Surviving Disruption:

Designing a Resilient 3PL Network

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ABSTRACT

Our project sponsor, a major third-party logistics provider in Japan, experienced a severe disruption that destroyed one of their primary distribution centers for a specific industry. This disruption led to increased lead times, degraded service levels, higher logistics costs, and the loss of a client. Consequently, our research focused on supply chain disruptions and resiliency. We aimed to answer three research questions: (1) what was the loss caused by the disruption? (2) how should the network be rebuilt to recover from the disruption? (3) how can resiliency be added to mitigate the risk of future disruptions? We addressed these questions by collecting real-world data, including data before, during, and after the disruption. We then developed mixed-integer linear programming models of the pre-disruption network and networks optimized with additional candidate distribution centers. Then a scenario-planning approach was employed to evaluate the costs and resiliency of these models. Our results revealed the loss caused by the disruption (7.4% cost increase), the estimated improvement of the company's disruption recovery plan (3.5% cost reduction), and the potential to achieve a more resilient network without additional costs. The results can be used not only to recover from the disruption but also to enhance the efficiency and resiliency of their logistics network. Furthermore, our research highlights the potential utilization of the developed network model for mitigating future risks and enabling contingency planning in the event of network disruptions.

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Charles E. Snow and Yusuke Tanaka

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Chapter 1. Introduction

Recent disruptive events, such as the spread of COVID-19 and the Russia-Ukraine war, have demonstrated the vulnerability of the global supply chain and emphasized the importance of resilience in supply chain networks. Additionally, efficient supply chains are a necessity for organizations to remain competitive in the face of fierce global competition.

Our sponsor company, a third-party logistics (3PL) service provider in Japan, provides logistics services, including transportation, warehousing, and freight forwarding, for various industries. Also, the company has an outsized footprint in the specific industry that our research focuses on, operating nine dedicated and eight multi-industry warehouses handling products in regions around the country.

In the early 2020s, the company's logistics network for that specific industry was severely impacted by a disruption that affected one of its major distribution centers (DCs) in the Kinki region of Japan. Kinki is a broad region located in the central-west part of Japan and consists of six prefectures, within which Osaka, the second-largest city in Japan, is situated. The disruption resulted in the total loss of the facility, causing increased logistics costs, degraded service levels, and the loss of a client.

In addition, the sponsor company suffered further adverse effects. Temporary operations, lasting several months, included relocating office workers to warehouses to meet the redirected demand from the lost facility until backup sites were ready. The increased transportation lead times from the temporary locations caused the service levels to deteriorate for their clients' customers. This led to the loss of a client that prioritized shorter lead times. The company's significant monetary losses and client churn strongly motivated the company to examine if and how the resiliency of its current supply chain network could be improved.

The company had not yet utilized optimization models for its network design or disruption mitigation strategies, but they were interested to see how these techniques could have informed their response to the adverse event and if they could have reduced the monetary losses and lead time degradations. The repercussions of the disruption have highlighted the importance of maintaining lead times in a disrupted network. Also, with demand for their services in Japan expected to grow, the company aims to increase the number of warehouses to meet this demand while replacing the existing backup facilities. Previously, the company had used qualitative factors when selecting a facility's location based on expert opinion and the availability of suitable land or commercial real estate at the time of decision-making. Going forward, they plan to use optimization models to evaluate the location of additional facilities.

This research uses travel distance as a proxy for lead time, as actual lead time is a complicated calculation involving operations and data outside of our scope. Going forward, this paper will use transportation distance and cost to evaluate our research scenarios.

1.1. Problem Statement and Research Questions

The sponsor company is now seeking to develop an optimal data-driven process to locate facilities in terms of resilience and efficiency. One suggested approach is to create a digital model of the supply chain network that can be used for the strategic planning of future networks. We hypothesize that creating a digital model of the supply chain network will improve their strategic planning.

Three key research questions arise from the context described above:

Research Question 1 (Q.1):

How did the warehouse disruption affect the company's logistics network costs and transportation distances?

Research Question 2 (Q.2):

How efficient is their pre-disruption, current, and planned network regarding total logistics cost, and can they be improved by adding additional DCs?

Research Question 3 (Q.3):

How resilient is their planned network, and can it be improved by adding an additional DC?

The answers to these questions will provide the company with a critical understanding of what happened, what the costs of their response to the crisis would have been with a more resilient network, and how to build a balanced resilient and efficient network for the future.

Firstly, the answer to Q.1 quantifies the actual impact the company experienced as a result of the disruption. Secondly, the answer to Q.2 assesses the effectiveness of their recovery plan, focusing on the development of a substitute facility. In addition, we explored alternative network configurations, such as the incorporation of a new DC in another region of Japan and forcing each manufacturer to use a third stock point. Currently most manufacturers maintain two stock points in the Kanto and Kinki areas. Finally, to answer Q.3, we evaluated the solutions derived from Q.2 in terms of resiliency. Specifically, we hypothesize that the addition of a third DC may lead to reduced total logistics costs and enhanced resiliency. Q.3 aims to quantify these effects, providing valuable insights into the potential benefits of such a configuration. The specific methods employed to answer these questions will be discussed in Chapter 3.

1.2. Research Scope

This research project aims to design a resilient and efficient 3PL network for a Japanese company by developing an optimizable mathematical model. This model is based on real-world data and can be optimized for various scenarios to gain strategic insights. The goal is to provide the sponsor company with insights from analyzing the supply chain disruption, newly developed network models, and disruption simulations. They can then use these insights to further mitigate the effects of risks on their supply chain.

Our project plan included the following steps: First, we collected the necessary data, such as customer demand and shipment data, from the company's system. Second, we conducted qualitative interviews to understand the potential risks the company faces and their mitigation plans for those risks. This qualitative information was utilized to develop risk scenarios for later analysis. Third, collected data was cleansed and validated. After validation, it was transformed into input for the optimization models. Fourth, the optimization models were developed with specialized software, incorporating information such as cost structure, business constraints, and customer demand. Fifth, the scenarios developed through interviews and communication with the sponsor company were integrated into the model. Lastly, those results were analyzed to deliver insights to the company.

Chapter 2. State of the Art

To best meet the project goals, we researched four main topics: supply chain resiliency (SCR), supply chain network design (SCND), supply chain disruptions, and supply chain risk mitigation. We researched these four topics in their general form and more specific categories of SCR and SCND. We learned that there is significant overlap among these topics as they have similar objectives. Under SCR, we discovered articles related to 3PL and lead time's relationship with SCR (distance instead of lead time in our research.) For SCND, we discovered papers related to 3PL and SCND under uncertainty. Our primary goals in researching SCR were to discover relevant ways to measure resiliency and establish strategies to improve it. We were also hoping to gain a better understanding of the latest techniques used in SCND and what unique considerations a 3PL company may have. We also researched categories of disruptions, how they affect supply chains, and what are effective ways to become resilient to their effects. Lastly, we gained a better understanding of supply chain risk mitigation and how it can work in coordination with SCND.

2.1. Supply Chain Resiliency

The concept of resiliency has been steadily gaining attention among supply chain professionals, largely as a response to recent global incidents such as the COVID-19 pandemic, the conflict in Ukraine, and the threat of other regional conflicts. However, despite its growing significance, there is no universally accepted definition of SCR. The interpretations of SCR differ across various research studies. Krikke & Gknatsas (2020), in their literature review, have compiled an assortment of these definitions in Table 1.

Table 1

Definitions of Supply Chain Resilience

Author	Supply Chain Resilience Definition
Rise et al. [19]	The ability to react to unexpected disruptions and restore normal supply network operations
Christopher and Peck [20]	The ability of a system to return to its original state or move to a new, more desirable state after being disturbed
Ponomarov and Holcomb [21]	The adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired
Ponis and Koronis [22]	The ability to proactively plan and design a Supply Chain network for anticipating unexpected disruptive (negative) events, respond adaptively to disruptions while maintaining control over structure and function and transcending to a post event robust state of operations, if possible, more favorable than the one prior to the event, thus gaining competitive advantage
Kim et al. [23]	We define supply network resilience as a network-level attribute to withstand disruptions that may be triggered at the node or arc level

Note. Reprinted from "Towards a Pro-Silience Framework: A Literature Review on Quantitative Modelling of Resilient 3PL Supply Chain Network Designs," by Krikke, H. R., & Gknatsas, E., 2020, *Sustainability (Basel, Switzerland)*, 12(10), p. 3. Copyright 2020 by the Authors.

In a broader context, resiliency in supply chain networks can be generally defined as the capability of a supply chain to anticipate, withstand, recover from, and adapt to various disruptions or unexpected events, thereby maintaining its functionality and effectiveness. Maharjan & Kato (2022) identified a variety of quantitative measures from their examinations of past research. They then classified these measures as proactive or reactive measures, corresponding to actions taken before or after a disruption, respectively. The measures were then broken down into the part of the network the measures were affecting; nodes, links, or both. Their table showing their classification is reproduced in Table 2. As represented in the table, Maharjan & Kato (2022) identified a lack of proactive and reactive link-based resiliency measures in the research. Prior to the disruption, the sponsor company was utilizing a significant number of the identified proactive node-based resilience measures, such as facility fortification, facility redundancy, lateral transshipments, multiple allocations of facilities and customers, demand coverage, and segregation/dispersion of facilities. As a 3PL, safety stock is not an available measure because the sponsor company has no say on the amount of total inventory, but they do have a say on where it is positioned. After the disruption, the sponsor company utilized all reactive node-based resilience measures identified by Maharjan & Kato (2022); flexible capacity at the facilities, reassigning of customers, and expansion of facility capacity. This reflects well on their preparedness and allowed them to respond quickly to the disruption. For example, they were able to serve customers from alternative DCs the very next day after a complete loss of a DC.

Table 2

Classification of Resilience Measures

S.N.	Resilience measure	Explanation	Classification
1	Multiple sourcing	Having multiple sources of supply.	Proactive node-based resilience measures
2	Safety stock	Prepositioning of inventories.	
3	Facility/Supplier fortification	Mainly includes retrofitting of buildings and structures.	
4	Node density, complexity, and criticality	Designing a supply chain network that has low node density, complexity, and criticality.	
5	Facility redundancy	Having more facilities than ordinarily needed.	
6	Lateral transhipment	Moving goods between nodes in the same echelon.	
7	Multiple allocation of facilities and customers	Allocating facilities and customers to more than one supplier and facility respectively.	
8	Alternative bill of materials	Having another list of components for import for each echelon.	
9	Demand coverage	Better network coverage by using proximity criteria.	
10	Segregation/dispersion (Suppliers/Facilities)	Reducing supply chain centralisation and facilities' concentration in the same region.	
11	Flexible capacity at the facilities	Flexibility of capacity at the facilities.	Reactive node-based resilience measure
12	Reassigning of customers	If originally assigned facility is disrupted customers are reassigned to available facilities.	
13	Expansion of facility capacity	Ability to increase the capacity of facilities post-disaster.	

Note. Reprinted from "Resilient supply chain network design: A systematic literature review," by Maharjan, R., & Kato, H., 2022, *Transport Reviews*, *42*(6), p. 747. Copyright 2022 by Informa UK Limited.

