addresses the mitigation strategies that have been used to reduce the impacts of such disruptions. The second subsection focuses on the implementation of the *fairness* concept in supply chain studies. Section 3 details the proposed model (*FAIRSCN*), including its assumptions and mathematical formulation. Section 4 presents an illustrative case study, associated with the distribution of multiple commodities through the road transportation network in Colombia. The final section presents the conclusions and future work.

2.2 LITERATURE REVIEW

In most cases, supply chain management does not directly involve decisions to recover the performance of infrastructure networks when a disruption occurs. However, the impacts of such disruption could result in a tremendous loss for SCN decision makers. Thereby, SCN decision makers need to have plans in order to deal with disruptions immediately after the occurrence of a disaster. In this section, the impact of disruptive events on the performance of supply chain networks is addressed. Also, several mitigation strategies (including *fairness* in supply chain) that have been done in the literature to reduce the impact disruption and to improve the supply chain performance are demonstrated.

2.2.1 *IMPACT OF DISRUPTIVE EVENTS*

There are several types of manmade and natural disasters, such as earthquakes, floods, hurricanes, and landslides, that can cause large disruptions in the adequate operation of SCN. Considering the importance of preparing for and recovering from disruptions in SCN, numerous studies have focused on describing, quantifying, and managing the impacts of such events. Moreover, researchers have examined the effects of disruption especially the disruptions within the system. For instance, Takamuhabwa et al. (2015) emphasize the large effects of disasters over SCN, particularly in the SCN boundaries, where most disruptions occur. There are some reasons that lead researchers to examine the impacts of the disruption on the SCN performance. First, the large associated impacts on economic sectors, where manmade and natural disasters such as the 9/11 attacks in 2001 and Hurricane Katrina in 2005 made the researchers focus more on the SCN disruptions and their effect on society. Second, the complexity of the SCN increases as it becomes more globalized; some of the suppliers are in different countries and the regulations are different in most of the countries. Therefore, researchers started to analyze the impact of disruptive events on global SCN performance. Third, the reliance on Just in

Time (JIT), as some supply chain (SC) decision makers started to increase their use of JIT approaches, which may increase the vulnerability of the system, the researchers started to find the best applicable strategies to implement JIT and to make the SCN more resilient to such events.

There have been some studies to mitigate the impact of disruption on the SCN. Some studies have focused on the pre-event mitigation, where they have used several methods to predict the impacts of the disruptions on the SCN performance. One of those methods is to have multi-suppliers with different types of products. Berger et al. (2004) developed a model to help in determining the appropriate number of suppliers in a network that reduces the impact of SCN disruptions. Anupindi and Akella (1993) focused on choosing the best available option of supplier candidates with different contract policies. The authors objective was to find the best combination of the available supplier candidates: either not to choose anyone, to choose the cheaper, or choose both of them during disruptive events. Developing plans to deal with disruption in the SCN by having the required number of suppliers ensure to maintain a resilient system and improve the SCN performance. Supplier selections have been used widely to evaluate or coordinate the relationship between buyers and suppliers. Responding to various client needs necessitates the buyer's capacity to connect with and operate effectively and efficiently with suppliers, making the buyer-supplier relationship important for all companies in a SC (Mettler & Rohner, 2009; Prahinski & Benton, 2004). Almost every choice in supply network management is influenced by supplier evaluation and selection (Ghadimi & Heavey, 2014; and Fazlollahtabar, 2016). Furthermore, the lot-sizing problem, initially introduced by Wagner and Whitin (1958) to cope with supplier selections, is one of the most significant difficulties that most businesses confront (Rezaei & Davoodi, 2012). Many academics have recently attempted to integrate the supplier selection and order lot-sizing challenges in order to harmonize diverse buyer tactics (Sodenkamp et al., 2016; Ghadimi et al., 2017; and Azadnia et al., 2015). Also, supplier selection, order allocation, and lot-sizing have changed recently due to the need to design sustainable communities or supply chain networks. As a consequence, the conventional supplier selection and order allocation problem has been transformed into a sustainable supplier selection and order allocation problem that incorporates environmental and social indicators and influencing variables into the selection and sourcing procedures (Azadnia et al., 2015). Even though the supplier selections are not within the study scope, it is essential when designing the SCN or the structure of communities' resilience.

Several studies have been conducted to measure the resiliency of SCNs during and after disruptive events. Those studies present the performance of the SCNs and the ability to resist disruptions and uncertainty. Lin and Wang (2011) examine the effect of disruption and uncertainty in the SCN. They considered supply/demand uncertainty in the network when applying both "make to order" and "make to stock" manufacturing processes. Their model was designed to have two stages; the 1st stage includes supply disruption while the 2nd stage includes demand uncertainty (Lin & Wang, 2011). In order to formulate and design the SCN model, they integrated all the plans of procurement, disruption, and manufacturing. Another study conducted by Schütz et al. (2009) focus on the uncertainty associated with SCN. They formulated a two-stage stochastic model to deal with the multi-commodity SCN problem. The 1st stage is designed to deal with choosing strategic locations, while the 2nd stage is designed to focus on the operational decisions. They considered two types of uncertainty; short- and long-term uncertainty in operational costs and required demand. Schütz et al. (2009) and Almaktoom et al. (2016) examined the importance to maintain the required service level (SL) at all the SC entities while minimizing the delay in the cycle time. However, this study did not consider the effects of a multi-commodity structure. Santoso et al. (2005) develop an SCN that consists of three stages and has a multi-product running in the network. The three stages were associated with suppliers, processing facilities (manufacturer and distribution center), and customers. They considered disruptions in the demand, supplier and available resources or capacity of the transportation methods. The objective was to minimize the total investment and operational costs to improve the SCN performance (Santoso et al., 2005). Another type of disruption that have been explored in the literature is the fluctuation in the demand or the suppliers' capacities that results to reduce the SCN performance. Fahimnia, B. and Jabbarzadeh, A. (2016) show the importance to have a resilient SCN against disruption not only on the in the suppliers' capacities while maximizing the SCN performance specially the environmental and social performance.

Some authors also have proposed several methods to improve commercial SCN resiliency against anthropogenic hazards. Munim et al. (2015) analyzed the impact of manmade disruptions on commercial logistics. They focused on the supplier flow and the disruption in warehousing, distribution centers, and transportation. Three different strategies are identified to improve the SCN resiliency in order to hinder the impact of disruptive events. Those three are (i) applying JIT strategies, (ii) implementing the lean production concept, and (iii) using single sourcing (Munim et al., 2015). JIT made the system more vulnerable, but it is possible to increase the SCN resilience by implementing strategies that help to apply JIT (Bouchery et al., 2016). In general, the focus on the SCN resilience has increased recently due to the implementation of JIT principles. SC decision makers need to implement such strategies to reduce the overall expenses; however, these strategies lead to make the SCN vulnerable when the unexpected events occur either within the SCN boundaries or in the transportation network.

One of the recent studies about mitigating disruptions in the transportation network and measuring the impacts of the disruptions on the SCN performance is conducted by Albertzeth et al. (2019). In their study, they consider four different strategies to mitigate disruptions in the transportation network. Those four strategies are (i) risk acceptance strategy (which is the current strategy in the system), (ii) flexible routing, (iii) redundancy in the stock level, and (iv) the combination between flexible routing and redundant stock strategies (Albertzeth et al., 2019). In order to measure the effectiveness of their model, the results are compared with respect to the service level and the total cost. In their study, they heavily investigate the impacts of transportation network disruptions on SCN performance and cover multiple mitigation strategies. However, it remains unclear how using strategies that consider relative service metrics (such as distribution *fairness*) may affect the SCN performance after disruptive events.

As we mentioned earlier, the high dependency on the transportation network makes other dependent networks susceptible to any disruption in the transportation network. Several disruptions have occurred lately that resulted in severe damages to the transportation networks and systems in various places. Thus, researchers have widely studied the disruption impacts on the transportation network, considering the nature of each disruption. Natural disruptions have affected significantly the transportation network, for instance, earthquakes, landslides, and storms. Several studies have examined the post-earthquake impacts on the transportation network and developed functions to measure the vulnerability of the network (e.g., Feng, Li, & Ellingwood, 2020; Park et al., 2001; Chang, 2000; Shiraki et al., 2007, Ghosh & Padgett, 2010; and Alipour & Shafei, 2016). Also, landslides and rainstorms have been considered in numerous researches and their effects on infrastructure networks (e.g., Sassu et al., 2017; Brenning, 2005; Postance et al., 2017). In our work, we design a model to deal with any disruption type that resulted in reducing the links' capacities or the suppliers' capacities, which is more general in dealing with the nature of the disruption.

Even though several studies in the academic literature have proposed diverse mitigation strategies to improve the overall performance of SCN, to our knowledge none of them have addressed the effects of *fair distribution* after disruptive events, or how such *fair distribution* strategies could be used to mitigate the impacts of disruption and provide a post-disruption plan to improve the SCN performance and increase the customers' satisfaction.

2.2.2 *NETWORK FLOW PROBLEM*

The network flow models have been widely used and implemented in various studies and research fields. Examining the flow of materials in the field of transportation, SC, power, communication, and all infrastructure networks has been comprehensively studied using network flows formulations. Some studies implemented network flow models in the field of infrastructure network water, power, and telecommunication (e.g., Ghorbani-Renani et al., 2020; Almoghathawi, González, & Barker, 2021; González et al., 2016; and Karakoc et al., 2019). In those studies, they modeled the flow of materials in the network between nodes considering that the links may fail and lose their functional, either fully or partially. Thus, the flows of materials depend directly on the capacity of the links and how these were affected by the disruptive event modeled.

Regarding multi-commodity structures, Ford and Fulkerson (1958) and Hu (1963) introduced the multi-commodity flow problem, and since then, it has been used and extended by many researchers. Various studies in the literature have used the multicommodity network flows models (in the context of minimum cost flow problem or the maximum flow problem) in the fields of SC, inventory control, and transportation (e.g., González et al. (2016), Guo et al., 2020; Karimi & Bashiri 2018; Khodayifar, S. 2021; Mejri et al., 2019; Guimarães et al., 2020; Heath, Mitchell, & Sharkey 2020). Salimifard and Bigharaz (2020) developed a summary of multiple key studies that consider multi-commodity flows with numerous applications in infrastructure, such as communications and transportation. However, to the authors' knowledge, none of these studies have explored the effects of following a fairness-based distribution within a multi-commodity network flows modeling approach to reduce the impacts of disruptions in transportation networks and SCN performance.

2.2.3 *FAIRNESS IN SUPPLY CHAIN NETWORK*

In SCN, most of the studies in *fairness* consider SCN strategies such as discount contracts, revenue sharing, and manufacturing sharing that could apply between suppliers, retailers, or both. A study that considers the quantity discount contract among a single supplier and two retailers SC is conducted to measure dual *fairness* between the two retailers, and how fulfilling the needs of each retailer could affect the other (Nie, and Du, 2017). Another type of *fairness* in SCN is the *fairness* concern. *Fairness* concern in SCN is evidenced when a firm wants to focus on the inequality among the SCN entities (Cui et al., 2007). Some studies have suggested using coordination strategies in order to improve the SCN *fairness*. Cui et al. (2007) described the implication of *fairness* concern among the SCN entities or parties. They defined the *fairness* concern as treating all entities equally during the critical situation and afterward. Katok, Olsen, and Pavlov (2014) presented a special case when SCN partners have private *fairness* concerns. They found that if the *fairness* concern is strong enough, the efficiency of coordinating the SCN by having a better coordination on the manufacturer's wholesale pricing strategy improves. On the other hand, for parties that satisfy *fairness* but not strongly enough, it would become difficult to coordinate such a strategy between suppliers and retailers in the SCN (Qin and Li, 2014). Another study shows that different *fairness* levels seeking by customers affect the decision of choosing distributional channels: direct and agent sealing (Yi, Wang, Liu, and Chen, 2018). Yi et al. (2018) examine which choice leads to maximize the manufacturer's profit based on the *fairness* preference customers seek. The results show that it is a good choice for the manufacturer to sell through a median agent to the customers when *customers strongly require fairness*. While the selling direct to the customers is recommended when the *fairness* concerns is weak (Yi et al., 2018).

Several recent studies started to focus on the term of *fairness* from different perspectives and implement them in their models' designs. For instance, Niu et al. (2017) found a similar outcome to what Du et al. (2014) obtained in their study, concluding that *fairness* concerns could result in a reduction of the total profit of the SCN, as *fair* suppliers would not accept to have access channels with other suppliers. Another study conducted by Li et al. (2017) analyzes the implementation of *fairness* concerns by the manufacturer in a cooperative advertisement that is applied in a dual channel system. The outcomes imply that the advertising in channels cannot be coordinated no matter how the effort is done by the manufacturer to apply the *fairness* concern. Another application that *fairness* is applied in is scheduling. Androutsopoulos, and Madas (2019) proposed a model that focuses on balancing the delay time and congestion when dealing with scheduling the fight queue. The authors focus on the trade-off between being *fair* or efficient with respect to scheduling processes of the planes in the airport and how they can balance the congestion' effects between all airplanes (Androutsopoulos et al., 2019).

Recently, there are some studies that started to focus on applying *fairness* concerns in the distribution system that include cases where agents start to compare their portions with what other peers or neighbors have. People and entities, in real-life situations, want to be treated equally compared to their peers and neighbors who share the same values and are similar to them (Festinger 1954; Li and Jain, 2015). Ho and Su (2009) considered *fairness* in distribution and peer-induced *fairness* by designing a game setting that had two groups of players; one representing a leader and the other with two followers. As expected, the peer-induced *fairness* is not acceptable by the follower that receives less compared to his peers. The results show that treating all followers equally (peer-induced *fairness*) is required by both followers. Another study by Ho et al. (2014) showcases the importance of having *fairness* among all retailers, by showing that retailers accepted to have less profit when applying peer-induced *fairness*, as long as all retailers are treated fairly. Also, some studies consider the *fairness* preference when allocating orders (e.g., Liu et al., 2018a; Liu et al., 2018b). Liu et al. (2018a) studied the effects of having different *fairness* concerns within logistic service supply chain (LSSC). The LSSC involves one logistic service integrator (LSI) and two functional logistic service providers (FLSP). The authors considered two types of *fairness* in their study: distributional *fairness* and peer-induced *fairness*. The results show that the LSI utility increases when applying peer-induced *fairness*. Liu et al. (2018 b) developed a multi-objective programming model that aims to maximize the profits of LSI and the total utility of FLSP. They applied *fairness* preferences within FLSP to distribute the order allocation when demand updates, and they analyze the impacts of demand updates on the lead time. The model is constructed into two stages. In the first stage, the model considers the *fairness* preferences of each FLSP to maximize the LSI profits, and the second stage is when the demand changes. The results show that the increase in the demand in the second stage results in improving the SC performance. However, when the demand decreases, the differences in the FLSPs' *fairness* preferences increase (Liu et al., 2018 b).

Our work is relatively connected to the studies that consider *fairness* in order allocation conducted by Liu et al. (2018a) and Liu et al. (2018b). In their studies, they examined the impact of applying *fairness* when allocating orders, while we are focusing on allocating the available resources when transporting commodities in the network. Also, we consider a multi-supplier node and a multi-demand node for each commodity which increases the complexity of the SCN. Another study has similar approach to our study was conducted by Androutsopoulos, and Madas (2019). They considered *fair distribution* to balance the delay time and congestion when scheduling the waiting time which each flight stays in the airport. In our study, we aim to balance the unmet demand percentage at each demand node for different commodities and avoid that the system becomes biased toward the node with highest demand in order to increase the customers' satisfaction and minimize the impacts of disruptions. In our study, we examine the system with *fairness* (100% fair system) and without *fairness* (0% fair system).

Based on the multiple studies that have been explored the concept of *fairness* in supply chain distribution, customers seek to be treated equally compared to their peers. However, to our knowledge, none of the previous studies have developed a mathematical model that focuses on seeking a *fair and equitable* allocation of the available transportation and distribution resources after a disruption occurs, while trying to reduce the impact of the disruption on customers and the performance of SCN. Moreover, none of the studies have examined if a *fairness*-oriented distribution strategy could in fact help reduce the immediate impacts of disruptions on the SCN performance. This section presents a mathematical and computational model that considers a disruption in the transportation network and focuses on mitigating the impacts of such disruptive event on the SCN performance. In particular, the chapter presents a novel multi-criteria mixed-integer programming (MIP) model to optimally allocate available transportation resources and distribute products and commodities fairly among all demand nodes, while procuring minimum target service levels (SL).

2.3 FAIRSCN MODEL

In this section, we present the proposed *fairness*-oriented SCN model (*FAIRSCN)*, starting by a discussion on the specific objectives of the model and the associated assumptions.

Then, we present a detailed model description, which includes the proposed mathematical formulation and the nature of the variables, constraints, and objective functions used.

2.3.1 *FAIRSCN MODEL DISCUSSION*

The purpose of this study in this section is to develop a model to fairly distribute the available transportation resources (e.g., flow capacity) among customers after disruptive events, while procuring a cost-efficient distribution configuration. In general, the proposed model is developed to study disruptive events that reduce the transportation capacity, such as damaged roads or a reduction in the number of vehicles, among others. Also, the proposed model is structured to consider disruptive events that result in a reduction of the suppliers' capacity. In addition, the model is built to procure that all customers reach minimum consensual service levels for each demanded commodity. The model is designed to deal with a multi-product structure, i.e., with multiple commodities running through the SCN. Additionally, service levels play a key role in the model, as they are used to determine the efficiency of the system by measuring the fraction of customers that were able to maintain desired SL after the disruption. Figure 2-1shows a depiction of the multi-layered network modeled, where the first layer represents the main transportation network that is used to deliver the freights, and the other layers show that flow of each commodity. In this depiction, each node could correspond to a supplier, transshipment, or demand node for any given commodity. Note that the same node may simultaneously serve as a supplier for one commodity and a customer for another.

Table 2-1: Sets

$\mathcal{N}$	Set of nodes
$\mathcal{A}$	Set of arcs
$\mathcal{L}$	Set of commodities
$\mathcal{N}_d^l$	Set of demand nodes
$\mathcal{N}_s^l$	Set of suppliers' nodes

2.3.2 *FAIRSCN MODEL DESCRIPTION*

The proposed SCN transportation model assumes that any given could be a supplier or customer for different commodities as shown in Figure 2-1. The proposed model considers the demands of each type of commodity in each node and seeks to supply them fairly among all demand nodes.

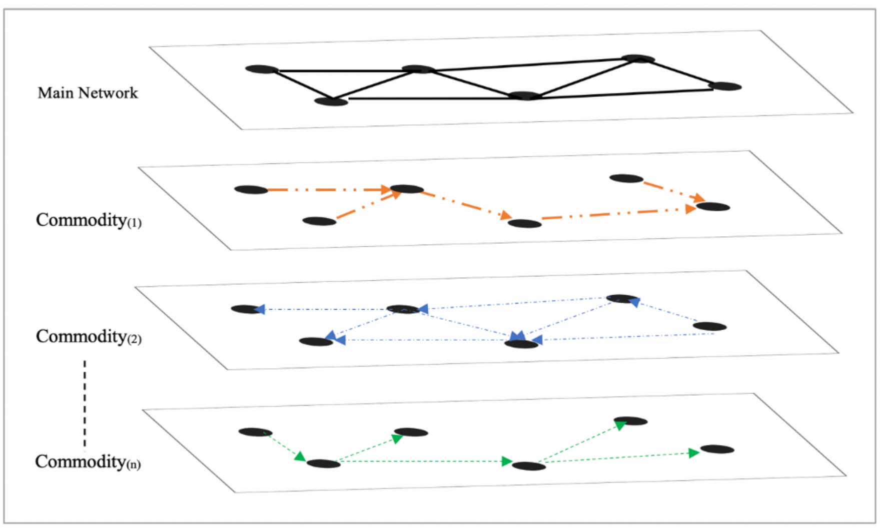

Figure 2-1. Multi-commodity supply chain network

Since there are multiple products or commodities running through the transportation network, the model helps to divide the shipment capacity equally with respect to the available commodities. Table 2-2 describes the parameters used in the proposed FAIRSCN model, which include the required service level of each commodity at each demand node, the supply or demand values for each node, and the flow costs, among others. Table 2-3 presents the decision variables used in the FAIRSCN model, associated with the flow of each commodity, the achievement of desired service levels, and relative *fairness*, among others.

The objective of this model is to improve the SCN resilience by applying the concept of *fairness* to distribute the available resources among demand sites fairly. The proposed FAIRSCN model has two objectives.

Table 2-2: Parameters

α_{il}	Minimum required Service level at node $i \in \mathcal{N}_d^l$ for commodity l
b_{il}	Supply/demand of commodity l at node i
c_{ijl}	Flow Cost per mile of using arc $(i, j) \in \mathcal{A}$ for commodity l
ω_l	Weight of commodity l that is shipped
y_{ij}	A continuous parameter between {0,1} 1 if arc is operational; and 0 otherwise
u_{ij}	Capacity of arc $(i, j) \in \mathcal{A}$
f_{il}^-	Cost of unmet demand at node $i \in \mathcal{N}_d^l$ for commodity l
f_{il}^+	Cost of excess supply at node $i \in \mathcal{N}_s^l$ for commodity l
m_{il}	Cost of not meeting minimum service level at node $i \in \mathcal{N}_d^l$ for commodity l
d_{ij}	Distance from node i to node j

Table 2-3: Decision variables

s_{il}^-	Unmet demand at node $i \in \mathcal{N}_d^l$ for commodity l
s_{il}^+	Excess supply at node $i \in \mathcal{N}_s^l$ for commodity l
x_{ijl}	Amount of flow through arc $(i, j) \in \mathcal{A}$ for commodity l
δ_{il}	A binary variable {0,1} 1 if a node $i \in \mathcal{N}_d^l$ did not get minimum service level; 0 otherwise
μ_{il}^-	Negative deviation from the total percentage of unmet demand at node $i \in \mathcal{N}_d^l$ for commodity l
μ_{il}^+	Positive deviation from the total percentage of unmet demand at node $i \in \mathcal{N}_d^l$ for commodity l
γ	Total percentage of unmet demand for all commodity

The first objective, denoted by ***O1***, is to minimize the associated costs, including transportation of commodities and the penalization associated with not supplying the demanded commodities or not reaching the desired service levels. The associated objective function is shown in Eq. (2-1). The first term in Eq. (2-1) represents the flow cost of each commodity per mile based on the type of. The second term of Eq. (2-1) is the cost of having unmet demand for each commodity at each demand node. The third term is the cost associated with having excess supply for each commodity at each supply node. Finally, the fourth term is associated with the cost of not meeting the minimum required SL for each commodity at each demand node.

minimize

$$O1 = \sum_{l \in \mathcal{L}} \left(\sum_{i,j \in \mathcal{A}} x_{ijl}\, c_{ijl} d_{ij} + \sum_{i \in \mathcal{N}_d^l} s_{il}^{-}\, f_{il}^{-} + \sum_{i \in \mathcal{N}_s^l} s_{il}^{+}\, f_{il}^{+} + \sum_{i \in \mathcal{N}_d^l} m_{il}\, \delta_{il} \right) \tag{2-1}$$

The second objective, denoted by ***O2***, represents the positive and negative percentage deviations of the unmet demand for each commodity at each demand node. This objective function is shown in Eq. (2-2).

minimize

$$O2 = \frac{\sum_{i \in \mathcal{N}_d^l} \sum_{l \in \mathcal{L}} \mu_{il}^{-} + \mu_{il}^{+}}{\left|\mathcal{N}_d^l\right|} \tag{2-2}$$

The importance of having the fairness-based distribution strategy in separate objectives is to compare the obtained results when aiming to reduce the overall costs without and with considering fairness. By using a bi-objective modelling approach, it is possible to examine the trade-offs between cost efficiency and fairness, so that decision makers and stakeholders can take informed decisions to support supply chain performance as well as equity between different economic sectors. The inclusion of an objective associated with measuring the fairness of a given distribution strategy is critical, since without it, the main goal would be to focus solely on reducing the total costs of transportation and unmet demands. However, this would cause that nodes or economic sectors with large demands will tend to absorb most of capacity utilization and available resources, negatively affecting the performance of other nodes or sectors with smaller demands. By forcing the model to minimize the sum of deviations from the mean percentage of unmet demand, the bias towards the nodes or sectors with highest demand is reduced.

To efficiently solve bi-objective optimization models such as the one proposed, diverse methods have been developed and used in the literature, including the weighted sum method and the ε-constraint method. In this study, we use the ε-constraint method because it has diverse advantages with respect to others, particularly when addressing MIP models. Mavrotas G. (2009) illustrated some of those advantages: i) When considering multi-objective MIP models, the ε-constraint can produce unsupported efficient solutions while the weighting method cannot (Steuer, R. E. 1986). ii) Approaches such as the weighted sum method requires a pre-solution scaling of each objective, which has a significant influence on the results. However, such scaling is not required when using the ε-constraint method. iii) When using the ε-constraint, the number and spread of generated efficient solutions can be controlled, while it is difficult to control these when using the weighted sum method.

To implement the ε-constraint method, one starts by setting one of the objectives as a primary objective, while fixing the feasible range of the others with upper and/or lower boundaries that are iteratively adapted. Additional details on how to implement the ε-constraint method can be found in Mavrotas G. (2009)

The model considers multiple constraints related to the original network capacities and the effects of the disruptive event (that reduce the transportation network capacity). For example, there may be unmet demands in case disruptions due to damage links, fluctuation in the demand, or shortages from the supplier side happen. Also, the model is designed to ensure that all demand nodes receive at least the minimum required service level SL. The first constraint is the flow balance constraint, which calculates the flow leaving each node substituted with the flow entering to each node. The aggregate of these values should equal the required demand of each node, if the node is a demand node, or the available commodities, if the node is a supply node. To consider any unmet demand or excesses supply in a node, the equation is balanced by two variables (s_{il}^{-}, s_{il}^{+}, respectively) for each commodity as presented in Eq. (2-3).

$$\sum_{j:(i,j)\in\mathcal{A}} x_{ijl} - \sum_{j:(j,i)\in\mathcal{A}} x_{jil} = b_{il} + s_{il}^{-} - s_{il}^{+} \begin{cases} -b_{il}, & Demand\ node \quad \mathcal{N}_d^l \subset \mathcal{N} \\ +b_{il}, & Supplier\ node \quad \mathcal{N}_s^l \subset \mathcal{N} \\ 0, & Transhipment\ node\ \mathcal{N}_T^l \subset \mathcal{N} \end{cases} \qquad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L} \tag{2-3}$$

Eq. (2-4) is to ensure that all demand nodes will receive at least the minimum required service level SL, α_{il}, by calculating the total flow leaving the demand node that is substituted from the total flow entering the demand node. If the model cannot deliver the minimum required SL, there is a penalty cost. In this equation, if the binary variable δ_{il} equals one, it means that the minimum required SL was not procured for commodity l in node i.

$$\sum_{j:(i,j)\in\mathcal{A}} x_{ijl} - \sum_{j:(j,i)\in\mathcal{A}} x_{jil} \quad \le \alpha_{il}\, b_{il}\ (1-\delta_{il}) \qquad \forall\, i \in \mathcal{N}_d^l, \forall\, l \in \mathcal{L} \qquad (2\text{-}4)$$

Eq. (2-5) is the link capacity that describes how much flow can be distributed through the SCN. The flow of each commodity is multiplied by the weight of each commodity (ω_l) that is in the shipment. The aggregate weight must be less than or equal to the capacity of the link (u_{ij}) if the link is functioning. The functionality of each link is represented by the parameter (y_{ij}), which is one if it is operational, and zero otherwise.

$$\sum_{l\in\mathcal{L}} \omega_l x_{ijl} \le u_{ij}\, y_{ij} \qquad \forall\, (i\,,\, j) \in \mathcal{A} \qquad (2\text{-}5)$$

Eq. (2-6) is associated with the total percentage of unmet demand (γ) in the SCN. Note that the model is built to distribute the resources fairly. Hence, we chose to calculate the absolute deviation from the percentage of unmet demand at each node for each commodity to the total percentage of unmet demand in the network. To do so, Eq. (2-7) calculates the absolute deviation using a linear representation, where (μ_{il}^- and μ_{il}^+) describe the positive and negative part of such deviation.

$$\frac{\sum_{i\in\mathcal{N}_d}\sum_{l\in\mathcal{L}} s_{il}^-}{\sum_{i\in\mathcal{N}_d}\sum_{l\in\mathcal{L}} b_{il}} = \gamma \qquad (2\text{-}6)$$

$$\left(\frac{\bar{s}_{ilt}}{b_{il}}\right) - \gamma + \mu_{il}^- - \mu_{il}^+ = 0 \qquad \forall\, i \in \mathcal{N}_d^l, \forall\, l \in \mathcal{L} \qquad (2\text{-}7)$$

Eqs. (2-8)-(2-14) represent the nature of each decision variable, indicating if they are nonnegative, continuous, or binary. x_{ijl} represents the flow through link (i, j) for each commodity l. While (s_{il}^-, s_{il}^+) represent the unmet demand at each demand node for each commodity and over supply at each supply node for each commodity, respectively.

γ represents the total percentage of unmet demand in the network. (μ_{il}^{-} and μ_{il}^{+}) describe the positive and negative deviation at each demand node for each commodity with respect to the total percentage of unmet demand.

$$x_{ijl} \geq 0 \qquad \forall (i,j) \in \mathcal{A}, \forall l \in \mathcal{L} \qquad (2\text{-}8)$$
$$s_{il}^{+} \geq 0 \qquad \forall i \in \mathcal{N}_s^l, \forall l \in \mathcal{L} \qquad (2\text{-}9)$$
$$s_{il}^{-} \geq 0 \qquad \forall i \in \mathcal{N}_d^l, \forall l \in \mathcal{L} \qquad (2\text{-}10)$$
$$\gamma \geq 0 \qquad (2\text{-}11)$$
$$\mu_{il}^{+} \geq 0 \qquad \forall i \in \mathcal{N}_d^l, \forall l \in \mathcal{L} \qquad (2\text{-}12)$$
$$\mu_{il}^{-} \geq 0 \qquad \forall i \in \mathcal{N}_d^l, \forall l \in \mathcal{L} \qquad (2\text{-}13)$$
$$\delta_{il} \in \{0, 1\} \qquad \forall i \in \mathcal{N}_d^l, \forall l \in \mathcal{L} \qquad (2\text{-}14)$$

2.4 CASE STUDY: ROAD-BASED DISTRIBUTION OF COMMODITIES IN COLOMBIA

The supply chain network SCN in this chapter is associated with the Colombian transportation infrastructure and the freight moving through it. We selected the Colombian transportation network, considering that the vast majority of the distribution of goods in Colombia is done via trucks. Additionally, several of the main cities in Colombia are located in the mountains, making the connectivity between cities highly susceptible to flooding and landslides. Thus, since the cities tend to have few roads to connect with each other, they can be easily isolated in case of natural disasters or any kind of disruptive events.

In this depiction of the Colombian transportation network used in for the case study, the nodes represent the major cities, and the arcs represent the transportation roads connecting them. In particular, the used network is composed of 51 nodes and 57 undirected arcs (or 114 directed arcs). The case study considers the 258 materials and products most representative for the Colombian supply chains, classified into six economic sectors (Clavijo-Buritica, et al., 2021). For this case study, we assume there is an aggregate commodity representing each economic sector, calculated based on the total weight and value associated with each individual product. Table 2-4 shows the information regarding each economic sector modelled and the total number of supply and demand nodes for each sector. Figure 2-2 presents the transportation network modelled, showing the cities and roads that connect them. In this case study, we measure the effect of the different random reductions in the network capacity on the SCN performance. We considered a different level of capacity reduction at different components. Then we examine the impact of the generated capacity reduction by measuring the SL at each demand node for each sector. Also, we measure the efficiency of the model by counting the number of demand nodes that do not receive the minimum required SL for each sector. Four different costs constitute the first objective. The unmet demand cost and the excess supply costs were considered similar, and the flow cost was considered to be proportional to the distance between the nodes. For the penalty cost of not maintaining the SL at each demand node for each sector. In this case study, we compare the effects in the distribution strategy of having large penalties for unmet SL versus having not penalization at all.

2.4.1 *RESULTS AND DISCUSSION*

In order to obtain the results of this case study, the model was tested considering different scenarios. The first scenario was to consider partial reductions in some of the links' capacities, where the selection of the disruptive links was randomly selected, by generating 50 random disruption scenarios at different reduction levels in the SCN capacity.

Table 2-4: The Colombia SCN information

Sector	Sector Description	Number of Supply Nodes	Number of Demand Nodes
1	Farming, forestry, hunting, and fishing	19	23
2	Mining and quarrying	5	7
3	Construction	7	16
4	Manufacturing industry	10	32
5	Commerce, repair, restaurants, and hotels	12	35
6	Transportation, storage, and communications	23	28

Figure 2-2: Road transportation network of Colombia

The second scenario was to consider partial reductions in suppliers' capacities for each sector, and how such changes in the suppliers' capacities could affect the performance of the SCN. The third scenario was to consider disruption or reduction in both links' capacities and suppliers' capacities for each sector. Each scenario has two different reduction levels (small and large reductions) and two different SL required by the demand site for each sector. For this case study, we used Python and Gurobi Optimizer

(Gurobi Optimization LLC., 2021) using an iMac with a 3.2 GHz Intel Core and 32 GB memory. The average solution time for each individual simulated disruption was less than a minute, showing the applicability of the proposed model in realistic scenarios.

2.4.1.1 *FIRST SCENARIO (Reduction in Links Capacities)*

To demonstrate this scenario, 50 random disruption scenarios were generated by considering different reduction percentages in the capacity for some links. Then the model calculated the flow of each sector at demand nodes, considering that some links are not functioning at the maximum due to the reduction in the links' capacities. The model aimed to fairly distribute the available commodities among all demand nodes and ensure that all demand nodes receive at least their minimum required SL. In order to run the model using both objectives and to develop the Pareto front, the ε-constraint method was used.

Figure 2-3 represents the average of the two objectives performance after running 50 random disruption scenarios at a low level of reduction in the capacities of the links. The vertical axis represents all costs that describe the first objective, while the horizontal axis represents the average percentage deviation of unmet demand at each demand node for each sector, which is the second objective. It can be seen that the two required SL have similar performance concerning the deviation of unmet demand behavior; however, the cost increases slightly when the SL increased to 70% Table 2-5 demonstrates the model performance associated with reducing the impact of the disruption on the demand nodes. Also, the unmet demand penalty cost for each sector at each demand node is equal, and all nodes were fairly treated. As shown in Figure 2-3, the maximum deviations of unmet demand among all nodes result in having the minimum total flow cost. However, the total flow cost increased when attempting to reduce the total deviations of unmet demand. Figure 2-4 represents the SCN performance and the average total flow cost and total deviation of 50 random disruption scenarios at a large level reduction in links capacities in the SCTN.

The model was run for a total of 100 runs, where for each set of 50 runs, we considered different SL values (30% and 70%). Both scenarios have similar behavior concerning the total deviation, which was large when aiming to achieve 30%SL. On the other hand, the total costs were larger when the SL was 70%, and the total deviations were small. The average (AVG) number and Standard Deviation (STD) of demand nodes that did not receive their minimum required SL listed in Table 2-5. The AVG and STD of the demand nodes that did not receive the minimum required SLs improved when applying the *fairness-based distribution strategy*.

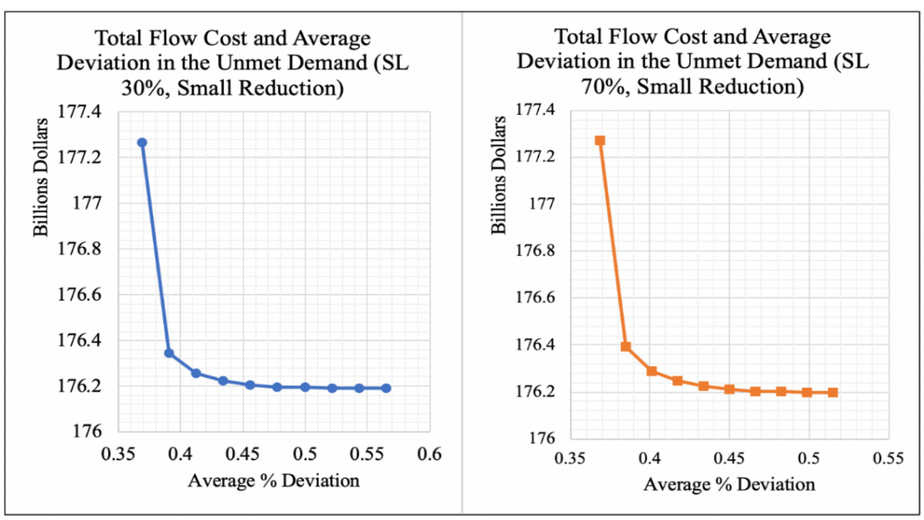

Figure 2-3. The AVG Performance of 50 Random (1st Scenario) with small reduction in links' capacities

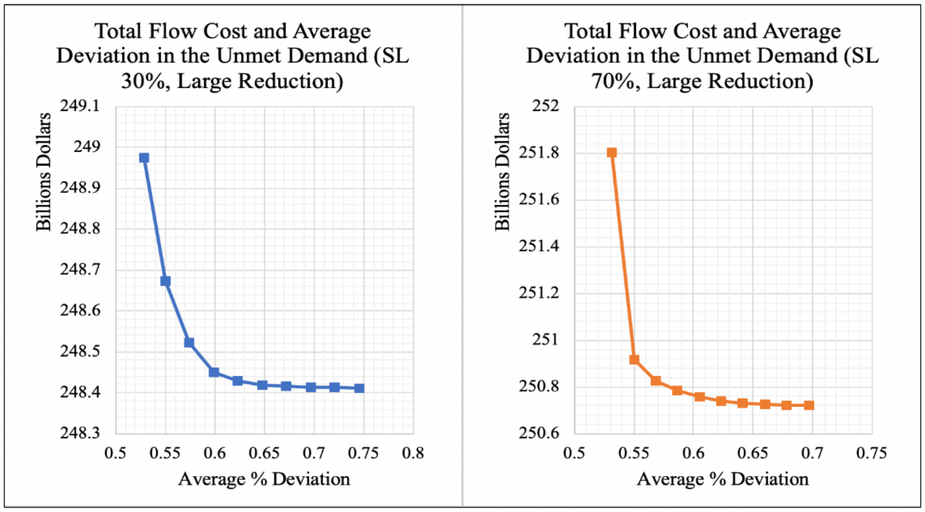

Figure 2-4: The AVG Performance of 50 Random (1st Scenario) with large reduction in links' capacities

The model efficiency is measured based on which AVGs are closer to the zero, and the *fairness-based* distribution output is closer to the zero. Considering a small reduction percentage in the links and SL 30%, the AVG number of demand nodes that did not receive the SL 30%, without *fairness-based distribution strategy*, is 14.9 nodes, and the STD is 5.101 per run. However, the results improve when the *fairness-based* concept was applied. Without applying *fairness-based distribution strategy* and the SL was set at 70% for each demand node for each sector, the AVG number of nodes that were not fully satisfied is 20.58 nodes, and the STD is 6.318 nodes. However, the AVG number of demand nodes reduces to 3.72 demand nodes for all sectors, and STD is 2.741 after applying the *fairness-based distribution strategy*. Also, the relative improvement *(RI)* and the price of fairness *(POF)* after applying the *fairness-based distribution strategy* are demonstrated in Table 2-5 as well. By using *fairness-based distribution*, the system performance improved significantly while the increase in the total cost (*POF)* is less than on percentage. Similarly, results are obtained when considering large reductions in the capacities of the links. The *fairness-based distribution* provides better solutions to reduce the impacts of disruption and ensured that the majority of the demand nodes receive their required SL during the disruption time. The model finds a way to distribute the available commodities fairly after the disruption events occurred to reduce the number of nodes that did not fully receive their required SL or part of it. The reason is that some of the suppliers were not able to distribute their resources due to limitations of links' capacities. These limitations resulted in the reduction of the total network capacity, thus causing unmet demands at some of the demand nodes.