This project examines the effect of increasing some already existing proactive node-based measures, specifically facility redundancy, multiple allocations of facilities and customers, and demand coverage. Our tested scenarios include adding additional DCs and assigning manufacturers to three DCs instead of the company policy of two.

2.2. Supply Chain Network Design

SCND plays a significant role in determining a company's operations and how its resources are spent. Consequently, it requires the decision-making of senior management. Their decisions on business policies, investments, and deployment issues will determine whether a company has a well-designed supply chain, and good SCND is an essential driver of operational efficiency and, therefore, competitiveness (Janjevic et al., 2022).

One of the main goals of SCND is to determine the quantity, location, and mission of warehouses and other facilities for a company (Martel & Klibi, 2016). Two common prescriptive analytical approaches to assist in these decisions are optimization and simulation. And to support good supply chain design, it is beneficial to combine these two methods (Janjevic et al., 2022).

One common optimization technique for SCND is mixed-integer linear programming (MILP). Its goal is to maximize or minimize a performance measure (e.g., profit or total cost) while observing defined constraints (e.g., warehouse capacity, customer demand). The maximization or minimization results in the calculation of optimal network parameters such as facility locations, number of facilities, and flows between nodes (Janjevic et al., 2022).

2.3. Network Design in a 3PL Context

In the context of 3PL supply chain networks (SCNs), Krikke & Gknatsas define resilience as the "capability of a 3PL SCN in the event of unexpected shocks of high-impact, low-probability of occurrence, to concurrently return to its original or improved situation and thrive amid disturbances without lowering its competitive advantage under normal operating conditions" (Krikke & Gknatsas, 2020, p. 3) The variety of resilience definitions Krikke and Gknatsas encountered are illustrated in Table 1. The literature shows a lack of combined supply chain resilience and operations research/management science (OR/MS) approaches. There is also sparse research on network design, specifically focused on the 3PL context. (Krikke & Gknatsas, 2020).

Krikke & Gknatsas were also unable to find papers related to low-frequency, high-impact events specifically affecting 3PL networks, with the exception of one paper by Janic (Janić,

2019) that examined heavy Easter Storms (Krikke & Gknatsas, 2020).

2.4. Supply Chain Network Design Under Uncertainty

The Covid-19 pandemic, the war in Ukraine, and geopolitical risks have placed supply chain front and center in many companies' minds and have even introduced the concept of supply chains to the public. As Janjevic et al. find: "One thing has become abundantly clear to supply chain managers in recent years: Disruption, uncertainty, and risk have all increased. Product demand, costs, freight transportation rates, lead times, exchange rates, and capacity requirements are naturally exposed to various sources of uncertainty." (Janjevic et al., 2022, p. 20)

The increasing relevance of supply chain disruptions forces companies to incorporate risk management and resilience into their supply chains. Failing to do so places a company at a significant disadvantage (Janjevic et al., 2022).

It is common for companies to design their supply chains for the assumption of expected conditions (e.g., average lead times). These designs will then be subjected to a range of scenarios to gauge the sensitivity. But, the probability and impact of these scenarios are not included in the design operation. To properly handle uncertainty, companies should incorporate uncertainty into their SCND process (Janjevic et al., 2022).

One approach to embedding this uncertainty in the design process is optimization modeling. Optimization is an essential tool for SCND, and although there are a variety of optimization techniques, Saragih states: "Literature on supply chain network design under uncertainty falls into three main categories: (1) Stochastic Optimization, (2) Robust Optimization, and (3) Fuzzy Optimization." (Saragih, n.d., p. 3)

First is stochastic optimization. Stochastic optimization incorporates parameters usually modeled on discrete scenarios with known probabilities (Govindan et al., 2017). These probability distributions are used instead of deterministic inputs. An example of this would be using a probability distribution instead of a specific value for a customer's demand. The problem can then be solved using continuous, chance-constrained, or scenario-based techniques (Saragih, n.d.). A subset of stochastic programs is two-stage stochastic programs. SCND decisions are often made in two stages, with the first stage representing long-term decisions, including the location of facilities and facility capacities. The second stage represents the operational and tactical decisions. These include determinations such as inventory, production, transportation, and routing. Two-stage stochastic programs are standard solutions to problems where the random variables are realized after the first stage decisions are made (Govindan et al., 2017).

The second is robust optimization (RO). RO can be used for problems where there is uncertainty in the variables, but instead of known probabilistic distributions, uncertain parameters can be modeled with continuous or discrete scenarios (Govindan et al., 2017). Saragih states: “In discrete scenarios, a decision-maker can minimize maximum costs across all scenarios (minimax cost) or minimize the difference between the worst and optimal solutions in a scenario (minimax regret)” (Saragih, n.d., p. 4)

Third is fuzzy optimization (FO). Like RO, FO is also intended to handle uncertainty. This technique allows the model to incorporate flexibility into both the objective function and the constraints (Govindan et al., 2017). There are two primary types of fuzzy mathematical programming - flexible programming and possibilistic programming. In the context of the traditional linear programming model, fuzzy objectives and sets are used to account for the ambiguity inherent in a decision-maker's goals and limitations. In essence, flexible programming caters to scenarios where goal values are adaptable, and constraints are not rigidly set.

Another approach, possibilistic programming, is another form of the traditional linear programming model. It is designed to handle uncertainties by modeling vague or imprecise data through possibility distributions. This approach is particularly beneficial when there is a lack of precise information regarding a model's parameters.

Furthermore, fuzzy mathematical programming allows for the handling of ambiguous coefficients and unclear preferences, highlighting its versatility in managing various forms of uncertainty in supply chain network design.

Though stochastic optimization, robust optimization, and fuzzy optimization are promising techniques for handling uncertainty, they are typically used for a different kind of uncertainty than what we are modeling. Our goal is not to examine the effects of uncertain demand or lead times but instead to model the effects of significant disruptions on the network. Scenarios are a more appropriate technique for these low-probability, high-impact events.

Low-probability, high-impact risks pose a unique challenge in uncertainty. There is a lack of historical data to calculate accurate probabilities, and even with their catastrophic impacts, their low probabilities limit their effect on supply chain design using traditional methods. Scenario planning is one technique that encourages proactive preparation for these possible events by allowing companies to understand the potential impacts. Also, a proactive approach using quantitative methods is a more efficient investment than incurring the costs of a reactive approach to a disruption (Janjevic et al., 2022).

Chapter 3. Data and Methodology

As described in Chapter 2, there is modest literature about resilient 3PL network design. Therefore, we applied optimization and scenario planning techniques to real-world disruption data of a 3PL network and analyzed how different network configurations affect its resiliency. Relevant data was collected from the company's systems (e.g., Warehouse Management System (WMS), Financial Management System (FMS), and additional files managed by each operating facility). The collected data were cleansed and summarized for further analysis using several analytical software programs.

For the optimization, we developed MILP models, a typical optimization method employed for SCND. Table 3 lists the common objective function terms considered in network optimization. Our objective function includes "Operating costs of facilities," "Inventory costs," "Transportation/shipment costs," and "Processing costs in facilities" as listed in Table 3. "Risk/Robustness measures" are not directly incorporated in the objective function but instead are measured after the optimization is run for each scenario.

The network model consists of three layers, i.e., manufacturers (company's clients), DCs (company's 3PL facilities), and customers (typically, wholesalers' warehouses). "Operating costs of facilities," "Inventory costs," and "Processing costs in facilities" are not considered for the manufacturers and customers in our model because the capacity, demand, and location of these layers are fixed. The method of data collection and the software used to answer the questions will be discussed in Sections 3.1 and 3.2. The detailed configuration of the MILP model will be discussed in Section 3.3. Specific methods and scenarios to resolve the three research questions will be described in Section 3.4.

Table 3

Major Objective Function Terms for Network Design

Objective function terms	Explanation
Location costs of facilities	The fixed costs of opening/closing facilities. The fortification costs of facilities are put in this category as well. Further, some papers utilized a single parameter for both opening and operating costs of facilities, and so we have also used **C1** for this case. In a few studies, closing facilities led to cost saving in the objective function that are represented by **C1'**.
Operating costs of active facilities	The operating costs of facilities after opening them. In some studies, facilities' operating cost is assumed as a fixed cost and in some others, it depends on the volume of products, which a facility can handle based on its capacity. Moreover, in some studies some fixed costs for active facilities are considered based on the products they handle or the processes they perform. We put these fixed costs in this category as well.
Inventory costs	The holding costs of working inventory, safety stock, or extra inventory in SC facilities are regarded as inventory costs.
Transportation/shipment costs	The transportation or shipment costs of products among different entities of a SC network. Moreover, the fixed shipment costs are considered in some studies.
Production/manufacturing costs	The costs of producing or manufacturing products in entities of a SC network.
Processing costs in facilities	The costs of handling products in warehouses, distribution centers, or other facilities of a SC network.
Capacity costs of facilities	The costs of establishing, expanding, or relocating the capacity of different facilities in a SC network.
Procurement costs	The costs of procuring raw materials, required components or finished products from corresponding suppliers. Further, the buying costs of used products in a CLSC or RL network are put in this category.
Fixed ordering costs	The fixed costs of placing an order from a SC facility to another one.
Supplier selection costs	The fixed costs for selecting the suppliers, which include establishing business with them.
Technology selection costs	The costs of selecting the technology for SC's facilities.
Costs of selection/establishment transportation links	The costs of establishing transportation links.
Capacity costs of transportation links	The costs of establishing or expanding capacity of transportation links in a SC network.
Shortage/backorder costs	The penalty costs related to not satisfying the customers' needs. Back order costs are also considered in this category.
Sales tax costs	The costs related to the tax of sales' products.
Recovery activities costs	The costs related to recovery activities in a RL network, which may include inspection, recycling, remanufacturing, repairing, or disposal costs. These costs are dependent on the type of activities in a RL network.
Routing costs	The costs related to transporting the products from one layer of a SC network to another one, which are calculated based on routing decisions.
Penalty costs in RL networks	The penalty costs related to not collecting the returned products in a RL network.
Cost saving from integrating facilities	The cost saving due to integrating some facilities in a CLSC network.
Penalty costs for not utilizing installed capacities	The penalty costs related to not utilizing the existing capacity in SC's facilities
Salvage values of products	The salvage values of unsold products in SC's facilities.
SC's income	The income of SC network, usually calculated as multiplication of the amount of sold products and their related prices.
SC's responsiveness	Different criteria exist for defining the responsiveness of a SC network, which has been discussed in Section 4.5.1. We put all these criteria in this category.
SC's flexibility	There are many criteria for measuring the flexibility of a SC network in the related literature. We put all these criteria in this category.
SC's environmental impacts	The effects of a SC network on the environment are often measured as its environmental impacts, which may include different terms.
SC's social responsibility	The influences of a SC network on the social issues are measured as its social responsibility, which may include different terms.
Risk/Robustness measures	Some studies have regarded the risk or robustness measures in their objective functions.

Note. Reprinted from "Supply chain network design under uncertainty: A comprehensive review and future research directions," by Govindan, K., Fattahi, M., & Keyvanshokooh, E., 2017, *European Journal of Operational Research*, 263(1), p. 118. Copyright 2017 by the Authors.

3.1. Data Collection

First, we retrieved the logistics and financial data of nine manufacturers served by

DC_01, the disrupted DC, before the disruption. The data was retrieved from the WMS and FMS databases for analysis. We also collected manually maintained data from the operating facilities. The nine manufacturers relied entirely on the company for their product storage and delivery, and their inventory was stored at DC_01 and eight other DCs. We also retrieved logistics data from these other eight DCs so we could investigate how the disruption affected the company's overall network. From the WMS, we retrieved inbound and outbound shipment details, transportation data, inventory data, and product masters. Inbound shipment details include product codes; lot numbers; source codes and locations; DC codes and locations; and the received amount in quantity, weight, and volume. From this data, we verified the percentage of a manufacturer's total shipment volume originating from each manufacturing site, broken down by product. The percentages needed to be calculated for each manufacturer at every DC that contained the manufacturer's product. These percentages were incorporated into the optimization model to replicate the inbound flow.

Outbound shipment details include similar data as the inbound shipments. But in addition, the outbound shipment details contain information on shipment numbers and transportation modes, such as less-than-truckload (LTL), full truckload (FTL), and parcel. This data represents the current flows from DCs to customers, and the shipment volumes to the customers are used as the customer demand for the optimization models. There may be discrepancies between the actual demand and shipment data, as unmet demand due to factors like stock-outs is not included in the shipment data. Nevertheless, since we could not obtain the true demand from the WMS, we opted to use shipment data as a proxy for demand.

Transportation data corresponds to the outbound shipments but is less granular and lacks product codes. But, it does contain transportation costs and distance for each shipment. We ran a regression analysis on this dataset to formulate linear equations for transportation costs in the optimization model. This data includes multiple transportation modes, and a separate regression analysis was applied for each transportation mode to improve accuracy. While transportation data could also be used as customer demand, like shipment data, we were unable to retrieve transportation data for all Manufacturer-DC combinations. Therefore, we used outbound shipment details as the basis for customer demand.

Inventory data includes product codes, DC codes, and inventory quantity. These data, together with outbound shipment details, were used to determine the inventory turns for each manufacturer. This was incorporated into the model to calculate the inventory based on shipment volume.

The FMS provides financial data. It contains daily to monthly cost data for each manufacturer-facility combination, including major logistics costs, such as operational, transportation, storage, and administrative costs. The transportation cost data, however, is aggregated daily or monthly and does not include detailed shipment information. Therefore, the transportation data described previously were used to formulate the transportation costs, and the financial data from the FMS were used for other logistics costs. The accuracy of the financial data was confirmed by comparing the aggregated expenses to the actual invoice data collected from operating facilities.

3.2. Software

A variety of software was used for each stage of analysis, specifically Microsoft Power BI (Power BI), Python and its data analytics libraries, and Coupa Supply Chain Design & Planning (SCD&P). Power BI is a general-purpose business intelligence software widely used in different industries. It has three primary functions: Extract-Transform-Load (ETL) with Power

Query (PQ) language, data modeling with Data Analysis eXpression (DAX) language, and data visualization. Because WMS data is separated by manufacturer-facility-month combinations and consists of a few hundred TSV (Tab-Separated Values) files, the ETL function was used to integrate these data. It was also used to mask the original data (e.g., delete specific names and exact addresses, as the sponsoring company required). After the data preparation was completed with the ETL function, a data model was developed with DAX. Using this data model, original data was transformed and aggregated into a form that can be utilized by SCD&P to perform optimization on supply chain network models. After the optimization was completed with SCD&P, the output was loaded into Power BI and visualized for the stakeholders.

Python was mainly used for regression analysis on the transportation data. It was also used to visualize the original data and optimization results and to complement the Power BI visualization capabilities.

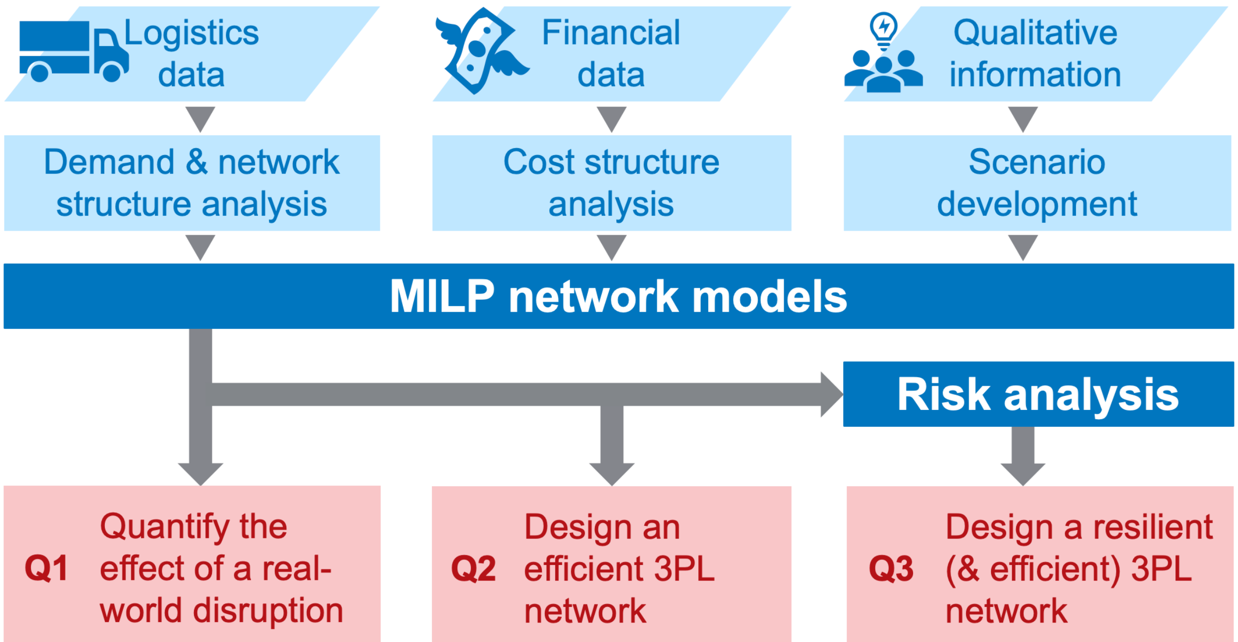
SCD&P is a commercial software focused on supply chain design, including SCND, vehicle routing optimization, multi-echelon inventory optimization, and safety stock optimization. We used SCD&P to model the logistics networks and formulate MILPs. A commercial solver, CPLEX, is included to solve optimization models.

3.3. Network Models

Figure 1 provides a comprehensive illustration of the overall research process, which effectively captures the end-to-end process of the analysis. Encompassing the various integral components, such as input data and source, sub-processes (demand & network analysis, cost structure analysis, and scenario development), optimization models, and research questions, this schematic representation elucidates the interconnected nature of these elements in the context of the analytical framework. In Section 3.3.1, a detailed formulation of the objective function and constraints is discussed.

Figure 1

Overview of the Research Process



In our study, we built MILP models to tackle the intricacies of multi-period, multi-product, and multi-echelon network optimization. Our models are based on a monthly period, starting from the month following a severe disruption that impacted one of the company's major DCs, and encompass nine months' worth of demand data. Instead of considering individual SKUs, products in our models are aggregated at the manufacturer level, with all SKUs from a single manufacturer treated as a single product. The networks are comprised of three echelons: manufacturing sites, DCs, and destinations, with no direct shipments allowed from manufacturing sites to destinations. This section provides a comprehensive overview of the models' specific components, including sets, variables, decision variables, an objective function, and constraints.

3.3.1. Sets

Our sets incorporate manufacturing sites, potential DCs, customers, manufacturers, transportation modes, and periods represented by *M*, *D*, *C*, *P*, *T*, and *H*, respectively.

Sets:

M = set of manufacturing sites m; let $M = \{1, 2, \ldots, m\}$;

D = set of potential DCs d; let $D = \{1, 2, \ldots, d\}$;

C = set of customers c; let $C = \{1, 2, \ldots, c\}$;

P = set of manufacturers p; let $P = \{1, 2, \ldots, p\}$;

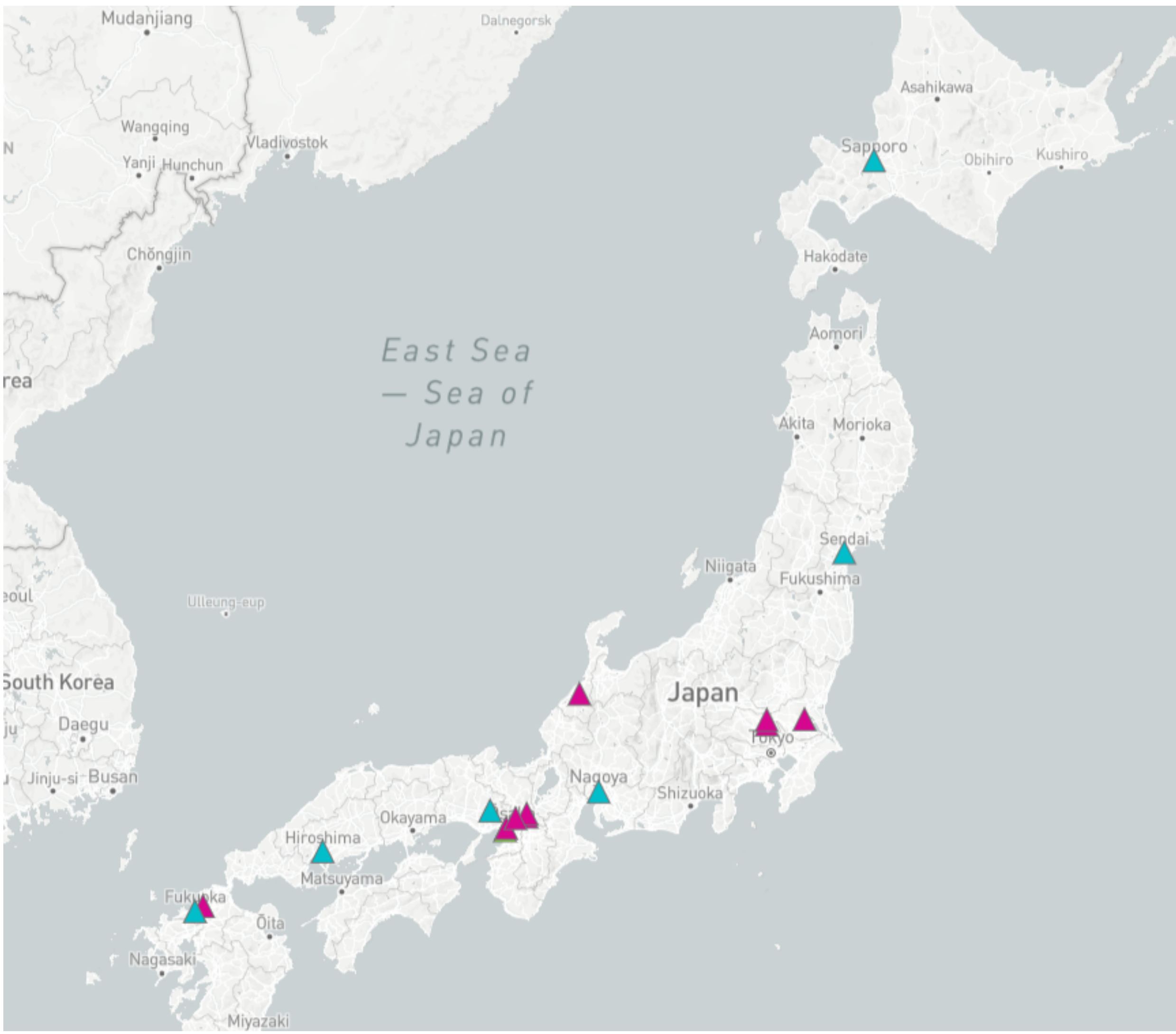
T = set of transportation modes t; let $T = \{1, 2, \ldots, t\}$;