Table 2-5: The model performance of covering the demand nodes needs (1st Scenario)

			Small Reduction			
	Without Fairness		With Fairness		***RI***	***POF***
	AVG	STD	AVG	STD		
30% SL	14.90	5.101	2.58	2.453	81.1%	0.59%
70% SL	20.58	6.323	3.72	2.740	79.4%	0.59%
			Large Reduction			
	Without Fairness		With Fairness		***RI***	***POF***
	AVG	STD	AVG	STD		
30% SL	18.30	5.751	3.60	1.920	76.9%	0.23%
70% SL	24.04	6.280	5.16	1.983	76.4%	0.43%

2.4.1.2 *SECOND SCENARIO (Reduction in Suppliers' Capacities)*

In this scenario, the objective is to measure the effect of having reductions in suppliers' capacity for each sector and how the model helps to distribute the available resources fairly. Similar procedures were followed to run and obtain the results of this scenario. 50 random scenarios were generated considering two different levels of reduction in each supplier node for each sector. The total cost and the total deviation in the SCTN are represented in Figure 2-5 and Figure 2-6. Figure 2-5 shows the behavior of the two objectives and how each objective influences the other. When aiming to achieve 30% SL at each demand node for each sector, the total deviation is higher compared to the results obtained when the SL was 70%, which is represented in the right graph.

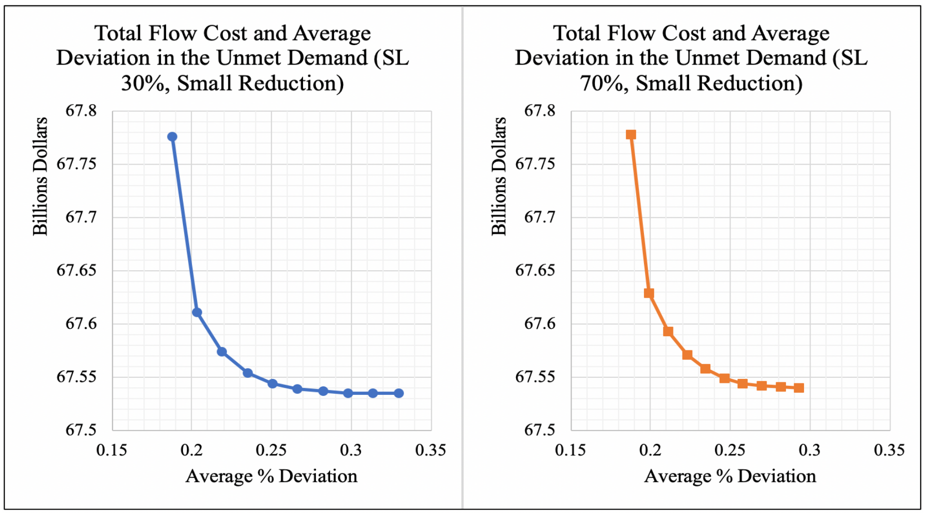

Figure 2-5: The AVG Performance of 50 Random Nodes (2nd Scenario) with small reduction in suppliers' capacities

Also, the AVG number and STD of demand nodes that did not receive the minimum required SL are listed in Table 2-6. It can be seen that the AVG and STD of the number of demand nodes that did not receive their SL are smaller when the *fairness-based distribution* is applied.

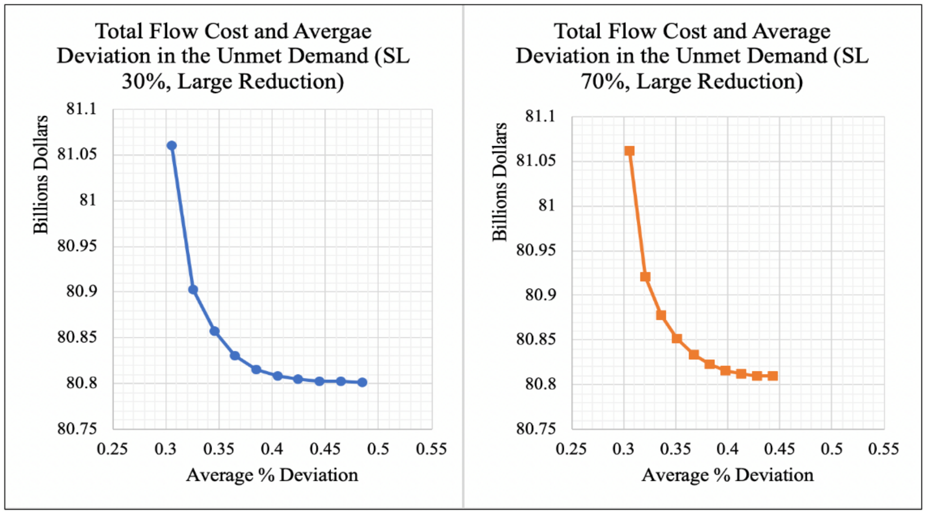

Figure 2-6: The AVG Performance of 50 Random Nodes (2nd Scenario) with large reduction in suppliers' capacities

The *fairness-based distribution* helped to reduce the impacts of the reduction on the suppliers' capacities for all sectors and distributed the available resources among almost all demand nodes fairly. Similar results as obtained in the 1st scenario concerning the improving percentage and the increase in the overall cost, applying the *fairness-based distribution* helps to increase the number of satisfied demand nodes, while the increment in the overall cost is at minimal.

Table 2-6: The model performance of covering the demand nodes needs (2nd Scenario)

	Without Fairness		With Fairness		***RI***	***POF***
Small Reduction						
	AVG	STD	AVG	STD		
30% SL	10.06	2.944	1.14	1.738	88.6%	0.34%
70% SL	14.34	4.312	2.52	2.063	84.3%	0.34%
Large Reduction						
	Without Fairness		With Fairness		***RI***	***POF***
	AVG	STD	AVG	STD		
30% SL	13.68	2.924	2.98	1.558	78.3%	0.32%
70% SL	21.52	4.348	4.96	1.678	77.0%	0.30%

2.4.1.3 *Third scenario (Reduction in Both Links' and Suppliers' Capacities)*

In this scenario, a combination of the reduction in links capacities and supplier nodes capacities have been done to measure how the model reduces the impacts of unpredicted events. The results regarding the total costs and the total deviations (Figure 2-7) are similar to the results obtained in the first scenario when the reduction level was small. The total costs and deviations are at the lowest level when aiming to achieve 30% SL, and the reduction level is large, which is presented in Figure 2-8 on the left graph. However, the total costs and total deviations in the unmet demand significantly increased when we aim to achieve a higher SL at 70%, which is presented in Figure 2-8 on the right side. Table 2-7 represents the AVG and STD of the number of unsatisfied demand nodes that did not receive their requirements during the disruptive events. When applying the *fairness-based distribution*, the model helped to reduce almost two-thirds of the unsatisfied demand nodes for all commodities comparing with the results when no *fairness-based distribution* is considered.

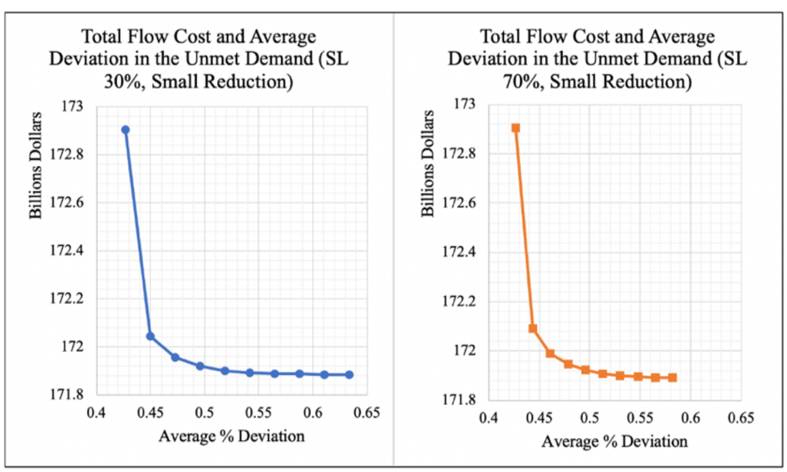

Figure 2-7: The AVG Performance of 50 Random Scenarios (3rd Scenario) with small reduction in both link and supplier capacities

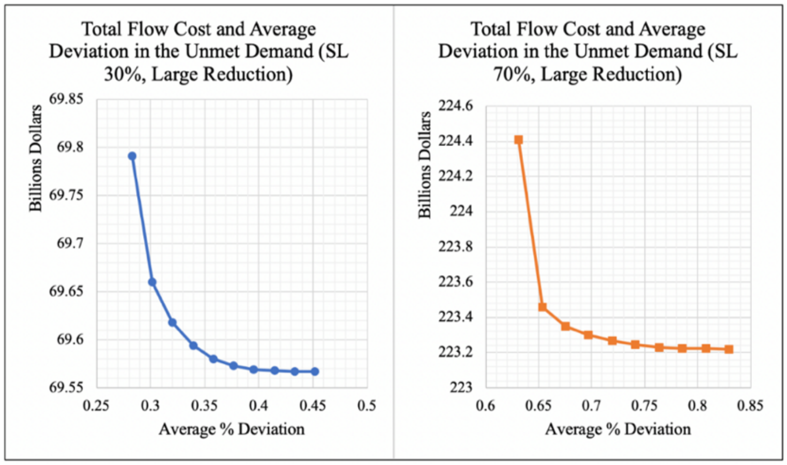

Figure 2-8: The AVG Performance of 50 Random Scenarios (3rd Scenario) with large reduction in both link and supplier capacities

By applying the fairness-based distribution method, the model calculated the percentage of each sector in the shipment going through the links and then tried to distribute the available resources at the suppliers' nodes fairly so that most of the demand nodes receive the minimum required SL. For example, suppose one of the commodities is dominating regarding the amount it has in the network, by applying fairness-based distribution. In that case, the model focuses on balancing each sector flow in the shipment. Figure 2-11 shows an example of the flow distribution in the network and the demand nodes of each sector considering the share of each sector in the total links' capacities. The thickness of the links and the line types represent the percentage each sector has in the shipment, and the blue (solid line) represents the usage of the links, and the red color (dashed line) indicates that the link was not used. At the same time the nodes are classified based on the type of nodes. The white nodes represent either suppliers' nodes or transshipment nodes, while the colored nodes represent the demand nodes of each sector. The green color indicates that the demand nodes received the minimum required SL while the red color indicates that the demand nodes did not receive the minimum required SL.

Another example of how the model works is demonstrated in Figure 2-12, which represents the flow of each sector concerning each sector demand with *fairness-based distribution* and without *fairness-based distribution*, and how the *fairness-based distribution* helps to improve the overall satisfaction. The difference between Figure 2-11 and Figure 2-12 is that Figure 2-11 describes the share of each sector in the total shipment in the SCTN (normalize based on the links' capacities), while Figure 2-12 represents the amount of the flow that each sector distributed with and without the *fairness-based distribution* (normalized based on each sector demand). In some sectors, the number of demand nodes that were not satisfied became worse when the *fairness-based distribution* was applied. Without the *fairness-based distribution*, the sectors with the highest demand dominated; thus, other sectors were affected, as shown in Figure 2-11 and Figure 2-12.

Table 2-7: The model performance of covering the demand nodes needs (3rd Scenario)

			Small Reduction			
	Without Fairness		With Fairness		***RI***	***POF***
	AVG	STD	AVG	STD		
30% SL	16.98	5.923	4.04	3.758	75.0%	0.57%
70% SL	23.8	7.396	5.8	3.949	76.3%	0.57%
			Large Reduction			
	Without Fairness		With Fairness		***RI***	***POF***
	AVG	STD	AVG	STD		
30% SL	23.28	6.731	6.96	3.653	70.5%	0.31%
70% SL	33.08	7.861	9.36	3.685	69.6%	0.53%

It can be observed that sector 6 was dominating when no *fairness-based distribution* was applied, and that resulted in having more unsatisfied demand nodes (in red). When using the *fairness-based distribution*, the model enforced the reduction of the relative use of transportation capacities associated with sector 6*;* thus, the other sectors could better supply their demands and improve the overall number of satisfied nodes. By just reducing sector 6 capacity utilization in the transportation network, the number of demand nodes that did not receive their minimum required SL for each sector reduces from 20 nodes to 5 nodes, as shown in Figure 2-11.

2.4.2 *PRICE OF FAIRNESS AND RELATIVE IMPROVEMENT:*

In this section, we address the improvement in the SCTN performance based on the satisfaction rate and the increase in the total cost when applying fairness, using what is called "Relative improvement (*RI*)" and "Price of Fairness (*POF*)", respectively.

(1) We defined the *RI* as the reduction in the total number of unsatisfied demanders in the system with the *fairness-based distribution* (UDF), compared to the number of unsatisfied demanders without the *fairness-based distribution* (UDWF), as shown in Eq. (2-15). This definition is similar to the application from Yao, Mandala, & Do Chung (2009), where they compared their robust solution to the nominal solution.

(2) The *POF* is well defined and used in many studies that consider *fairness*. The origin application of *POF* was to measure the reduction in utilization when applying fairness (Bertsimas, Farias, and Trichakis, 2011). Also, another form of applying *POF* to measure the increment in the total cost when applying fairness

was used by Ye, Zhang, and Dekker, (2017). So, we defined the POF as the increase in the total cost when applying fair distribution compared to the total cost without fair distribution as shown in Eq. (2-16).

$$RI = \frac{\text{UDWF} - \text{UDF}}{\text{UDWF}} \tag{2-15}$$

$$POF = \frac{Total\ cost\ with\ fairness - Total\ cost\ without\ fairness}{Total\ cost\ without\ fairness} \tag{2-16}$$

The RI and the POF for each scenario are listed in Table 2-5, Table 2-6, and Table 2-7. The RI of each scenario compared to the POF for each scenario show that applying fair distribution is worth in term of the total costs the fair distribution adds to the total cost.

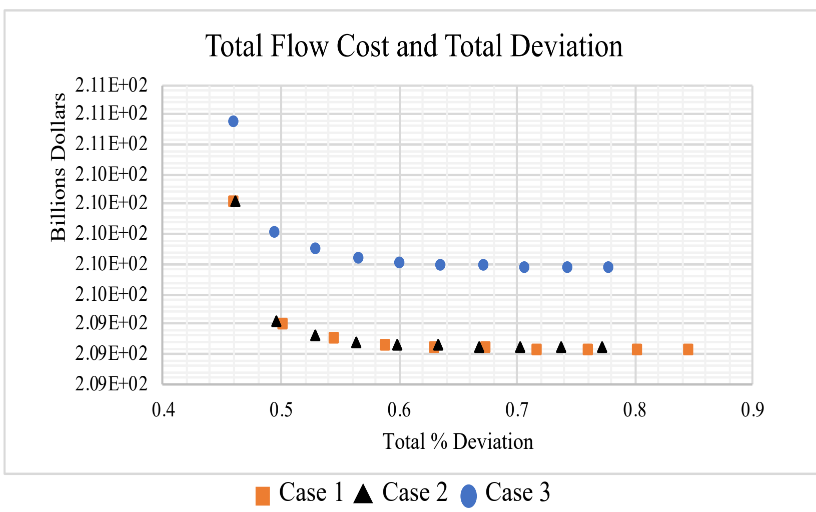

Figure 2-9: Comparison of all SL cost cases

2.4.3 *SENSITIVITY ANALYSIS*

Each cost parameter in the objective can be directly determined and calculated, except the cost of not maintaining the required SL (in which case, this may be seen as a subjective metric associated with the reputation and credibility of each firm). The purpose of conducting the sensitivity analysis is to measure the model performance when the SL cost changes. The model was examined in three different cases, where each case had different SL costs.

The three cases were designed based on the changes in the SL cost. Case 1 was when the SL weight was set to equal zero, while Case 2 was when the weight of the SL cost was set to be equal to the weight of other components in objective 1, as presented in Eq. (2-1).

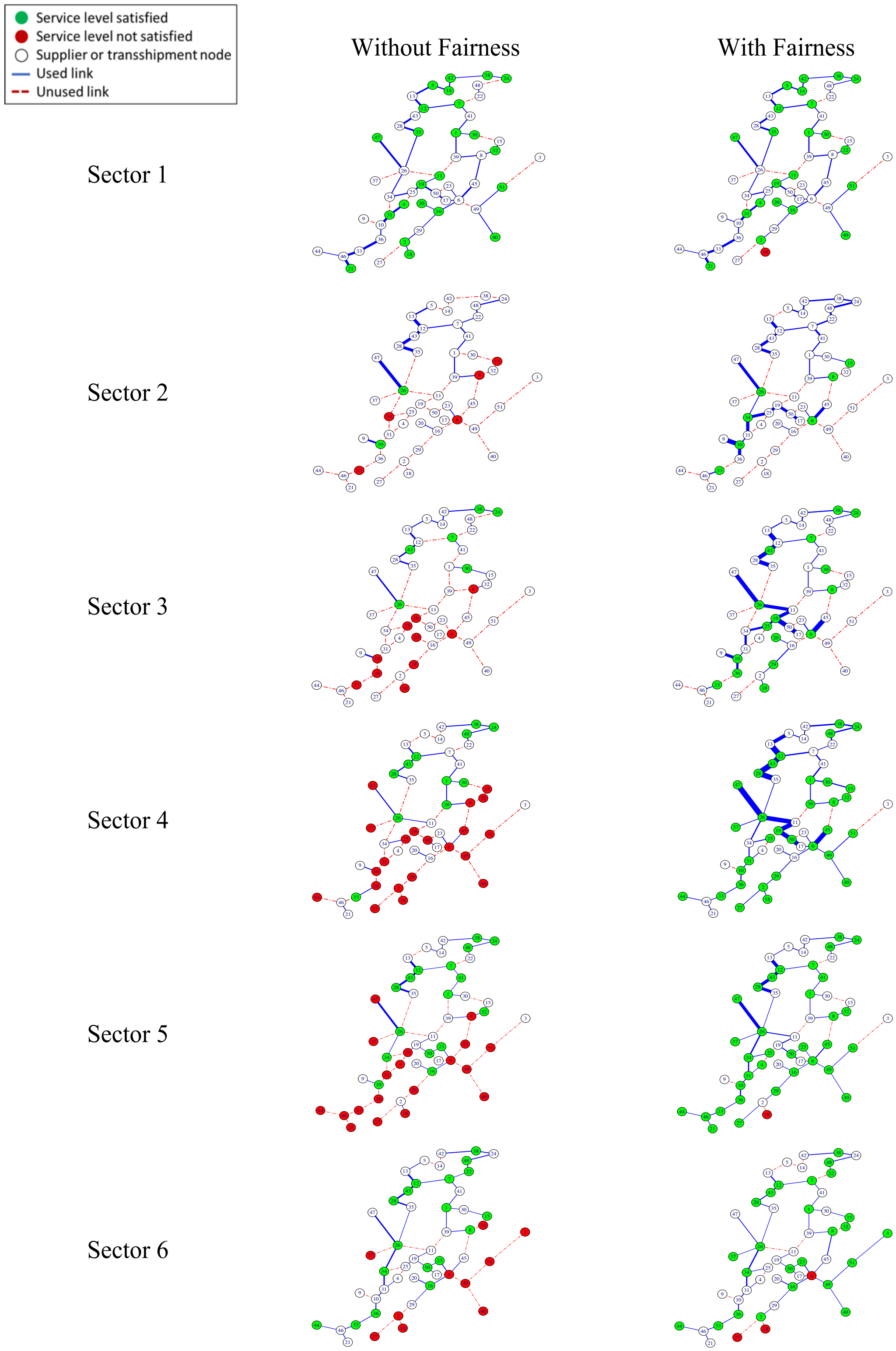

Figure 2-10: Comparison of the flows (with respect to each sector demand) with fair and no fair distribution within each sector when SL cost is neglected (Case 1)

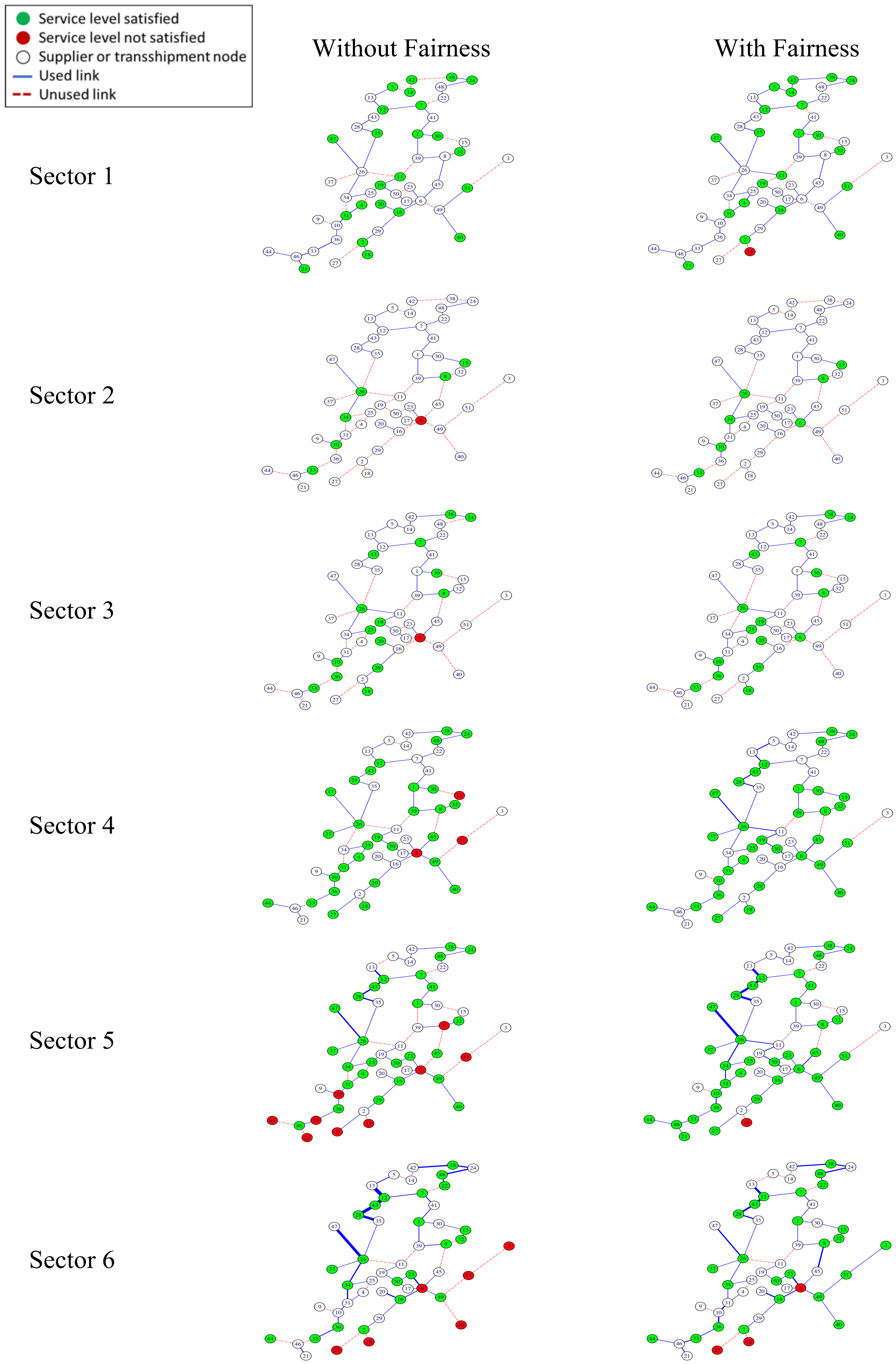

Figure 2-11: Comparison of the flows (with respect to the links' capacities) with fair distribution and no fair distribution when SL cost is medium (Case 2)

Case 3 was when the weight assigned to the SL cost was set to be larger than all the weights assigned to other components in objective 1, to give priority to maintaining the SL at most demand nodes.

The performances of Cases 1 and 2 were comparable for the overall costs, as presented in Figure 2-9; however, the performance of each case was significantly different concerning the satisfaction rate, as shown in Figure 2-10-2-12. when the no *fairness-based distribution strategy* was applied. Moreover, the performance of both Cases; 1, and 2, improved significantly when implementing the *fairness-based distribution strategy* concerning the satisfaction rate (Figure 2-10-2-12).

Case 3 was developed to measure the effects of the SL cost when the cost is higher than the combination of all the other cost parameters in objective 1. Thus, the model prioritizes delivering the required SL at all demand nodes, while considering the other costs in the objective function. The results change in such a way that the *fairness-based distribution*, in some cases, provides a suboptimal solution compared to no *fairness-based distribution*, as demonstrated in Figure 2-13. However, the total cost was significantly high compared to the other two cases, as shown in Figure 2-9. This happened regarding the differences in commodities' demands. The model reduced some of the nodes' demands for the sectors that have the highest demand in the shipment to the level of the minimum required SL and increased other sectors' percentages in the shipment. Thus, the overall performance overcomes the *fairness-based distribution* performance.

The changes in the cost or penalty associated with not meeting an adequate SL determine the priority of the model, and how the flow should be distributed among all demand nodes. When setting the SL cost too large, the model focuses on maintaining the SL at each demand node. However, the distribution costs increase. Then, the *fairness-based distribution strategy* might lower the SL at certain demand nodes in order to distribute the available resources fairly concerning unmet demand percentage deviations at each demand node, as shown in Figure 2-13.

The *fairness-based distribution strategy* provides similar performance in all three cases and satisfied most of the demand nodes except five nodes (in red). However, when the SL cost is too large, the *fairness-based distribution* solution concerning the number of unsatisfied demand nodes is worse compared to the results when no *fairness-based distribution strategy*, as described in Figure 2-13. As a result, the cost to maintain that performance is high, as shown in Figure 2-9. The total flow cost and the total percentage deviations in the unmet demand for all sectors are demonstrated in Figure 2-9 given that each shape represents one of the analysis cases. In order to maintain the SL at all demand nodes, Case 3, the overall costs increased significantly, and the unmet demand deviations were similar to the Case 2 performance, shown in Figure 2-9.The results show that there was an overlap in the overall cost at the highest point of Case 1 and Case 2. However, the performance of Case 2 concerning the total percentage deviations in the unmet demand were smaller compared to the performance of Case 1.

The sensitivity analysis was conducted to examine the impact of any changes in the first objective. We chose to study the effect of changing the SL cost because, in real life, it is difficult to estimate the cost of not achieving the SL.

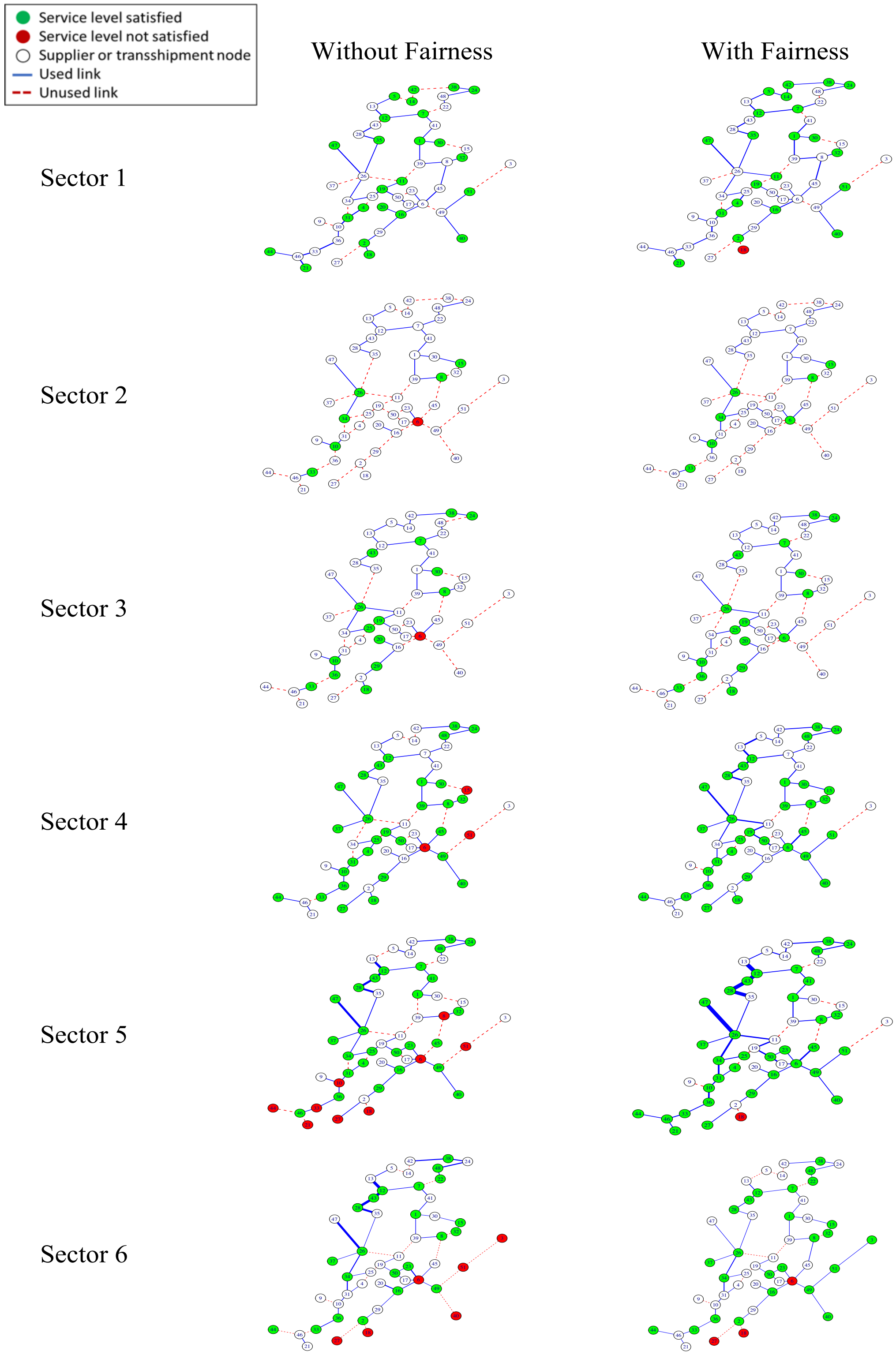

Figure 2-12: Comparison of the flows (with respect to each sector demand) with fair and no fair distribution within each sector when SL cost is medium (Case 2)

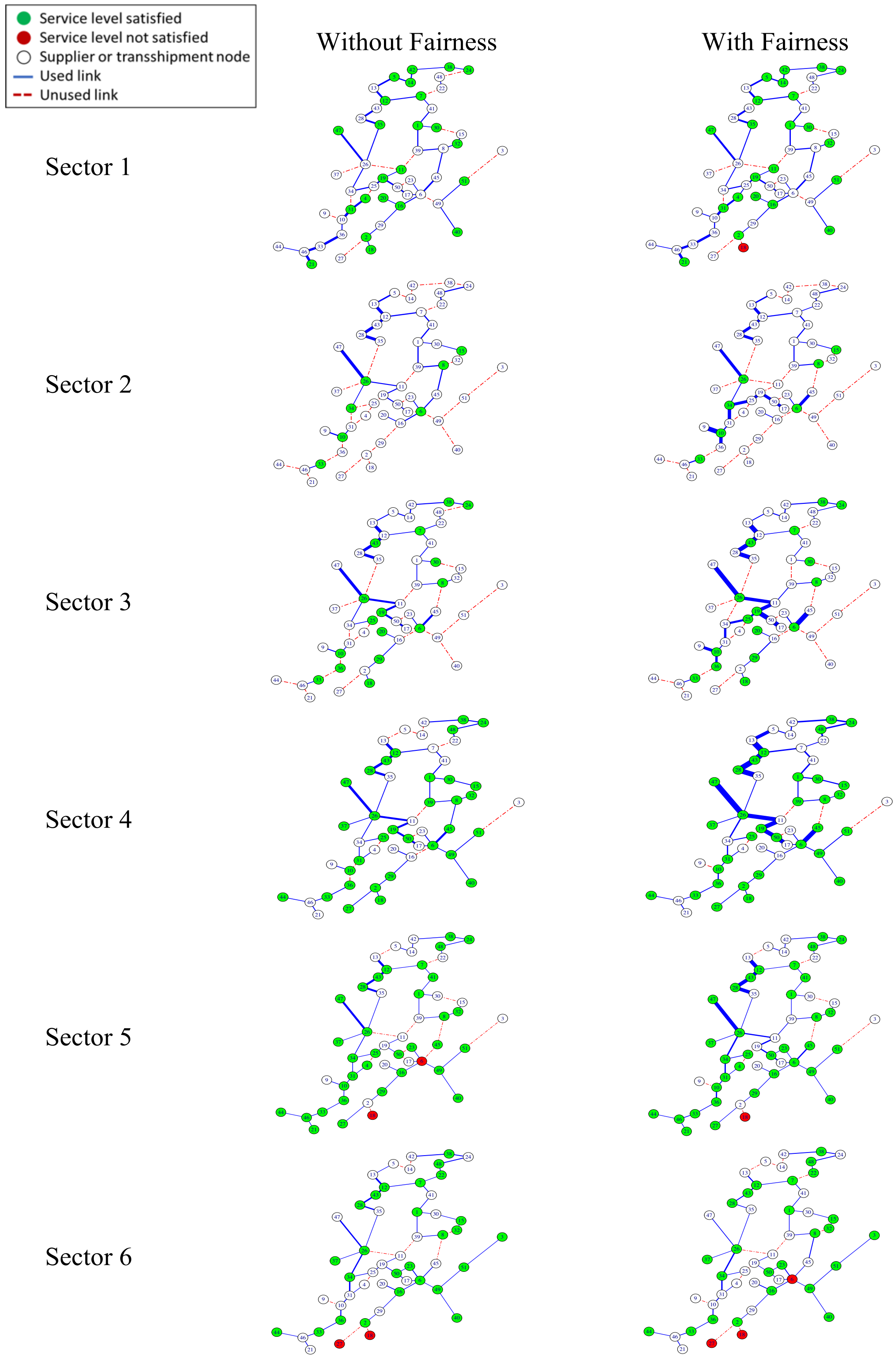

Figure 2-13: Comparison of the flows (with respect to each sector demand) with fair distribution and no fair distribution when SL cost is large (Case 3)

As expected, any changes in the SL cost plays a significant role in determining the distribution plans of available products in the SCN. The larger the SL cost, the higher the overall cost, examined in Case 3. Neglecting the SL cost resulted in having many demand nodes left unsatisfied when no *fairness-based distribution* is applied, proven in Case 1.

The optimality is to maintain higher satisfaction rates and the optimal overall cost; thus, SL cost should equal to the other components in objective 1, studied in Case 2. By setting the SL cost similar to other components in objective 1, the model helped to reduce the impacts of the disruption and ensured that most of the demand nodes obtain the minimum required SL and be provided at the minimum with the least amount of the available commodities immediately after the disruption occurred.

2.5 CONCLUSIONS AND FUTURE WORK

Due to interdependencies between transportation and supply chain networks (SCN), SCN become more susceptible to disruptive events. As a result, SCN decision-makers or firms must develop strategies that help to reduce the impact of disruptions and improve the SCN performance and overall resilience. Several studies have suggested using traditional risk management strategies in order to mitigate SCN disruptions (Jüttner and Maklan, 2011). However, unexpected disruptive events are difficult to mitigate using traditional risk management techniques (Pettit, Fiksel and Croxton, 2010). In some cases, the SCN are highly susceptible to disruption due to lower redundancy in the SCN and its associate transportation network. For example, Colombia transportation network has a low redundancy, so small disruptions may disconnect several cities. Therefore, it is important to have an immediate plan to distribute the available resources fairly to reduce the impact of the disruption.

2.5.1 *MAIN CONCLUSIONS*

In this chapter, we developed a multi-criteria mixed-integer programming model in order to mitigate and reduce the impact of disruption on SCN. The model distributes the available recourses fairly after unpredicted events or capacity reduction occur so that the number of demand nodes that do not receive the minimum required SL get reduced. Furthermore, the model has been developed not only to deal with disruptions but also to deal with any fluctuation occurs in the SCN capacity as a result of unpredicted events. The results show that the model efficiently helped to fairly distribute the available resources such that most of the demand nodes receive their minimum requirements. After running the model for different scenarios at different capacity reduction levels and different SL, the *fairness-based* solution provided better distribution strategies to cover most of the demand nodes.

2.5.2 *MANAGEMENT INSIGHT*

This chapter provides a significant insight into distributing the available resources after a disruptive event. The SCN decision-makers must deal with diverse disruptive events in the underlying transportation network; however, restoration of the transportation network after disruptive events is often not within the SCN decision-makers' control. Thus, this study centers on providing efficient distribution plans that consider the state of the transportation network after a disruptive event, so that the overall distribution costs are minimized, while an equitable distribution of commodities is procured. From our analysis we can see that applying a fairness-based distribution strategy reduces the number of unsatisfied customers and reduces the percentage of unmet demand for each commodity at each demand node. The SCN decision-makers can apply the fairness-based distribution strategies to keep most of the customers connected to the suppliers, by providing a certain amount of SL until the system returns to normal performance. Moreover, the SCN decision-makers can apply a fair distribution to increase the satisfaction rate of the SCN performance by maintaining the required SL at each customer when the available commodities are not enough to fulfil the entire demand in the network.

The insights provided by this chapter can be of great value to not only SCN stakeholders but also local governments, so that they can develop a set of incentives (and/or penalties) to promote the cooperation of SCN decision-makers from different regions and economic sectors to work jointly toward an equitable distribution of commodities and resources. Since the customers in our studies represent the people who live in the cities, procuring a fair distribution of commodities and resources after a disruptive event (where resources are scarce) will help to enhance the capacity of SC decision-makers to supply the population with the minimum required SL, in order to cover the basic needs of the population. A fair and equitable accessibility to commodities and general resources is actively sought by diverse state and federal entities, including the Department of the Transportation of the United States (2012) and Federal Highway Administration of the United States (2012), as it improves the resilience of the communities and the wellbeing of the population (Martens & Golub 2018).

2.5.3 *LIMITATIONS AND FUTURE WORK*

The proposed model could be extended in multiple directions. The developed model in this article is static, and it is developed to deal with the immediate impacts of the disruption without considering time recovery plans. Thus, the model could be improved by considering a recovery plan that considers time-dependent changes during the restoration phase after a disruptive event. Also, the model was developed to deal with disruption in the downstream section of the SCN. Therefore, the model could be expanded to deal with additional echelons, by considering the disruption and uncertainty at different stages of the SCN. Another factor that could be added to the model is calculating the required inventory level at each supplier node so that suppliers could reduce the impact of disruption and uncertainty in the network and increase the SCN resiliency.

CHAPTER 3: FAIR RESTORATION PLANS TO IMPROVE SUPPLY CHAIN NETWORK RESILIENCE[2]

3.1 INTRODUCTION

The contribution of this work focuses on designing a mathematical model for optimal restoration that reduces the impacts of unpredicted events that disturb the performance of the road transportation network and propagate to other dependent networks such as SCNs while considering a fair distribution of commodities between demand nodes and economic sectors. The concept of *fairness-based distribution* was explored by Abushaega et al. (2021), where the authors showed that implementing *fairness-based distribution* strategies improved the overall satisfaction rate in post-disruption scenarios. The impacts of disruptions were reduced significantly by maintaining the minimum required service level at most demand nodes (Abushaega et al., 2021). However, their study did not consider the restoration processes and how travel times are affected by the disruptions in the road transportation network. In this chapter, we focus on the SCN resilience in post-disruption events and how the SCN performance changes while the road transportation network is restored. For this purpose, in this chapter we propose a multi-criteria nonlinear mixed integer programming (NMIP) model optimally restore the disrupted components in the road transportation network, while simultaneously optimizing the fair distribution of commodities in the SCN for enhanced performance and service levels. The proposed model deals with a multi-supplier, multi-demander, and multi-commodity framework with shared transportation capacities. The model provides

[2] The content in Chapter 3 was submitted as a journal paper, titled "Fair Restoration Plans to Improve Supply Chain Network Resilience", in the Reliability Engineering and Systems safety Journal.

two different restoration plans to recover the road transportation network. One of the restoration plans considers the number of unmet demand quantity (a cost-effectiveness approach) only. In contrast, the other one considers the *fairness-based distribution* added to the cost-effectiveness approach. Most of the restoration studies have been designed to restore the disrupted components based on a cost-effectiveness perspective (as discussed in Section 3.2). However, it is imperative to simultaneously consider fairness metrics (Zheng et al., 2019) for improved socio-economic effects throughout the entire population.

This chapter is structured as follows: Section 3.2 presents a literature review of restoration models for transportation networks and SCN, as well as the consideration of fairness in this context. The proposed model is detailed in Section 3.3. In Section 3.4, then we present the results and analyses associated with an illustrative case study: the transportation of goods in Colombia. Finally, conclusions and future work are discussed in Section 3.6.

3.2 LITERATURE REVIEW

Due to the complexity of the infrastructure networks and the high interdependency on them, researchers have started to explore the impacts of disruptions on such networks and measure the networks' performance. One of the dependent networks that require the road transportation network in order to connect to its customers is the SCN. SCNs highly depends on the transport networks to distribute freights among their customers. However, SCN performance is connected to road transportation network conditions. The need to have a resilient SCN to reduce the impact of disruption in the transportation network is essential and improves the SCN performance. Several studies have explored the area of SCN resilience and provided useful solutions to reduce the impact of disruptions. Also, several studies have defined SCN resilience. Christopher and Peck (2004) defined SC resilience as the SC capability to recover and return to normal performance after being disrupted. Falasca et al. (2008) described SC resilience as SC's ability to reduce the impacts of disruptions and the likelihood of disruption and reduce the recovery process until the SC performance returns to normal status. Two studies which have defined the SC resilience and covered most of the resilience aspects are Ponomarov and Holcomb in 2009 and Kamalahmadi and Mellat-Parast in 2016. Ponomarov and Holcomb (2009) described the SC resilience as the SC capability to prepare for unpredicted disruptions and the ability to restore the SC performance to the desired level of SC connectedness in the entire entities that will ensure the continuity of the system operation. Kamalahmadi and Mellat-Parast (2016) defined SC resilience as the system capability to adapt to reduce the dealing disruptive events, resist the impact of the disruption spreading, and fast recovery based on effective plans to restore the SC performance. In this proposal, we combine Ponomarov and Holcomb's definition (2009) and Kamalahmadi and Mellat-Parast (2016). We define the SCN resilience as the ability of the system to adapt and reduce the effects of disruptive events and uncertainty while maintaining the desire SL at most of the demanders until the system return to the normal status.

The SC resilience has not been explored extensively, especially from the quantitative aspects. Most of the SC resilience are qualitative studies and did not include the mathematical models or operation research tools to measure SC resilience. Fiksel (2003) surveyed how SC companies or decision-makers react to disruptions in order to keep the competitiveness performance. Tukamuhabwa et al. (2015) provided a paper that focuses on reviewing conceptual studies that could improve SC resilience. Another study was conducted by Kamalahmadi and Mellat-Parast (2016) to analyze the existing definition of SC resilience and the principles of SC resilience. On the other hand, several surveys have illustrated the importance of using quantitative studies to measure the effects of disruptions on the SC performance (Fahimnia et al., 2015a, and Snyder et al., 2016). A systematic review was conducted by Hosseini, Ivanov, and Dolgui (2019) to analyze the quantitative studies that deal with SC resilience. They covered most of the mathematical aspects that were used to improve SC resilience. From the outcome of their research, we can conclude that none of the researchers has considered developing a mathematical model that helps to reduce disruptions' impacts by providing a *fairness-based restoration or distribution* plan to improve the SC resilience considering a multi-commodity framework.

The heavy reliance of SC on infrastructure networks in distributing products raises the awareness of securing those networks against disruptions. Unfortunately, protecting infrastructure networks is not always possible against natural disasters or human-made disruptive events. For instance, the impacts of several disruptions recently occurred that have resulted in devastating damages to the transportation networks and systems in different places and countries were considered. Therefore, researchers have been analyzing those impacts and their nature on the performance of the transportation network. Various natural disruption types have disturbed the transportation network's performance significantly, for instance, earthquakes, landslides, and storms. Numerous studies have conducted in order to examine the impacts of post-earthquakes' events on the road transportation network and infrastructure networks and introduce frameworks that measure networks' vulnerabilities (e.g., Feng, Li, & Ellingwood, 2020; Park et al., 2001; and Alipour & Shafei 2016; Ransikarbum & Mason 2016; and Kermanshah & Derrible 2016). Also, researchers have studied the impacts of landslides and rainstorms on the performance of infrastructure networks (e.g., Sassu et al., 2017; and Postance et al., 2017). The mentioned studies have examined the functionality of their models considering a specific disruption type; however, in our study, we design a model in such a way to deal with any disruption that obstructs the connectivity of the road transportation network and reduce their capacities. So, it is essential to have effective restoration planes that provide specific strategies to schedule and prioritize the recovery processes in case a disruption occurs. Several studies have developed restoration strategies to restore infrastructure networks. Guha et al. (1999, May) proposed an approximation algorithm that helps restore the power network and minimize the required time to reconnect the demand sites. Lee et al. (2007) illustrated a mathematical model that aims to minimize the restoration cost of the disrupted elements in the infrastructure networks. One of the limitations that were not covered in Lee et al. (2007) was to assign tasks to the work crews. Gong et al. (2009) used the result of Lee et al. (2007) and considered assigning the repair crews in the model. Kalinowski et al. (2015) developed a mathematical model that focuses on maximizing the flow while restoring one arc at each time period. Nurre and Sharkey (2014) developed a model that focuses on dispatching the work crews. The model has four different categories: maximizing the flow, minimizing the total costs, finding the shortest path the crews can use, and finding the minimum spanning tree.

These studies have considered restoring each network individually and have not covered the interdependency between networks.

Several researchers have developed restoration models to recover infrastructure networks' performance and consider the interdependency between several networks. Studying the effects of disruption on the water, power, gas networks, and the interdependency between them has been done by (González et al., 2016; and Gomez et al. 2019). González et al. (2016) considered not only the physical interdependency between the networks but also the geographical interdependency and how each one is affected by one network being disrupted. Gomez et al. 2019 extended the work González et al. (2016) and considered the socioeconomic aspect in the recovery processes to improve infrastructure resilience. Another study that explored the interdependency between infrastructure networks considers the limitations of work crews' availability and how long the system would take to be restored. They focused on recovering the networks' performance to the normal status by reducing the unmet demand amount in the networks before and after the disruptions occur (Almoghathawi, Barker, & Albert, 2019). These studies focused on examining the disruption effects of infrastructure networks and designed mathematical restoration models. However, they did not include the road transportation network and its effect on the performance of other dependent networks.

Due to the importance of the road transportation network, several researchers have conducted studies to develop restoration programming models considering different types of disruption. Some researchers developed mathematical models to deal with post-event disruptions caused by storms (Liu et al., 2007; and Ramachandran et al., 2015). Ramachandran et al. (2015) proposed a framework that aims to reduce the restoration time of the SC strategic infrastructure components. They developed a restoration model that seeks to increase the connectivity between nodes while restoring the disrupted components. Gong et al. (2014) developed a restoration model that deals with the interdependencies of several infrastructure networks and a SCN in order to increase the resilience of the SCN. Their model is developed to assist SCN decision-makers in getting benefits of other networks' restoration plans to increase the SCN resilience (Gong et al., 2014). Another study is conducted by Gedik, Medal, Rainwater, Pohl, & Mason, (2014) to develop a restoration model for a railroad network to improve the SCN resilience against disruptions. The objective was to identify the critical components in the network, and how they can reduce the SCN performance in case they get disrupted (Gedik et al., 2014).

Some studies consider the restoration of the road transportation infrastructure network; thus, other service networks such as SCN can be resilient to disruptive events. Miller-Hooks, E. (2012) developed a mathematical model that aims to improve road transportation infrastructure network resilience. The model considers the limited budget to improve the current system (Miller-Hooks, E., 2012). Hishamuddin, Sarker, and Essam (2013) developed an integer nonlinear programming model to define the optimal production and order quantities for the supplier and retailer and the time it takes to recover subject to transportation disruptions. They considered the disruption occurs to the shipments while delivering them. They used a simple SC series with one supplier and one retailer and assumed the demand to be deterministic. Another study, published in 2011, was about developing a framework that helps evaluate the infrastructure network's resilience by analyzing two hypothetical scenarios of hurricanes happening in two different cities and measuring the effect on a petrochemical SCN (Vugrin, Warren, & Ehlen, 2011). They used quantitative and qualitative measures to analyze the effects of the disruption. A recent study was conducted to design a restoration plan based on the cost-effectiveness perspective and the resilience perspective (Mao et al., 2020). They developed a bi-objective nonlinear programming model aiming to maximize the network resilience using two metrics: resilience of cumulative loss and restoration rabidity resilience. Their results show that it is essential to have more than one resilience metric in order to restore the network performance.

Since most of the studies in restoring infrastructure networks focused on restoring the unmet demand in the network, the models focus on restoring the nodes with the highest demands that leaf the nodes with less demand have less impact in the restoration processes. Based on the explored studies, none has integrated the *fairness-based distribution* in the restoration processes as part of the optimization model; thus, the nodes with the highest demand are not restored first while neglecting other demand nodes. Unlike other studies that focus on restoring the total unmet demand in the network (e.g., González et al., 2016; Almoghathawi et al., 2019), we aim to minimize the total unmet demand in the SCN, maximize the number of satisfied demand nodes considering the *fairness-based distribution*, minimize the total travel time, and return the SCN performance to the normal level after restoring the disrupted components in the road infrastructure network. In our study, all demand nodes should be treated fairly during the recovery time; thus, each demand node receives at least a portion of the demand, which is the minimum required service level (SL) until the network performance is fully restored.

3.3 FRSCN MODEL

3.3.1 *MODEL ASSUMPTIONS AND DISCUSSION*

In order to design and develop this *fairness-based restoration* SCN (FRSCN) model, several assumptions have been considered, and they are addressed in this section. The first assumption is that the model deals only with disruption downstream of the SCN. Second, the model allows us to have stocks at supplier nodes; however, the stock level is not used in the second shipment. Also, the connection between the road transportation infrastructure decision-makers and the SCN decision-makers is centralized. Thus, the SCN decision-makers are aware of the restoration plans that are suggested by road transportation network management.

This study aims to develop a model that provides two different restoration plans to restore the disrupted components in the network. The SC decision could then distribute the available commodities among all customers or demanders fairly during disruptive events while recovering the road transportation network. The model is also built to ensure that most demanders receive at least the minimum SL of each commodity based on an agreement between Suppliers and Demanders. The model is designed with a multi-supplier, multi-demander, and multi-commodity framework running through the SCN, and the unmet demand for each commodity at each demand node is calculated. The SL plays a key role in the model to determine the system's efficiency by at least maintaining the minimum required SL at the demand nodes. This model deals with unpredicted events in the downstream (road transportation network) of the SCN, as shown in Figure 3-1. Supply Chain Network. The model also deals with a multi-supplier and a multi-demander for different commodities that share the same road transportation network simultaneously, as shown in Figure 3-2.

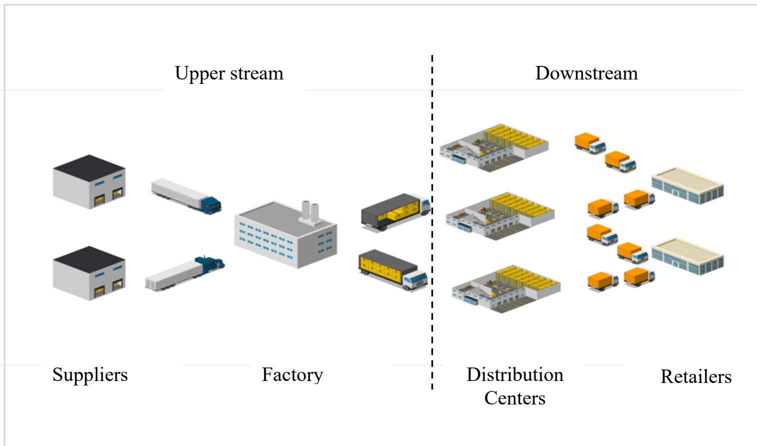

Figure 3-1. Supply Chain Network

3.3.2 *MODEL DESCRIPTION:*

The objective of this study is to design a mathematical model that helps to improve the SC resilience post-disruption providing a *fairness-based distribution* to restore the SCN infrastructure network. Disruptions in road transportation network impact flows of commodities; thus, the travel time increases based on the road connectivity and functionality. The model has two objectives. The first objective, Eq. (3-1), aims to minimize the travel time of moving from node *i* to node *j* for commodity *l* for each time period *t* ($\boldsymbol{x_{ijlt}}$). ψ_{ijt} represents any convex delay volume function (DVF) or travel time function. Several DVFs that measure the effects of congestion when traveling between two nodes or points. Bureau of Public Roads (BPR) has been used widely in road transportation studies when considering congestion (United States. Bureau of Public Roads, 1964). The original Davidson function is also one of the travel time functions that measure travel congestion (Taylor, M.A.P. 1997). Two other functions that are used widely in the research are Akcelik delay function, which was developed by Akcelik, R. (1991), and Conical delay function (Spiess, H. 1990). However, in this study, we used the BPR function to examine the impacts of disruptions on the total required travel time.

Table 3-1. Sets

$\mathcal{N}$	Set of nodes
$\mathcal{A}$	Set of arcs
$\mathcal{T}$	Set of periods for recovery processes
$\mathcal{L}$	Set of commodities
$\mathcal{N}_d^l$	Set of demand nodes
$\mathcal{N}_s^l$	Set of suppliers' nodes
$\mathcal{E}$	Set of Intervals

Table 3-2. Parameters

α_{il}	Minimum required Service level at node $i \in \mathcal{N}_d^l$ for commodity l
b_{il}	Net flow at node i for commodity l
c_{ijl}	Flow Cost per mile of using arc $(i, j) \in \mathcal{A}$ for commodity l
ω_l	Weight of commodity l that will be shipped
u_{ij}	Capacity of arc $(i, j) \in \mathcal{A}$
f_{ilt}^-	Cost of unmet demand at node $i \in \mathcal{N}_d^l$ for commodity l at time t
f_{ilt}^+	Cost of excess supply at node $i \in \mathcal{N}_s^l$ for commodity l
γ_t	Total percentage of unmet demand for all commodities at time t
a_{ij}	Ideal travel time from node i to node j
p_{ijt}	Usage of resources to restore arc (i, j) at time t
$\hat{u}_{ijt}$	Intervals capacity of arc (i, j) at time t
$\hat{\psi}_{ijt}$	Intervals of travel time function of arc (i, j) at time t

Table 3-3. Decision Variables

s_{ilt}^-	Unmet demand at node $i \in \mathcal{N}_d^l$ for commodity l at time t
s_{ilt}^+	Excess supply at node $i \in \mathcal{N}_s^l$ for commodity l at time t
x_{ijlt}	Amount of flow through arc $(i, j) \in \mathcal{A}$ for commodity l at time t
y_{ijt}	A binary parameter {0,1} 1 if arc is operational at time t ; and 0 otherwise

$\hat{y}_{ijt}$	A binary variable {0,1} 1 if arc (i, j) is to be restored at time t; and 0 otherwise
δ_{ilt}	A binary variable {0,1} 1 if a node $i \in \mathcal{N}_d^l$ did not get minimum service level at time t ; and 0 otherwise
μ_{ilt}^{-}	Negative deviation from the total percentage of unmet demand at node $i \in \mathcal{N}_d^l$ for commodity l at time t
μ_{ilt}^{+}	Positive deviation from the total percentage of unmet demand at node $i \in \mathcal{N}_d^l$ for commodity l at time t
z_{ijt}	Travel time from node i to node j at time t
ϕ_{ijt}	New Travel time from node i to node j at time t

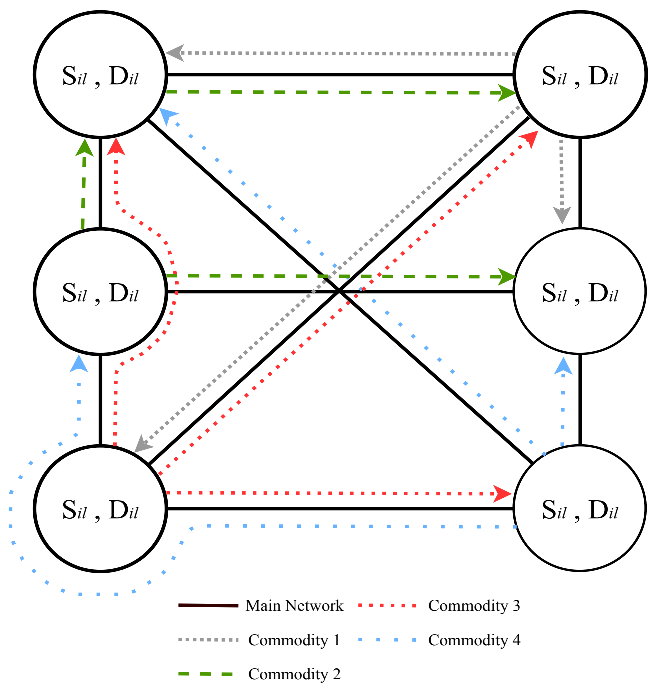

Figure 3-2: Re-configurated SCN

minimize

$$O1 = \sum_{t \in \mathcal{T}} \sum_{(i,j) \in \mathcal{A}} \sum_{l \in \mathcal{L}} \psi_{ijt}\, x_{ijlt} \tag{3-1}$$

The second objective, Eq (3-2), represents the total penalty costs associated with mot delivering the required demand to customers. Eq. (3-2) consists of three different components. The first one is the penalty cost of having shortage or unmet demand at each demand node ($s_{ilt}^{-}\ f_{ilt}^{-}$), and the second component is the penalty cost of having oversupply at each supply node ($s_{ilt}^{+}\ f_{ilt}^{+}$) for each commodity at each time period, which represents the second and third terms respectively. The third component is the cost of the percentage deviation in the SCN concerning the unmet demand at each demand node for each commodity for each t period ($\beta \left(\frac{\sum_{i \in \mathcal{N}_d^l} (\mu_{ilt}^{-} + \mu_{ilt}^{+})}{|\mathcal{N}_d^l|} \right)$). In this objective, the restoration plan is influenced by which component has more weight in making the restoration plan's decision.

minimize

$$O2 = \sum_{t \in \mathcal{T}} \sum_{l \in \mathcal{L}} \left(\sum_{i \in \mathcal{N}_d^l} f_{ilt}^{-}\, s_{ilt}^{-} + \sum_{i \in \mathcal{N}_s^l} f_{ilt}^{+}\, f_{ilt}^{+} + \beta \left(\frac{\sum_{i \in \mathcal{N}_d^l} \mu_{ilt}^{-} + \mu_{ilt}^{+}}{|\mathcal{N}_d^l|} \right) \right) \qquad (3\text{-}2)$$

The third Objective, Eq. (3-3), represents the available budget to restore the disrupted components. The road transportation management provides this budget. Thus, it is switched to be a constraint in the model since the SCN managements are not enveloped in making the decision on which component to be restored first. As a result, all the restoration constraints are limited by the Eq. (3-3) which will be assumed in this study.

$$O3 = \sum_{t \in \mathcal{T}} \left(\sum_{(i,j) \in \mathcal{A}} (\hat{y}_{ijt} - Y_{ij}^{0}) g_{ijt} \right) \tag{3-3}$$

The next constraint is Eq. (3-4) the flow balanced constraint, which calculates the amount of the flow moving in and out each node for each commodity at each time period (x_{ijlt}). The amount of the flow depends on the capacity of each node (b_{il}). Also, this constraint calculates the quantity of unmet demand at each demand node and excess supply at each supplier node presented in the right-hand side of Eq. (3-4) (s_{ilt}^{-}, s_{ilt}^{+}) respectively.

$$\sum_{j:(i,j) \in \mathcal{A}} x_{ijlt} - \sum_{j:(j,i) \in \mathcal{A}} x_{jilt} = b_{il} + s_{ilt}^{-} - s_{ilt}^{+} \begin{cases} -b_{il}, & Demand\ node \quad \mathcal{N}_d^l \subset \mathcal{N} \\ +b_{il}, & Supplier\ node \quad \mathcal{N}_s^l \subset \mathcal{N} \\ 0, & Transhipment\ node\ \mathcal{N}_T^l \subset \mathcal{N} \end{cases} \quad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L}, \forall\, t \in \mathcal{T} \tag{3-4}$$

Eq. (3-5) is developed to ensure the received amount at the demand nodes is at least equal to the minimum required SL for each commodity (α_{il}). The flow is calculated at each demand node for each commodity at each time period. If the flow is less than the SL, then ($\delta_{ilt} = 1$), otherwise 0.

$$\sum_{j:(i,j) \in \mathcal{A}} x_{ijlt} - \sum_{j:(j,i) \in \mathcal{A}} x_{jilt} \leq \alpha_{il} * b_{il}\ (1 - \delta_{ilt}) \qquad \forall\, i \in \mathcal{N}_d^l, \forall\, l \in \mathcal{L}, \forall\, t \in \mathcal{T} \tag{3-5}$$

The links capacity and how much each commodity has in the shipment are presented in Eq. (3-6). This constraint ensures that the total flow of each commodity at each time period will not exceed the link capacity if the link is operational (y_{ijt}). (y_{ijt}) indicates if the link is operational or not.

$$\sum_{l\in\mathcal{L}} \omega_l * x_{ijlt} \leq u_{ij} * y_{ijt} \qquad \forall\,(i\,,\,j) \in \mathcal{A}, \forall\, t \in \mathcal{T} \tag{3-6}$$

Eq. (3-7) represents the total percentage of unmet demand for all commodities at each time period. The importance of calculating the total percentage of unmet in the SCN is that the percentage of unmet demand at each node will be balanced, as presented in Eq.(3-8). If the total unmet demand percentage is larger than the percentage of unmet demand at the demand node then (μ_{ilt}^{-}, μ_{ilt}^{+}) will be equal to the deviation of the two value to meet the equality to zero.

$$\frac{\sum_{i\in\mathcal{N}_d^l}\sum_{l\in\mathcal{L}} s_{ilt}^{-}}{\sum_{i\in\mathcal{N}_d^l}\sum_{l\in\mathcal{L}} b_{il}} = \gamma_t \qquad \forall\, t \in \mathcal{T} \tag{3-7}$$

$$\left(\frac{s_{ilt}^{-}}{b_{il}}\right) - \gamma_t + \mu_{ilt}^{-} - \mu_{ilt}^{+} = 0 \qquad \forall\, i \in \mathcal{N}_d^l, \forall\, l \in \mathcal{L}, \forall\, t \in \mathcal{T} \tag{3-8}$$

The restoration processes are subjected to six constraints. The first one is Eq. (3-9), which equalizes the variable y_{ij1} to the disruption scenario. As a result, the links' capacities changes based on the disruption level. Eq. (3-10) is to ensure that the value of the disruption cannot exceed 1. Eq. (3-11) shows that the link y_{ijt} is equal to the y_{jit} in order to equalize links conditions. Each time period, only one component can be fixed, as shown in Eq. (3-12). Since the road condition in both directions is equal, as stated in Eq. (3-11), two links need to be fixed in each recovery period in case of disruption as demonstrated in Eq. (3-13). To ensure that the functionality of the link is being restored once, and the link functionally does not become worse than the time period before, the model is constrained to Eq. (3-14).

$$y_{ij1} = Y_{ij}^{0} \qquad \forall\, (i\,,\, j) \in \mathcal{A}, \forall\, t \in \mathcal{T} | t = 1 \qquad (3\text{-}9)$$

$$y_{ijt} \; \leq 1 \qquad \forall\, (i\,,\, j) \in \mathcal{A}, \forall\, t \in \mathcal{T} \qquad (3\text{-}10)$$

$$y_{ijt} \; = \; y_{jit} \qquad \forall\, (i\,,\, j) \in \mathcal{A}, \forall\, t \in \mathcal{T} \qquad (3\text{-}11)$$

$$\sum_{t \in \mathcal{T}} \hat{y}_{ijt} \; \leq 1 \qquad \forall\, (i, j) \in \mathcal{A} \qquad (3\text{-}12)$$

$$\sum_{(j,i) \in \mathcal{A}} \hat{y}_{ijt} \; \leq 2 \qquad \forall\, t \in \mathcal{T} | t > 1 \qquad (3\text{-}13)$$

$$y_{ijt} \leq Y_{ij}^{0} + \sum_{\acute{t}=1}^{t} \hat{y}_{ij\acute{t}} \qquad \forall\, (i, j) \in \mathcal{A},\; t \in \mathcal{T} | t > 1 \qquad (3\text{-}14)$$

Eqs. (3-15)-(3-23) represents each decision variable’s nature, indicating if they are nonnegative, continuous, or binary. The following up tables represent the sets, parameters, and decision variables used to design the mathematical model described before. The meaning of each parameter and to which set it belongs is addressed in Table 3-1, Table 3-2, and Table 3-3.

$x_{ijlt} \geq 0 \qquad \forall (i,j) \in \mathcal{A}, \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \qquad (3\text{-}15)$

$s^{+}_{ilt} \geq 0 \qquad \forall i \in \mathcal{N}^{l}_{s}, \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \qquad (3\text{-}16)$

$s^{-}_{ilt} \geq 0 \qquad \forall i \in \mathcal{N}^{l}_{d}, \forall l \in \mathcal{L}, \forall t \in \mathcal{T} \qquad (3\text{-}17)$

$\gamma_{t} \geq 0 \qquad \forall t \in \mathcal{T} \qquad (3\text{-}18)$

$\mu^{+}_{il} \geq 0 \qquad \forall i \in \mathcal{N}^{l}_{d}, \forall l \in \mathcal{L} \qquad (3\text{-}19)$

$\mu^{-}_{il} \geq 0 \qquad \forall i \in \mathcal{N}^{l}_{d}, \forall l \in \mathcal{L} \qquad (3\text{-}20)$

$\delta_{il} \in \{0, 1\} \qquad \forall i \in \mathcal{N}^{l}_{d}, \forall l \in \mathcal{L}, \qquad (3\text{-}21)$

$y_{ijt} \in \{0, 1\} \qquad \forall (i,j) \in \mathcal{A}, \forall t \in \mathcal{T} \qquad (3\text{-}22)$

$\hat{y}_{ijt} \in \{0, 1\} \qquad \forall (i,j) \in \mathcal{A}, \forall t \in \mathcal{T} \qquad (3\text{-}23)$

3.3.3 *PIECEWISE APPROXIMATION*

Due to the large computational time resulted because of the non-linearity in the first objective $O1$, Eq. (3-1), applying the piecewise approximation was required. The new objective and linearized constraints will be stated next. The new objective after linearizing the first term of Eq. (3-24) is to minimize the required travel time to deliver most of the required demands to the customers' sites.

minimize

$$\widehat{O1} = \sum_{t \in \mathcal{T}} \sum_{(i,j) \in \mathcal{A}} \phi_{ijt} \qquad (3\text{-}24)$$

This new objective is presented in Eq. (3-24) subjected to several constraints. Eq. (3-25) represents the intervals ($\hat{u}_{ijte_2}$) of the links' capacities while Eq. (3-26) represents the intervals in the travel time ($\widehat{\psi}_{ijte_1e_2}$) when moving certain quantities of frights. Eq. (3-27) helps to determine the slope between the flow and the travel time. Those intervals are determined based on the original capacity and ideal travel time in the ideal situation when there is no disruption, as shown in Figure 3-3. The more the intervals, the more accurate the solutions. Eqs. (3-28) and (3-29) represent the nature of the variables.

$$\sum_{l\in\mathcal{L}} x_{ijlt} \leq \sum_{e_1\in\mathcal{E}} \sum_{e_2\in\mathcal{E}} \hat{u}_{ijte_2}\ \lambda_{ijte_1e_2} \quad \forall(i,j)\in\mathcal{A}, \forall\, t\in\mathcal{T}, \forall\, e_1e_2\in\mathcal{E} \tag{3-25}$$

$$\sum_{e_1\in\mathcal{E}} \sum_{e_2\in\mathcal{E}} \widehat{\psi}_{ijte_1e_2}\ \lambda_{ijte_1e_2} = \phi_{ijt} \quad \forall(i,j)\in\mathcal{A}, \forall\, t\in\mathcal{T}, \forall\, e_1e_2\in\mathcal{E} \tag{3-26}$$

$$\sum_{e_1\in\mathcal{E}} \sum_{e_2\in\mathcal{E}} \lambda_{ijte_1e_2} = 1 \quad \forall(i,j)\in\mathcal{A}, \forall\, t\in\mathcal{T}, \forall\, e_1e_2\in\mathcal{E} \tag{3-27}$$

$$\lambda_{ijte_1e_2} \geq 0 \quad \forall\,(i,j)\in\mathcal{A}, \forall\,\mathrm{t}\in\mathcal{T}, \forall\, e_1e_2\in\mathcal{E} \tag{3-28}$$

$$\phi_{ijt} \geq 0 \quad \forall\,(i,j)\in\mathcal{A}, \forall\,\mathrm{t}\in\mathcal{T} \tag{3-29}$$

3.3.4 *SATISFACTION RATE (PERFORMANCE METRIC):*

Numerous studies have developed their performance measures in order to measure their models' efficiencies. The resilience measure is one of the well-studied measures in the literature. In this study, we use the SL as a performance measure from which we measure the SCN resilience. The number of unsatisfied demanders is calculated at each recovery time and, the smaller the number, the higher the SL. The satisfaction rate ($\mathcal{R}_t$) is addressed in Eq. (3-30). The obtained result of Eq. (3-30) is within {0,1}. The closer to the {1}, the higher the ($\mathcal{R}_t$). Thus, we define the ($\mathcal{R}_t$) as the total percentage of satisfied demanders in the SCN at each time period before and after the disruption occurs.

$$\mathcal{R}_t = \frac{\sum_{i\in\mathcal{N}_d^l}\sum_{l\in\mathcal{L}}(1-\delta_{ilt})}{|\mathcal{N}_d^l|} \qquad \forall\, t \in \mathcal{T} \qquad (3\text{-}30)$$

$$\mathcal{R}_t \begin{cases} \mathcal{R}_t = 1, & \text{at least the SL is maintained} \\ \mathcal{R}_t < 1, & \text{otherwise} \end{cases}$$

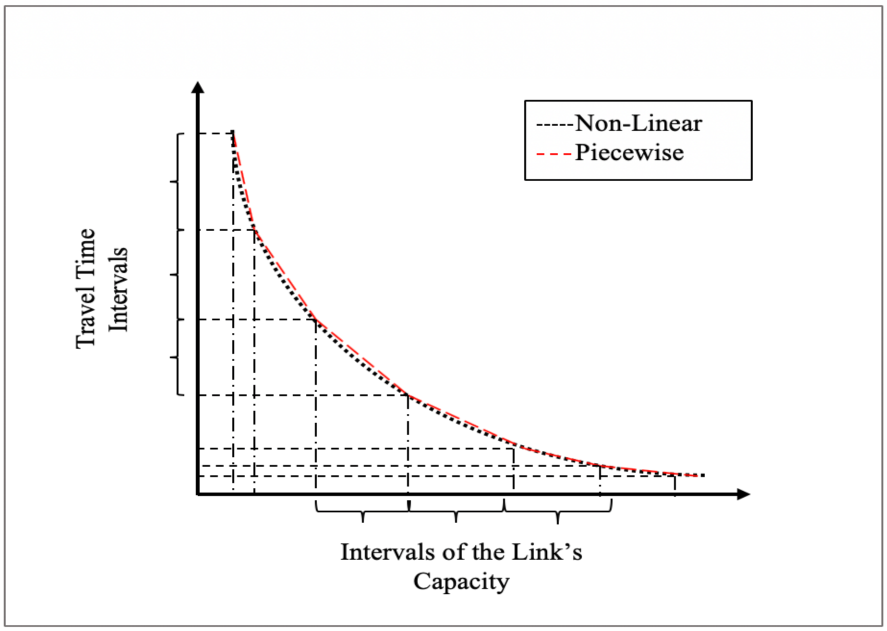

Figure 3-3: Piecewise approximation

3.4 CASE STUDY

In this chapter, the Colombia Road Transportation Network and the flow of moving fright between its cities are being examined to measure the model efficiency. The SCN heavily depending on the road network to disrepute commodities to different cities (Demanders). The network is highly susceptible to disruptive events due to the geography of the country. Most cities are located in mountains that make the road network less redundant.

Moreover, the cities are easy to isolate when a disruption occurs, causing damage to the road transportation network. The SC decision-makers depend on vehicles to distribute freights within the country.

The network consists of 51 nodes (major cities) and 57 arcs (roads) undirected (114 arcs). There are 258 commodities considering the Colombia SC running through the network and being clustered into six sectors (Clavijo-Buritica, et al., 2021). Those commodities are required to be supplied to the right demanders. Each sector has different suppliers, demanders, and required quantity. Each node can be a supplier, a transshipment, and a demand node for different commodities. Table 3-4 represents each sector's information regarding the number of suppliers and demanders and the total required resources being required by the customers. The Colombia road transportation network is presented in Figure 3-4. In this case study, we examine the effects of disruptive events at different severity levels in the road transportation network on the performance of the SCN. We are also examining the effectiveness of the proposed model on restoring the disrupted components that keep most of the demanders satisfied by receiving a particular SL until all components are restored by considering two different restoration plans: no *fairness-based distribution* and with *fairness-based distribution*. The penalty costs of unmet demand and over-supply are assumed.

Due to Colombia's road transportation network properties, we are using the BPR travel time delay function. Most of the roads in Colombia are within mountains; thus, the road capacity is limited to one lane in each direction. The more the truck on the road, the higher the travel time and higher congestion. The two objectives are subjected to some constraints and boundaries. The first constraint Eq. (3-31) the travel time to move the frights from node *i* to node *j*. This time function is called the Bureau of Public Roads (BPR) (United States. Bureau of Public Roads, 1964). The BPR function has been used widely and considered in many research papers (e.g., Hajibabai & Ouyang, 2013; and Tan, Yang, & Zhang, 2017). There is an ideal travel time which is a_{ij}. When the link capacity reduces, the travel time increases accordingly, and when the link capacity returns to its normal condition, the travel time is equal to the ideal travel time.

$$\psi_{ijt} = z_{ijt} = a_{ij} * \left(1 + \mathrm{A}\left(\frac{x_{ijlt}}{u_{ijt}}\right)^{\mathrm{B}}\right) \quad \forall\,(i\,,\,j) \in \mathcal{A}, \forall\, l \in \mathcal{L}, \forall\, t \in \mathcal{T} \tag{3-31}$$

Table 3-4. The Colombia SCN information

Commodity	**Number of Supply Nodes**	**Number of Demand Nodes**	**Total available resources of all commodities (in Tons)**	**Total required demand for all commodities (in Tons)**	**Total Number of Nodes**
1	19	23	24,779	24,779	51
2	5	7			
3	7	16			
4	10	32			
5	12	35			
6	23	28			

Figure 3-4. Road transportation network of Colombia

3.5 RESULTS AND DISCUSSION

3.5.1 *RESULTS*

In order to conduct this study and examine the efficiency of the proposed model, three different disruption categories were applied: small disruption (10% of the links are disrupted), moderate disruption (20% of the links are disrupted), and large disruption (30% of the links are disrupted). Each category level is generated 100 times with different selections of the disrupted components. The model starts by calculating the unmet demand at each demand node for each commodity before the disruption occurs. After the disruption occurs, the model starts to provide a restoration plan in order to reduce the impact of the disruption on the demanders. The model is run twice for each disruption category level considering the *fairness-based distribution* and *no fairness-based distribution* when restoring the disrupted links in the road transportation network.