H = set of periods h; let $H = \{1, 2, \ldots, h\}$

The models encompass nine manufacturers and 26 manufacturing sites, as each manufacturer operates more than one in-house and outsourced site. While there are a total of 16 potential DCs, the number of sites utilized varies across different scenarios, as detailed in Section 3.4. Figure 2 shows the locations of DCs considered in the models. Although the original data includes 6,507 customers, these customers were aggregated into individual municipalities, resulting in 932 customer destinations within the model. Figure 3 shows the geographical customer demand distribution. Five transportation modes are featured in our model, namely parcel (dry), parcel (reefer), LTL (dry), LTL (reefer), and FTL, with variable and fixed transportation costs depending on factors such as geographical regions of origin, destination, and shipment weight. Section 3.5. provides a comprehensive analysis of transportation costs. Lastly, the models comprise of nine periods, each lasting one month, with the first period commencing the month (two days later to be exact) after the company experienced the severe disruption, allowing for a quantitative evaluation of the disruption's impact.

Figure 2

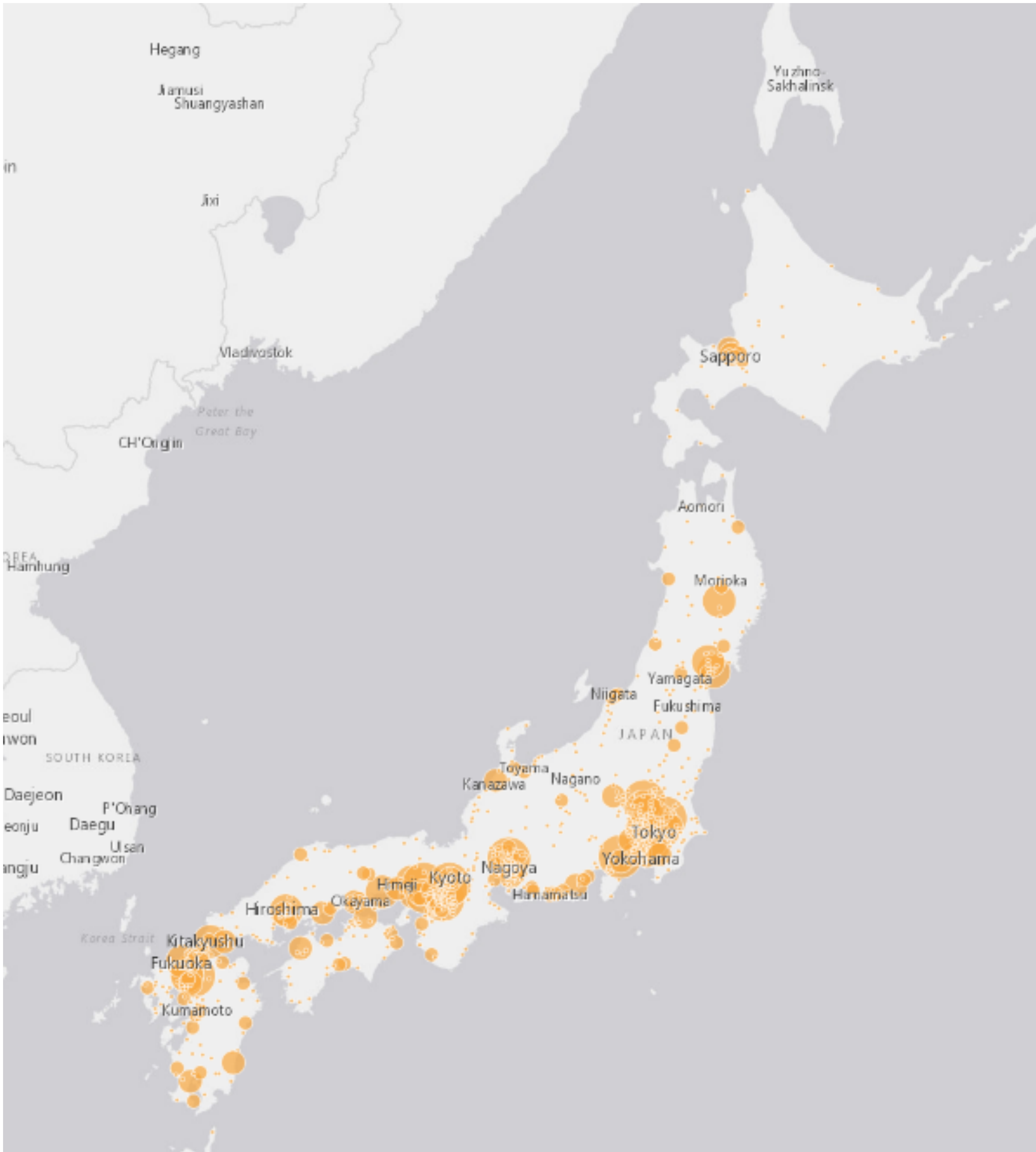
Existing and Potential DCs Included in the Model



Note. Locations indicated in red are existing DCs. Locations indicated in blue are potential DCs.

Figure 3

Geographical Distribution of the Customer Demand



Note. Showing the demand distribution of the data used for optimization. The demand is aggregated into municipalities. The size of the bubble corresponds to the demand in weight.

3.3.2. Variables

We introduced the following variables to construct the model.

Variables:

w_{cpth} = demand for manufacturer p at customer c by mode t in period h

lm_{md} = transportation distance between manufacuturing site m to DC d

ld_{dc} = transportation distance between DC d to customer c

i_{p} = annual inventory turns for manufacture p

f_{t} = average units of shipment for transportation mode t

ct_{t} = cost of shipping one unit of product for one unit of distance by mode t

cu_{t} = fixed cost of a shipment for mode t

cs = cost of storing one unit of product per period

cf_{ph} = Fixed cost of hosting manufacture p at any single DC in period h

co_{p} = warehouse handling cost of one unit of product of manufacturer p

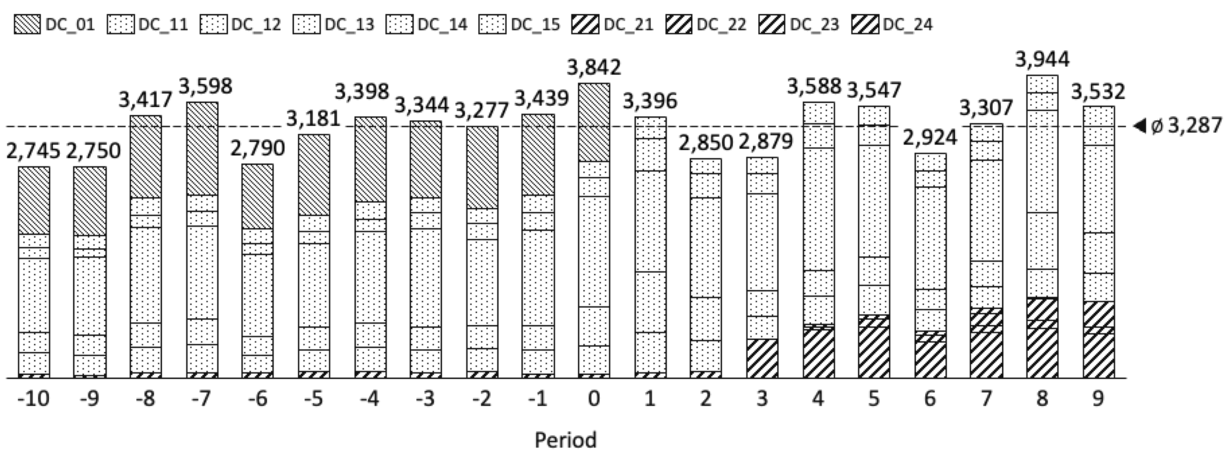
rm_{mp} = percentage of production units at manufacturing site m for manufacturer p

Customer demand, w_{cpth}, is derived from shipment data extracted from the WMS. Figure 4 displays the monthly demand weight by DCs. We collected shipment data for 20 periods, with each period representing one month. The average demand is 3,287 metric tons per month, and seasonality is evident as demand decreases in January and February, then rises in March and April. DC_01 is the DC that was disrupted in Period 0, which is reflected in Figure 4 showing its shipment volume drops to zero. For several months, other DCs (DC_11 to DC_15) handled the redirected demand, and temporary facilities (DC_21 to DC_24) located close to

DC_1 began operations to cover the shortfall. Demand before Period 1 was used for setting variables and understanding the network structure but not for optimization. Demand from Periods 1 to 9 was used for the optimization scenarios.

Figure 4

Monthly Demand (Metric Ton) by DCs



Note. Summarized from the shipment data extracted from the WMS. The length of the period is one month. DC_01 was disrupted at the end of Period 0. Temporary substitute facilities (DC_21 to 24) eventually started to operate after Period 3.

To capture the proximity between all nodes, we introduced a measurement, lm_{md}: distance (in kilometers). As mentioned previously, distance was used as a proxy for lead time. Actual road distances for each combination of nodes were calculated using Bing Maps API.

Annual inventory turns (i_{p}) are dependent on manufacturer *p*, and the inventory level at each DC is determined by the throughput and inventory turns of each manufacturer. Notably, our model does not take the risk-pooling effect into account.

The percentage of production units at each manufacturing site for a specific manufacturer is established by rm_{mp}, mandating that all DCs source from upstream manufacturing sites according to the designated percentages.

All the cost-related variables, ct_{t}, cu_{t}, cs_{p}, cf_{ph}, and co_{p}, are discussed in detail in Section 3.5.

3.3.3. Decision Variables

We considered three decision variables in our model.

Decision Variables:

Y_{pdh}

$= \{1, \text{if a DC for manufacture } p \text{ is located at } d \text{ in period } h; 0, \text{otherwise}\};$

U_{pmdth}

$= \text{amount of product of manufacturer } p \text{ from manufacturing site m to DC d by mode t in period h};$

X_{cpdth}

$= \{1, \text{if customer } c \text{ receives product of manufacturer } p \text{ from DC } d \text{ by mode } t \text{ in period } h; 0, \text{otherwise}\}$

Y_{pdh} and X_{cpdth} are both binary variables. Y_{pdh} represents whether a manufacturer is allocated to a certain DC, and X_{cpdth} represents whether a customer is allocated to a certain DC. U_{pmdth} represents the interfacility flow from manufacturing sites to DCs.