In order to measure the model performance, we calculate the percentage number of unsatisfied demanders for all commodities in the SCN when the disruption occurs and during the recovery processes for both restorations approaches. Then we calculate the relative improvement (RI) when we apply the *fairness-based distribution* approach compared to the restoration results based on the cost-effectiveness approach using Eq. (3-32) (Yao, Mandala, & Do Chung, 2009).

$$RI = \frac{\sum_{t \in \mathcal{T}} \mathcal{R}_t \ without\ Fairness - \sum_{t \in \mathcal{T}} \mathcal{R}_t \ with\ Fairness}{\sum_{t \in \mathcal{T}} \mathcal{R}_t \ without\ Fairness} \tag{3-32}$$

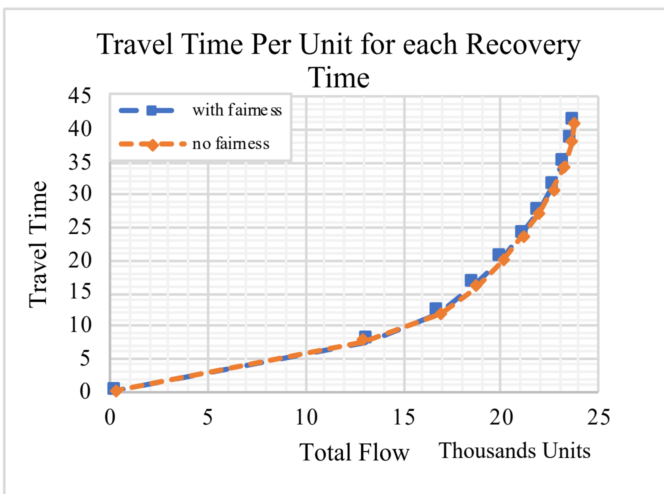

Figure 3-5. The average travel time of commodities during the recovery time (10% Disruption Level)

Table 3-5. Average Percentage of Unsatisfied Demanders (10% Disruption Level)

Pareto Points	**Without Fairness**	**With Fairness**	RI**(%)**	POF**(%)**
1	10.19	1.25	87.72	1.18
2	11.45	1.28	88.87	1.38
3	15.70	2.05	86.92	1.37
4	17.69	2.37	86.58	1.41
5	20.03	3.33	83.38	1.46
6	21.59	4.14	80.82	1.52
7	24.58	5.34	78.28	1.73
8	24.60	5.51	77.60	1.89
9	27.39	9.30	66.05	2.01
10	37.68	12.05	68.02	2.67
11	100.00	100.00	0.00	-

Another performance that helps to measure the model efficiency is Price of Fairness (POF). The POF was developed to measure the efficiency of implementing the *fairness-based distribution* and its impacts on the system's utilization (Bertsimas, Farias, and Trichakis, 2011). In our study, we used the POF to measure the model performance with respect to the total travel time during the restoration processes, as seen in Eq. (3-33). We defined the POF as the total travel time (TT) with *fairness-based distribution* compared to the TT without *fairness-based distribution.*

$$POF = \frac{TT\ with\ Fairness - TT\ without\ Fairness}{TT\ without\ Fairness} \qquad (3\text{-}33)$$

3.5.1.1 *FIRST SCENARIO*

After generating the random disruption at 10% disruption category level, ten links were disrupted for each run in the 100 times that resulted in reducing the SCN performance and increasing the unmet demand in the network. The tradeoff between the model objectives is presented in Figure 3-6. Figure 3-6 demonstrates the performance of the model's two objectives when there is no *fairnees-based distribution* and with *fairness-based distribution*. The X-axis represents the total travel time, and Y-axis represents the penalty costs associated with not delivering the required demand to the right customers. Figure 3-6 also shows the model performance when considering the satisfaction rate of the demanders at different Pareto frontier points. The points on each line represent the optimal solution for the two objectives and represent the average performance of the 100 runs. The dots line (orange color) demonstrates the performance of the model when considering no *fairness-based distribution* in the model, while the dashed line (blue color) shows the performance of the model when there is the *fairness-based distribution* being applied to enhance the restoration plan. The model shows a higher satisfaction rate when applying the *fairness-based distribution* than the results when no *fairness-based distribution* being applied. At point one, the satisfaction rate illustrates that the *fairness-based distribution* maintained a higher satisfaction rate during the recovery time and kept most of the demanders satisfied by delivering 90% of their required demand until the SCN was restored. Similar behavior was obtained when we examined the model performance at the fifth and ninth points of the Pareto chart. Another performance measure, which is the percentage of supplied quantity to the demanders during the recovery time, is demonstrated in Figure 3-6.

The *fairness-based distribution* and no *fairness-based distribution* supplied the same quantities. However, the *fairness-based distribution* managed to maintain a higher satisfaction rate, as discribed previously. The average percentage of unsatisfied demanders for the 100 runs for all points on the Pareto frontier is demonstrated in Table

3-5. We can see that when applying *fairness-based distribution*, the percentage of unsatisfied demanders are low compared to the results obtained when no *fairness-based distribution* is applied. Also, the improvement of applying the the *fairness-based distribution* is denoted in Table 3-5, as well. The travel time of each restoration plan is demonstrated in Figure 3-5. Figure 3-5 shows each restoration approach’s performance and how the travel time behaves when applying each approach. The average travel time slightly increases (POF) when applying the *fairness-based distribution* due to the focus on maintaining higher satisfaction rates within the demanders, as listed in Table 3-5. The last value is zero due to having zero travel time in the denominator.

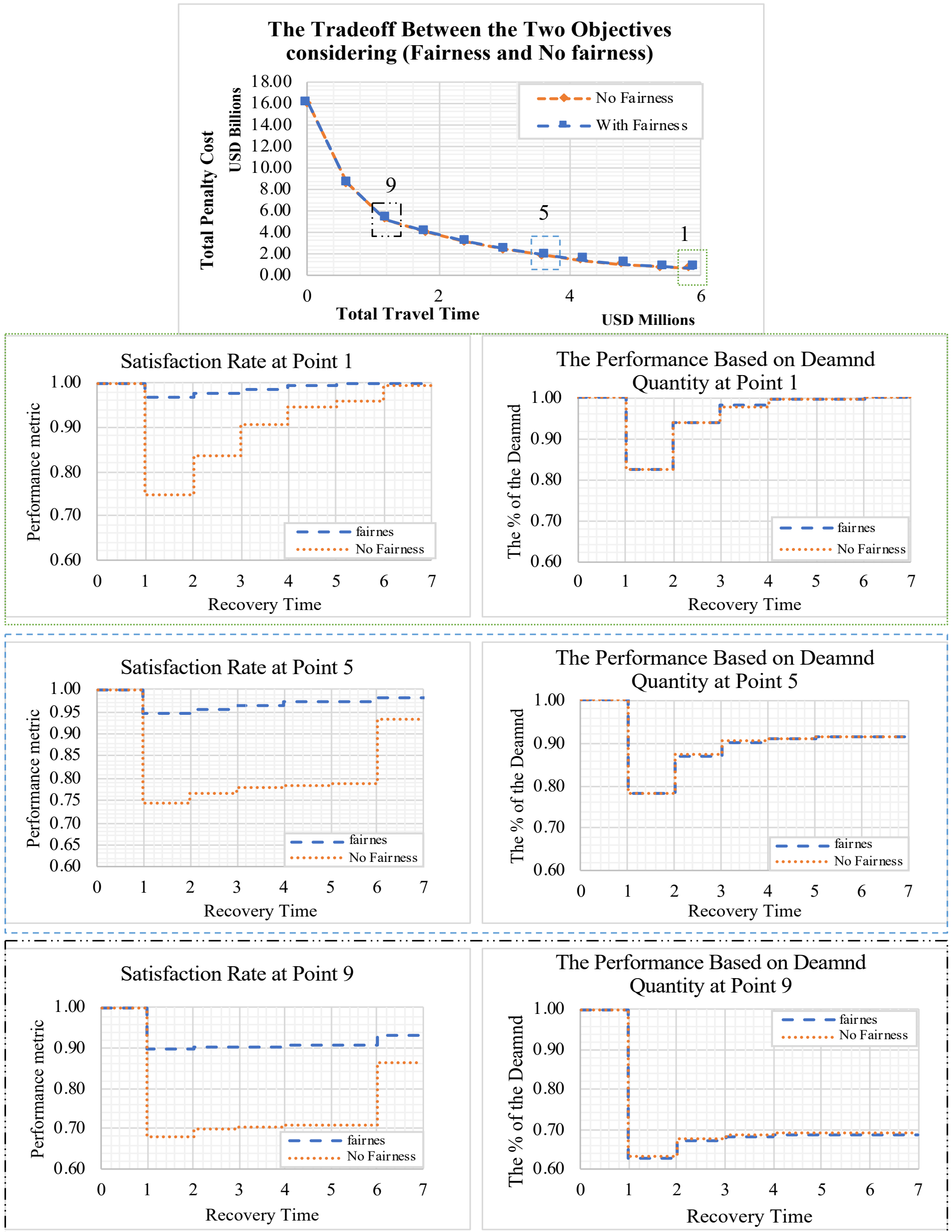

Figure 3-6. The performance of fairness and no fairness distribution at 10% disruption level at three different points on the pareto curve listed in Table 3-5

3.5.1.2 *SECOND SCENARIO*

Similar procedures, as in the first scenario, were followed to run the model and obtain the results in this scenario. The *fairness-based distribution* shows a higher satisfaction rate at all points in the Pareto frontier comparing to the solution when no *fairness-based* *distribution* is applied, as shown in Figure 3-9 subfigures "Satisfaction rate at points 1, 5, and 9." Using the same amount of the supplied quantity at each recovery period, as presented in "*The performance based on Demand Quantity at points 1, 5, and 9*" subfigures in Figure 3-9, allocating the available commodities considering the *fairness-based distribution* results in higher satisfaction rates at all the pareto points for the three selected points. Those subfigures are examples of how the *fairness-based distribution* helps to maintain a higher satisfaction rate. Also, the average percentage of unsatisfied demanders for the 100 runs are presented in Table 3-6. We can observe that the *fairness-based distribution* performed better when looking at the improvement obtained after applying the *fairness-based distribution*, as depicted in Table 3-6. The gap between the *fairness-based distribution* and no *fairness-based distribution* is relatively high because the disruption is moderate, considering that 20% of the available links were not functioning at their optimum capacity. The travel time of each restoration approach is demonstrated in Figure 3-7. The travel time to deliver the required demand quantities for both approaches almost the same, with a slight increase (POF) at the final point of the *fairness-based distribution* result when delivering the maximum quantity of all commodities, as depicted in Table 3-6.

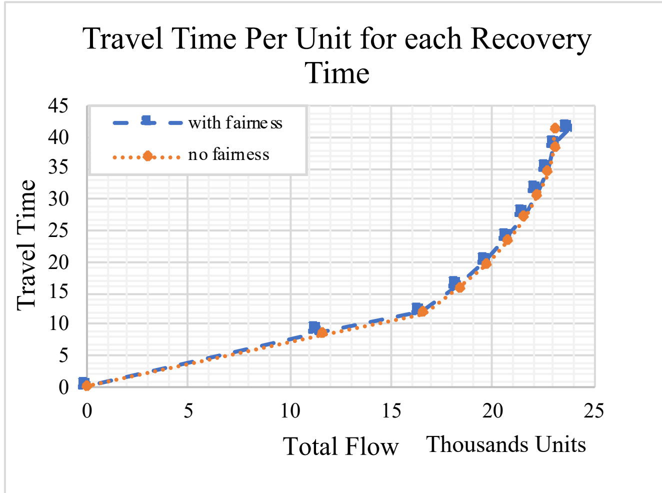

Figure 3-7. The average travel time of commodities during the recovery time (20% Disruption Level)

Table 3-6. Average Percentage of Unsatisfied Demanders (20% Disruption level)

Pareto Points	Without Fairness	With Fairness	*RI*(%)	*POF*(%)
1	14.37	2.34	83.68	0.17
2	14.37	2.35	83.65	1.64
3	17.89	2.64	85.22	1.68
4	20.87	3.20	84.68	1.76
5	23.13	3.94	82.94	1.78
6	25.01	4.79	80.84	1.87
7	27.57	5.92	78.51	2.03
8	27.94	6.14	78.02	2.23
9	30.92	9.82	68.25	2.34
10	41.75	12.32	70.49	3.86
11	100.00	100.00	0.00	-

3.5.1.3 *THIRD SCENARIO*

In the third scenario, the severity of the disruption increased and was considered 30% of the road network. After generating 100 disruption scenarios at a 30% severity level, the model calculated the number of unsatisfied demanders considering both the solution approaches: no *fairness-based* and with *fairness-based distributions*. Also, the model calculates the available amount of quantities for all commodity types that can be allocated to the demanders while recovering the disrupted elements in the road transportation network. The performance of the model considering the large disruption level is demonstrated in Figure 3-10 and Table 3-7. Figure 3-10 shows the tradeoff between the total travel time and the cost of unsupplied quantity to the customers. Also, the satisfaction rate of the demanders at three of the Pareto points is shown in Figure 3-10. Additionally, the percentage of the demand being supplied to the demanders during the recovery time. We can see that the *fairness-based distribution* performance overcame the performance when designing the restoration model, emphasizing the cost-effectiveness only considering the same available commodities being distributed in the network. Table 3-7 represents the average percentage of unsatisfied demanders at each point on the Pareto curve. Also, we can see that the *fairness-based distribution* solution overcame the model performance when there is no *fairness-based distribution* applied. Moreover, the improvement when we applied the *fairness-based distribution* is shown in Table 3-7, as well. It can be seen that from point 1 to point 8, the improvement of applying the *fairness-based distribution* is more than 70%, and the model performance at point one, point five and point nine are illustrated in Figure 3-10. The travel time of each restoration approach is demonstrated in Figure 3-8, and the POF shows the differences between the two approaches as listed in Table 3-7. Similarly, to the other two scenarios that the travel time of the *fairness-based distribution* results slightly increases due to the emphasis on reaching most of the demanders in order to maintain the required SL.

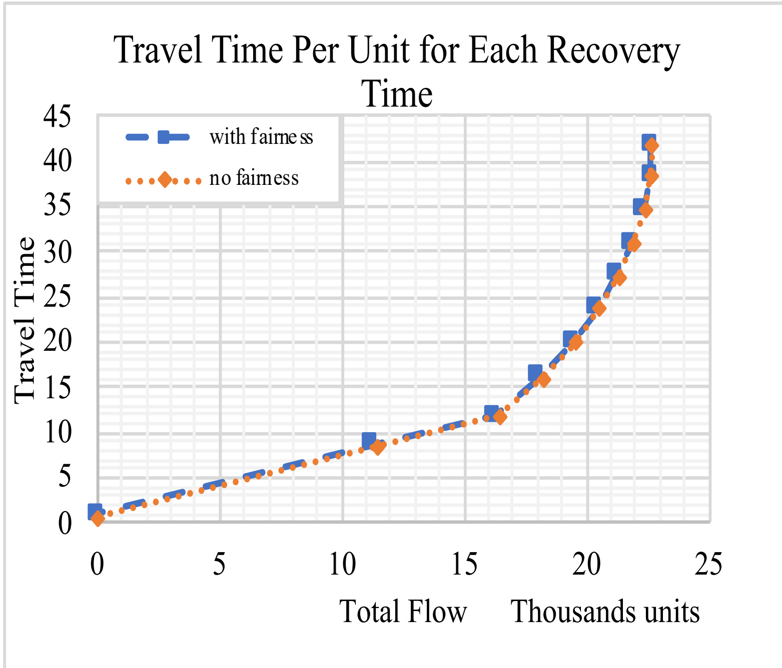

Figure 3-8. The average travel time of commodities during the recovery time (30% Disruption Level)

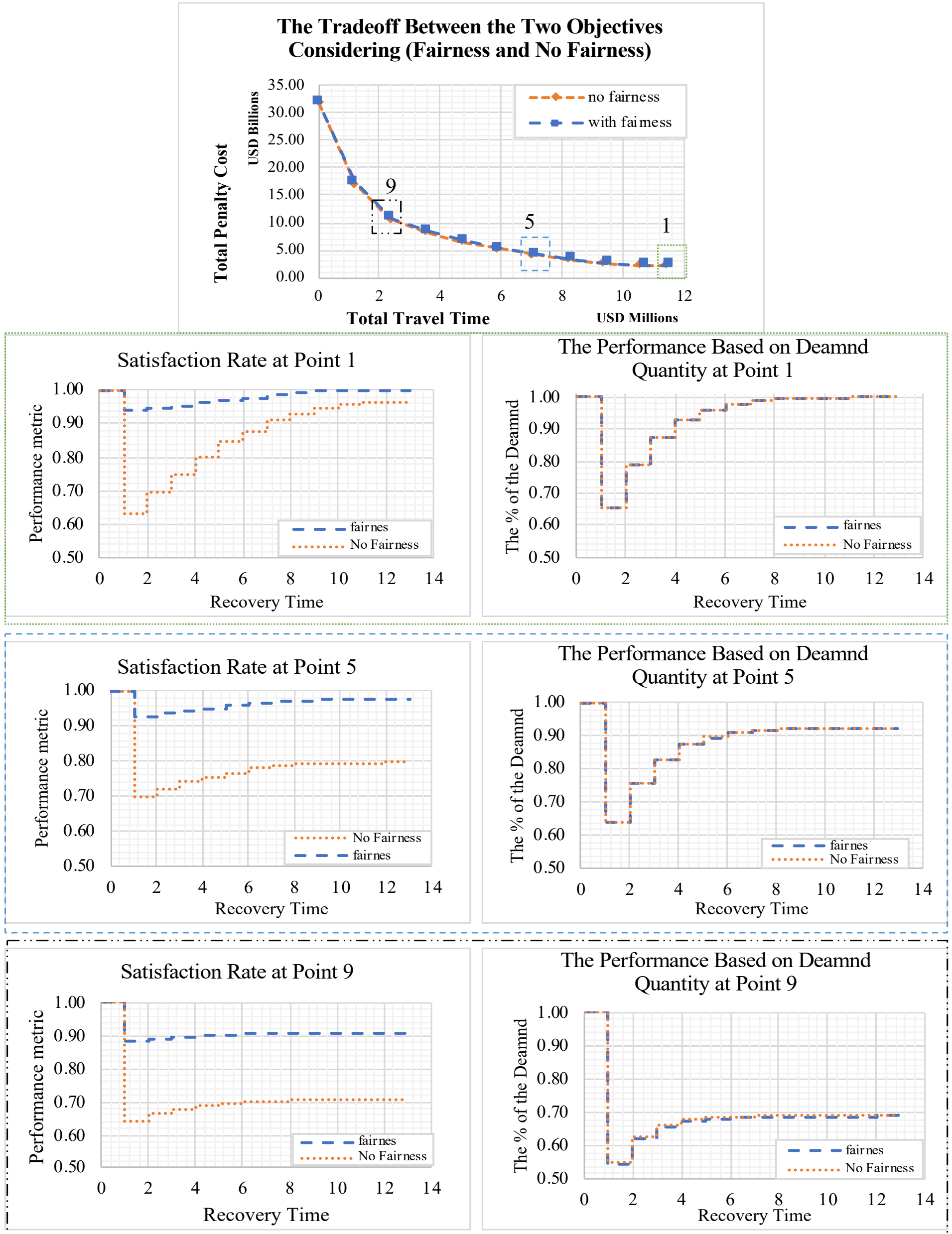

Figure 3-9. The performance of fairness and no fairness distribution at 20% disruption level at three different points on the pareto curve listed in Table 3-6

Table 3-7. Average Percentage of Unsatisfied Demanders (30% Disruption level)

Pareto Points	Without Fairness	With Fairness	*RI*(%)	*POF*(%)
1	16.38	3.22	80.33	0.08
2	15.32	3.22	78.99	0.06
3	18.20	3.32	81.77	0.23
4	21.45	3.85	82.03	0.31
5	23.03	4.49	80.48	0.37
6	24.59	5.33	78.32	0.44
7	26.91	6.36	76.37	0.65
8	27.05	6.59	75.64	0.81
9	29.57	10.29	65.20	1.05
10	40.39	12.38	69.35	2.88
11	100.00	100.00	0.00	-

3.5.2 *DISCUSSION*

The obtained results show the difference between the restoration plans: with *fairness-based distribution* and the restoration based on the unmet demand (no *fairness-based distribution*). The results highlighted the improvement of the *fairness-based distribution* added to the SCN performance, as shown in Table 3-5 to Table 3-7. Table 3-5 to Table 3-7 demonstrate that the average number of unsatisfied demanders for all commodities during the restoration time. The *fairness-based distribution* shows noticeable improvement when applied, as we can see in Table 3-5 to Table 3-7.. At the first Pareto point, the gap between the *fairness-based distribution* and no *fairness-based distribution* at the final recovery period was small because, at this point, most of the disrupted components have been restored as presented in Figure 3-6, Figure 3-9, and Figure 3-10. However, the improvement was significant for all other points on the Pareto frontier when applying the *fairness-based distribution restoration plan. Moreover, the POF on* *travel time when considering the fairness-based distribution* was not significant, as presented in Table 3-5 to Table 3-7.. We see that there are no differences when comparing the two restoration plans' performances concerning the total travel time as being approved by the *POF which* were at minimum for all scenarios. As we mentioned, the last values in the POF columns are not calculated because of having zero value in the denominator.

Another example of how the *fairness-based distribution* improves the satisfaction rate at most of the demanders for all commodities is shown in Figure 3-11 and Figure 3-12. Figure 3-11 and Figure 3-12 demonstrate the changes in the delivered demand percentage of one of the 100 scenarios conducted at a 20% severity disruption level. We can see that with the *fairness-based distribution* each commodity performance improved and maintained almost the satisfaction rate or at the minimum the required SL at each demand node. The number of inward spikes in the figure reduced significantly faster during the restoration processes when applying the *fairness-based distribution* approach added to the cost-effectiveness approach. We noticed that by reducing some of the dominating demand nodes to the satisfaction rate level, other commodities performances were fully efficient and *fair* in terms of meeting demanders' needs, as shown in Figure 3-11and Figure 3-12.

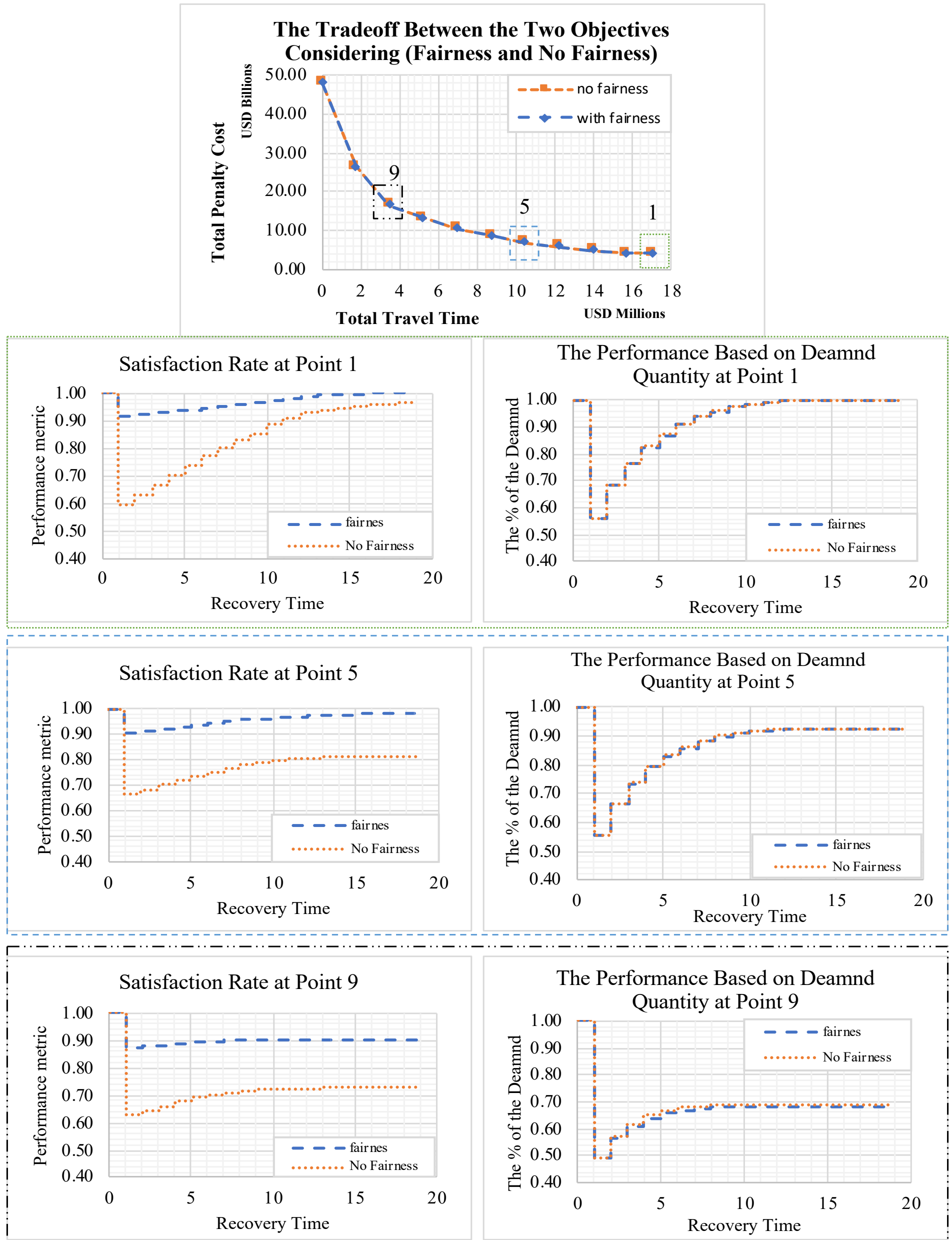

Figure 3-10. The performance of fairness and no fairness distribution at 30% disruption level at three different points on the pareto curve listed in Table 3-7

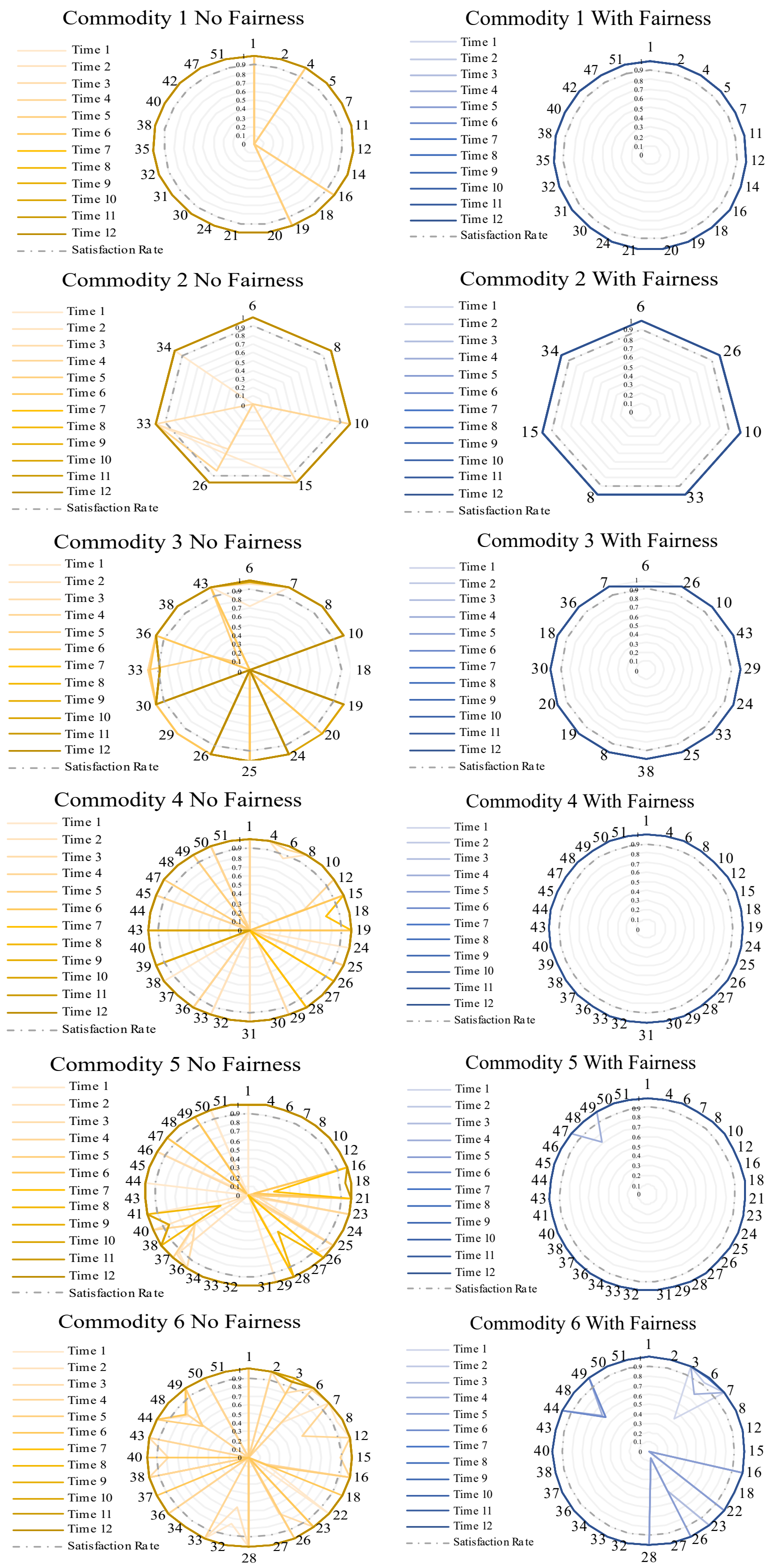

Figure 3-11. The model performance for one of the 100 scenarios considering the demand percentage at each node for each commodity at each recovery period at (Point 1 in Table 3-6)

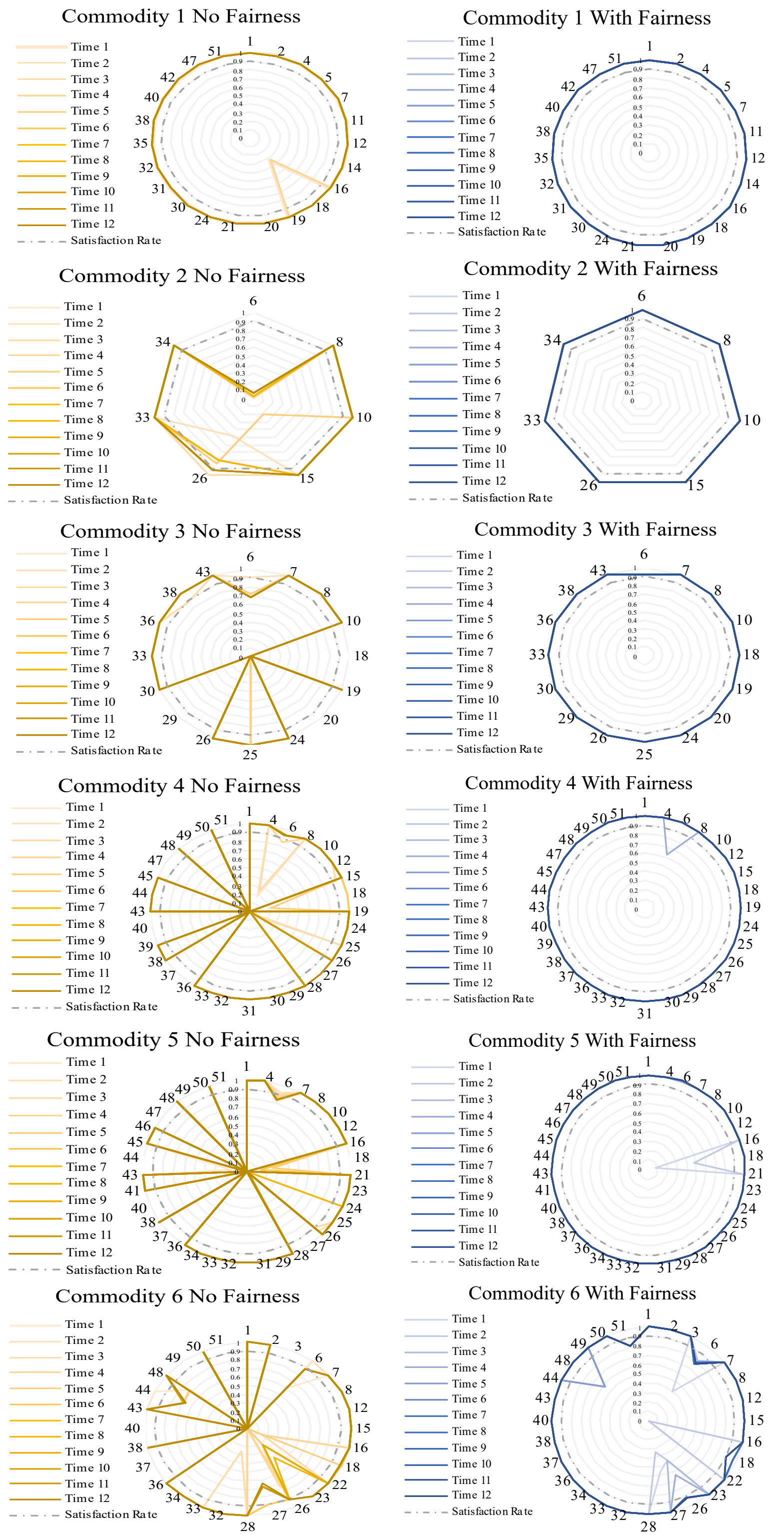

Figure 3-12. The model performance for one of the 100 scenarios considering the demand percentage at each node for each commodity at each recovery period at (Point 5 in Table 3-6)

Furthermore, the *fairness-based distribution* and no *fairness-based distribution* restoration plans show similar performance concerning the total travel time. Figure 3-6, Figure 3-9, and Figure 3-10 shows that the trade-off between the total travel time and overall cost is the same considering the two restoration plans. In the three figures, we see that *fairness-based distribution* results in having a higher satisfaction rate and maintains higher than 85% satisfaction rate in the worst-case scenario when the disruption happens. Moreover, the performance of both restoration plans concerning the average travel time per unit for each recovery time was almost the same for all three scenarios, as presented in Figure 3-5, Figure 3-7, and Figure 3-8. However, there was a slight increase in the travel time when applying the *fairness-based distribution*. The model emphasized maintaining at least the required SL at most of the demanders for all commodities. Thus, the *fairness-based distribution* maintains almost the same time to distribute the total demand without increasing the congestion level to the road transportation network. Accordingly, by applying the *fairness-based distribution*, the SCN performance is almost the same. Thus, the SC decision-makers can trust the implementation of the *fairness-based distribution* during the disruption time in order to increase the customers' satisfaction, particularly when the disruptive events are not within the SC decision-makers' authorities.

In this study, we addressed the importance of having another metric beside the unmet demand quantity or a cost-effectiveness perspective in the system to build the restoration plan (Mao et al., 2020). When designing the restoration based on the unmet demand quantity (e.g., González et al., 2016; and Almoghathawi et al., 2019), the model connects the demand nodes that request the highest demand neglecting the other demand nodes which prevent of achieving the SL of all demand nodes. By forcing the model to adapt to the *fairness-based distribution*, the model starts to connect most of the demand nodes and supply them with at least the required SL in order to satisfy their needs then to minimize the total unmet demand level in the SCN.

3.6 CONCLUSION, LIMITATIONS, AND FUTURE WORK:

The reliance on the road transportation network to move frights increases in recent years. Therefore, ensuring customer satisfaction becomes difficult due to the unpredicted events that disrupt the frights' flows. Several disruptive events have reduced the SCN performance and resulted in tremendous losses to the SC decision-makers. Consequently, several restoration models have been developed in the literature, however, most of which focus on the unmet demand or cost-effectiveness perspective to reduce the disruption impacts on the networks' performance (e.g., Vugrin et al., 2011, González et al., 2016, and Almoghathawi et al., 2019). In our study, we present a restoration plan that considers the *fairness-based distribution* of commodities among all demanders in order to reduce the impacts of the disruptive events by connecting most of the demand nodes and maintain their required SL during the recovery processes.

This chapter developed a multi-criteria non-linear mixed-integer programming (NMIP) model to demonstrate two different restoration plans: no *fairness-based distribution* and with *fairness-based distribution*. No *fairness-based distribution* emphasizes restoring the disrupted components in order to reduce the unmet demand quantities in the SCN; thus, the overall cost is minimized during the recovery periods. While the *fairness-based distribution* focuses on fairly distributing the available resources among demand nodes fairly and restoring the unmet demand. The objective of this model is to develop a restoration model that helps to improve the SCN resiliency by reducing the impact of the disruption on all demand nodes. The obtained results show that the *fairness-based distribution* manages to achieve a higher satisfaction rate concerning the number of demanders that receive the required SL during the recovery time. The results show that the *fairness-based distribution* performs similarly to the solution when there is no *fairness-based distribution* being applied for the total cost and total travel time. We conclude that the *fairness-based distribution* influenced the model to maintain a higher satisfaction rate and did not increase overall costs.

3.6.1 *MANAGEMENT INSIGHT*

This work provides a significant insight into dealing with disruption and constructing restoration plans to recover the disrupted components in the SCTN; thus, the network performance returns to the normal performance status. Diverse studies have been conducted to restore the network's performance after the occurrences of disruptions; however, most of which design the restoration plans based on cost-effectiveness perspective or the amount of unmet demand. Our work is designed to restore the SCTN based on cost-effectiveness perspective and the *fairness-based distribution* to ensure that most of the demanders maintain their SLs' requirements. The reliance on the *fairness-based distribution* results in a higher satisfaction rate of supplying the required SL at most of the demanders compared to the result when focusing only on the cost-effectiveness performance. While the price of fairness was at minimum. By implementing the *fairness-based distribution* the travel time was almost the same when applying just the cost-effectiveness (no *fairness-based distribution*). Thus, the SCN decision-makers can rely on the *fairness-based distribution* during the recovery processes of restoring the disrupted components in order to maintain a higher satisfaction rate and keep the demanders connected to their suppliers.

3.6.2 *FUTURE WORK*

In this model, several potential ideas could be improved for future work. For example, we did not consider all stages in the SCN. The main focus was on the disruption in the downstream part of the SCN. Another potential idea that could be explored is considering the stocks in the network and how we could use them for the next shipment. The decision between the transportation network decision-makers and the SC decision-makers is centralized. The model can be designed in such a way that each decision-maker has its plans; then, different approaches could be explored, for instance, using game theories approaches to come up with a solution that helps both managements. In this chapter, we focused only on restoring the SCN performance to normal status; however, we can extend the model by restoring the shortages cumulated during the recovery time. The proposed model considered that each commodity is independent, and there are no physical or economic interdependencies between commodities.

CHAPTER 4: FAIRNESS-BASED DISTRIBUTION TO RESTORE PHYSICAL AND ECONOMIC INTERDEPENDENCIES IN SUPPLY CHAIN TRANSPORTATION NETWORK

4.1 INTRODUCTION

In response to the various disruptions that have occurred to the road transportation network, the SCN decision-makers need to propose effective plans to reduce the impact of disruptive events. Thus, in this chapter, we present a bi-objective mixed integer programming (MIP) model that intends to minimize the economic impacts of road traffic disruption on SCN performance while using a fairness-based distribution. The impact is specifically assessed based on the SCN's capacity to meet demand needs and sustain service levels (SL) at demand nodes. The model assesses the performance of each sector that is dependent on the transportation network both before and after the disruption. We consider the economic interdependencies between the SCN's sectors and the required material that each sector requires from other sectors to produce and meet the demands needed while implementing a *fairness-based distribution* method to distribute commodities and reduce the unmet demand percentage at the majority of the demand nodes. The *fairness-based distribution* shows significant improvement in meeting most of the demand nodes' requirements (Abushaega et al., 2020; and Abushaega & González, 2020). It was implemented to reduce the post-disruption impact on SCN performance. The model considers a complex system of multi-suppliers, demanders, and multi-commodities. Each node in the network can produce all of the commodities to some extent but not necessarily fulfil the demand required by the node itself. Thus, the need to keep the nodes (e.g., cities) connected via the links (e.g., roads) is essential in order to meet the demand at the majority of the nodes. The motivation for conducting this study is to develop a mathematical framework that helps to obtain the maximum satisfaction rate among demanders when disruptive events occur. The model is also designed to measure the impact of the physical dependencies existing between the SCN and the transportation network. Thus, such disruptions propagate and result in reducing the performance of the SCN as a consequence of the economic interdependencies that exist.

The remainder of this chapter is organized as follows. Section 2 provides a detailed literature review that addresses: (i) the Input-Output (I-O) model and (ii) the SCN and infrastructure restoration studies that employ the I-O model. Section 3 presents the proposed methodology and mathematical notation. Section 4 addresses the case study examined to evaluate the proposed model, while the results obtained, and discussion are addressed in Section 5. Section 6 represents the conclusion of this study, in which we address the highlights of the study and recommendations for future improvement.

4.2 LITERATURE REVIEW

In this section, the Input-Output model's originality is addressed, and several applications that have implemented it in their study are addressed. Also, SCN restoration and the impact of disruption to the transportation network on SCN performance are addressed.

4.2.1 *THE LEONTIEF INPUT-OUTPUT MODEL AND ITS EXTENSIONS:*

The origin of the Input-Output Model (I-O Model) was developed in 1966 by Wassily Leontief (Leontief, W. 1986), for which he won a Nobel Prize, as depicted in Eq. (4-1). Eq. (4-1) demonstrate the relationships between different economic sectors and the total requirement demand that each sector needs to produce. x_l represents the total output of industry l, $\sum_{\hat{l}\in\mathcal{L}} a_{l\hat{l}}\, x_{\hat{l}}$ demonstrates the input of industry l needed to produce $\hat{l}$, while c_l represents the final demand of industry l. The main application of this model was to measure the economic impact of different economic sectors' performance. Since then, the model has been widely used in economic studies, but several areas have implemented it in studies, such as supply chain, infrastructure networks, and fuel industries. Also, between 1980 and 2010, the model has been widely used to study disruption's impact and was one of the ten most important accomplishments in risk analysis (Greenberg et al., 2012). Moreover, the numerous amounts of data that are available from the Bureau of Economic Analysis (BEA) (OCED 2008), and the list of countries sharing their information on the OECD website and presented in De Backer's work, which explains the wide implementation of the I-O model (De Backer & Miroudot, 2014).

$$x_l = \sum_{\hat{l}\in\mathcal{L}} a_{l\hat{l}}\, x_{\hat{l}} + c_l \quad \Rightarrow \quad x_l = Ax + c \quad \Rightarrow \quad x_l = (I - A)^{-1} * c \qquad (4\text{-}1)$$

Several studies have implemented either the I-O model or its extended version, the Inoperability Input-output Model (IIM), in order to measure the interdependency among the infrastructure networks and how such disruptions in any network hinder the overall performance (Santos, & Haimes, 2004; Pant et al., 2011; Pant et al., 2014; and Whitman et al., 2019). Some of these studies developed mathematical frameworks to measure the impact of disruption on the sector's performance, considering its interdependency. For example, Whitman et al. (2019) develop a framework that helps decision-makers to understand more clearly the dock-specific resource allocation strategies in order to increase the port preparedness against unexpected events. They combined a dynamic risk-based interdependency model with weighted multi-criteria techniques. Another example is Pant et al. (2011), who addressed the impact of disruption on the flow of commodities in an inland port. Among these studies, few have highlighted the impact of the disruption to the physical road transportation network on the flow of commodities and the effects on sectors' economic performance due to economic interdependency. A multi-regional analysis has been used to consider the effects of the interdependencies between regions (Isard et al., 1998), and it was extended by Miller and Blair (2009) to consider the inter-regional interdependencies. Few studies have considered the multi-regional I-O model and the effects of transportation network disruption on the economic performances of various industries. Darayi, Barker, and Santos (2017) studied the impacts of transportation network disruption to provide an assessment measure for ranking the network components by integrating the flow of commodities along with the economic interdependencies of various sectors. Park et al. (2011) considered the impacts of malevolent disruption to highway flow change capacity on the state and industry-specific economic performance. Darayi, Barker, and Nicholson (2019) developed a mathematical model that integrates a flow of commodities model with an economic interdependency model in order to strengthen the adaptive network capacity. They measured the performance of the network using a static resilience performance measure and evaluated the performance after a disruption occurs. They also focused on the rerouting effects of the flow of commodities on economic interdependency (Darayi et al., 2019).

Our study examines the impact of disruption to the transportation network on economic interdependency and its effects on the distribution of the commodities to the demanders in various regions. Also, we propose a *fairness-based distribution* strategy to ensure that most of the demand nodes receive at least the required SL while the transportation network is being restored and avoid bias occurring towards the node with the highest demand order.

4.2.2 *FAIRNESS DURING DISRUPTIVE EVENTS:*

The fairness concern and its importance have been a popular topic to deal with crises and unpredicted events, especially during the covid-19 time. Researchers have started to explore fairness and equity and their effects on society during disruptive events. One of the well-studied areas is the implementation of equity during the evacuation processes and humanitarian relief operations. For example, Huang et al. (2012) examined the trade-ff between efficiency, efficacy, and fairness when developing a rerouting model to reduce the impacts of disasters on people in the area of humanitarian relief operations. Their study's outcome is that the operational cost, efficiency, increases when focusing on efficacy and equity due to the need to cover more affected areas, not only focusing on the most affected area. Another study in the area of Humanitarian relief operations was proposed by Huang et al. (2015). They proposed a multi-objective optimization model that consists of three objectives components: delay cost, lifesaving utility, and fairness in order to allocate a distribution center that aims to provide resources to affected areas. In their study, they found that applying fairness helps to balance the delay time between the affected regions by minimizing the total deviations in the delay time. Another study that proposes a mathematical optimization model to allocate a distribution relief center to aid the affected regions was presented by Baharmand et al. (2019). They highlighted that if fairness and equity were integrated into the optimization model, the model would significantly change, and more impacted areas would be covered. We can see that fairness and equity are essential to cover more affected areas and avoid bias towards the largest population groups.

Other areas of study are SC order allocation and scheduling and dispatching. Liu et al. (2018) proposed a multi-objective model which maximizes the logistic service integrator's (LSI) profit and the functional logistic services providers' (FLSP) utilities. They implemented different fairness preference levels for each FLSP to increase the profit of the LSI while studying the change in the demand levels. They found that when the demand increases, the profit increases. However, the decrease in the demand levels increases the fairness preference level among the FLSP. Fairness and equity were also used in the scheduling problems. Androutsopoulos and Madas (2019) studied the implementation of fairness when designing the waiting time that aircraft take in the queue until they take-off or be assigned to specific gates. They implemented fairness to balance the deviations in the delay time of each aircraft compare to other carriers. As we can observe from previous studies, the fairness concept has been implemented in various areas to reduce the unpredicted disruptive events' impacts, maximize the SC profit when allocating orders, or reduce the delay time scheduling the aircraft queue problems. Moreover, fairness and equity should be considered not only in the responsiveness stage to disruption but also during the restoration processes until the system is restored fully.

4.2.3 *SUPPLY CHAIN TRANSPORTATION NETWORK RESTORATION:*

The awareness of the need to study and secure the infrastructure networks against disruption, from the SC decision-makers' perspective, increased due to the heavy reliance on those networks. Some disruptions, unfortunately, are difficult to anticipate, such as natural disasters or targeted attacks. For instance, the tsunami that occurred in Japan in 2011 forced some Toyota plants to shut down or reduce their production capacity; even though the plants were not located at the site of the tsunami, the impact on the transportation network resulted in shortages of raw materials (Hosseini, Ivanov, & Dolgui, 2019). Moreover, several incidents, including earthquakes, floods, hurricanes, and landslides, have occurred recently worldwide, causing huge damage to the infrastructure networks, including the transportation network. Thus, researchers are examining the impact of such events on various infrastructure networks; for example (Alipour & Shafei 2016); Ransikarbum & Mason 2016; Kermanshah & Derrible 2016; and Feng, Li, & Ellingwood 2020) examined the impact of earthquakes on the connectivity of the transportation network and developed the fragility curve for the transportation elements. Other studies consider the disruption caused by storms (e.g., Liu, Davidson, & Apanasovich, 2007; and Ramachandran et al., 2015). Other types of disruption that have been examined, together with their impact on the transportation network and other infrastructure networks, are landslides and rainstorms (Sassu, Giresini, & Puppio, 2017; and Postance et al., 2017). Numerous studies have been conducted in the restoration areas, that consider natural disasters in the design of model uncertainty; thus, the studies examined the proposed models with regards to unexpected disruption events (e.g., González et al., 2016; Gomez et al., 2019; and Almoghathawi, Barker, & Albert, 2019). Those studies examine models related to specific types of disruption; however, in our study, we examine our model in relation to any disruption scenario, whether natural or human-made, to provide restoration plans that will help to keep the transportation network intact.

Several studies have considered the restoration of the transportation network in order to improve SCN performance (Chen & E. Miller-Hooks 2012; Vugrin, Warren, & Ehlen, 2011; and Mao et al., 2020). Chen and E. Miller-Hooks (2012) studied the effects of transportation network disruption on the performance of the SCN and proposed a mathematical model that aims both to restore the disrupted components and to improve transportation network resilience. Vugrin et al. (2011) developed a qualitative and quantitative framework for analyzing the effect of disruption to the infrastructure network on a petrochemical SCN. They aimed to increase the resilience of the infrastructure networks, considering two hypothetical disruption scenarios. A recent study conducted by Mao et al. (2020) considers the restoration of the logistic network of the SCN, based on two different resilient metrics: the cost-effectiveness method and restoration rapidity. The outcomes of these studies highlighted the effectiveness of having more than one metric available to restore network performance. Gong et al. (2014) also studied the interdependency between the infrastructure network and the SCN and developed a restoration model to restore the disrupted components in the infrastructure networks and improve SCN resilience. Álvarez et al. (2014) proposed a mixed-integer programming model that aims to restore the disrupted roads of the SCN infrastructure by allocating crews and resources. They examined their model considering a single SCN infrastructure and a single commodity. Rose and Dormady (2018) developed a framework to restore the economic performance that has been impacted by disruption along with reconnecting the disrupted components within the road transportation network.

The aforementioned studies considered the dependency between the road transportation network and other infrastructure networks or service networks, such as SCN. To the author's knowledge, none of them considered the economic impacts of disruption to the transportation network on the performance of distributing flows as a component of the restoration process while fairly distributing the commodities to increase the satisfaction rate at most of the demand nodes. Faturechi and Miller-Hooks (2015) review the studies that have measured the performance of the transportation network during disasters. One of the findings is that there are limited studies that have examined the economic impact of disruption to the transportation network. Darayi et al. (2019) examined the economic impacts of disruption to the transportation network on the flows of commodities, considering supplied demanders networks. They measured the resilience of the network when considering rerouting the flow of materials. However, they did not consider the restoration of the disrupted components, since they employed a static resilience performance measure, which is not the case in our study. Another study that considers the economic interdependencies among SCNs was conducted by Goldbeck, Angeloudis, and Ochieng (2020), who developed a mathematical model to increase SCN resilience after the logistically-disrupted components have been restored. Our work differs from their study because we consider the dependency between the SCN and the transportation infrastructure network. Moreover, our work considers a *fairness-based distribution*, which Park et al. (2011), Goldbeck et al. (2020), Darayi et al. (2019), and Darayi et al. (2017) did not include in their studies.

4.3 MODEL

The purpose of this model is to improve SCN performance and make it more resilient when disruptive events impact on the transportation network. The model considers two entities that are involved in making decisions. When the road transportation network is disrupted, the SCN decision-makers are not the ones who determine the restoration process. The road transportation network decision-makers develop a restoration plan, based on the available budget, to restore all the disrupted components. Then the SCN decision-makers adapt their system based on the road transportation decision-makers' plans. A bi-objective mixed integer programming (MIP) model that considers a fairness-based distribution during the restoration process to mitigate and restore the performance of the SCN is proposed. Given the differences that might occur when making restoration decisions, the bi-objective model helps to address such differences that may arise between the two decision-making entities. The model assumptions and a detailed description of the model's notations are presented. We will end this section by describing the performance metrics used in this study.

4.3.1 *MODEL ASSUMPTION*

In this study, we propose a bi-objective SCN restoration model that improves SCN performance by effectively restoring the road transportation network after disruptions occur. In order to design the model, the following assumptions are made:

- The likelihood of a component being disrupted in the transportation network is random.

- The time it takes to restore disrupted components is a function of the component's length.
- Some of the components need to be 100% restored in order to function.
- The relation between the transportation decision-makers and SCN decision-makers is centralized in terms of which links are scheduled to be restored, while the total available budget and resources are not considered.
- The total production of each region or department of each sector is based on the calculation by Haddad et al (2018).
- Some regions have more than one node, so the maximum production capacity for each sector at each node in such a region is assumed based on the ratio of the city population's percentage to the total region's population.

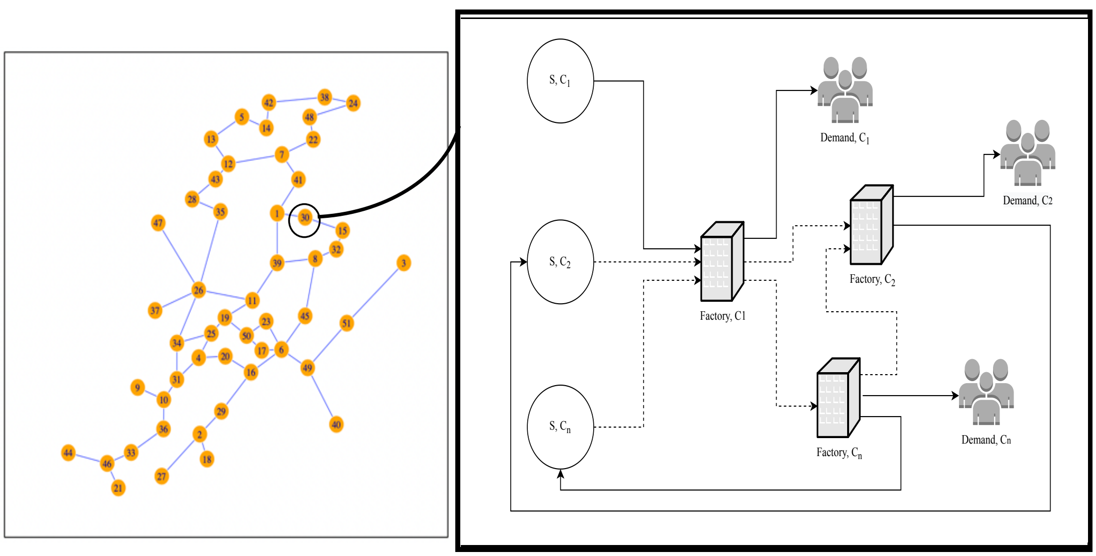

Figure 4-1. Supply chain network interdependency

4.3.2 *MODEL DESCRIPTION*

The model also focuses on keeping the highest number of demand nodes connected to the supplier nodes by providing some of their required demand or service level during disruptive events until the system has been restored to its normal status. The SCN examined in this study considers the interdependency of a multi-economical sector and how each sector depends on other sectors in order to fulfil the required demand, as demonstrated in Figure 4-1. One of the properties that the SCN has is that each node (city) can be a supplier, demand, or a transshipment node. For example, some of the cities meet the demand of their people (internal demand) so their extra production is distributed to other cities that have a demand that they cannot meet. The model list of sets, decision variables, and parameters are described in Table 4-1, Table 4-2, and Table 4-3.

Table 4-1. Sets

$\mathcal{N}$	Set of nodes
$\mathcal{A}$	Set of arcs
$\mathcal{T}$	Set of periods for recovery processes
$\mathcal{R}$	Set of resources to be used in the recovery processes
$\mathcal{L}$	Set of commodities

Table 4-2. Parameters

$\mathcal{D}_{ilt}$	Demand for each demand node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
ϱ_{il}	The maximum capacity each node $i \in \mathcal{N}$ can preduce for commodity $l \in \mathcal{L}$
$\mathcal{I}_{il}$	Extra capacity of production at node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$
α_{il}	The required service level at node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$
b_{il}	flow at node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$ in tons
d_{ij}	Distance in mile of arc $(i, j) \in \mathcal{A}$
c_{ij}	Shipping cost of using arc $(i, j) \in \mathcal{A}$
u_{ij}	Capacity of arc $(i, j) \in \mathcal{A}$
Y_{ij}^{0}	A continues parameter between {0,1} shows the initial functionality of a link post disruption. If 1, arc is functioning, and 0 otherwise
$\hat{g}_{ilt}$	The cost of restoring a disruptive arc $(i, j) \in \mathcal{A}$ at time $t \in \mathcal{T}$
Δ_{ij}	The proportional required time it takes to restore an arc $(i, j) \in \mathcal{A}$
ϑ_{rt}	Total available resources and crews $r \in \mathcal{R}$ at time $t \in \mathcal{T}$
v_{ijrt}	The required resources and crews $r \in \mathcal{R}$ to restore an arc $(i, j) \in \mathcal{A}$ at time $t \in \mathcal{T}$

f_{ilt}	Cost of unmet demand at node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
$a_{il\hat{l}}$	Interdependency matrix between commodities for nodes $i \in \mathcal{N}$

Table 4-3. Decision Variables

B_{ilt}	Net flow at node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
s^-_{ilt}	Unmet demand at node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
s^+_{ilt}	Excesses supply at node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
x_{ijlt}	Amount of flow through arc $(i, j) \in \mathcal{A}$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
y_{ijt}	A binary variable {0,1} 1 if arc is functioning at time $t \in \mathcal{T}$; and 0 otherwise
$\hat{y}_{ijt}$	A binary variable {0,1} 1 if arc (i, j) is to be restored at time $t \in \mathcal{T}$; and 0 otherwise
δ_{ilt}	A binary variable {0,1} 1 if a node $i \in \mathcal{N}$ did not get minimum service level at time $t \in \mathcal{T}$; and 0 otherwise
γ_t	Total percentage of unmet demand for all commodities at time $t \in \mathcal{T}$
μ^-_{ilt}	Negative deviation from the total percentage of unmet demand at node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
μ^+_{ilt}	Positive deviation from the total percentage of unmet demand at node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
χ_{ilt}	Total output of flow at node $i \in \mathcal{N}$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$

$$min \sum_{t\in\mathcal{T}} \sum_{l\in\mathcal{L}} \left(\sum_{i\in\mathcal{N}} (f^-_{ilt}\, s^-_{ilt} + f^+_{ilt}\, s^+_{ilt}) + \sum_{(i,j)\in\mathcal{A}} d_{ij} c_{ij} x_{ijlt} + \beta \left(\frac{\sum_{i\in\mathcal{N}} (\mu^-_{ilt} + \mu^+_{ilt})}{|\mathcal{N}^l|} \right) \right) \tag{4-2}$$

$$min \sum_{(i,j)\in\mathcal{A}} \sum_{t\in\mathcal{T}|>1} \hat{g}_{ilt} \big(\hat{y}_{ijt} - Y^0_{ij} \big) \tag{4-3}$$

$$\chi_{ilt} - \left(\sum_{\hat{l}\in\mathcal{L}} a_{il\hat{l}}\,\chi_{i\hat{l}t}\right) - \mathcal{D}_{ilt} + s_{ilt}^{-} - s_{ilt}^{+} = B_{ilt}\begin{cases} -B_{ilt}, & Demand\ node \\ +B_{ilt}, & Supplier\ node \\ 0, & Transhipment\ node \end{cases} \quad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L},\ \forall\, t \in \mathcal{T} \tag{4-4}$$

$$\chi_{ilt} \le \varrho_{il}(1 + \mathcal{I}_{il}) \quad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L},\ \forall\, t \in \mathcal{T} \tag{4-5}$$

$$\sum_{j:(i,j)\in\mathcal{A}} x_{ijlt} - \sum_{j:(j,i)\in\mathcal{A}} x_{jilt} = B_{ilt} \quad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L},\ \forall\, t \in \mathcal{T} \tag{4-6}$$

$$\left(\frac{s_{ilt}^{-}}{D_{ilt}}\right) \ge \alpha_{il}\, D_{ilt}\,(1 - \delta_{ilt}) \quad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L},\ \forall\, t \in \mathcal{T} \tag{4-7}$$

$$\sum_{l\in\mathcal{L}} \omega_{il}\, x_{ijlt} \le u_{ij}\, y_{ijt} \quad \forall\, (i, j) \in \mathcal{A}, \forall\, t \in \mathcal{T} \tag{4-8}$$

$$\frac{\sum_{i\in\mathcal{N}}\sum_{l\in\mathcal{L}} s_{ilt}^{-}}{\sum_{i\in\mathcal{N}}\sum_{l\in\mathcal{L}} D_{ilt}} = \gamma_t \quad \forall\, t \in \mathcal{T} \tag{4-9}$$

$$\left(\frac{s_{ilt}^{-}}{D_{ilt}}\right) - \gamma_t + \mu_{ilt}^{-} - \mu_{ilt}^{+} = 0 \quad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L}, \forall\, t \in \mathcal{T} \tag{4-10}$$

$$y_{ij1} \le Y_{ij}^{0} \quad \forall\, (i, j) \in \mathcal{A}, \forall\, t \in \mathcal{T} | t = 1 \tag{4-11}$$

$$y_{ijt} \le Y_{ij}^{0} + \sum_{r\in\mathcal{R}}\sum_{\acute{t}=1}^{t} \Delta_{ij}\hat{y}_{ijr\acute{t}} \quad \forall\, (i,j) \in \mathcal{A},\ t \in \mathcal{T} | t > 1 \tag{4-12}$$

$$\sum_{(j,i)\in\mathcal{A}} \hat{y}_{ijrt}\, v_{ijrt} \le \vartheta_{rt} \quad \forall\, r \in \mathcal{R}, \forall\, t \in \mathcal{T} | t > 1 \tag{4-13}$$

$$x_{ijlt} \ge 0 \quad \forall\, (i,j) \in \mathcal{A}, \forall\, l \in \mathcal{L}, \forall\, \mathrm{t} \in \mathcal{T} \tag{4-14}$$

$$s_{ilt}^{-},\ s_{ilt}^{+},\ \mu_{ilt}^{+},\ \mu_{ilt}^{-},\ \chi_{ilt} \ge 0 \quad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L}, \forall\, \mathrm{t} \in \mathcal{T} \tag{4-15}$$

$$B_{ilt} = free\ of\ sign \quad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L},\ \forall\, t \in \mathcal{T} \tag{4-16}$$

$$\gamma_t \ge 0 \quad \forall\, \mathrm{t} \in \mathcal{T} \tag{4-17}$$

$$\delta_{ilt} \in \{0, 1\} \quad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L},\ \forall\, t \in \mathcal{T} \tag{4-18}$$

$\hat{y}_{ijrt} \in \{ 0 , 1 \}$ $\forall\, (i,j) \in \mathcal{A}, \forall\, r \in \mathcal{R}, \forall\, t \in \mathcal{T}$ (4-19)

$y_{ijt} \in \{ 0 , 1 \}$ $\forall\, (i , j) \in \mathcal{A}, \forall\, t \in \mathcal{T}$ (4-20)

The objective of the model is to provide a restoration plan for the SCN to improve overall performance and increase SCN resilience. The objective of the model is two-fold. The first objective, Eq. (4-2), aims to minimize the overall costs, which include the unmet demand cost and the excesses supply cost ($f_{ilt}(s_{ilt}^{-} + s_{ilt}^{-})$), the shipping cost per mile ($d_{ij}c_{ij}x_{ijlt}$), and the cost of implementing fairness in the SCN $\beta\left(\frac{\sum_{i\in\mathcal{N}}(\mu_{ilt}^{-}+\mu_{ilt}^{+})}{|\mathcal{N}^{l}|}\right)$. We consider fairness to avoid bias towards the node with the highest unmet demand when there is any deficit in SCN performance. The second objective, Eq. (4-3), aims to minimize the cost of restoration based on the available budget. This objective is determined by the transportation decision-makers and what form the restoration process will take. The SCN decision-makers are aware of this objective's outcome under the assumption of the centralized relation between the SCN and the decision-makers of the transportation network.

Eq. (4-4) represents the total output (production) at each supplier node for each commodity. The left-hand side consists of three components: (i) is (χ_{ilt}) which is the total production of each sector, (ii) is ($a_{il\hat{l}}\ \chi_{i\hat{l}t}$) which represents the production required by the other sector based on the interdependency matrix, and (iii) is (D_{ilt}) which is the internal demand required by the people in each node (city). All of these represent the Input-Output Model, which is described in Eq. (4-1). The right-hand side indicates the amount of flow entering or leaving the node for each commodity at each time point. The (B_{ilt}) is a free sign variable that indicates the nature of the node. The (B_{ilt}) can have a negative value, which means that the node is a demand node, a positive value, which indicates that the node is a supplier node, or zero, which means that the node is a transshipment node. The (s_{ilt}^{-}, and s_{ilt}^{-}) represent the unmet demand and excess supply at each node for each commodity at each time point, respectively. Eq. (4-5) represents the maximum capacity that each node can produce for each commodity. The right-hand side is assumed to be the ideal production capacity when there is no disruption to the system plus a certain level that is being restored for critical situations. Eq. (4-6) represents the maximum capacity that each node can produce for each commodity. The right-hand side is assumed to be the ideal production capacity when there is no disruption to the system and a certain level is restored for critical situations. Eq. (4-7) represents the achievement of a service level, whether it is maintained at each node for each commodity or not. Eq. (4-8) is to maintain the amount of flow of commodities within the arc (i, j) 's capacity, considering the functionality of the link. The variable ($\boldsymbol{y_{ijt}}$) is a binary variable that indicates the functionality of the link. If ($\boldsymbol{y_{ijt}}$ = 1), the link is functional; and zero otherwise. The percentage of unmet demand for all commodities at each time period in the network is calculated by Eq. (4-9). The total percentage of unmet demand for each time period is compared to the unmet demand percentage at each node for each commodity at each time point in order to calculate the deviation between the unmet demand percentage at each node for each commodity, as depicted in Eq. (4-10).

Eq. (4-11) represents the initial status of the links' functionality at time ($t = 1$). If the functionality of a link is less than 1, ($\boldsymbol{Y_{ij}^{0}}$), then that link is unavailable for use until it is completely restored. Eq. (4-12) ensures that the link is operational once it has been restored, based on the time required for the crews to complete each restoration period for each link ($\boldsymbol{\Delta_{ij}}$). Eq. (4-13) represents the available resources that are required to restore the disrupted components. The required resources include the materials, crews, and equipment that are needed to restore each disrupted link. Eqs. (4-14)-(4-20) represent the nature of the decision variables within the proposed model.

4.3.3 *PERFORMANCE MEASURES*

This study used two different measures to test the model performance when applying both distribution methods. Relative improvement (RI) and the price of fairness (POF) are used to measure the model's efficiency, based on the number of nodes that receive a zero demand and the increase in the transportation cost.

- We defined the relative improvement as the reduction in the number of demand nodes that received zero of their demands when considering a fairness-based distribution (DNF), compared to the number of demand nodes that receive zero of their demands without the fairness-based distribution (DNWF), as shown in Eq. (4-21). This definition is similar to the original definition of Yao, Mandala, and Do Chung (2009). Also, Abushaega et al. (2021) and Abushaega and Gonzalez (2021) employed this in their studies.

$$RI = \frac{|\text{DNWF} - \text{DNF}|}{\text{DNWF}} \tag{4-21}$$

- The POF has been used in several studies in which fairness is employed, and was introduced initially by Bertsimas, Farias, and Trichakis (2011) to measure the changes in performance utilization when applying fairness. However, other studies used the POF to measure the changes in the total costs (e.g., Ye, Zhang, & Dekker 2017; and Abushaega and Gonzalez 2020). In this study, we considered the POF as the changes in the total transportation (TC) cost when applying fairness-based distribution in order to improve SCN performance during disruptions, as shown in Eq. (4-22).

$$RI = \frac{|\,\text{TC with fairness} - \text{TC without fairness}|}{\text{TC without fairness}} \tag{4-22}$$

4.4 CASE STUDY

This chapter studies, as an example SCN, the Colombia transportation network, the flow of commodities passing through it and the cities that the network connects. One of the main reasons for examining the Colombia transportation system is that the country depends mainly on trucks to distribute the available commodities due to geographical attributes. Most of the main cities are located in mountainous areas, which makes the network less resilient to disruptions (e.g., floods, landslides, and earthquakes).

Figure 4-2. Columbia's road transportation network

4.4.1 *COLOMBIA FLOWS OF MATERIALS DATA AND I-O DATA*

This study examined the flow of commodities of more than 200 different products and aggregated them into five different economic sectors being distributed within cities. The data represent the flow between cities as origin-destination (O-D) information of most of Colombia's main cities. The following table, Table 4-4, addresses the sector's information and the number of the origin nodes, supply node, representing the departments (states) in the country. Each department is represented by at least one node. It was difficult to assume that some nodes are not demanding flows of some of the commodities; thus, we considered that all 51 nodes are demand nodes for each sector, based on each city's population.

The road transportation network of Colombia is less redundant, and some of the regions are not connected with other regions by the road network. We see that, in Figure 4-2, the road network is centered on the western side of the country, while the eastern side of the country is mostly connected via unpaved roads. In Figure 4-3, we see the regions or departments of Colombia. For more information regarding the nodes' (cities') names and the region that they represent, see Appendix 1. The eastern regions were neglected in this study, and their total production and demand were removed from the data. Most of these regions are self-sustaining; for further information, see Haddad et al. (2018).

Figure 4-3. Colombia's regions (*Provinces map of Colombia*, n.d.)

Table 4-4. The Colombia SCN information O-D table

Sector	Sector Description	Number of Supply Nodes	Number of Demand Nodes	Total output (in Tons)	Total output (in millions)
1	Farming, forestry, hunting, and fishing	51	51	1,759,261	$25,102.1
2	Mining and quarrying	51	51	149,712	$26,275.8
3	Construction	51	51	82,196	$35,359.1
4	Manufacturing industry	51	51	2,746,591	$8,765.7
5	Transportation, storage, and communications	51	51	67,556,897	$21,851.4

Other data required for this model are the Input-Output Table (I-O Table) of the economic sectors' interdependencies. These data relate to the economic purchases of 13 of Colombia's sectors and the total demand being purchased by the entire country. The data provide information on the total amount of transactions in USD between the sectors and how much each sector needs from the other sectors, as shown in Table 4-5, representing the A matrix in Eq. (4-1) needed to measure the economic interdependency and its effect in case a disruption occurs OCED (2008). The original matrix for the entire country was integrated along with the information listed in Haddad et al. (2018) regarding the contribution of each region to the total production of each economic sector. Thus, the interdependency matrix is not the same for each region. The total demand being requested by each sector represents the entire demand of all cities and other sectors that are not included in this study. Due to the lack of full information on the flow of commodities between cities in the O-D table and how much each city required, we assumed a distribution based on the population of each city. Also, we considered other sectors in the I-O table as part of the total demand that needed to be fulfilled or produced by each of the five sectors of this case study, listed in Table 4-5.

Table 4-5. Interdependency matrix between the economic sectors (SCNs) in Colombia (values in million USD)

Sector	1	2	3	4	5	Demand	Total Output
1	1,672.9	0.8	244.0	15.7	0.8	22,493.3	25,102.1
2	26.5	1,162.5	854.0	1,657.9	43.6	22,493.6	26,275.8
3	48.5	74.1	342.7	21.7	76.7	34,729.4	35,359.1
4	50.5	205.9	2,468.4	1,069.9	40.5	4,896.1	8,765.7
5	435.3	1,367.7	991.5	203.5	1,056.0	17,710.7	21,851.4

4.5 RESULTS & DISCUSSION

In this study, the proposed model was tested considering the road transportation network and the SCN of Colombia. The model is designed to deal with any disruption to the road network that results in reducing the flow of commodities or the SCN's performance. Moreover, the model examines the effects of different levels of restoration budgets and their impacts on the performance of the SCN. To solve the two driven objectives; SC management, and the transportation management, we used the ε-constraint method, which one of the objectives is set to be a constraint while minimizing the other objective within the maximum and minimum values of the restricted objective, as described in Vira and Haimes (1983). Fifty random disruption scenarios were generated related to disruption to the road transportation network. There are two assumptions that were considered when obtaining the results: (i) the probability of the links' (roads') failure was equal when generating the disruption scenarios since the model is not designed to be tested for a specific type of disruption; (ii) to reduce the model's computational time, rapid restoration process, and complexity, we assumed the number of crews that are available for each restoration time can work on a maximum of eight disrupted components. All of the analysis represents the model performance when minimizing objective 1, SC management, represented in Eq. (4-2), considering both the *fairness-based distribution* and no *fairness-based distribution* in order to show the importance of implementing the former to increase the satisfaction rate. Also, the main component in objective 1, Eq. (4-2), is to minimize the total transportation cost; we examined the differences in the transportation costs at each Pareto point, as depicted in Figure 4-4, and point 1 represents the model's performance when there is no budget available to restore any disrupted components. We see that the transportation cost increases when the restoration budget increases until it reaches a point where the transportation cost for both methods remains steady. Both solution methods performed similarly, with minimal differences in the total transportation costs, which are listed in Table 4-6 as POF, at some of the Pareto points.

Moreover, the results obtained using both solution methods with respect to measuring the satisfaction number of demand nodes, which did not receive their required SL, at different levels of restoration budgets, are demonstrated in Table 4-6. From the table, we can see that the number of unsatisfied demand nodes that are affected by the road transportation network's disruption is comparable when no restoration budget is available to restore the disrupted components, especially at point 1. Both solution methods maintained similar performance when the restoration budget is limited, with a slight improvement in the average number of unsatisfied demand nodes when no *fairness-based distribution* is applied, as depicted in Table 4-6. The performance changed when there is enough restoration budget towards the *fairness-based distribution*. The relative improvement shows the difference between the two solution methods and how the *fairness-based distribution* improves the SCN's performance when the restoration budget increases. The POF shows the differences in the total transportation cost when the *fairness-based distribution* is implemented and when it is not.

Table 4-6. The average number of unsatisfied demand nodes at each Pareto Point

Pareto point	No fairness	With Fairness	RI (%)	POF (%)
1	620.00	620.00	0.00	0.98
2	603.23	609.06	-0.97	-1.04
3	503.52	504.26	-0.15	-0.41
4	440.22	446.32	-1.39	-0.38
5	389.96	380.32	2.47	-0.16
6	330.64	326.68	1.20	-0.28
7	301.41	300.13	0.42	0.33
8	290.56	268.06	7.74	-0.07
9	264.56	259.24	2.01	0.25
10	263.72	261.38	0.89	0.33
11	271.41	254.72	6.15	0.17

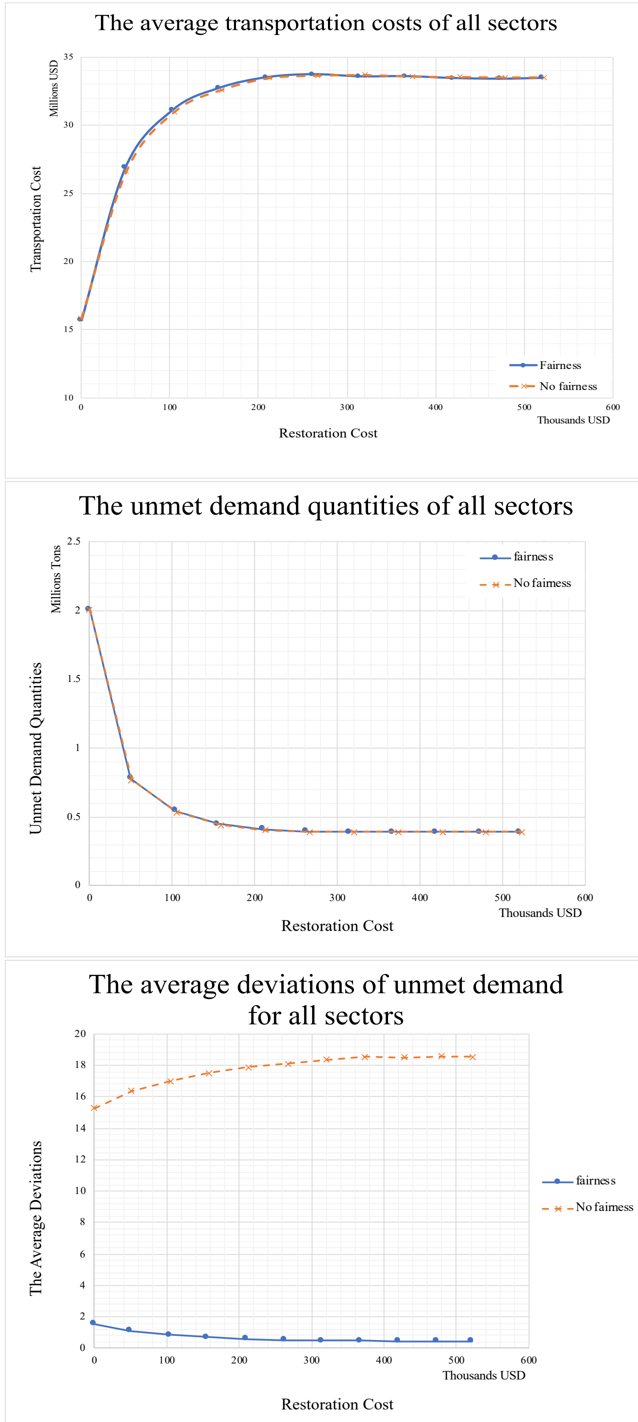

Figure 4-4. Comparison of the average transportation costs, the average unmet demand quantities, and the average deviation in the unmet demand with and without the application of the *fairness-based distribution* at different level of restoration budgets.