3.3.4. Objective Function

Incorporating the described sets, variables, and decision variables, we build the following objective function that minimizes the total logistics cost.

Objective Function:

$$Min \sum_{m\in M}\sum_{d\in D}\sum_{p\in P}\sum_{t\in T}\sum_{h\in H} ct_{\mathrm{t}} lm_{\mathrm{md}} U_{\mathrm{pmdth}} +$$
$$\sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{t\in T}\sum_{h\in H}\left(ct_{\mathrm{t}} ld_{\mathrm{dc}} + co_{\mathrm{p}} + i_{\mathrm{p}} cs_{\mathrm{p}} + \frac{cu_{\mathrm{t}}}{f_{\mathrm{t}}}\right) w_{\mathrm{cpth}} X_{\mathrm{cpdth}} +$$
$$\sum_{p\in P}\sum_{d\in D}\sum_{h\in H} cf_{\mathrm{ph}} Y_{\mathrm{pdh}} \tag{1}$$

Equation (1), the objective function, aims to minimize the total logistics cost, which is comprised of several components. The first term represents the transportation or shipment costs associated with interfacility flow from manufacturing sites to DCs. The second term encompasses inventory costs, processing costs in facilities, and the transportation or shipment costs related to customer flow from DCs to customers. Within the transportation or shipment costs, both variable and fixed costs are accounted for. Lastly, the third term represents the operating costs of the facilities.

3.3.5. Constraints

To constrain the models and represent reality, we introduced the five constraints listed below. These are base constraints utilized in all scenarios. Constraints specific to each scenario are described in Section 3.4.

Constraints:

$$\sum_{d\in D} X_{\mathrm{cpdth}} = 1, \forall c \in C, p \in P, t \in T, h \in H \tag{2}$$

$$\sum_{c\in C}\sum_{t\in T} w_{\mathrm{cpth}} X_{\mathrm{cpdth}} = \sum_{m\in M}\sum_{t\in T} U_{\mathrm{pmdth}}, \forall d \in D, p \in P, h \in H \tag{3}$$

$$\sum_{d \in D} \sum_{t \in T} U_{\text{pmdth}} = \sum_{c \in C} \sum_{t \in T} rm_{\text{mp}} w_{\text{cpth}}\, , \forall p \in P, m \in M, h \in H \tag{4}$$

$$MY_{\text{pdh}} \geq \sum_{c \in C} \sum_{t \in T} X_{\text{cpdth}}\, , \forall p \in P, d \in D, h \in H \tag{5}$$

$$Y_{\text{pdh}}, X_{\text{cpdth}} \in \{0, 1\}, \forall c \in C, p \in P, d \in D, h \in H \tag{6}$$

$$U_{\text{pmdth}} \geq 0, \forall p \in P, m \in M, d \in D, t \in T, h \in H \tag{7}$$

Equation (2) guarantees that each customer's demand for each manufacturer's products by each transportation mode in each period is satisfied by one and only one DC. Equation (3) ensures that the total flow of goods through the distribution centers, considering different transportation modes, matches the customers' demands. Equation (4) constrains that all customer demands are met while accounting for the fixed production percentage of each manufacturing site of the manufacturer. Equation (5) enforces the constraint that Y_{pdh} must be equal to one when there is a flow of a product from a manufacturer at a DC. The variable *M* represents a large constant number, often referred to as the "big M" constraint in optimization models. Equation (6) is a binary constraint for decision variables Y_{pdh} and X_{cpdth}. Finally, Equation (7) ensures that the interfacility flows, U_{pmdth}, are positive. These are our base constraints, but for the optimization scenarios described in Section 3.4, additional scenario-specific constraints are also explained.

3.4. Optimization Scenario

As outlined in Section 1.1, we address three research questions using optimization scenarios. For answering Q.1, we assessed the loss cost resulting from the disruption the company experienced. For answering Q.2, we evaluated the efficiency of the planned networks intended to replace the lost DC and investigated alternative network configurations. The answer to Q.2 offers a fixed, optimal solution for facility locations and network flows. To answer Q.3, we measured the resiliency of the solutions derived from answering Q.2. To do this, we disrupt one DC at a time from the Q.2 scenario solutions, and observed the impact of low-probability, high-impact disruptions on the DC. The findings from answering Q.2 and Q.3 equipped us with valuable insights to propose a network that balances efficiency and resiliency for the sponsor company. The overview of the scenarios are organized in Table 4.

Baseline and Scenario 1 address Q1. Baseline calculates the actual cost incurred by the company following the disruption, while Scenario 1 calculates the logistics costs under the assumption that the disruption did not occur and the company could continue to operate its original pre-disruption network. By comparing these two scenarios, we can estimate the disruption's effect on logistics costs and transportation distance.

Scenario 2 to 4_i address Q.2. The company plans to replace its disrupted facility by developing a new DC at a predetermined location in the near future. Scenario 2 will adhere to the plan, i.e., the location of the new DC and the allocations of manufacturers to the new and existing DCs. Scenario 3 alleviates the manufacturer allocation constraint but only uses the DCs from their plan. In Scenario 4_i, we add a further additional DC to the model to investigate a new strategy. The company's current strategy is to allocate two DCs in different regions of Japan, mainly the Shuto (includes Tokyo) and Kinki (includes Osaka) regions, to each manufacturer. In case of a disruptive event, they can continue to ship orders from the second DC. Scenario 4_i also investigates the potential of allocating a third DC to each manufacturer. Here, *i* refers to one potential DC location in each of the five following regions: Hokkaido, Tohoku, Chubu, Chugoku, and Kyushu. Therefore, there are five sub-scenarios under Scenario 4_i. Scenarios 2 to 4_i are compared in terms of logistics costs and service levels to determine the most efficient network.

Table 4

List of Optimization Scenarios

Phase	Scenarios	Description	Mfr. allocation to DC	Customer allocation to DC	Additional DC	Inventory locations per mfr.
Baseline	Baseline	Estimated network IF the disruption did not happen	Fixed to pre-disruption	Fixed to pre-disruption	no	-
	Scenario 1	Actual network (Pre- and Post-disruption)	Actual allocation	Actual allocation	no	-
Cost optimization	Scenario 2	Planned network with DC_41	Fixed to the plan	Optimized	DC_41	2
	Scenario 3	DC_41 is added, and the Mfr. allocation is optimized	Optimized	Optimized	DC_41	2
	Scenario 4_i (*i* = Potential additional DCs)	one more potential DC is added, and MFG allocation is optimized	Optimized	Optimized	DC_41 + 1	3
Resiliency	Scenario 2'_j (*j* = a DC to disrupt)	Fixing the solution of Scenario 2, disrupt used DC one by one	Fixed to Scenario 2	Optimized	DC_41	2
	Scenario 3'_j (*j* = a DC to disrupt)	Fixing the solution of Scenario 3, disrupt used DC one by one	Fixed to Scenario 3	Optimized	DC_41	2
	Scenario 4'_i_j (*j* = a DC to disrupt)	Fixing the solution of Scenario 4_i, disrupt used DC one by one	Fixed to Scenario 4_i	Optimized	DC_41 + 1	3

Note. List of optimization scenarios conducted in our research. Scenarios with subscripts *i* and *j* include sub-scenarios.

Scenario 2'_j to 4'_i_j address Q.3. Here, *j* denotes the DCs selected in Scenario 2 to 4_i as a result of the cost minimization optimization. These scenarios are created to assess the resilience of the solutions of Scenario 2 to 4_i by closing one DC in each scenario to measure the impact of potential low-probability, high-impact disruptions. This strategy was chosen because closing a single DC at a time reflects realities similar to what the sponsor company faced. By running optimizations on these scenarios, we can quantify the impact of the disruptions with measures such as logistics costs and transportation distance. We compare the scenarios by these measures to determine the most resilient network configuration.

To develop these risk scenarios, we conducted interviews with the sponsor company to ask: what are the major risks their supply chain faces and what are their potential risk mitigation plans. The lists of risks and mitigation plans are displayed in Table 5.

Table 5

Risks the Company's Supply Chain Faces and Potential Mitigation Plans

Risks	Mitigation options
• **Earthquake** • **Tsunami** • **Floods** • **Fire** • Electric power failure • Typhoon • Higher trucking rate • Labor scarcity	• **Inland DC locations** • **Other DC locations (e.g. Nagoya)** • **Multiple inventory locations** • **Ship from different location** • Emergency power generators • DC with shock-absorbing structure for earthquakes • Truck fuel storage • Warehouse automation (to cope with labor scarcity) • Cross training for employees • Standardized System/equipment

Note. The list is created from the information collected from the discussion with the company in the regular meeting held on November 9, 2022. The blue type indicates the risks and mitigations relevant to our research.

These risks can be separated into three categories:

1. Low-probability, high-impact risks (earthquake, tsunami, floods, fire)
2. High-probability, low-impact risks (electric power failure, typhoon)
3. External environment change (higher trucking rate, labor scarcity)

For this project, because our research focuses on the severe disruption the company suffered and how to mitigate these types of potential future disruptions, we decided to focus on low-probability, high-impact risks, and their mitigation plans. These are displayed in blue in Table 5. It is important to note that a mitigation plan can apply to more than one high-impact risk.

Although there are countless sources of risks, Rice (2021) argues that there are only seven ways a supply chain can fail. These are represented by the loss of the seven core capacities:

1. Capacity to acquire materials
2. Capacity to ship and/or transport products
3. Capacity to communicate
4. Capacity to convert raw materials into products
5. Human resources capacity
6. Capacity to maintain financial flows
7. Capacity to distribute products to customers, including consumers

We analyzed how the disruption affected these seven core capacities in Table 6. It had little to no impact on capacities 1, 3, and 6; a medium impact on 4, 5, and 7; and a significant impact on capacity 2. Rice (2021) defines a resilient supply chain as “one that can recreate or maintain the capabilities that support each of these seven operational capacities.” In this perspective, to build a resilient network, we need to design a network that can recreate the capacities to ship, convert and distribute products and maintain human resource capacity even after a high-impact risk event, (e.g., floods, fire, earthquake, and tsunami).

Table 6

Disruptions Effect on the Seven Core Capacities of Supply Chain Resilience

#	Supply chain resilience core capacities	The disruption
1	The capacity to acquire materials (maintain supply)	This capacity is not affected because suppliers of the manufacturers were not affected by the disruption
2	The capacity to ship and/or transport products	Requires years to rebuild the DC. Demand can be fulfilled from other DCs with higher cost and longer lead time.
3	The capacity to communicate	IT system was hosted on cloud or remote data center and switch the shipping location in the same day.
4	The capacity to convert (internal manufacturing operations)	Because a large amount of inventory was lost at once, some of the manufacturers took months to rebuild inventory.
5	The human resources (personnel) capacity	Increased capacity was required in other DCs to fulfill redirected demand.
6	The capacity to maintain financial flows	Inventory and facility were mostly insured, and the company was large enough to withstand other financial loss.
7	The capacity to distribute products to customers including consumers	Because a large amount of inventory was lost at once, some of the customers could not obtain certain products.

In Sections 3.4.1 to 3.4.8, more information about each scenario and additional formulations for specific scenarios, such as additional variables and constraints, will be discussed in detail.

3.4.1. Baseline: Actual Flow After the Disruption

This scenario calculates the actual costs incurred by the company following the disruption, as detailed in Section 3.3. Therefore, the DC that was disrupted is not utilized in this scenario. To achieve this, we need to constrain customer allocations to the DCs, reflecting real-world conditions. As a result, we introduce a new variable, rc_{cpdht}, and incorporate a constraint (Equation (7)) specifically for this scenario.

Variable:

rc_{cpdht}

$=$ percentage of fulfilled demand for manufacturer p at customer c from DC d by mode t in perod h.

Constraint:

$$w_{\mathrm{cpth}} X_{\mathrm{cpdth}} = rc_{\mathrm{cpdht}} w_{\mathrm{cpth}}, \forall d \in D, c \in C, h \in H, p \in P, t \in T \qquad (7)$$

This constraint forces the model to represent the actual flow that occurred during the model horizon and, therefore, accurately estimates the financial impact of the disruption on the company while adhering to the actual Customer-DC allocations that occurred in practice. The computed cost was reviewed by the company to guarantee the accuracy of the model.

3.4.2. Scenario 1: What if the Disruption Did Not Happen

In this scenario, we estimate the logistics costs under the assumption that the disruption did not occur, and the network continues to operate as it did prior to the disruption. To achieve this, we introduce one additional variable rd_{cpdt}, and a constraint (Equation (8)), allowing us to model the network's performance without the effects of the disruption.

Variable:

rd_{cpdt}

$=$ percentage of fulfilled demand for manufacturer p at customer c in a specific prefecture from DC d.

Constraint:

$$\sum_{t \in T} w_{\text{cpth}} X_{\text{cpdth}} = \sum_{t \in T} rc_{\text{cpdt}} w_{\text{cpth}} \text{ , } \forall d \in D, c \in C, h \in H, p \in P \tag{8}$$

To compute rd_{cpdt}, we analyzed a year's worth of data prior to the disruption, aggregating demand into prefectures and calculating the percentage of demand served by each manufacturer and DC. As the pre-disruption data did not include customers who were added after the disruption, we opted to aggregate demand by prefecture in order to represent all customers.

By comparing the cost difference between the Baseline and Scenario 1, we can determine the monetary loss attributed to the disruption. Additionally, we assess the transportation distance differences from DCs to customers between the two scenarios to understand the impact of the disruption. This analysis allows us to quantify the financial and operational consequences of the disruption to the company's logistics network.

3.4.3. Scenario 2: Replacing the Disrupted DC According to Plan

In Scenario 2, we model the company's plan to replace the disrupted facility. Their plan includes the exact location of the facility and the allocation of manufacturers to each facility. The replacement facility is in the Kinki area of Japan, the same are as the disrupted facility. To represent their plan in the model, we created a set S^{plan} that consists of manufacturer (*p*) and DC (*d*) combinations according to the company's replacement plan and added a constraint defined below.

Constraint:

$$\sum_{c\in C}\sum_{t\in T}\sum_{h\in H} X_{\mathrm{cpdth}} = 0, \forall \neg S^{\mathrm{plan}} \tag{9}$$

Here, S^{plan} represents the planned allocation of manufacturers to DCs.

3.4.4. Scenario 3: Optimizing the Manufacturer Allocations to DC

In scenario 3, we continue to use the DCs from the company's plan but optimize the allocation of manufacturers to DCs.

Constraints:

$$\sum_{p\in P}\sum_{c\in C}\sum_{t\in T}\sum_{h\in H} X_{\mathrm{cpdth}} = 0, \forall \neg d^{\mathrm{plan}} \tag{10}$$

$$\sum_{c\in C}\sum_{t\in T}\sum_{d\in D} X_{\mathrm{cpdth}} = 2, \forall p \in P, h \in H \tag{11}$$

Here, d^{plan} refers to the unique set of DCs in the company's plan. This scenario evaluates the efficiency of this plan by comparing it to the optimal allocation. To adhere to the company's current policy of assigning two DCs for each manufacturer, we set the number of DCs for each manufacturer to be two in Equation (11).

3.4.5. Scenario 4_i: Adding Third DC for Each Manufacturer

In Scenario 4_i, we explore the potential improvement in network efficiency of adding a further additional DC and allocating a third DC to each manufacturer. After discussions with the company, we identified a potential location for a new DC in each of the Hokkaido, Tohoku, Chubu, Chugoku, and Kyushu regions of Japan. Here, *i* refers to one potential location in each region, resulting in five sub-scenarios under Scenario 4_i. To model this, we added two new constraints to our base model.

Constraints:

$$\sum_{p \in P} \sum_{c \in C} \sum_{t \in T} \sum_{h \in H} X_{\mathrm{cpdth}} = 0, \forall \neg d_{\mathrm{i}}^{\mathrm{plan}} \tag{12}$$

$$\sum_{c \in C} \sum_{t \in T} \sum_{d \in D} X_{\mathrm{cpdth}} = 3, \forall p \in P, h \in H \tag{13}$$

In these constraints, $d_{\mathrm{i}}^{\mathrm{plan}}$ refers to the potential DCs the model can choose from. This set comprises the DCs that the company plans to utilize (d^{plan} from Equation (10)) and the added potential DC *i* for each sub-scenario. By incorporating these constraints, the model can assess the impact of adding a DC in each of the identified regions, providing insights into potential improvements in network efficiency.

3.4.6. Scenario 2'_j: Disrupt Each DC in Scenario 2

In Scenario 2'_j, the optimized network structure from Scenario 2_j is fixed, and the selected DCs denoted by *j* of the Scenario 2_j solutions are disrupted one by one to see the potential impact of a disruption that might occur to each DC. To model this, we introduced two constraints to the base model.

Constraints:

$$\sum_{c \in C} \sum_{t \in T} \sum_{h \in H} X_{\mathrm{cpdth}} = 0, \forall \neg S^{\mathrm{P}} \tag{9}$$

$$\sum_{p \in P} \sum_{c \in C} \sum_{t \in T} \sum_{h \in H} X_{\mathrm{cpdth}} = 0, \forall \neg d_{\mathrm{j}}^{\mathrm{plan}} \tag{14}$$

The first constraint (Equation (9)) is the one used in Scenario 2. The second constraint (Equation (14)) is a slightly different version of Equation (10). While d^{plan} is a set of DCs the company plans to use, $d_{\mathrm{j}}^{\mathrm{plan}}$ is the same set of DCs, except that it excludes DC *j* to model the disruption for each sub-scenario.

3.4.7. Scenario 3'_j: Disrupt Each DC in Scenario 3

The concept of Scenario 3'_j is the same as the Scenario 2'_j except for the following: First, S^{plan} in Equation (9) of the Scenario 3'_j is replaced by S^{SC3}, which is the optimized allocation of the manufactures (*p*) to DCs (*d*) as a result of Scenario 3's optimization run. Second, $d_{\mathrm{j}}^{\mathrm{plan}}$ in Equation (14) is replaced by $d_{\mathrm{j}}^{\mathrm{SC3}}$, which is a unique set of DCs that is selected as a solution to Scenario 3's optimization but excludes the DC *j* from the set to represent the disruption.

3.4.8. Scenario 4'_i_j: Disrupt Each DC in Scenario 4_i

Again, the concept of Scenario 4'_i_j is the same as the Scenario 2'_j except for the following:

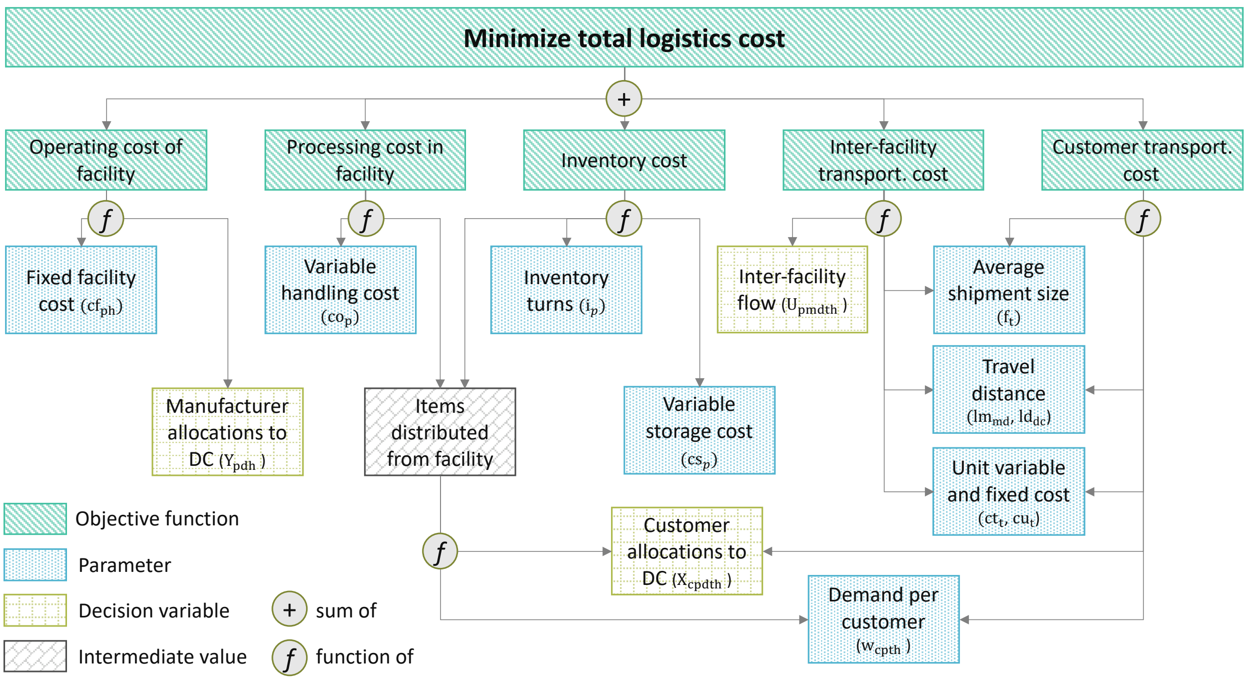
First, S^{plan} in Equation (9) of the Scenario 2'_j is replaced by $S_{\mathrm{i}}^{\mathrm{SC4}}$, which is the optimized allocation of the manufactures (*p*) to DCs (*d*) as a result of Scenario 4_i optimization run. Second, $d_{\mathrm{j}}^{\mathrm{plan}}$ in Equation (14) is replaced by $d_{\mathrm{ij}}^{\mathrm{SC4}}$, which is a unique set of DCs that are selected as a solution to Scenario 4_i's optimization but excludes the DC *j* from the set to represent the disruption.