It is expected that the *fairness-based distribution* increased the total transportation cost due to the greater distance that needed to be considered to reach the majority of the demand nodes, as depicted at the top of Figure 4-4. However, in some cases, the *fairness-based distribution* POF was negative, which indicates that the *fairness-based distribution* decreases the total transportation costs and maintains higher satisfaction rates at some of the Pareto points, especially points 5, 6, and 8. The top subfigure of Figure 4-4 shows the total transportation cost for both solution methods for different levels of restoration budget. It can be seen that both methods performed similarly, with small differences that are demonstrated in Table 4-6 under the POF's column. The middle subfigure of Figure 4-4 represents the unmet demand quantities of all sectors at different levels of restoration budgets assigned to restore the disruptive components. Both solution methods almost performed the same with respect to the number of unmet demand quantities with a slight increase in the restoration cost when no *fairness-based distribution* was applied. The last subfigure of Figure 4-4 demonstrates both solution methods' performance regarding the deviations in the unmet demand for all sectors. We can see that the *fairness-based distribution* method reduces the deviations in the unmet demand for all sectors at all nodes significantly compared to the no *fairness-based distribution* method. From Figure 4-4, it can be observed that the *fairness-based distribution* solution method required fewer restoration budgets to restore the network performance by serving the required SL to most of the demand nodes while using the same quantities to distribute among the demand nodes. All of that was achieved with a negligible increment in the transportation cost, as listed in Table 4-6.

The performance of the model with and without the application of the *fairness-based distribution* with respect to the percentage to which the demand nodes' requirement are met when minimizing the SC management objective, point 11 in Table 4-6, is depicted in Figure 4-5. The color degree represents the model's performance at different restoration's times. The darker the color, the closer it is to the time when the disruption occurred. In Figure 4-5, we highlighted the percentage of the met demand, and emphasized the inward sparks and how far they exceed the required SL Both solution methods performed identically for the first three restoration times for all sectors except for sector 5, the Transportation sector which, when applying the *fairness-based distribution,* node 42 in the region of Magdalena, which was most impacted by the disruption, was one of the largest demand nodes in the sector. The model distributed the shares of node 42 and covered the required SL at most of the demand nodes requiring Sector 5.

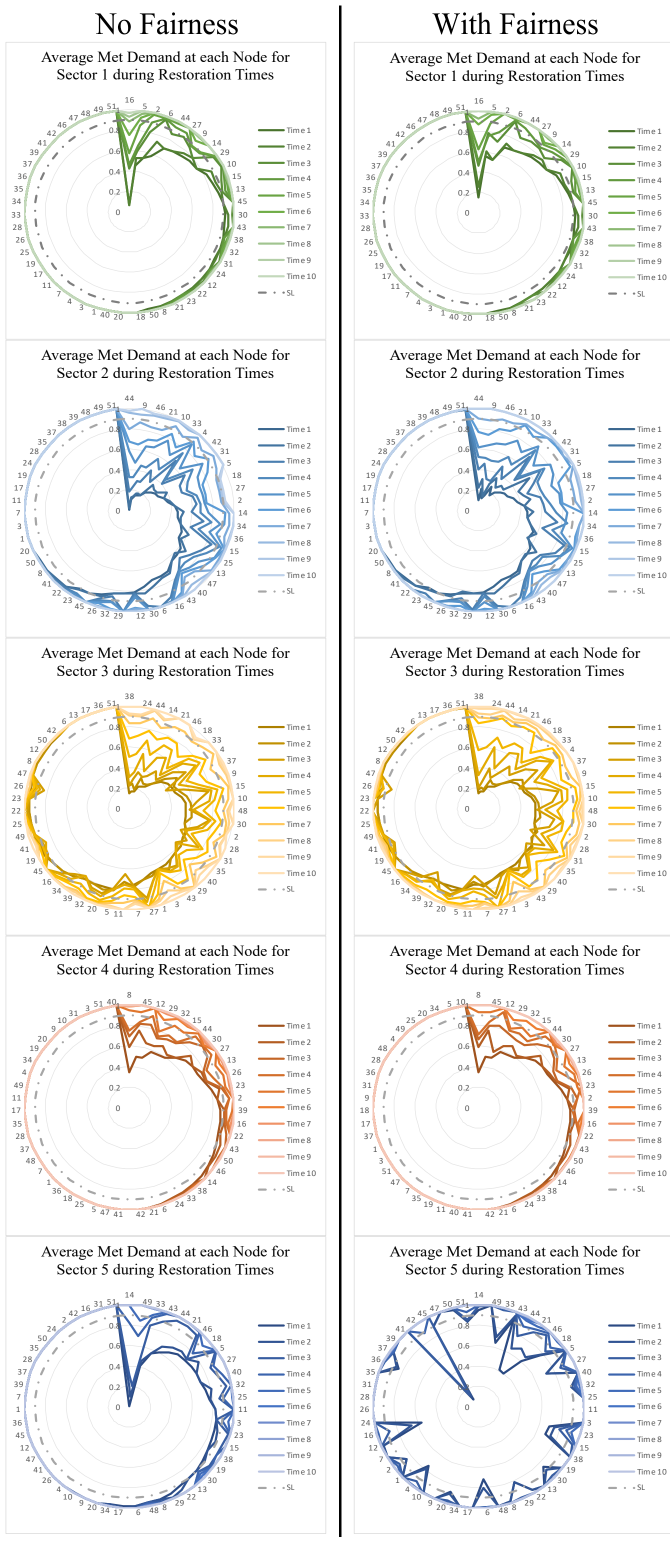

Figure 4-5. Comparison of the degree of demand met at each node for each sector (commodity) with and without the application of the *fairness-based distribution* and during the restoration times.

Also, sector 5 represents the largest sector in terms of the total demand or output compared to other sectors; thus, the *fairness-based distribution* reduces the share of sector 5 in the shipments during the restoration process and gives priority to other sectors that were significantly impacted by the disruption. The overall performance improved with respect to maintaining the required SL at most of the nodes when the *fairness-based distribution* was implemented. Although this improvement was not significant, still the *fairness-based distribution* enhances the system, with a negligible increase in the transportation cost at some of the Pareto points, as depicted in Figure 4-4 and listed in Table 4-6.

The economic performances of the examined sectors are presented in Figure 4-6. From the figure, it can be seen that some sectors were significantly affected, especially sector 2, the Mining Sector, whose economic performance dropped by 35% of its total performance. Sectors 1 and 3, Agriculture and Manufacturing, respectively, were impacted significantly as well. The *fairness-based distribution* helps to restore the impacted sectors faster in terms of achieving the required SL than when no *fairness-based distribution* is implemented. The *fairness-based distribution* achieved the SL at the majority of the demand nodes faster compared to the no *fairness-based distribution* solution, as presented in Figure 4-7, which shows the unsatisfied demand nodes in each economic sector during the restoration process under both solution methods. We can see that the *fairness-based distribution* maintains fewer unsatisfied nodes during the restoration process for all sectors except sector 4, even though both methods achieved zero unsatisfied nodes at the same time in some sectors.

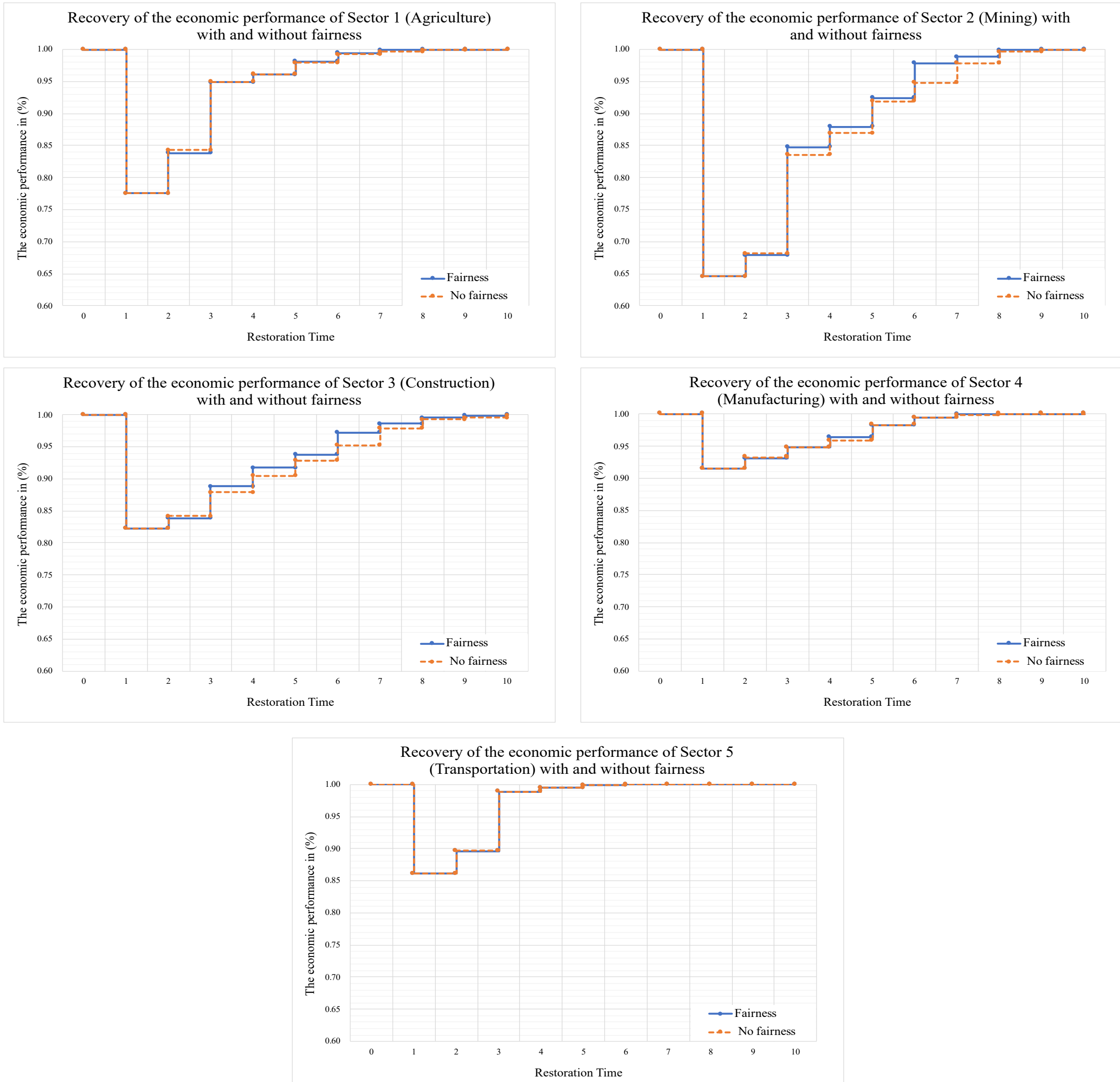

Figure 4-6. Comparison between the recovery of the sectors' economic performance with and without the application of the *fairness-based distribution*, representing the model's performance at point 11, minimizing the SC management objective, in Table 4-6.

The economic performance reflects each sector's output in terms of money, and each sector has a total output that cannot be exceeded. Also, the output of each node or city can exceed the production capacity of that city. Thus, the *fairness-based distribution* reduces the production capacity of certain sectors during the restoration process in order to restore the impacted sectors. Therefore, it is anticipated that some sectors' economic performance will remain constant when the *fairness-based distribution* is implemented, especially those sectors that are less impacted by the disruption. As a result, both solution methods performed similarly during the restoration process.

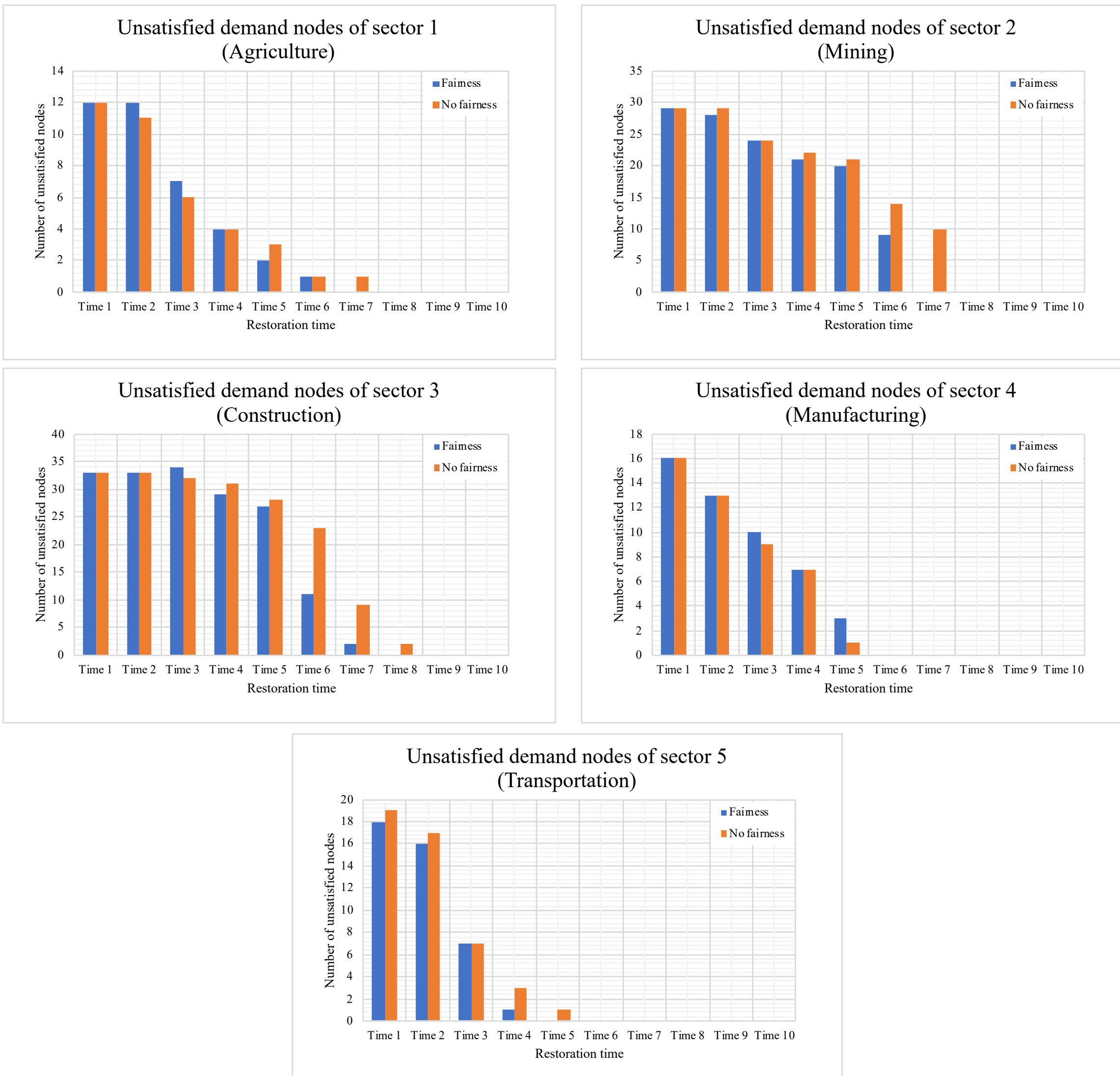

Figure 4-7. Comparison between the number of unsatisfied demand nodes with and without the application of the *fairness-based distribution*, representing the model's performance at point 11, minimizing the SC management objective, in Table 4-6.

Table 4-7. Unsatisfied demand nodes at various SLs

	Pareto point	No fairness	With Fairness	RI (%)		No fairness	With Fairness	RI (%)
95% Service Level	1	660.00	660.00	0.00	85% Service Level	560.00	560.00	0.00
95% Service Level	2	624.04	629.58	-0.89	85% Service Level	565.56	568.56	-0.53
95% Service Level	3	519.86	521.28	-0.27	85% Service Level	473.28	472.74	0.11
95% Service Level	4	454.22	461.5	-1.60	85% Service Level	415.56	417.18	-0.39
95% Service Level	5	400.96	391.94	2.25	85% Service Level	369.62	360.2	2.55
95% Service Level	6	341.48	337.1	1.28	85% Service Level	313.6	309.44	1.33
95% Service Level	7	311.2	310.5	0.22	85% Service Level	285.36	285.22	0.05
95% Service Level	8	299.6	276.2	7.81	85% Service Level	275.18	253.66	7.82
95% Service Level	9	271.9	266.98	1.81	85% Service Level	249.98	245.3	1.87
95% Service Level	10	271.76	269.08	0.99	85% Service Level	249.56	246.94	1.05
95% Service Level	11	279.24	262.18	6.11	85% Service Level	256.7	240.54	6.30
75% Service Level	1	530.00	530.00	0.00	65% Service Level	470.00	470.00	0.00
75% Service Level	2	531.04	532.42	-0.26	65% Service Level	494.98	495.74	-0.15
75% Service Level	3	445.02	442.44	0.58	65% Service Level	413.16	412.06	0.27
75% Service Level	4	390.06	388.04	0.52	65% Service Level	362.04	358.84	0.88
75% Service Level	5	348.98	339.56	2.70	65% Service Level	322.54	314.04	2.64
75% Service Level	6	294.46	290.82	1.24	65% Service Level	272.82	270.08	1.00
75% Service Level	7	269.88	268.72	0.43	65% Service Level	250.76	250.02	0.30
75% Service Level	8	258.62	238.26	7.87	65% Service Level	239.74	221.78	7.49
75% Service Level	9	234.84	230.38	1.90	65% Service Level	218.74	214.74	1.83
75% Service Level	10	234.4	231.16	1.38	65% Service Level	218.86	215.72	1.43
75% Service Level	11	240.78	225.64	6.29	65% Service Level	224.62	210.2	6.42
55% Service Level	1	430.00	430.00	0.00				
55% Service Level	2	433.2	429.16	0.93				
55% Service Level	3	370.12	367.76	0.64				
55% Service Level	4	322.64	316.12	2.02				
55% Service Level	5	286.92	278.96	2.77				
55% Service Level	6	241.24	238.54	1.12				
55% Service Level	7	221.96	221.22	0.33				
55% Service Level	8	212.96	195.28	8.30				
55% Service Level	9	193.26	189.14	2.13				
55% Service Level	10	193.28	190.02	1.69				
55% Service Level	11	198.18	185.08	6.61				

4.5.1 *SENSITIVITY ANALYSIS*

In the main analysis, the targeted SL was 90%, and we can see that the *fairness-based distribution* performance was below that of the no *fairness-based distribution* when the restoration budget was less than or equal to 30% of the required budget to restore all of the disrupted components. Thus, we wished to test whether the SL could change the model's performance with respect to the number of unsatisfied demand nodes. Table 4-7 represents the model's performance for the two solution methods, considering a different SL each time. We measure the model's performance according to whether the RI% is positive or negative. If the RI is positive, the *fairness-based distribution* is improving the system, and if negative, otherwise. We can see that the model's performance when targeting 95% remains the same for the first four points in the table, which represents the model's performance when a smaller budget is assigned to restoring the disrupted components. However, when we reduce the required SLs' percentages, the *fairness-based distribution* begins to over-perform the model's outcomes when no *fairness-based distribution* is applied. The lower the SL, the higher the *fairness-based distribution* performance. Although the performance of the no *fairness-based distribution* remains higher for the first few points, the *fairness-based distribution* reduces the gap at those three points when the SL is reduced.

The reason why the *fairness-based distribution* performed worse when a restoration smaller budget is assigned to restore the disrupted components is because the *fairness-based distribution* forces the model to balance the unmet demand percentages in the majority of the nodes. Thus, a node that is significantly affected plays a substantial role in reducing the other nodes' demands. For example, if one node receives 30% of its demand, the *fairness-based distribution* tries to balance that percentage with the majority of the nodes such that the overall unmet demand percentage is reduced so, when we reduce the required SL, we see that the *fairness-based distribution* maintains the SL at the majority of the demand nodes.

4.6 CONCLUSIONS AND FUTURE WORK

In this article, a bi-objective restoration model was developed to measure and study the impacts of disruption to the transportation network on the economic performance of the SCN. Two solution methods, *fairness-based distribution* and no *fairness-based distribution*, were proposed to distribute the available commodities that each sector needs to deliver to the demand nodes while restoring the disrupted components within the SCTN. The model considered different random disruption scenarios for each solution method. The results show that the *fairness-based distribution* successfully reduced the number of demand nodes that were impacted by the disruption to the transportation network. Due to the dependency between the transportation network and the SCN, the impact of the disruption was significant for some of the economic sectors with respect to the satisfaction rate with maintaining the required SL at the majority of the nodes. The *fairness-based distribution* improved the total met demand percentage for all sectors when sufficient budget was allocated to restore the disrupted components within the SCTN. Also, the satisfaction rate percentage increased during the restoration process when we consider lower SL to maintain, even if the restoration budget was insufficient to restore all of the disrupted components. As a consequence of implementing the *fairness-based distribution*, the transportation costs increased compared to the no *fairness-based distribution* method. This increment is called the *price of fairness* (POF), which was <1%

of the transportation cost associated with the no *fairness-based distribution* solution. This percentage fluctuated, based on the degree of restoration budget available. Moreover, both solution methods helped to restore each sector's economic performance, considering the interdependencies among the sectors, since the difference between the two solution methods is in the way in which the available commodities are distributed.

This chapter highlights the impact of disruption to the transportation network, considering the physical interdependency with the SCN and economic interdependency within the SCN. Usually, the SC decision-makers must deal not only with disruptions within the SCN but also with unpredicted events that impact the transportation network. Thus, SC decision-makers must provide sufficient strategies to reduce those events' impacts and sustain their demand nodes' satisfaction rates. In this study, we provide a distribution plan to reduce the impact of disruptions on the performance of several economic sectors within the SCN. By applying the *fairness-based distribution* method, the number of unsatisfied demand nodes (nodes that received less than the required SL) becomes reduced. using the same quantities that are available for distribution among the demand nodes. Also, the model was tested considering different levels of restoration budget provided by the transportation decision-makers, and the *fairness-based distribution* shows either an improvement in the RI or a reduction in the POF. When the *fairness-based distribution* increases the satisfaction rate by reducing the number of nodes that did not receive their SL, the POF increases, but by less than 1%. Thus, the SC decision-makers can rely on the *fairness-based distribution* solution during the disruption time and restoration process to keep the demand nodes satisfied with the minimum SL they can provide in a fair manner compared to the other demand nodes until the system is restored fully and revers to its normal status. The *fairness-based distribution* method restored the economic performance of the SCN sectors faster than the method where no *fairness-based distribution* was applied, especially for the most impacted sectors. Thus, considering it as a distribution strategy during the time of the disruption ensures that the economic performance of the SCN will recover quicker while maintaining a high satisfaction rate at the majority of the demand nodes. Because no *fairness-based distribution* method focuses on the demand nodes requiring the largest quantity and fulfils their need first, the number of unsatisfied nodes grows compared to that occurring when the *fairness-based distribution* method is applied.

This study could be extended and improved by considering other factors that were not included in this initial attempt. In this study, the model assumed that each sector's production costs are the same at all supplier (city) nodes. Thus, considering different production costs will change the production location's priority where shortages arise within the total outputs in different locations. Studying the interdependency not only between industries but also between regions and cities would provide a better understanding of the economic performance of each region. Another factor that could be considered for future work is the impact of having stock or an inventory for each sector and how to reschedule the delivery of the stock quickly without exceeding the. Also, the model considered the uncertainty regarding the available capacity within each link at each time but did not include uncertainty in the SCN (e.g., uncertainty regarding demand or uncertainty in the interdependency matrix between the SC sectors).

CHAPTER 5: ENHANCING THE RESILIENCE OF SUPPLY CHAIN TRANSPORTATION NETWORKS USING FAIRNESS-BASED DISTRIBUTION STRATEGIES UNDER UNCERTAINTY[3]

5.1 INTRODUCTION

In recent years, there has been a great deal of research undertaken on disruptive events and their implications on supply chains and infrastructure networks. Diverse studies that investigate the effects of unpredicted events on the performance of supply chain networks stress that supply chains are continuously striving to fulfil customer requests and maintain good service levels at all times, while also striving to maintain a cost-effective operation (Altay & Ramirez, 2010; Ho et al., 2015). However, both natural and human-made disruptive occurrence continually hamper the performance and operations of supply networks. These disruptions have the potential to cause considerable losses to the supply chain management and stakeholders in both the short- and long-term by lowering the supply chain's capacity to produce and fulfil the customers' demands (Ho et al., 2015). According to the United Nations Office for Disaster Risk Reduction (UNISDR), catastrophes caused an estimated $1.4 billion of damage from 2005 to 2012, affecting around 1.7 million people. Over a decade, China, the United States, the Philippines, India, and Indonesia suffered the most catastrophes (Satake, 2014). Natural catastrophes can hamper the operation of a transportation system, especially road transportation, which is a growing concern for the transport sector (Mitsakis et al., 2014). Because of their reliance on the road transportation infrastructure to carry items to customers,

[3] The content in Chapter 5 was submitted as a journal paper, titled "Enhancing the Resilience of Supply Chain Transportation Networks using Fairness-based Distribution Strategies under Uncertainty", in the Computer and Industrial Engineering Journal.

suppliers, or enterprises with raw materials, they are prone to interruption. Among the various modes of transportation, the road transportation network is the most commonly utilized to convey freight and products. According to the Federal Highway Administration, more than 50 million tons of freight (worth $48 billion) were dispersed via the transportation system in the United States on a daily basis in 2012 (Strocko et al., 2014). Trucks handled 70% of this overall freight distribution (Margreta, Ford, and Grube 2014; Government Accountability Office 2013). To mitigate the effects of disruptive events, the United States government underlined the need to improve the preparation of vital infrastructure systems, one of which is the transportation network (Yusta, Correa, & Lacal-Arántegui, 2011). Given this, it is critical to create efficient mathematical and computational models in order to prepare the road networks for disruptions and build cost-effective distribution methods for supply chain transportation networks (SCTN) during the post-disruption stage. Simultaneously, the disturbing components are restored, especially after a disruptive event has impacted them.

In response to the disruption that occurred to the road transportation networks and resulted in tremendous costs for several dependent networks (i.e., SCNs), the road transportation network decision-makers need to mitigate the road networks to ensure that as many of the SCN demand nodes as possible remain connected to their supplier nodes by fairly allocating the available mitigation budget. Thus, we propose a bi-objective, robust, mitigation MIP model that aims to retrofit the road network against the worst-case disruption scenario that might hinder the performance of the SCN. One of the objectives is to force the model to allocate the mitigation budget fairly in order to reduce the bias toward nodes or commodities with the highest demand requests. Also, the road transportation decision-makers need to have sufficient restoration plans for the post-disruption stage to ensure the resiliency of the SCN. The SCN resilience is achieved by maintaining the required service level at most of the demand nodes foe all commodities until the SL is fully maintained. Therefore, a bi-objective, fairness-based distribution MIP model is designed to restore the disrupted components while restoring the SCN satisfaction rate. One of the objectives focuses on minimizing the SCN total costs, while the other minimizes the total restoration cost. Integrating the mitigation during the pre-disruption stage with a fairness-based distribution when restoring the disrupted components during the post-disruption stage enhances the SCN performance and increases the overall service level.

The chapter is structured as follows. Section 2 includes a complete literature analysis, with an emphasis on (i) supply chain studies that include restoring networks when disruptions occur and (ii) numerous studies that explore pre- and post-disruption stages, as well as coping with uncertainty. Section 3 describes the proposed model in-depth, including its assumptions and mathematical derivation. Section 4 presents an exemplary case study related to distributing different goods via Colombia's road transportation network, while Section 5 addresses the collected results and discussion. Finally, section 6 is the concluding section, and presents the main findings and future work.

5.2 LITERATURE REVIEW

In this section, numerous studies on the topics of SCN disruption, SCN restoration, pre-disruption mitigation, post-disruption restoration, pre-and post- disruption studies, and robustness are addressed to highlight the importance of having an integrated framework that aims to mitigate and improve the road networks while also enhancing SCN resiliency and recoverability, respectively.

5.2.1 *SUPPLY CHAIN RESTORATION*

Several studies consider the restoration of the road transportation infrastructure network; thus, other service networks, such as SCN, can be resilient to disruptive occurrences. Miller-Hooks (2012) created a mathematical model for increasing the resilience of road transportation infrastructure networks, which takes into account the limited funds available to enhance the present system (Miller-Hooks, 2012). Hishamuddin et al. (2013) created an integer nonlinear programming model to determine the ideal production and order amounts for the supplier and store, as well as the time required to recover from transportation interruptions. They evaluated the disturbance that occurs to the cargo while being delivered by assessing a basic SC series with one supply and one retailer, assuming deterministic demand. Another study, published in 2011, focused on building a methodology to evaluate the resilience of infrastructure networks by studying two hypothetical scenarios of storms occurring in two distinct cities and quantifying the effect on a petrochemical SCN (Vugrin, Warren, & Ehlen, 2011). The researchers analyzed the impact of the disturbance using quantitative and qualitative indicators. Ramachandran et al. (2015) presented a framework aimed at decreasing the time required to restore the SC strategic infrastructure components. They created a restoration model that aimed to enhance the node connection while repairing the disturbed components. Gong et al. (2014) created a restoration model that addresses the interdependence of numerous infrastructure networks and an SCN in order to improve the SCN's resilience. Their methodology was created to help SCN decision-makers to reap the advantages of other networks' restoration efforts in order to boost SCN resilience (Gong et al., 2014). A recent study focused on building a restoration strategy based on the cost-effectiveness and resilience perspectives (Mao et al., 2020). They created a bi-objective nonlinear programming approach to maximize network resilience using two metrics: cumulative loss resilience and restoration rabidity resilience. Th findings indicate that having more than one resilience indicator is critical for restoring network performance. Gedik et al. (2014) created a restoration model for a train network in order to increase the SCN's resistance to disruptions. The goal was to determine the network's essential components and how they might impair SCN performance if these are disrupted (Gedik et al., 2014). In the aforementioned studies, the restoration process is based on the total cost of shipping or unmet demand costs in the systems, which differs from the proposed study, where we emphasize implementing a fairness-based distribution while restoring the disrupted components.

5.2.2 *MITIGATION AND RESTORATION STUDIES*

Transportation networks are susceptible to interruption and damage due to malicious attacks and natural disasters, and even by accident. Numerous studies have focused on reducing the impact of disruptive events by retrofitting these networks (i.e., Yücel et al., 2018; Karamlou et al., 2016; Lu et al., 2016; Dong et al., 2015), while other studies explore instead network recoverability after the disruption takes place by improving network resilience (i.e., González et al., 2016; Gomez et al. 2019; Almoghathawi et al., 2019; Karakoc et al., 2019; Morshedlou et al., 2018; Almoghathawi and Barker, 2019). Retrofitting transportation networks includes allocating a budget to strengthen the network against disruptive events that may occur during the pre-disaster phase. Yücel et al. (2018) intended to improve network accessibility after a disaster by strengthening the network links as an investment decision. They proposed a new approach to predicting post-disaster network status using Bayesian network representation. Karamlou et al. (2016) proposes a bi-objective, mixed integer programming to find the optimal retrofitting plan of the bridges in the transportation network, where the cost is minimized in the first objective, and a critical value bounds the resilience. Lu et al. (2016) presents a bi-level, stochastic programming model to find the optimal retrofitting resource allocation for bridges. In the upper level, the bridge retrofitting cost and traffic delays are minimized under uncertainty. In the lower-level problem, the focus is on the nonlinear relationship between traffic capacity and the cost of retrofitting each bridge. Dong et al. (2015) introduces a multicriteria optimization approach to find the optimal retrofitting strategy, which depends on three attributes (i.e., social, economic, and environmental), measured in different units. On the other hand, network resilience can be restored to its former state more quickly during the post-disaster phase by preparing a recovery plan including the necessary recourses. (González et al. (2016) and Gomez et al. (2019) investigate the impact of an interruption to the water, electricity, and gas networks, as well as their interdependence. González et al. (2016) analyze the physical and geographical interdependence of the networks and how each one is affected by the disruption of another. Gomez et al. (2019) expand on the work of González et al. (2016) by taking into account the socioeconomic aspects of the recovery process in order to increase infrastructure resilience. Almoghathawi et al. (2019) developed a bi-objective, mixed-integer programming model to provide a restoration plan for the failed components of interdependent networks, with the objective of maximizing network resilience and minimizing the restoration cost. In another study by Karakoc et al. (2019), a bi-objective, mixed integer program is introduced to provide a restoration plan to maximize resilience and minimize the social index in the other objective. Morshedlou et al. (2018) introduced a restoration planning model that schedules work crews to restore the disrupted components of the infrastructure network following a disruptive event. The objective is to produce a restoration plan that maximizes network resilience. Almoghathawi and Barker (2019) propose two-component importance measures to identify the critical network components that influence not only the other components in the network but also the components in other networks. However, the decisions made during the pre-disaster phase to reduce the impact of the disruptive events can affect network resilience during the post-disaster phase. The aforementioned studies failed to consider both the pre- and post-disruption stages, with each study focusing on and examining only one stage.

More recently, researchers have integrated the pre-disaster and post-disaster decision-making process (i.e., Edrissi and Askari 2020; Zhang et al., 2018; Zhou et al., 2019; Liao et al., 2018). Edrissi and Askari (2020) propose a bi-level Stackelberg game approach to find the optimal budget allocation among three infrastructure agencies, given that a master agency allocates the budget. The problem is solved using a meta-heuristic particle swarm algorithm. The objective of this study is to minimize the loss of property and lives by both mitigating the infrastructure and improving its resilience to earthquakes. Zhang et al. (2018) present a decision framework that covers the stages of a disaster—pre-disaster mitigation, post-disaster emergency response, and long-term recovery plan formulated as multicriteria optimization. Zhou et al. (2019) develop a bi-level stochastic programming model to find the optimal pre-disaster retrofitting plan and post-disaster restoration cost for transportation networks, based on simulated annealing and Frank-Wolfe Algorithms. Liao et al. (2018) found a link between network resilience, preparedness and recovery activities using a mathematical model. Two recent studies that considered the pre- and post-disruption stages when designing the mathematical models are proposed to enhance the infrastructure networks (Ghorbani-Renani et al., 2020; Ghorbani-Renani, González, & Barker, 2021). Ghorbani-Renani et al. (2020) proposed a tri-level protection interdiction-restoration model to improve infrastructure resilience by protecting the most vulnerable components in the infrastructure network against potential disruption then restoring the system when a disruption disturbs the network flow. The model provides a significant insight into the importance of protecting and mitigating those components against such disruption. The model was computationally hard to solve efficiently; thus, they extended the work by providing a decomposition approach to solve the model efficiently (Ghorbani-Renani et al., 2021). Our work differs in terms of implementing mitigation processes, where we consider a fair, robust budget allocation to avoid the bias toward areas where the demand is greater than in others. Also, we implement a fairness-based distribution during the post-disruption stage to maintain a higher satisfaction rate among the demand nodes while restoring the disrupted component and recovering SCN performance.

Disruptions to transportation networks are highly uncertain, since their severity, location, and impact are impossible to predict. When the probability distribution of the uncertain parameter is known, a stochastic programming approach is used. A scenario-based approach, using Monte Carol simulation or chance constraint programming, can be implemented, as used by Kimms and Maiwald (2018) to address road capacity uncertainty using bi-objective optimization. Ukkusuri and Waller (2008) developed a linear programming model to help to allocate a budget for capacity improvement, given the uncertain demand using chance constraint programming. The output of the uncertain model is compared with the nominal model. When the probability distribution of the disruptive event is unknown, robust optimization tends to be the most appropriate approach. In robust optimization, feasibility is the main concern, since an infeasible model is useless. Robust optimization provides tolerant solutions, to some degree, to the variability of the parameters, with the goal of maintaining feasibility. The concept of inexact linear programming was introduced by Soyster (1973). The feasible region is defined as a set containment instead of convex inequalities, known as the box uncertainty set. Box uncertainty is easy to implement, but too conservative, since it compromises a substantial portion of the feasible region, since all parameters are set to their worst level. The ellipsoidal uncertainty set was introduced by Ben-Tal and Nemirovski (1998) to control the level of conservatism. The weak spot of the ellipsoidal uncertainty approach is that it can be computationally demanding depending on the size of the problem, since it uses conic quadratic models to provide a solution. Later, Bertsimas and Sim (2004) introduced the polyhedral uncertainty approach, which is a generalization of box uncertainty. Liu et al. (2009) investigate the improved resilience and robustness of the bridge network under limited retrofitting resources. The main challenge is to capture the interdependency among individual transpiration facilities and consider the high uncertainty existing in the decision environment. Chang et al. (2012) present a methodology to find the optimal bridge retrofitting plan to maximize post-disaster flow capacity under the uncertainty of earthquakes using the Monte Carlo simulation approach. Dong et al. (2014) introduce a multicriteria optimization model to find a retrofitting plan for bridge networks under uncertainty. The conflicting criteria considered are the sustainability of a bridge network and the total cost of retrofit actions. Mohaymany and Nikoo (2020) introduce a multicriteria stochastic approach with the objectives of network connectivity, vulnerability, and length to mitigate the effect of disasters on a transportation network, specifically roadside tree blockages during a tropical cyclone. Hu et al. (2021) propose a tri-level, two-stage, multicriteria stochastic optimization model for retrofitting transportation networks by introducing a new metric to evaluate its performance. Zhou et al. (2020) study the implementation of a joint location transportation model, considering various gray parameters, demand, and road networks, to enhance the distribution of materials in the early post-disruption stage. They develop a mixed integer, nonlinear, bi-level programming model, where the upper level aims to minimize the transportation cost while the lower level aims to maximize fairness.