3.5. Cost Structure

All the cost variables listed in Section 3.3.1 are calculated from past financial data and logistics data extracted from the company's systems. In this section, the source of data and the calculation process for each variable is explained in detail. Figure 5, adapted from Winkenbach & Janjevic (2023), shows the overview of the models' cost structure.

Figure 5

Overview of the Models' Cost Structure



Note. Adapted from "Session 07: Last-mile Logistics Network Design" by Winkenbach, M., & Janjevic, M., 2023, *SCM.293 / 11.263 / 1.263 Urban Last-Mile Logistics.* p. 19. Copyright 2023 by the Authors.

3.5.1. Operating Costs of Facilities

Operating costs of facilities (cf_{ph}) represent the fixed expenses incurred by the company when managing a manufacturer at a DC. These costs primarily stem from the IT systems and hardware required to operate for a manufacturer at a DC. While dependent on the manufacturer

(p), these costs remain consistent across different DCs (d). For manufacturers where we could not gather this specific cost information, we utilized the average value from other manufacturers as a substitute.

3.5.2. Processing Costs in Facilities

Processing costs in facilities (co_{p}) represent the variable expenses needed to ship one unit (kg) of product from DCs to customers. These costs vary significantly among manufacturers due to differences in product attributes and order profiles. For example, some manufacturers produce heavy products, such as certain types of liquids, resulting in lower costs per kg compared to others. Regarding order profiles, some manufacturers receive orders in pallets or cases, while others require individual item picking, which significantly impacts operational efficiency.

To compute the unit cost, we collected ten months' worth of demand data for each manufacturer, along with the operational costs incurred during the same period. These operational costs encompass handling, management, packaging material return, and other related expenses. We have not incorporated the regional wage difference in our current model, so the processing costs are dependent on manufacturers but not DCs.

3.5.3. Inventory Costs

Inventory costs (cs_{p}) primarily consist of the expenses incurred to store one kg of product for each manufacturer. To calculate inventory levels, we introduced inventory turns (i_{p}) to convert the flow (throughput of DC) into inventory. Inventory turns are calculated using ten months' worth of shipment data for each manufacturer, along with the end-of-month inventory data for the same period, and then averaging the values for each manufacturer. Furthermore, we calculated the inventory cost for each manufacturer using the end-of-month inventory data and corresponding cost information from the same period.

It is important to note that inventory costs in this model only include the storage costs that the company invoices to the manufacturer and do not account for the capital cost of the inventory, which is typically owned by the clients. Additionally, our current model does not incorporate stepwise inventory turns, meaning that the inventory turns remain constant across different levels of throughput.

3.5.4. Transportation/Shipment Costs

Our transportation dataset encompassed a diverse array of classifications, enabling us to dissect the information into distinct and meaningful categories. These classifications encompassed the origin of the journey at the distribution center, the destination at the customer's address, the incurred cost, the transportation mode (LTL, FTL, Parcel), and the distinction between cold-chain and dry trailer transport. To accurately compute travel distance, we employed the address-matching service provided by the Center for Spatial Information Science at The University of Tokyo for geocoding municipalities (Center for Spatial Information Science, n.d.). We calculated separate costs for each transportation mode and cold/dry combinations. For LTL, we delved deeper and partitioned the data, computing costs anchored to the origin DC for the dry cargoes and to the destination region for the cold. The rationale behind this approach was the sheer volume of LTL shipments, providing ample data for further subdivision, and the importance of calculating accurate estimates for this majority shipment type.

To model the costs of the various network configurations, we needed to calculate the transportation costs. Our transportation data contained one row for each shipment from a DC to a customer. Two additional fields that we created were DC Area and Destination Area. DC Area represents the region that a DC is in (multiple DCs can be in the same region), and Destination Area is the region where the delivery to the customer is made. The Areas are 01_Hokkaido', '02_Tohoku', '03_Shuto', '04_Chubu', '05_Hokuriku', '06_Kinki', '07_Chugoku', '08_Shikoku', '09_Kyushu. "Area" used in this context is analogous to US regions like the Northeast or Pacific Northwest. But Hokkaido is a special case where it is both an area and a prefecture.

The DCs and customer information were used to geocode the origin and destination of each shipment using the University of Tokyo's CSV Address Matching Service (Center for Spatial Information Science, n.d.). We were then able to calculate the distance for each shipment as a new field. This allowed us to create a field calculated by shipment Weight*Distance. Coupa has different cost representations available, and this is the option for Coupa that we thought was most appropriate. We then removed rows with data containing null values in any of the following fields: DC, Manufacturer, Weight, Cost, Distance, Mode, Temperature, or Destination.

Before starting the regressions, we divided the data into four modes and temperature: cold chain (cold) or not (dry). The three modes are Less than Truck Load (LTL), Full Truck Load (FTL), and Parcel. There exists every combination of these parameters except FTL Cold, for example: LTL Cold, LTL Dry, FTL Cold, FTL Dry, Parcel Cold, Parcel Dry. FTL Cold was excluded, however, because there were single-digit rows in this category. We then further divided the transportation data into more specific categories to increase the accuracy of the transportation cost representation. LTL Dry data was divided by DC Area. LTL Cold, Parcel Dry, and Parcel Cold were divided by Destination Area. This is because the LTL Cold, Parcel Dry, and Parcel Cold prices are determined by the destination of the delivery, while LTL dry prices are determined by the starting location. For Parcels, this may be intuitive, but it was not intuitive that LTL Dry and LTL Cold contracts would be structured this way. We first observed this relationship after analyzing the data, so we then investigated with the company. After informing them of the pattern we were observing, they confirmed that was how LTL contracts are defined.

There was not enough data to run a separate regression for each FTL region.

We ran a regression on each mode-temperature pair (e.g., LTL Cold) with Weight*Distance as the independent variable and cost as the independent variable. We noticed Parcels (both Cold and Dry) with Destination Areas of 03_Shuto and 06_Kinki had poor results compared to Parcels delivered to other areas. Those two areas contain large DCs for the two most populous regions in Japan, with Shuto containing Tokyo and Kinki containing Osaka and Kyoto. We hypothesized that most of the Parcels being delivered in those areas were also originating in those areas. Furthermore, since Parcel rates were determined by originating area and destination area, the distance would not matter for intra-area shipments.

We examined the data and determined that a vast majority of parcels delivered in those areas were indeed also originating in their respective area. After changing the independent variable from Weight*Distance to Weight for Shuto and Kinki, our regressions produced more accurate results. Parcels arriving in other areas mainly had origin areas different than their delivery areas. So, for these shipments, Distance served as a proxy for how far away the originating Area was, which affected the cost along with Weight. Unfortunately, we needed to continue to use Weight*Distance as the independent variable for Shuto and Kinki instead of only Weight. Otherwise, the optimization model would assign the same transportation cost to a Parcel delivered to Kinki and originating in Kinki as one delivered from Hokkaido.

We then reconsolidated the LTL Dry data into DCs located in eastern Japan and those located in western Japan. This is because some of our new network configurations were testing the addition of DC locations in areas with no current DCs. We, therefore, would not have estimated transport costs for those new areas. By dividing the data into eastern and western Japan, we could use eastern Japan's cost estimate for any new DCs in the eastern half of Japan and western Japan's cost estimate for any new DC in the western half of Japan. LTL Cold, Parcel Dry, and Parcel Cold do not have this problem because the data was divided by destination area, and the destination area for each shipment does not change even if that shipment is modeled using a previously non-existent DC. Table 7 shows the transportation combinations where we calculated an individual cost using regression.

Table 7

List of Transportation Modes, Temperatures, and Origin/Destination Combinations

Mode	Temp	DC/Destination area
LTL	Dry	DC, Eastern Japan
LTL	Dry	DC, Western Japan
LTL	Cold	Destination, 01_Hokkaido
LTL	Cold	Destination, 02_Tohoku
LTL	Cold	Destination, 03_Shuto
LTL	Cold	Destination, 04_Chubu
LTL	Cold	Destination, 05_Hokuriku
LTL	Cold	Destination, 06_Kinki
LTL	Cold	Destination, 07_Chugoku
LTL	Cold	Destination, 08_Shikoku
LTL	Cold	Destination, 09_Kyushu
Parcel	Dry	Destination, 01_Hokkaido
Parcel	Dry	Destination, 02_Tohoku
Parcel	Dry	Destination, 03_Shuto
Parcel	Dry	Destination, 04_Chubu
Parcel	Dry	Destination, 05_Hokuriku
Parcel	Dry	Destination, 06_Kinki
Parcel	Dry	Destination, 07_Chugoku
Parcel	Dry	Destination, 08_Shikoku
Parcel	Dry	Destination, 09_Kyushu
Parcel	Cold	Destination, 01_Hokkaido
Parcel	Cold	Destination, 02_Tohoku
Parcel	Cold	Destination, 03_Shuto
Parcel	Cold	Destination, 04_Chubu
Parcel	Cold	Destination, 05_Hokuriku
Parcel	Cold	Destination, 06_Kinki
Parcel	Cold	Destination, 07_Chugoku
Parcel	Cold	Destination, 08_Shikoku
Parcel	Cold	Destination, 09_Kyushu

Chapter 4. Results

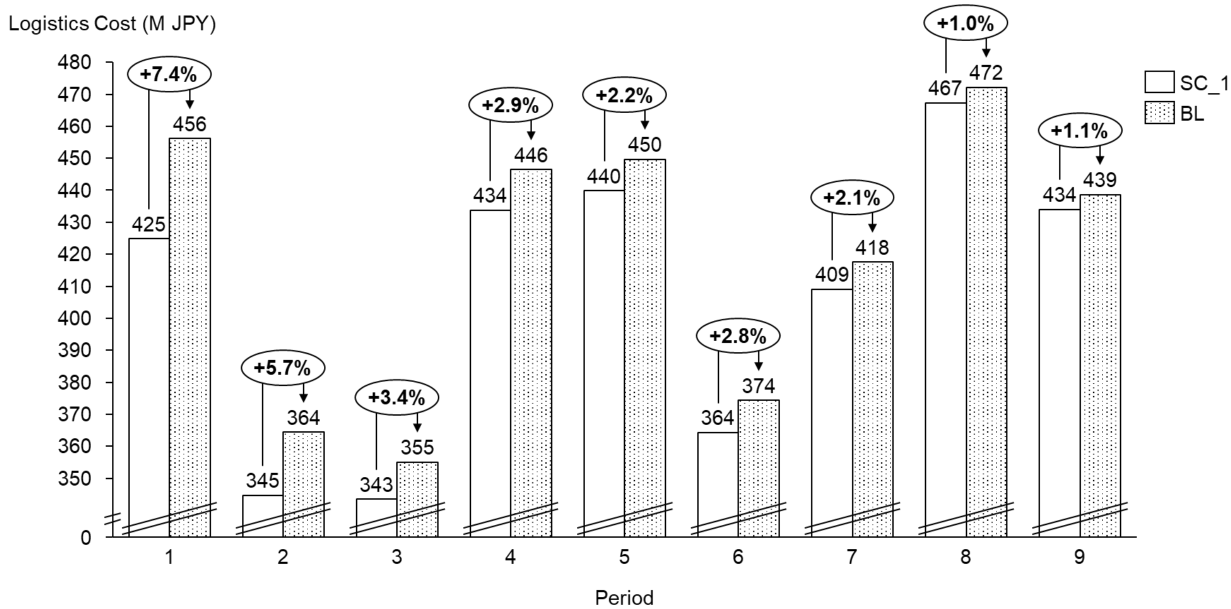
In this chapter, we discuss the results of the optimization scenarios discussed in Chapter 3.