To the authors' knowledge, none of the studies have integrated fairness-based budget allocation with mitigating the road transportation network or implemented a fairness-based distribution while restoring the disruptive component and recovering the SCN performance simultaneously. Several studies considered restoring the disrupted components, while others consider mitigating the networks. Furthermore, the studies tend to mitigate and retrofit the components based on their importance among the other nodes when mitigating the networks. As a consequence, the mitigation budget is allocated unfairly. Imposing a fairness-based distribution when allocating the mitigation budget maximizes the degree of fairness among all of the demand nodes in the SCTN.

5.3 MODEL

In this section, we propose two bi-objective models in order to enhance SCN performance and maintain adequate SL at most of the demand nodes, since unpredicted events may disturb the flow of commodities in the road transportation network. The first model is associated with the pre-disruption stage, while the other is associated with the post-disruption stage. Each model and its constraints, sets, variables, and parameters will be addressed separately in this section.

5.3.1 *PRE-DISRUPTION MODEL*

The pre-disruption model focuses on mitigating potential disruptions in the road transportation network. The model examines the worst-case disruption scenario that can occur in a road network and result in significant impacts on SCN performance. Thus, we developed a bi-objective model that aims to provide a robust solution to such disruptions. The model consists of two objectives, one of which is related to the SCN total costs while, at the same time, the other one helps to maintain fairness in the system to avoid bias in the distribution of the mitigation budget in the areas where demand is high.

The graph examined in this model consists of sets of nodes and arcs $G = (\mathcal{N}, \mathcal{A})$, cities, and roads, respectively. The network's nodes are composed of various types of subset nodes: a set of supplier nodes$\mathcal{N}_s^l \subset \mathcal{N}$, a set of demand nodes$\mathcal{N}_d^l \subset \mathcal{N}$, and a set of transshipment nodes $\mathcal{N}_T^l \subset \mathcal{N}$. Also, a set of mitigation strategies $\mathcal{K}$ is given in this model. All of the required sets, parameters, and decision variables are listed in tables (Table 5-1-Table 5-3)

Table 5-1. Sets

$\mathcal{N}$	Set of nodes
$\mathcal{A}$	Set of arcs
$\mathcal{L}$	Set of commodities
$\mathcal{N}_s^l$	Set of suppliers' nodes of all commodities, where $\mathcal{N}_s^l \subset \mathcal{N}$
$\mathcal{N}_d^l$	Set of demand nodes of all commodities, where $\mathcal{N}_d^l \subset \mathcal{N}$
$\mathcal{N}_T^l$	Set of Transshipment nodes of all commodities, where $\mathcal{N}_T^l \subset \mathcal{N}$
$\mathcal{K}$	Set of mitigation strategies
Ω	Set of disruption scenarios

Table 5-2. Parameters

ξ	Total available resources to protect the network for each mitigation strategy $k \in \mathcal{K}$
Y_{ij}^0	A continuous parameter between {0,1} 1 if the arc is fully operational
u_{ij}^*	The initial capacity of arc $(i, j) \in \mathcal{A}$ before investment
ω_l	Weight of commodity l that will be shipped
C_{ij}^k	Resources to mitigate arc $(i, j) \in \mathcal{A}$ for each mitigation strategy $k \in \mathcal{K}$
$f_{il\omega}^-$	Cost of an unmet demand at node $i \in \mathcal{N}_d^l$ for commodity $l \in \mathcal{L}$ for disruption scenario $\omega \in \Omega$
$f_{il\omega}^+$	Cost of an excess supply at node $i \in \mathcal{N}_s^l$ for commodity $l \in \mathcal{L}$ for disruption scenario $\omega \in \Omega$
η_{ij}	The maximum capacity of each link arc $(i, j) \in \mathcal{A}$ can be enhanced

Table 5-3. Decision Variables

$\bar{y}_{ij}^k$	A continuous variable between {0,1} shows the protection rate of each arc $(i, j) \in \mathcal{A}$ for each mitigation strategy $k \in \mathcal{K}$
$\mathfrak{C}$	The upper limit of the total deviation in the unmet demand
$s_{il\omega}^-$	Unmet demand at node $i \in \mathcal{N}_d^l$ for commodity $l \in \mathcal{L}$ for disruption scenario $\omega \in \Omega$
$s_{il\omega}^+$	Excess supply at node $i \in \mathcal{N}_s^l$ for commodity $l \in \mathcal{L}$ for disruption scenario $\omega \in \Omega$
$\mu_{il\omega}^-$	Negative deviation from the total percentage of unmet demand at node $i \in \mathcal{N}_d^l$ for commodity $l \in \mathcal{L}$ for disruption scenario $\omega \in \Omega$
$\mu_{il\omega}^+$	Positive deviation from the total percentage of an unmet demand at node $i \in \mathcal{N}_d^l$ for commodity $l \in \mathcal{L}$ for disruption scenario $\omega \in \Omega$
γ_ω	Total percentage of an unmet demand for all commodities for disruption scenario $\omega \in \Omega$

The pre-disruption model focuses on mitigating the road transportation network by either increasing the road capacity, adding lanes or building landslide barriers in the areas where increasing the number of road lanes is impractical due to geographical challenges. To achieve this, a bi-objective, mixed integer programming (MIP) model is constructed. The first objective, Eq. (5-1), aims to minimize the upper limit of the total transportation costs, unmet demand costs, and oversupply costs in the SCN for all disruption scenarios. The second objective, Eq. (5-2), aims to reduce the upper limit of the total deviation in the unmet demand at all demand nodes, cities, for all commodities for all disruption scenarios. The two objectives are subjected to sets of constraints. The first constraint, Eq. (5-3), represents the total available budget for mitigating disruptions to the road transportation network. Both mitigation strategies should be less than or equal to the available budget ζ assigned by the road transportation management. Eq. (5-4) represents the flow balance constraint, which measures the flow leaving and entering in order to determine the nature of the node. If $b_{il} \geq 0$, the node is a supplier node for the given commodity. If $b_{il} \leq 0$, the node is a demand node for the given commodity. If $b_{il} = 0$ then the node is a transshipment for the given commodity. Eq. (5-5) represents the available mitigation strategies: increasing the road capacity or building barriers that protect the roads from the impacts of disruption. If $\bar{y}_{ij}^{\boldsymbol{k}} = 1 \; where \; k = 1$, the model chooses to increase the road capacity; thus, the road capacity increases based on the parameter (ξ_{ij}^{1k}). If $\bar{y}_{ij}^{\boldsymbol{k}} = 1 \; where \; k = 2$, the model then chooses to build barriers to protect the road against disruptions; thus, the road's initial capacity is protected based on the parameter (ξ_{ij}^{2k}). Eq. (5-6) calculates the total unmet demand percentages for all commodities, for all demand nodes, for each disruption scenario, by calculating the total minimize $\boldsymbol{O1} = Z$ (5-1)

minimize $\boldsymbol{O2} = \mathfrak{C}$ (5-2)

Subject to:

$$\sum_{(i,j)\in\mathcal{A}}\sum_{k\in\mathcal{K}} C_{ij}^{k}\,\bar{y}_{ij}^{\boldsymbol{k}} \leq \zeta \tag{5-3}$$

$$\sum_{j:(i,j)\in\mathcal{A}} x_{ijl\omega} - \sum_{j:(j,i)\in\mathcal{A}} x_{jil\omega} = b_{il} + s_{il\omega}^{-} - s_{il\omega}^{+} \begin{cases} -b_{il}, & Demand\ node\quad \mathcal{N}_d^l \subset \mathcal{N} \\ +b_{il}, & Supplier\ node\quad \mathcal{N}_s^l \subset \mathcal{N} \\ 0, & Transhipment\ node\ \mathcal{N}_T^l \subset \mathcal{N} \end{cases} \qquad \forall\, i \in \mathcal{N}, \forall\, l \in \mathcal{L}, \forall\, \omega \in \Omega \tag{5-4}$$

$$\sum_{l\in\mathcal{L}} x_{ijl\omega} \leq \left(u_{ij}^{*}\,(\xi_{ij}^{1k} + \xi_{ij}^{2k})\,\bar{y}_{ij}^{\boldsymbol{k}}\right) Y_{ij\omega}^{0} \qquad \forall\,(i\,,\,j) \in \mathcal{A}, \forall\, k \in \mathcal{K}, \forall\, \omega \in \Omega \tag{5-5}$$

$$\frac{\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{N}_d^l} s_{il\omega}^{-}}{\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{N}_d^l} b_{il}} = \gamma_{\omega} \qquad \forall\,\omega \in \Omega \tag{5-6}$$

$$\left(\frac{s_{il\omega}^{-}}{b_{il}}\right) - \gamma_{\omega} + \mu_{il\omega}^{-} - \mu_{il\omega}^{+} = 0 \qquad \forall\, i \in \mathcal{N}_d^l, \forall\, l \in \mathcal{L}, \forall\,\omega \in \Omega \tag{5-7}$$

$$\mathrm{Z} \geq \sum_{l\in\mathcal{L}}\left(\sum_{(i,j)\in\mathcal{A}} x_{ijl\omega}\, d_{ij} c_{ij} + \sum_{i\in\mathcal{N}_s^l} s_{il\omega}^{+}\, f_{il\omega}^{+} + \sum_{i\in\mathcal{N}_d^l} s_{il\omega}^{-}\, f_{il\omega}^{-}\right) \qquad \forall\omega \in \Omega \tag{5-8}$$

$$\mathfrak{C} \geq \left(\frac{\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{N}_d^l}(\mu_{il\omega}^{-} + \mu_{il\omega}^{+})}{\sum_{l\in\mathcal{L}}|\mathcal{N}_d^l|}\right) \qquad \forall\,\omega \in \Omega \tag{5-9}$$

$$s_{il\omega}^{+} \geq 0 \qquad \forall\, i \in \mathcal{N}_s^l, \forall\, l \in \mathcal{L}, \forall\,\omega \in \Omega \tag{5-10}$$

$$\mu_{il\omega}^{+}\,, \mu_{il\omega}^{-}\,, s_{il\omega}^{-} \geq 0 \qquad \forall\, i \in \mathcal{N}_d^l, \forall\, l \in \mathcal{L}, \forall\,\omega \in \Omega \tag{5-11}$$

$$\mathfrak{C} \geq 0 \tag{5-12}$$

$$\gamma_\omega \geq 0 \qquad \forall\, \omega \in \Omega \tag{5-13}$$

$$\bar{y}_{ij}^{\boldsymbol{k}} \geq 0 \qquad \forall\, (i,j) \in \mathcal{A}, \forall\, k \in \mathcal{K} \tag{5-14}$$

unmet demand quantities in the network divided by the total demand of all of the demand nodes for all commodities. Eq. (5-7) calculates the positive and negative deviation when comparing the unmet demand percentage at each node, for each node, for each disruption scenario, with the total unmet demand percentage in the network, as calculated in Eq. (5-6). Eq. (5-8) represents the upper bound of the total costs in the SCN. The larger the Z value, the worse the SCN performance. Eq. (5-9) calculates the total upper bound of the total deviation in the unmet demand at all nodes for all commodities and all disruption scenarios. The larger the $\mathfrak{C}$ value, the more unfair the system. Eqs. (5-10)-(5-14) represent the nature of the decision variables in the model.

5.3.2 *POST-DISRUPTION MODEL*

During the post-disruption stage, a bi-objective MIP model is proposed to examine SCN performance when unpredicted events disturb the flow of commodities within the road transportation network and examine SCN recoverability when the disrupted components are restored. The model tests SCN performance under different level percentages of restoration budgets. A 100% restoration budget means that the budget is enough to restore all of the disrupted components in that particular disruption scenario. When the budget is 0%, it means that there is no budget to restore any of the disrupted components. The model's constraints, sets, variables, and parameters are addressed below.

Along with a list of the sets described in the pre-disruption model, two sets are added to the post-disruption model, as shown in Table 5-4. It is given that a set of time $\mathcal{T}$ represents the model performance at different time periods and the required times that are needed to restore the network performance, and also, a set of restoration resources $\mathcal{R}$ that represents the available resources and crews to restore the disrupted components in the road network. The decision variables parameters are listed in Table 5-5 and Table 5-6, respectively.

Table 5-4. Sets

$\mathcal{T}$	Set of Time
$\mathcal{R}$	Set of restoration resources

Table 5-5.Parameters

u_{ij}	Available capacity of arc $(i\,,\,j) \in \mathcal{A}$ after mitigation
f_{ilt}^{-}	Cost of an unmet demand at node $i \in \mathcal{N}_d^l$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
f_{ilt}^{+}	Cost of an excess supply at node $i \in \mathcal{N}_s^l$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
$\hat{g}_{ilt}$	Cost of restoring a disrupted arc $(i\,,\,j) \in \mathcal{A}$ at time $t \in \mathcal{T}$
Δ_{ij}	Proportional time required to restore an arc $(i\,,\,j) \in \mathcal{A}$
ϑ_{rt}	Total available resources and crews $r \in \mathcal{R}$ at time $t \in \mathcal{T}$
v_{ijrt}	The resources and crews $r \in \mathcal{R}$ required to restore an arc $(i\,,\,j) \in \mathcal{A}$ at time $t \in \mathcal{T}$
y_{ijt}	A continuous parameter between {0,1} 1 if the arc is fully functioning at time $t \in \mathcal{T}$; and < 1 otherwise
α_{il}	The required service level at node $i \in \mathcal{N}_d^l$ for commodity $l \in \mathcal{L}$
d_{ij}	Distance in miles of the arc $(i\,,\,j) \in \mathcal{A}$
c_{ij}	Shipping cost of using the arc $(i\,,\,j) \in \mathcal{A}$

Table 5-6. Decision Variables

s_{ilt}^{-}	Unmet demand at node $i \in \mathcal{N}_d^l$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
s_{ilt}^{+}	Excess supply at node $i \in \mathcal{N}_d^l$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
x_{ijlt}	Amount of flow through arc $(i\,,\,j) \in \mathcal{A}$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
$\hat{y}_{ijt}$	A binary variable {0,1} 1 if arc $(i\,,\,j)$ is to be restored at time $t \in \mathcal{T}$; and 0 otherwise

δ_{ilt}	A binary variable {0,1} 1 if a node $i \in \mathcal{N}_d^l$ did not receive the minimum service level at time $t \in \mathcal{T}$; and 0 otherwise
γ_t	Total percentage of unmet demand for all commodities at time $t \in \mathcal{T}$
μ_{ilt}^-	Negative deviation from the total percentage of unmet demand at node $i \in \mathcal{N}_d^l$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$
μ_{ilt}^+	Positive deviation from the total percentage of unmet demand at node $i \in \mathcal{N}_d^l$ for commodity $l \in \mathcal{L}$ at time $t \in \mathcal{T}$

Eq. (5-15) represents the objective of the post-disruption model. The objective consists of four components: the total flow costs for all commodities at each time ($c_{ij}\ d_{ij}\ x_{ijlt}$), the total excess supply costs at each supply node for all commodities at each time ($f_{ilt}^+\ s_{ilt}^+$), the total unmet demand cost for all commodities at each time ($f_{ilt}^-\ s_{ilt}^-$), and the total deviation in the unmet demand for all commodities at each time ($\mu_{ilt}^- +\ \mu_{ilt}^+$). Eq. (5-16) represents the flow entering and leaving the supplier nodes, while Eq. (5-17) represents the flow entering and leaving the nodes for each restoration time. The required service level (SL) that each demand node requires is calculated using Eq. (5-18), and is indicated by the binary variable (δ_{ilt}). If (δ_{ilt}) $= 1$, the SL is not maintained and if (δ_{ilt}) $= 0$, otherwise. Eq. (5-19) is the road capacity constraint for all commodities for each restoration time. The total percentage of unmet demand in the network for each time period and the deviation between the unmet demand percentage compared to the total unmet demand percentage in the network are calculated in Eqs. (5-20) and (5-21) respectively. Eq. (5-22) represents the initial status of each link at time $t = 1$, and Eq. (5-23) shows that the link functionality is ($y_{ijt} \leq 1$). Eq. (5-24) is designed to guarantee that the disrupted link will be restored fully, based on the proportional time that crews require (Δ_{ij}). The available resources and crews to restore the disrupted components are represented in Eq. (5-25). Eqs. (5-26)-(5-29) represent the nature of each decision variable.

$$min\ O1 = \sum_{t\in\mathcal{T}}\sum_{l\in\mathcal{L}}\left(\sum_{i,j\in\mathcal{A}} c_{ij}\ d_{ij}\ x_{ijlt} + \sum_{i\in\mathcal{N}_s^l} f_{ilt}^{+}\ s_{ilt}^{+} + \sum_{i\in\mathcal{N}_d^l} f_{ilt}^{-}\ s_{ilt}^{-} + \beta\left(\frac{\sum_{i\in\mathcal{N}_d^l}(\mu_{ilt}^{-} + \mu_{ilt}^{+})}{|\mathcal{N}_d^l|}\right)\right) \tag{5-15}$$

$$min\ O2 = \sum_{(i,j)\in\mathcal{A}}\sum_{t\in\mathcal{T}|>1} \hat{g}_{ijt}\left(\hat{y}_{ijt} - Y_{ij}^{0}\right) \tag{5-16}$$

Subject to:

$$\sum_{j:(i,j)\in\mathcal{A}} x_{ijlt} - \sum_{j:(j,i)\in\mathcal{A}} x_{jilt} = b_{il} - s_{ilt}^{+} + s_{ilt}^{-}\begin{cases} -b_{il}, & Demand\ node\ \ \mathcal{N}_d^l \subset \mathcal{N} \\ +b_{il}, & Supplier\ node\ \ \mathcal{N}_s^l \subset \mathcal{N} \\ 0, & Transhipment\ node\ \mathcal{N}_T^l \subset \mathcal{N} \end{cases} \quad \forall\, i\in\mathcal{N}, \forall\, l\in\mathcal{L}, \forall\, t\in\mathcal{T} \tag{5-17}$$

$$\sum_{j:(i,j)\in\mathcal{A}} x_{ijlt} - \sum_{j:(j,i)\in\mathcal{A}} x_{jilt} \le \alpha_{il} * b_{il}\,(1-\delta_{ilt}) \quad \forall\, i\in\mathcal{N}_d^l, \forall\, l\in\mathcal{L}, \forall\, t\in\mathcal{T} \tag{5-18}$$

$$\sum_{l\in\mathcal{L}} x_{ijlt}\, w_l \le u_{ij}\, y_{ijt} \quad \forall\,(i\,,\,j)\in\mathcal{A}, \forall\, t\in\mathcal{T} \tag{5-19}$$

$$\frac{\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{N}_d^l} s_{ilt}^{-}}{\sum_{l\in\mathcal{L}}\sum_{i\in\mathcal{N}_d^l} b_{il}} = \gamma_t \quad \forall\, t\in\mathcal{T} \tag{5-20}$$

$$\left(\frac{s_{ilt}^{-}}{b_{il}}\right) - \gamma_t + \mu_{ilt}^{-} - \mu_{ilt}^{+} = 0 \quad \forall\, i\in\mathcal{N}_d^l, \forall\, l\in\mathcal{L}, \tag{5-21}$$

$$y_{ij1} = Y_{ij}^{0} \quad \forall\,(i\,,\,j)\in\mathcal{A}, \forall\, t\in\mathcal{T}|t=1 \tag{5-22}$$

$$y_{ijt} \le 1 \quad \forall\,(i\,,\,j)\in\mathcal{A}, \forall\, t\in\mathcal{T} \tag{5-23}$$

$$y_{ijt} \le Y_{ij}^{0} + \sum_{r\in\mathcal{R}}\sum_{\acute{t}=1}^{t} \Delta_{ij}\hat{y}_{ijr\acute{t}} \quad \forall\,(i,j)\in\mathcal{A},\ t\in\mathcal{T}|t>1 \tag{5-24}$$

$$\sum_{(j,i)\in\mathcal{A}} \hat{y}_{ijrt}\, v_{ijrt} \leq \vartheta_{rt} \qquad \forall\, r \in \mathcal{R}, \forall\, t \in \mathcal{T} | t > 1 \qquad (5\text{-}25)$$

$$s_{ilt}^{-}\,,\ s_{ilt}^{+}\,,\ \mu_{ilt}^{+}\,,\mu_{ilt}^{-}\ \geq\ 0 \qquad \forall\, i \in \mathcal{N}_d^l, \forall\, l \in \mathcal{L}, \forall\, \mathrm{t} \in \mathcal{T} \qquad (5\text{-}26)$$

$$\gamma_t \quad \geq\ 0 \qquad \forall\, \mathrm{t} \in \mathcal{T} \qquad (5\text{-}27)$$

$$\delta_{ilt} \ \in \{\, 0\ ,\ 1 \,\} \qquad \forall\, i \in \mathcal{N}_d^l, \forall\, l \in \mathcal{L},\ \forall\, t \in \mathcal{T} \qquad (5\text{-}28)$$

$$\hat{y}_{ijrt} \ \in \{\, 0\ ,\ 1 \,\} \qquad \forall\, (i,j) \in \mathcal{A}, \forall\, r \in \mathcal{R}, \forall\, \mathrm{t} \in \mathcal{T} \qquad (5\text{-}29)$$

In this study, we consider the two models to be bi-objective models in order to integrate a fairness-based distribution along with other costs associated with SCN properties: transportation, unmet and oversupply costs. It is feasible to examine the tradeoff between cost efficiency and fairness using a bi-objective modelling approach so that decision-makers and stakeholders may make educated decisions to enhance supply chain performance as well as the degree of fairness between different economic sectors. The addition of a target for measuring the degree of fairness of a distribution plan is crucial since, without it, the focus would primarily be on lowering the overall transportation costs and unmet demands. However, this will lead to the bigger demand nodes or economic sectors absorbing the majority of capacity utilization and available resources, thereby impacting the performance of the smaller ones. The bias toward the nodes or sectors with the highest demand is decreased by pushing the model to minimize the sum of the deviations from the mean percentage of the unmet demand. Various approaches, such as the weighted sum technique and ε-constraint approach, have been developed and utilized in the literature to solve bi-objective optimization models such as the one proposed. We adopt the ε -constraint approach in this work because it offers several advantages over other methods, particularly when dealing with MIP models. Some of these benefits were highlighted by Mavrotas G. (2009): i) the ε-constraint may yield unsupported efficient solutions in multi-objective MIP models, where the weighting technique cannot (Steuer, R. E. 1986); ii) methods like the weighted sum technique require the pre-solution scaling of each objective, which has a substantial impact on the outcomes (scaling is unnecessary when utilizing the -constraint approach, however); and iii) when utilizing the ε-constraint, the quantity and distribution of the created efficient solutions can be controlled but, when using the weighted sum approach, this is challenging.

To use the ε-constraint approach, the first step is to make one of the objectives the major objective, and then fix the feasible range of the others, using iteratively adapted upper and lower limits. Mavrotas G. (2009) provides more information on how to implement the ε-constraint technique.

5.3.3 *PERFORMANCE MEASURES*

In this part, we examine how fairness improves SCN performance based on satisfaction rates and how it increases overall transportation costs, using terms like "Relative Improvement" (RI) and "Price of Fairness" (POF), respectively.

(1) As indicated in Eq. (5-30), the RI is defined as the decrease in the overall number of dissatisfied demanders in the system with mitigation and a fairness-based distribution (UDMF), compared to the number of dissatisfied demanders without mitigation and a fairness-based distribution (UDWMF). This term is comparable to Yao et al. (2009)'s application, in which they contrasted their robust solution with a nominal solution.

(2) The POF is well-defined and has been used in several studies on fairness. The original purpose of POF was to determine the reduction in usage when fairness was applied (Bertsimas, Farias, and Trichakis, 2011). Also, Ye et al. (2017) employed a different method of using POF to calculate the increase in overall cost when adopting fairness. As a result, we defined the POF as the difference between the total transportation costs with mitigation and a fairness-based distribution (TTCMF) and total transportation costs without mitigation and a fairness-based distribution (TTCWMF) (Abushaega et al., 2021), as shown in Eq (5-31).

(3) Also, we consider Jain's index to measure the performance of our model at demand nodes. Jain et al. (1999) proposed Jain's fairness index to measure the throughput at the bottleneck nodes. In our analysis, we used Jain's index ($\mathcal{J}_t$), illustrated in Eq. (5-32), to indicates how fair is our solution considering the number of flows that the demand nodes received (∇_{ilt}) out of their demands. (∇_{ilt}) represents the flow of commodities at the demand node for each commodity minus the unmet demands that weren't sent due to disruptions each time ($b_{il} - S_{ilt}^{-}$). The ($\mathcal{J}_t$) is bounded by ($\frac{1}{n} \leq \mathcal{J}_t \leq 1$), as shown in Eq. (5-33). The higher the Jain's index ($\mathcal{J}_t$), the fairer the system is. For instance, there are various fairness indices, for instance, Gini index, unfairness, Max-min index, and Jain's index, which have been used in the literature widely to measure the trade between fairness and efficiency. The implementations of most of them are challenging due to the nature of their structure or the computational time they required if the size of the network is large. So, we just considered Jain's index to measure the efficiency of the proposed model without integrating it into the model structure.

$$RI(\%) = \frac{\text{UDWMF} - \text{UDMF}}{\text{UDWF}} \tag{5-30}$$

$$POF(\%) = \frac{TTCMF - TTCWMF}{TTCMF} \tag{5-31}$$

$$\mathcal{J}_t = \frac{\left(\sum_l \sum_{i \in \mathcal{N}_i^l} \nabla_{ilt}\right)^2}{n \times \sum_l \sum_{i \in \mathcal{N}_i^l} (\nabla_{ilt})^2} \qquad \forall\, t \in \mathcal{T} \tag{5-32}$$

$$\frac{1}{n} \leq \mathcal{J}_t \leq 1 \qquad \forall\, t \in \mathcal{T} \tag{5-33}$$

These three performance measures are used in the post-disruption model while restoring the disrupted components in the road transportation network. They highlighted the SCN performance when a disruption occurs and the impact of implementing a fairness-based distribution on the total transportation network.

5.4 CASE STUDY

In this article, the supply chain network (SCN) is linked to Colombia's transportation infrastructure and the freight that moves through it. We chose the Colombian transportation network since trucks are used for the vast majority of goods distributed in Colombia. Additionally, several of Colombia's major cities are located in mountainous regions, making intercity connections vulnerable to flooding and landslides. As a result, because cities tend to have few roadways connecting them, they can be easily separated in the event of natural catastrophes or other disruptive events.

In this study, Colombia's road transportation network is used to examine the model efficiency. The nodes indicate the major cities, and the arcs the transportation roads that connect them in the Colombian road transportation network. The road network is made up of 51 nodes and 57 undirected arcs (or 114 directed arcs). The case study covers the

258 most representative materials and products of the Colombian supply chain, which are divided into six economic sectors (Clavijo-Buritica, et al., 2021). For the purpose of this case study, we suppose that each economic sector has an aggregate commodity, that is calculated based on the overall weight and value of each individual product. Table 5-7 lists the data for each economic sector modeled and the total number of supply and demand nodes in each sector. Figure 5-1 depicts the modelled road transportation network, which includes Colombia's major cities and the highways that connect them. In this case study, we examine the impact of various random network capacity reductions on SCN performance. Initially, the study focuses on protecting the roads against the worst-case disruption scenario that could affect SCN performance. The disruption level is considered less than or equal to 10% of the total number of roads in the network, and the mitigation budget is assumed to be sufficient to mitigate 10% of the roads. Due to the geographical challenges associated with the Colombia road transportation network, two different mitigation strategies are considered: mitigation 1 involves increasing the number of lanes, and mitigation 2 entails building barriers to protect the roads from landslides. Figure 5-2 shows each mitigation strategy and the links associated with it. After mitigating the road network, the network is examined against various random disruptions, in which we test the network robustness and SCN resilience to fulfill the demand nodes' needs while restoring the disrupted components. We measure SCN performance by measuring the SL at each demand node for each sector and count the number of demand nodes that fail to receive the minimum needed SL for each sector. In the mathematical model, some penalty costs were assumed, for instance, the costs of the unmet demand and surplus supply and the transportation cost, which was assumed to be

proportionate to the distance between the nodes, and the cost of implementing a fairness-based distribution.

Table 5-7. The Colombia SCN information

Sector	Sector Description	Number of Supply Nodes	Number of Demand Nodes
1	Farming, forestry, hunting, and fishing	19	23
2	Mining and quarrying	5	7
3	Construction	7	16
4	Manufacturing industry	10	32
5	Commerce, repair, restaurants, and hotels	12	35
6	Transportation, storage, and communications	23	28

Figure 5-1. Road transportation network of Colombia (Abushaega et al., 2021)

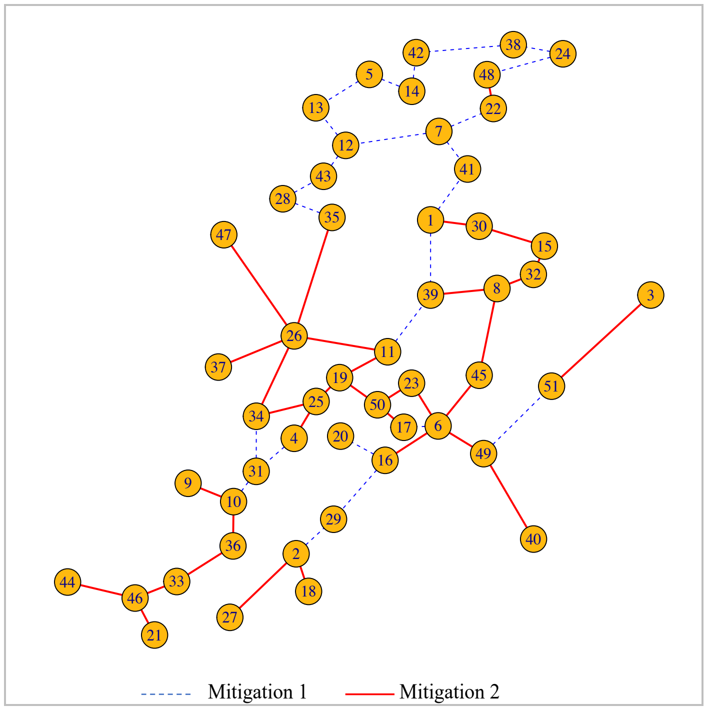

Figure 5-2. The mitigation strategies and their candidate links

5.5 PROCEDURES, RESULTS, AND DISCUSSION

In this study, the model is designed to consider the pre- and post-conditions of the road network and SCN performance. During the pre-disruption stage, the model focuses on protecting the road transportation network against the worst-case disruption scenario in order to increase the robustness of the road transportation network. Thus, SCN performance is less impacted by any imminent disruption. The analysis of this case study is divided into two parts: the pre- and post-disruption stages.

5.5.1 *PRE-DISRUPTION ANALYSIS*

In this section, the model was designed to provide a robust solution that considers the worst-case disruption scenarios. When consulting an expert regarding the disruption severity level that has occurred in the examined case study, it was mentioned that the most severe disruption that happened to the Colombia road transportation network involved less than 10% of the network component failing at the same time. Thus, we generated 4,000 random disruption scenarios, where we consider that up to 10% of the links might fail simultaneously. The distribution of the 4,000 disruption scenarios' impacts is depicted in Figure 3. Since the model is designed to consider the worst-case scenarios, we focused our analysis on the last category in Figure 5-3, which represents the most devastating disruption scenarios. We found that four scenarios lie within the category range. These four disruption cases had catastrophic impacts on SCN performance; thus, they were investigated as listed in Table 5-8 and depicted in Figure 5-4. The four cases shared most of the disrupted links, with a few changes in some of them. We can see that Case 1 resulted in the highest reduction, at 84.77% of the total commodities, in SCN performance.

The model was designed to protect the road network against the worst-case scenario; thus, Case 1 was selected as the worst-case, and the network needed to be mitigated to prevent such severe disruption occurring. Figure 5-5 represents the mitigated links in the road network, selected by our robust fairness SCN model from the 4,000 disruption scenarios. After mitigating the network against the worst-case scenario, the information regarding the road capacity and probability of the links being disrupted were updated, based on the selected links.

Table 5-8. Impacts on the amount of distributed flows

Cases	Number of disrupted links	Impact on the supplied demand of all commodities
Case 1	6	84.77%
Case 2	6	84.03%
Case 3	5	84.03%
Case 4	5	84.01%

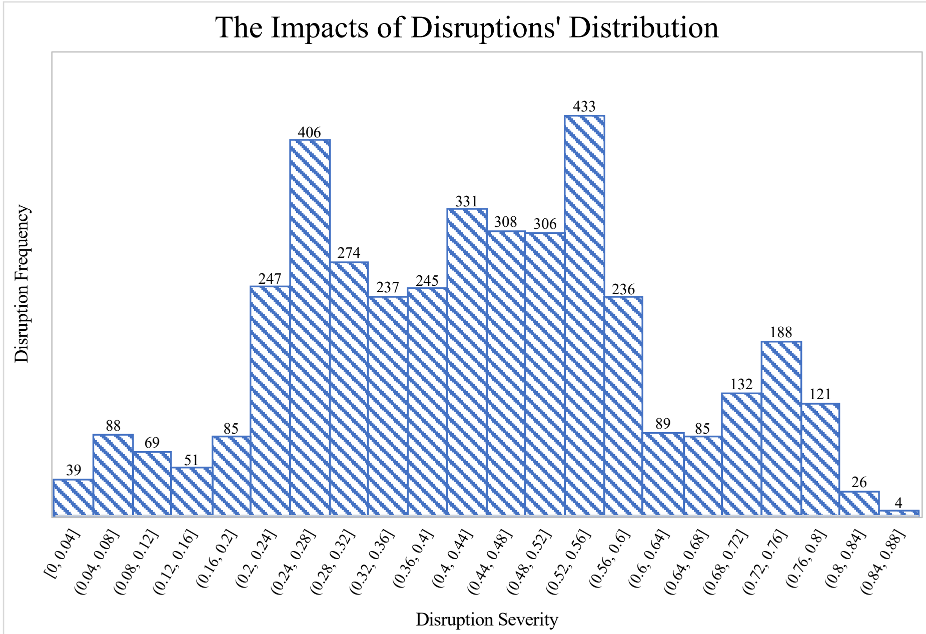

Figure 5-3. The distribution of the 4,000 disruption scenarios and their impacts on the SC flows of commodities. 0 means no effect and 1.00 means 100% effect.

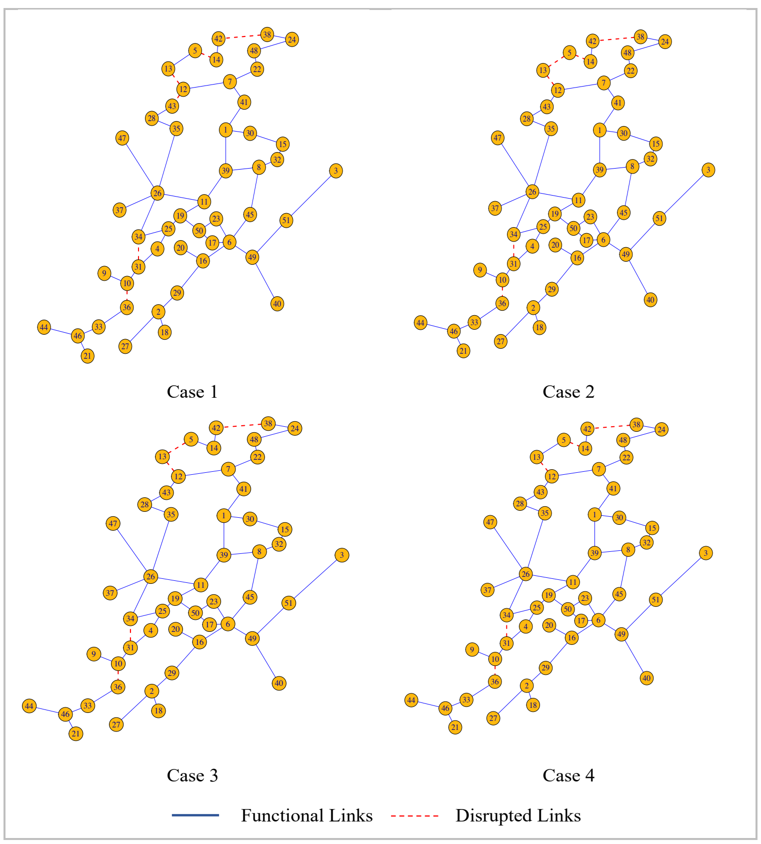

Figure 5-4. Lists of worst-case disruption scenarios

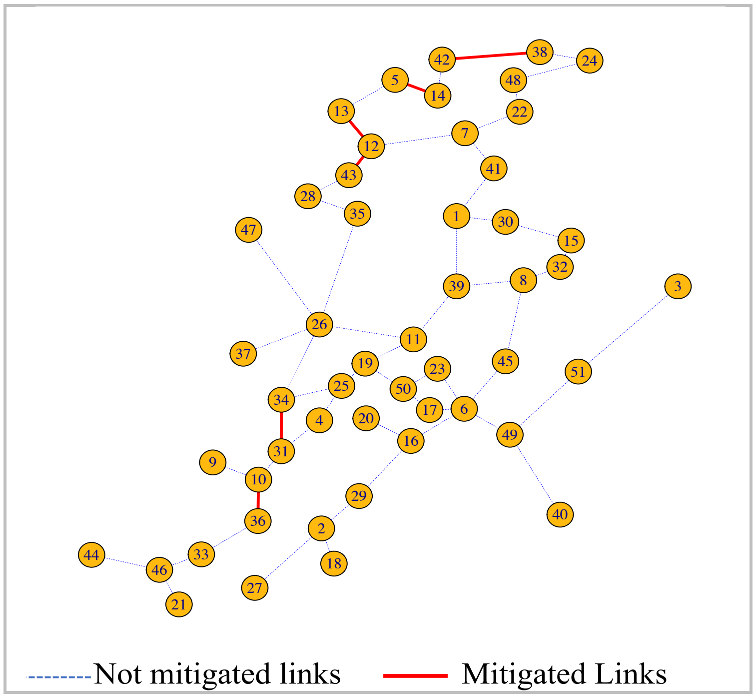

Figure 5-5. The selected disruption scenario to be mitigated

5.5.2 *POST-DISRUPTION ANALYSIS*

After fairly mitigating the road network against the worst-case disruption scenario, the model examined SCN performance and resilience against road disruptions. One hundred disruption scenarios were generated, with 15% of the total network components being disrupted simultaneously. The model aims to test SCN performance when the network was mitigated and apply a fairness-based distribution during the restoration process, or when it was not mitigated, and no fairness-based distribution was applied during the restoration process. Table 5-9 represents the average number of unsatisfied demand nodes for all commodities at different levels of restoration budget. It can be seen that applying mitigation along with a fairness-based distribution reduced the number of unsatisfied demand nodes significantly, as indicated by the RI in Table 5-9. The improvement in the satisfaction rate was due to the changes in the road capacity and the way of distributing the available commodities while restoring the disrupted components in the road transportation network. At time 1, where no restoration was made, the mitigation and a fairness-based distribution solution reduces the number of unsatisfied demand nodes significantly, with an 86% improvement; however, this improvement results in increasing the total transportation cost (POF), as depicted in Figure 5-6 and presented in Table 5-10. Figure 5-6 shows the total transportation costs of delivering the allowable quantities of commodities at each restoration time when considering the mitigation and a fairness-based distribution solution and the no mitigation, no fairness-based distribution solution. In Table 5-10 at times 4 and 5, the POF percentages when there was no restriction on the restoration budget were higher compared to the solution when the restoration budget was restricted due to the available capacity to move more products within the network since it has already been mitigated and enhanced against disruption. Thus, a fairness-based distribution forced the model to move more freight to supply the more demand nodes with their required SL.

Table 5-9. The average number of unsatisfied demand nodes during the restoration time at different restoration budget levels

Restoration Time	No mitigation no fairness		With mitigation and fairness		RI%	
	Restoration Budget		Restoration Budget		Restoration Budget	
	50%	100%	50%	100%	50%	100%
Time 1	36.13	36.13	5.03	5.03	86%	86%
Time 2	28.52	28.91	4.18	4.17	85%	86%
Time 3	23.33	23.29	3.13	2.96	87%	87%
Time 4	19.03	17.98	2.66	2.01	86%	89%
Time 5	15.63	9.43	2.37	1.38	85%	85%
Time 6	15.63	3.12	2.37	0.51	85%	84%
Time 7	15.63	0.73	2.37	0.13	85%	82%
Time 8	15.63	0.11	2.37	0.02	85%	82%
Time 9	15.63	0	2.37	0	85%	~

Table 5-10. The effect of price of fairness (POF) on the total transportation costs due to the implementation of a fairness-based distribution

Restoration Time	POF%	
	Restoration Budget	
	50%	100%
Time 1	24.31%	24.31%
Time 2	8.45%	8.30%
Time 3	6.18%	6.00%
Time 4	2.14%	3.14%
Time 5	1.35%	1.53%
Time 6	1.35%	0.43%
Time 7	1.35%	0.13%
Time 8	1.35%	0.01%
Time 9	1.35%	~

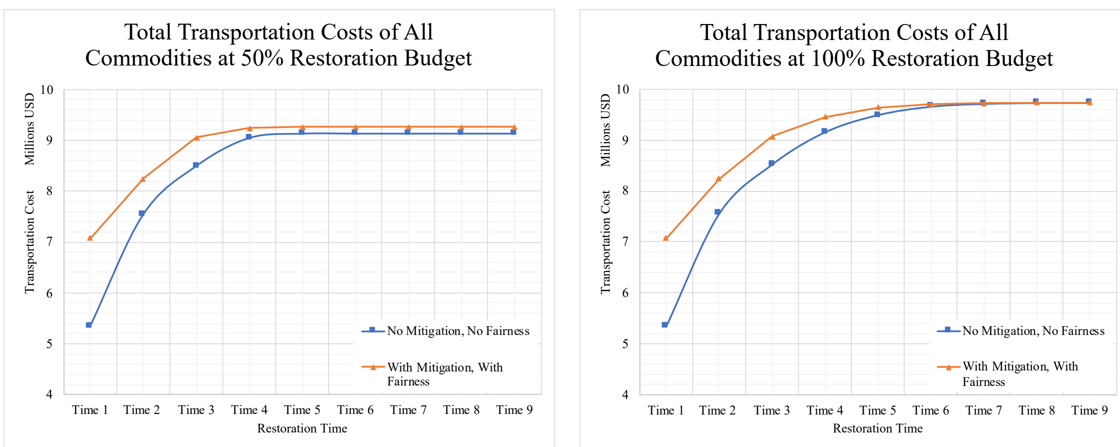

Figure 5-6. A comparison of the total transportation costs for distributing all commodities under both solution approaches: the no mitigation, no fairness solution and the with mitigation, with fairness solution, while considering two restoration budget levels: 100% means sufficient budget to restore all of the disrupted components, and 50% means sufficient restoration budget to restore half of the disrupted components.

The two solution approaches performed differently when distributing the total commodities among the demand nodes. In Figure 5-7, the percentage of the total demand percentage of each solution approach during the restoration times under different restoration budget levels is depicted. It can be seen that, at time 1, the reduction in the total demand percentages was significant when the network was not mitigated compared to the mitigated solution. Also, the demand percentages during the restoration process recovered faster to normal status when a sufficient budget was assigned to restore all of the disrupted components. When the budget was sufficient to restore only half of the disrupted components, the mitigation and fairness solution was able to distribute a higher demand percentage to the demand nodes compared to the no mitigation, no fairness solution. Also, when fully using the half restoration budget (50%), the no mitigation, no fairness solution did not reach the mitigation and fairness solution level. Even though the difference was minimal, the improvement in the satisfaction rate among the demand nodes was significant, as presented in Table 5-9 under the column of RI% (restoration budget 50%).

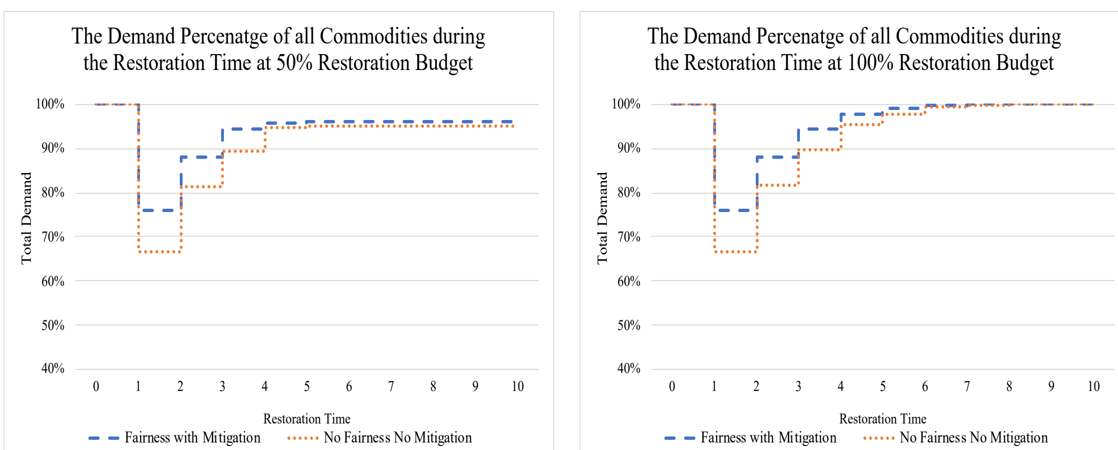

Figure 5-7. A comparison of the total demand percentages for all commodities under both solution approaches: the no mitigation, no fairness solution and the with mitigation, with fairness solution, while considering two restoration budget levels: 100% means sufficient budget to restore all of the disrupted components, and 50% means sufficient restoration budget to restore half of the disrupted components.

Another comparison between the proposed solutions is depicted in Figure 5-8 and Figure 5-9. These figures show the impacts of the disruptions on each sector and commodity as well as the impacts on each solution approach, considering two restoration budget levels being assigned to restore SCTN performance. Figure 5-8 represents the performance of each commodity when the budget was insufficient to restore the disrupted components. In Figure 5-8, Column (a), it can be seen that almost all of the commodities were impacted significantly when we measure the satisfaction rate at each demand node, considering that no mitigation was performed before the disruption and no fairness-based distribution was applied after the disruption occurred. The more the inward spikes, the higher the impact on the satisfaction rate. In Column (b), the network was mitigated before the disruption occurred, and no fairness-based distribution was applied after it occurred. When a fairness-based distribution was added in Column (c), the majority of the commodities or sectors maintained the SL, except for commodities 4 and 6, when restoring some of the disrupted components. We can see that the impacts of the disruptions reduced when we compare Column (b) with Column (d), as the latte shows that, when a fairness-based distribution was applied to the mitigation solution, the impacts of disruptions on the satisfaction rate were minimal during the restoration time.

In Figure 5-9, similar behaviour may be observed in Figure 5-8, except that all solution approaches restored SCN performance to normal after restoring all of the disrupted components in the road transportation network. Figure 5-9 represents the performance of each sector, considering different solution approaches during the restoration process, assuming that the budget is sufficient to restore all of the disrupted components. In both Figure 5-8 and Figure 5-9, when we compare Column (a) with Column (d) and link the result to Table 5-9, we see that the improvement is significant. Thus, we conclude that mitigating the network against the worst-case scenario and applying a fairness-based distribution when disruptions occur will ensure that the impacts of any potential disruption will be minimal with regard to the demand nodes' satisfaction rates.

Also, the performance of the SCN was measured using Jain's fairness index to show how disruption impacted the SCN's ability to deliver goods and how fair the system was. In Table 5-11, we can evaluate if the system is fair or efficient in delivering the required demand by comparing the value at Time 1 when disruptions took place. Time 9 when all components were restored, and the flow of commodities became normal. The larger the value at Time 1 than Time 9, the fairer the system was to reduce disruptions impacts on all demand nodes. At Time 1, when the fairness-based distribution was not considered in the model, the model was efficient in reaching the dominating nodes that require most of the demand. On the other hand, when considering the fairness-based distribution, the model increases the fairness by reaching more demand nodes with some of their required demands to reduce the number of neglected nodes.

Table 5-11. Jain's fairness index to measure the flows of goods received by all demand nodes for all sectors during the restoration times at 100% budget level

	No Mitigation No Fairness	Mitigation No Fairness	No Mitigation with Fairness	Mitigation with Fairness
Time 1	0.081	0.075	0.143	0.143
Time 2	0.091	0.066	0.093	0.093
Time 3	0.073	0.071	0.079	0.079
Time 4	0.060	0.067	0.071	0.071
Time 5	0.061	0.067	0.061	0.068
Time 6	0.066	0.069	0.069	0.069
Time 7	0.069	0.069	0.069	0.069
Time 8	0.069	0.069	0.069	0.069
Time 9	0.069	0.069	0.069	0.069

The impacts of implementing the fairness-based distribution can be seen in Figure 5-9. To investigate more about the performance of each sector differently, we used Jain's index to measure how fair each sector was during the restoration processes, as demonstrated in Table 5-12. We can see that most of the sectors were fluctuating when no fairness distribution was considered in the model. The gap between Time 1 and Time 9 was large for most sectors except for sector 1, which was the only sector that was less impacted by disruptions, as depicted in Figure 5-9. In Figure 5-9, the performances of most of the sectors were impacted significantly when the disruption started. In Table 5-12, when comparing Jain's index of no fairness solutions to the fairness solutions, we see that by fairly allocating the resources of sector 6, other sectors' performances were steady and remained efficient during all restoration times. Also, this can be supported by analyzing the performance of all sectors when the fairness distribution was considered in the model in Figure 5-9.

Table 5-12. Jain's index for each sector during the restoration processes at 100% restoration budget

	Restoration	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6
No Mitigation No Fairness	Time 1	0.303	0.289	0.262	0.307	0.177	0.204
	Time 2	0.303	0.358	0.126	0.066	0.085	0.174
	Time 3	0.303	0.333	0.178	0.071	0.098	0.152
	Time 4	0.339	0.448	0.148	0.071	0.098	0.134
	Time 5	0.339	0.445	0.163	0.069	0.094	0.136
	Time 6	0.300	0.504	0.169	0.070	0.103	0.145
	Time 7	0.300	0.504	0.169	0.070	0.108	0.153
	Time 8	0.300	0.504	0.169	0.070	0.108	0.153
	Time 9	0.300	0.504	0.169	0.070	0.108	0.153
Mitigation No Fairness	Time 1	0.300	0.457	0.329	0.281	0.100	0.181
	Time 2	0.300	0.474	0.191	0.231	0.106	0.146
	Time 3	0.300	0.404	0.187	0.071	0.107	0.155
	Time 4	0.300	0.504	0.167	0.071	0.103	0.147
	Time 5	0.300	0.504	0.169	0.070	0.103	0.149
	Time 6	0.300	0.504	0.169	0.070	0.108	0.153
	Time 7	0.300	0.504	0.169	0.070	0.108	0.153
	Time 8	0.300	0.504	0.169	0.070	0.108	0.153
	Time 9	0.300	0.504	0.169	0.070	0.108	0.153
No Mitigation with Fairness	Time 1	0.301	0.504	0.169	0.070	0.168	0.266
	Time 2	0.301	0.504	0.169	0.070	0.108	0.171
	Time 3	0.301	0.504	0.169	0.070	0.108	0.135
	Time 4	0.301	0.504	0.169	0.070	0.108	0.136
	Time 5	0.300	0.504	0.169	0.070	0.108	0.153
	Time 6	0.300	0.504	0.169	0.070	0.108	0.144
	Time 7	0.300	0.504	0.169	0.070	0.108	0.153
	Time 8	0.300	0.504	0.169	0.070	0.108	0.153
	Time 9	0.300	0.504	0.169	0.070	0.108	0.153
Mitigation with Fairness	Time 1	0.300	0.504	0.169	0.070	0.108	0.283
	Time 2	0.300	0.504	0.169	0.070	0.108	0.182
	Time 3	0.300	0.504	0.169	0.070	0.108	0.164
	Time 4	0.300	0.504	0.169	0.070	0.108	0.152
	Time 5	0.300	0.504	0.169	0.070	0.108	0.147
	Time 6	0.300	0.504	0.169	0.070	0.108	0.153
	Time 7	0.300	0.504	0.169	0.070	0.108	0.153
	Time 8	0.300	0.504	0.169	0.070	0.108	0.153
	Time 9	0.300	0.504	0.169	0.070	0.108	0.153

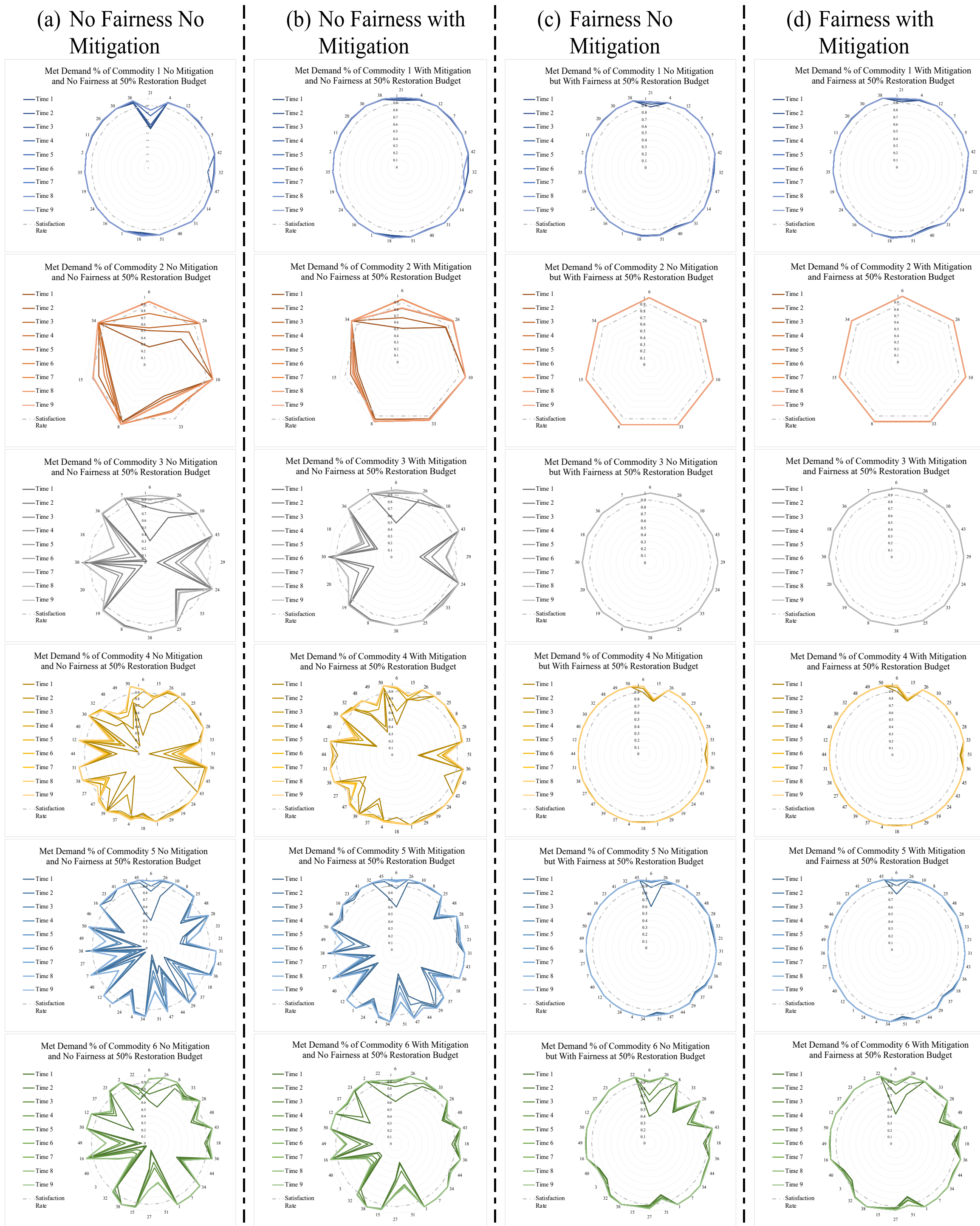

Figure 5-8. Comparison between the proposed solution approaches on the performance of each sector in the SCN considering the restoration budget is limited (50%) and not enough to restore all disrupted components. (a) when no mitigation no fairness solution, (b) mitigation no fairness solution, (c) no mitigation but with fairness solution, (d) mitigation and fairness solution

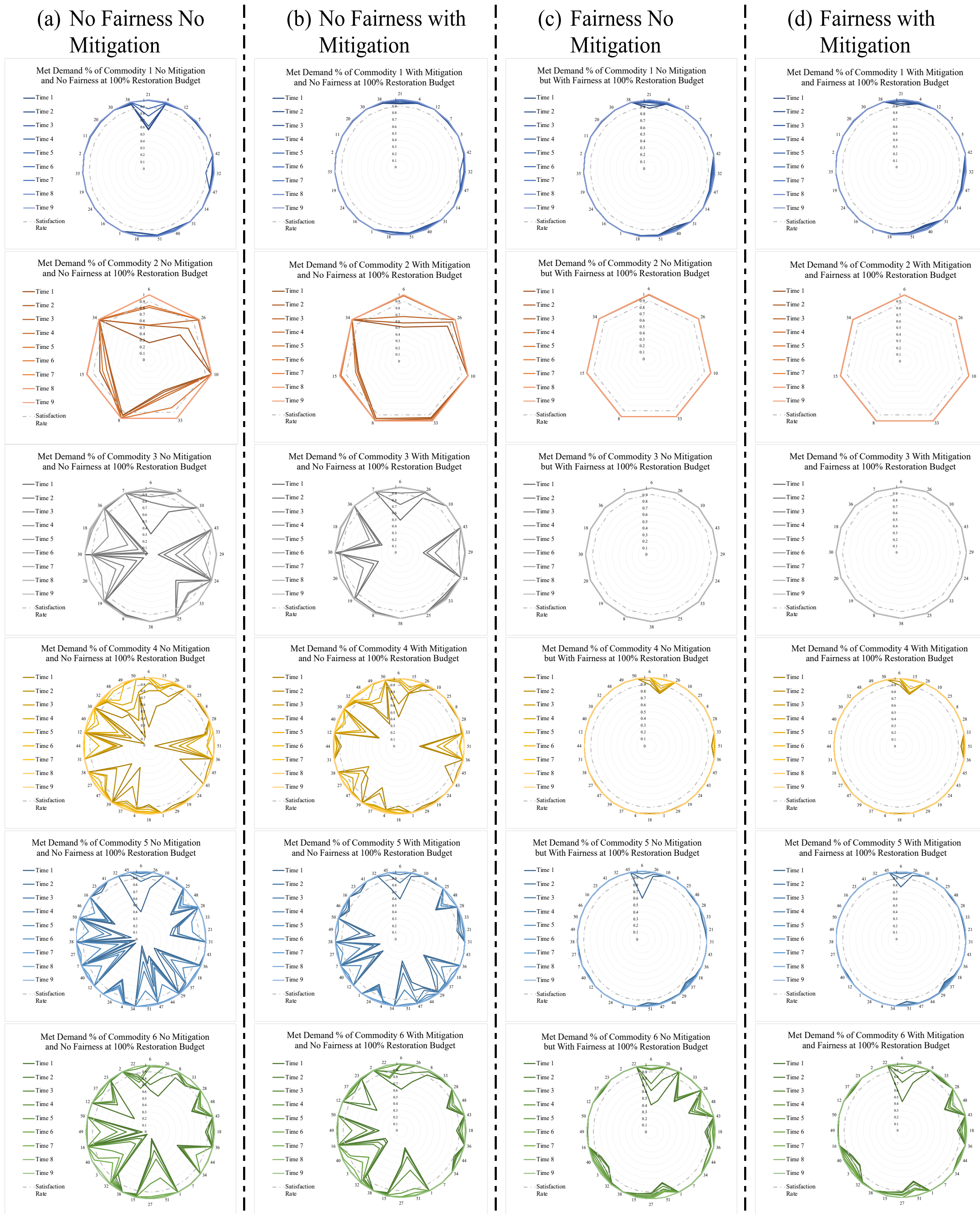

Figure 5-9. Comparison between the proposed solution approaches regarding the performance of each sector in the SCN, assuming that the restoration budget is unlimited (100%) and sufficient to restore all of the disrupted components. (a) the no mitigation, no fairness solution, (b) the mitigation, no fairness solution, (c) the no mitigation but with fairness solution, (d) the mitigation and fairness solution

5.6 CONCLUSION AND FUTURE WORK

The dependency on using road networks by SCNs to distribute goods has increased significantly. However, unpredicted events, such as significant natural catastrophes or human-made disruptions, have caused substantial disturbances in SC operations in recent years. As a result, the SC decision-makers must learn how to manage, control, and recover from such disasters.

This study proposes two mathematical models to enhance SCN resiliency and increase the SC demand nodes' satisfaction rate. The first model provides a robust solution against the worst-case scenario that the Colombia road transportation network may face, resulting in a devastating impact on SCN performance. The second model considers the pre-disruption phase, where SCN performance was tested against various disruptions after mitigating the road transportation network. In both models, we propose a fairness-based distribution strategy to allocate the available mitigation budget in such a way that the majority of the demand nodes are connected to their suppliers in the pre-disruption model, and integrate it to maintain a higher satisfaction rate among the demand nodes in the SCN in the post-disruption model. Integrating both approaches enhanced SCN resilience and robustness in terms of maintaining higher SL at the majority of the demand nodes, as shown in this study.

5.6.1 *MANAGEMENT INSIGHT*

In this study, significant findings were highlighted regarding the implication of a fairness-based distribution when modeling the pre- and post-disruptions effects on SCN performance. The SC decision-makers must deal with various unpredicted events, including road transportation disruptions. Thus, cooperating with the transportation decision-makers to improve SCN performance against such disruptions would increase SCN resilience. Furthermore, integrating a fairness-based distribution into the mitigation processes, to allocate fairly the available mitigating budget, with the post-disruption analysis, where a fairness-based distribution was implemented to maintain the required SL level at most of the demand nodes, while restoring the disrupted components in the road transportation network, would enhance SCN resilience. From our analysis, mitigating the road transportation network reduces the impact of disruption on the demand nodes in the SCN, as the results and figures show. Also, without considering the mitigation during the pre-disruption stage, the fairness-based distribution approach helps significantly to improve the satisfaction rate at each node for each commodity during the post-disruption stage. Moreover, integrating both approaches mitigation, and a fairness-based distribution provides a robust, efficient solution for all potential disruptions. Thus, decision-makers can promote the implementation of a fairness-based distribution by developing sets of incentives (and/or penalties) to encourage the SC decision-makers to cooperate, especially during disruptions.

5.6.2 *LIMITATION AND FUTURE WORK*

This work can be expanded in various aspects. The pre-disruption model is designed to consider uncertainty only under a disruption scenario. Thus, the model could include more uncertain parameters, such as the available supply material or the number of suppliers, since we are testing an SCN. Also, the chapter assumed that the information is available (a centralized system) to both sides: the transportation network decision-makers and SCN decision-makers. The model could be extended to be more decentralized in terms of sharing information where a united management works to identify the best decision to serve its system. Another way to extend this work is to consider a multi-echelon SCN, as our study considers disruption in the downstream of the SCN.

CHAPTER 6: CONCLUSION AND FUTURE RESEARCH

In this chapter, we review the dissertation's contributions and propose some recommendations for future work.

6.1 CONCLUSION

In this dissertation, an integrated framework was proposed to improve the SCN resiliency. In order to enhance the SCN resiliency, three solution approaches were proposed; (i) to response to disruptions, (ii) restore disruptive components of road transportation network, and (ii) mitigate the critical components in the road transportation network; thus, the SC management maintain higher satisfaction rate at most of the demand nodes. A fairness-based distribution was integrated along with each solution approach to fairly allocate the available resources during the disruption time. Each solution approach was addressed in separate study and was presented in different chapter of this dissertation.

6.1.1 *RESPONSIVENESS SOLUTION APPROACH*

To limit and lessen the impact of disruptions on SCTN performance, we created a multi-criteria mixed-integer programming model in Chapter 2. After unanticipated events or capacity shortfalls, the suggested model distributes available commodities fairly, reducing the number of demand nodes that do not receive the minimum required SL. The results reveal that the model effectively assisted in the equitable distribution of available commodities, ensuring that the majority of demand nodes got their minimum requirements. The fairness-based method gave improved distribution strategies to cover most of the demand nodes after running the model for several scenarios, at different capacity decrease levels, and varied SL. Furthermore, in all three evaluated scenarios, the relative improvement (RI) in the satisfaction rate based on the number of satisfied demanders improved by over 70%, which was a considerable improvement over the solution when the fairness-based distribution approach was not used. Chapter 2 delves into how to distribute the available goods following a disruptive occurrence. The SCN decision-makers must cope with a wide range of disruptive events in the underlying transportation network; nevertheless, the restoration of the transportation network following disruptive events is frequently beyond their control. As a result, the focus of this chapter is on developing effective distribution plans that take into account the health of the transportation network following a disruptive event, in order to reduce total distribution costs while ensuring an equitable distribution of commodities. Using a fairness-based distribution strategy minimizes the number of disappointed consumers and the proportion of unmet demand for each commodity at each demand node, according to our findings. By offering a sufficient level of SL until the system returns to normal performance, SCN decision-makers can use fairness-based distribution tactics to keep the majority of consumers connected to the providers. Furthermore, when the available commodities are insufficient to meet the total demand in the network, SCN decision-makers can use a fair distribution to raise the satisfaction rate of SCN performance by maintaining the required SL at each customer.

Not only SCN stakeholders, but also local governments, can benefit from the insights offered in Chapter 2 in order to design a set of incentives (and/or punishments) to encourage SCN decision-makers from various areas and economic sectors to collaborate on an equal allocation of commodities and resources. Because the customers in our studies are individuals who live in cities, ensuring a fair allocation of commodities and resources after a disruptive event (when resources are scarce) will aid SC decision-makers in providing the population with the minimum required of SL in order to meet the population's basic needs. Various state and federal institutions, like the Department of Transportation of the United States (2012) and the Federal Highway Administration of the United States (2012), are actively seeking a fair and equitable access to commodities and general resources, as it enhances community resilience and population wellbeing (Martens & Golub 2018).

6.1.2 *RESTORING THE DISRUPTED COMPONENTS*

In recent years, the reliance on the road transportation network to convey frights has increased. As a result of the unpredicted incidents that disturb the frights' flow, ensuring customer happiness becomes challenging. Several disruptive occurrences have hindered the SCN's performance and resulted in tremendous losses to the SC's decision-makers. As a result, various restoration models have been established in the literature (e.g., Vugrin et al., 2011, González et al., 2016, and Almoghathawi et al., 2019), the majority of which focus on unmet demand or cost-effectiveness to mitigate the disruption consequences on network performance. We provided a restoration strategy in Chapter 3 that analyzes the fairness-based allocation of commodities among all demanders in order to mitigate the effects of disruptive incidents by connecting the majority of demand nodes and maintaining their required SL during the recovery operations.

We used a multi-criteria non-linear mixed-integer programming (NMIP) model in Chapter 3 to show two possible restoration plans: no fairness-based distribution and fairness-based distribution. No fairness-based distribution prioritizes the restoration of disrupted components in order to reduce unmet demand quantities in the SCN, lowering the overall cost during recovery periods. The fairness-based distribution, on the other hand, is concerned with properly allocating available resources among demand nodes and recovering unfulfilled demand. The goal of this model is to provide a restoration model that aids in improving SCN resiliency by lessening the impact of a disruption across all demand nodes. According to the findings, the fairness-based distribution achieves a greater satisfaction rate in terms of the number of demanders who receive the requisite SL throughout the recovery time. The results show that both solutions approached when no fairness-based distribution is used, or the fairness-based distribution is used performs similarly with respect to the total cost and total travel time. The fairness-based distribution, we infer, led the model to retain a greater satisfaction rate while having no effect on overall expenses.

6.1.3 *RESTORING THE SC ECONOMIC PERFORMANCE*

In Chapter 4, a bi-objective restoration model was designed to measure and investigate the effects of road transportation network disruption on the SCN's economic performance. To distribute the available commodities that each sector needs to send to the demand nodes while repairing the disrupted components within the SCTN, two solution methods were proposed: fairness-based distribution and no fairness-based distribution. For each solution approach, the model examined several random disruption scenarios. The findings reveal that the fairness-based distribution effectively decreased the number of demand nodes affected by the road transportation network interruption. Because the transportation network and the SCN are so interdependent, the disruption had a considerable impact on various economic sectors in terms of satisfaction with maintaining the required SL at the majority of nodes. When enough budget was granted to repair the interrupted components inside the SCTN, the fairness-based allocation enhanced the overall met demand percentage for all sectors. Also, even though the restoration budget was insufficient to repair all of the affected components, the satisfaction rating % grew through the repair process when we considered lower SL to maintain. Transportation expenses increased as a result of using the fairness-based distribution approach rather than the non-fairness-based distribution approach. The price of fairness (POF), which was 1% of the transportation cost associated with the no-fairness-based distribution strategy, is the name for this increase. This percentage changed depending on how much budget was available for restoration. Furthermore, both solution approaches assisted in the restoration of each sector's economic performance, taking into account the interdependencies across sectors, because the difference between the two solution approaches is in the distribution of available commodities.

The impact of disruption to the transportation network is discussed in Chapter 4, which takes into account the physical interdependence with the SCN as well as the economic interdependence inside the SCN. Typically, SC decision-makers must cope with not only SCN disruptions but also unanticipated occurrences that have an influence on the transportation network. As a result, SC decision-makers must devise suitable ways to reduce the effects of these events while maintaining the satisfaction rates of their demand nodes. We propose a distribution strategy in this study to minimize the impact of interruptions on the performance of many economic sectors within the SCN. The number of dissatisfied demand nodes (nodes that got less than the needed SL) is lowered when the fairness-based distribution technique is used. using the same quantities available for distribution among demand nodes. The model was also evaluated with various levels of restoration budget provided by transportation decision-makers, and the fairness-based distribution showed either an increase in the RI or a decrease in the POF. The POF improves by less than 1% when the fairness-based distribution boosts the satisfaction rate by reducing the number of nodes who did not receive their SL. As a result, SC decision-makers may rely on the fairness-based distribution method to keep demand nodes content with the least SL they can give in a fair way compared to other demand nodes during the interruption period and restoration process until the system is fully recovered and reverts to its regular position. The approach of fairness-based distribution recovered the SCN sectors' economic performance faster than the approach of no fairness-based allocation, especially for the most afflicted sectors. As a result, using it as a distribution method during the disruption assures that the SCN's economic performance recovers faster while maintaining a high level of satisfaction at the majority of demand nodes. Because no fairness-based distribution approach concentrates on the demand nodes that require the most amount and meets their needs first, the number of unsatisfied nodes increases as compared to when the fairness-based distribution approach is used.

6.1.4 *PRE- AND POST-DISRUPTION ANALYSIS OF THE SCTN*

In Chapter 5, we propose two mathematical models to improve SCN resilience and maximize the satisfaction rate of SC demand nodes. The first model provides a robust solution against the worst-case scenario that the Colombian road transportation network may encounter, which would have a disastrous influence on SCN performance. The second model takes into account the pre-disruption phase, in which SCN performance was evaluated against various disruptions after the road transportation network was mitigated. We propose a fairness-based distribution strategy in both models to allocate the available mitigation budget in such a way that the majority of demand nodes are connected to their suppliers in the pre-disruption model, and integrate it to maintain a higher satisfaction rate among demand nodes in the SCN in the post-disruption model. As shown in Chapter 5, combining both techniques improved SCN resilience and robustness in terms of sustaining greater SL at the majority of demand nodes.

In Chapter 5, significant findings were emphasized about the implications of a fairness-based distribution when estimating the impact of interruptions on SCN performance. The SC decision-makers must cope with a variety of unexpected situations, including road transportation interruptions. As a result, collaborating with transportation decision-makers to improve SCN performance in the face of such interruptions will strengthen SCN resilience. From our analysis and findings, mitigating the road transportation network decreases the impact of interruptions on the demand nodes in the SCN. A fairness-based distribution also helps to improve the satisfaction rate during the post-disruption stage without taking into account mitigation during the pre-disruption stage. Moreover, combining both mitigation and a fairness-based distribution provides a robust and an efficient solution against all potential disruptive events. Thus, decision-makers can support the implementation of a fairness-based distribution by designing sets of incentives (and/or punishments) to encourage SC decision-makers to collaborate, particularly during interruptions.

6.2 FUTURE WORK

In this dissertation, multiple potential research extensions can be recommended to enhance the implications of the proposed models and the remarks that have been highlighted.

6.2.1 *SUPPLY CHAIN NETWORK UPPER STREAM*

In this study, when designing the SCN, we design the network to consider the downstream of the SCN only. Considering the disruptions in the upper stream part of the SCN will maximize the SCN resilience by enhancing the SCN components to adapt to unpredicted events and changes and applying fairness-based distribution when allocating the raw materials or selecting the suppliers to which the raw materials will be sent. Also, considering the SCN upper stream number of the tiers in the network will increase; thus, studying the impacts of disruption will provide more insightful feedback to the SC decision-makers and identify which tier is the most susceptible in the network.

6.2.2 *A MULTI-MODAL SUPPLY CHAIN NETWORK*

This study focuses only on the road transportation network, where only commodities are distributed via trucks. This work can be extended to consider various transportation modes: trains and airplanes. Due to globalization, the SCNs are connected overseas where the management needs to bring materials or to reach a client. Considering a multi-modal SCN would improve the overall performance by mitigating the most susceptible components against various disruptions; thus, the resiliency of the SCN increases. Implementing the fairness-based distribution along with studying a multi-modal SCN will be an interesting topic to explore.

6.2.3 *DECENTRALIZATION*

The decision between various managements is difficult to coordinate. In this study, we consider the relationships between SCNs' decision-makers and the road transportation management are centralized, which is each entity is aware of the current situation and how it should react along with others. Therefore, if each management starts to work and plan differently to maximize its performance, the overall performance of the SCNs will be different. Also, in this study, we consider the restoration processes based on the flows of commodities, assuming that the decision between the different entities is centralized. Therefore, if the road transportation management changes the restoration processes based on other measurements, the SCNs' decision-makers have to adapt their system accordingly to reduce the impacts of disruption on their performance.

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APPENDICES

Appendix 1. The location of each node and what city and region it represents

Node	City	Department	Node	City	Department
1	Aguachica	Cesar	30	Ocaña	Norte de Santander
2	Altamira	Huila	31	Palmira	Valle del Cauca
3	Arauca	Arauca	32	Pamplona	Norte de Santander
4	Armenia	Quindio	33	Pasto	Nariño
5	Barranquilla	Atlantico	34	Pereira	Risaralda
6	Bogota	Bogota	35	Planeta rica	Córdoba
7	Bosconia	Cesar	36	Popayan	Cauca
8	Bucaramanga	Santander	37	Quibdo	Chocó
9	Buenaventura	Valle del Cauca	38	Riohacha	La Guajira
10	Cali	Valle del Cauca	39	San alberto	Cesar
11	Campoalegre	Huila	40	San jose del gua.	Guaviare
12	Carmen de bolivar	Bolívar	41	San roque	Antioquia
13	Cartagena	Bolívar	42	Santa marta	Magdalena
14	Cienega	Magdalena	43	Sincelejo	Sucre
15	Cucuta	Norte de Santander	44	Tumaco	Nariño
16	Espinal	Tolima	45	Tunja	Boyacá
17	Facatativa	Cundinamarca	46	Tuquerres	Nariño
18	Florencia	Caquetá	47	Turbo	Antioquia
19	Honda	Tolima	48	Valledupar	Cesar
20	Ibague	Tolima	49	Villavicencio	Meta
21	Ipiales	Nariño	50	Villeta	Cundinamarca
22	La paz	Santander	51	Yopal	Casanare
23	La vega	Cauca			
24	Maicao	La Guajira			
25	Manizales	Caldas			
26	Medellin	Antioquia			
27	Mocoa	Putumayo			
28	Monteria	Córdoba			
29	Neiva	Huila			