4.1. Research Question 1 (Q.1)

The answer to Q.1 examines the impact of a warehouse disruption on the company's logistics network in terms of cost and transportation distance (a proxy for lead time). To address this question, we developed two scenarios: Baseline and Scenario 1. The Baseline scenario accurately replicates the network and logistics flow that transpired after the disruption. In Scenario 1, we used the same demand data as the Baseline but removed the disruption's effect by continuing to use the disrupted DC (DC_01) and maintaining the pre-disruption flow, allowing us to compute the logistics cost. Figure 6 illustrates the cost difference by period between the two scenarios.

Figure 6

Total Logistics Cost of Baseline and Scenario 1 by Period



Note. Created from optimization result of Baseline (BL) and Scenario 1 (SC_1). The length of a period is one month.

In Period 1, immediately following the disruption, the total logistics cost increased by 31 million JPY (+7.4%) as a direct consequence of the incident. However, the company initiated the launch of a temporary facility near the affected site to accommodate the demand previously served by the disrupted location. Consequently, by Period 9, the additional costs incurred due to the disruption were reduced to a mere 5 million JPY (+1.1%). Figure 7 shows the timeline of the temporary facilities' openings.

Figure 7

Manufacturer Allocations to Existing DCs

Mfr.	Disrupted facility	Facilities in other areas that served redirected demand from disrupted facility until temporary facilities were open					Temporary facilities and go-live month				Planned facility
	DC_01	DC_11	DC_12	DC_13	DC_14	DC_15	DC_21	DC_22	DC_23	DC_24	DC_41
MFG_01	✓				✓	✓				Period 3	
MFG_02	✓	✓					Period 4	Period 8			✓
MFG_03	✓			✓				Period 7			✓
MFG_04	✓		✓								
MFG_05	✓		✓						Period 4		✓
MFG_06	✓		✓					Period 11			✓
MFG_07	✓			✓				Period 11			
MFG_08	✓			✓				Period 9			✓
MFG_09	✓			✓						Period 2	✓

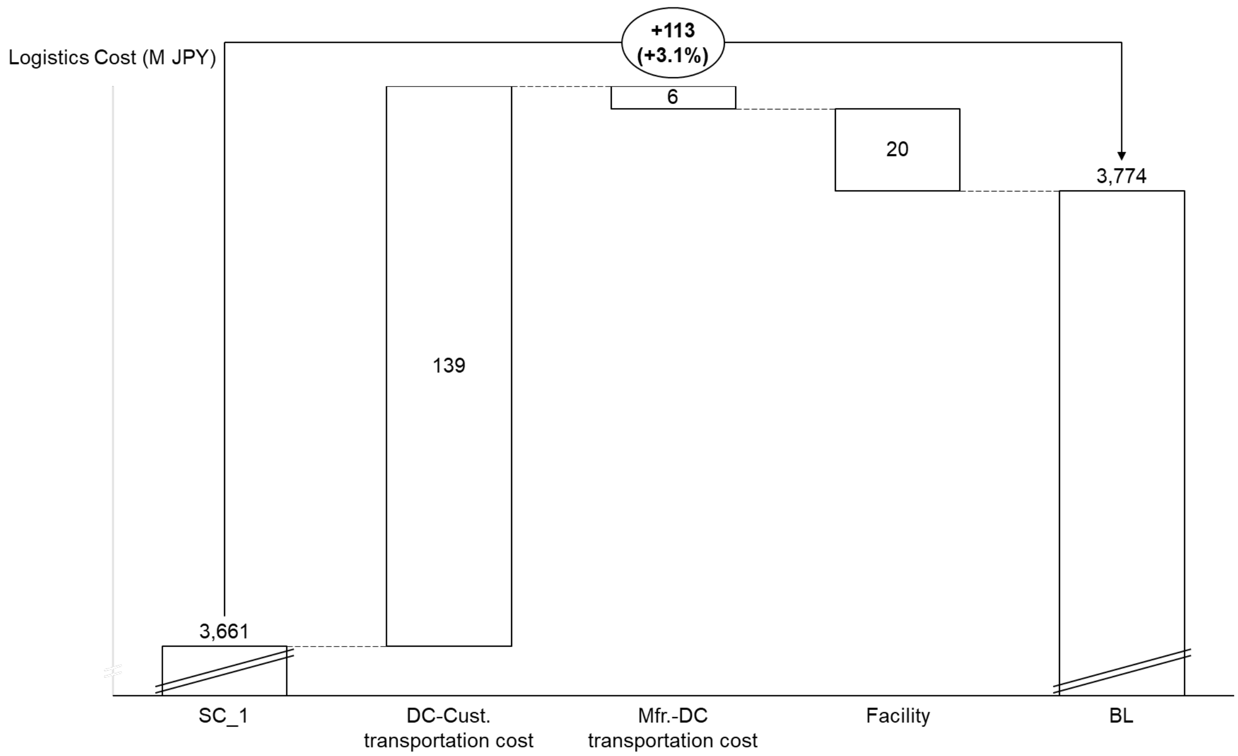
Note. All manufacturers considered in our research stored inventory in DC_01, which was the disrupted facility. After the disruption, their products were shipped from facilities indicated in blue. They continued to fulfill most of the demand from these facilities but at higher transportation costs. Eventually, the company opened temporary facilities indicated in yellow, which are closer to DC_01. DC_41 is the planned DC that will replace the disrupted DC_01.

Figure 8 illustrates the total logistics costs for both Baseline and Scenario 1, as well as the factors contributing to the differences in total costs. Over the course of nine periods, the total cost for Scenario 1 amounts to 3,661 million JPY, while the Baseline registers a total cost of 3,774 million JPY, as depicted in the graph. The estimated additional cost resulting from the disruption is 113 million JPY. As can be observed in the graph, the largest contributor to this increase is the DC-Customer transportation costs, which escalated by 139 million JPY. This outcome is understandable, considering that the disruption of the DC in the Kinki region necessitated covering the demand previously met by this facility through other DCs, primarily in

Shuto. Consequently, both transportation distance and costs increased.

Figure 8

Waterfall Chart: Comparison of Total Logistics Costs between Scenario 1 and Baseline



Note. Created from optimization result of Baseline (BL) and Scenario 1 (SC_1). The logistics cost is the sum of nine periods.

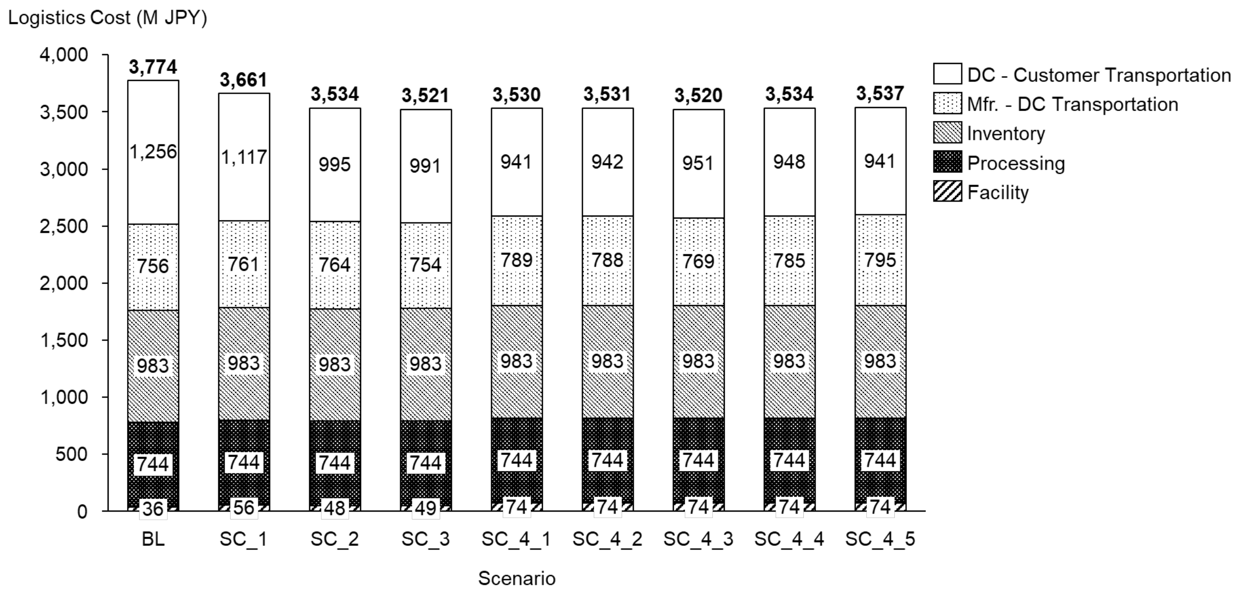
4.2. Research Question 2 (Q.2)

Q.2 examines the future network after the substitute facility is launched. In addition, we examined the possibility of adding a further additional DC to the network and enforcing a third stock point for each manufacturer. To address this question, we developed three scenarios: Scenario 2, Scenario 3, and Scenario 4_i. Keep in mind that Scenario 4_i includes five sub-scenarios denoted by *i*, where each sub-scenario represents an additional new DC in one of five various regions of Japan. Scenario 2 replicates the network and logistics flow of the company's plan of adding a substitute DC near the disrupted DC, (DC_01). The sponsor company's plan includes the specific location of the substitute facility and the allocation of manufacturers to each DC. In Scenario 3, we alleviate the manufacturer allocation constraint to allow the model to optimize the allocation. The intent is to examine the efficiency of their current plan. In Scenario 4_i, in addition to the locations utilized in Scenario 2, we added one more potential location and forced each manufacturer to be assigned to three DCs.

Figure 9 illustrates the total logistics costs of all scenarios except resiliency scenarios. First, when comparing Scenario 2 and Scenario 3, the cost difference amounts to a mere 13 million JPY over nine months, indicating that there is no significant difference between the company's manufacturer allocation plan and the optimal allocation. Second, among the various scenarios, Scenario 4_3 demonstrates the lowest cost at 3,520 million JPY over nine months. In this scenario, we introduced a new DC in Nagoya, which is situated in the central part of Japan. All other scenarios resulted in higher costs than Scenario 3, suggesting that the addition of a facility contributes to the overall increase in logistics costs. However, Scenario 4_3 was the exception and proved to be marginally more cost-effective than Scenario 3.

Figure 9

Comparison of Total Logistics Cost for Cost Optimization Scenarios



Note. Created from the optimization results of all cost optimization scenarios. The logistics costs are the sum of nine periods.

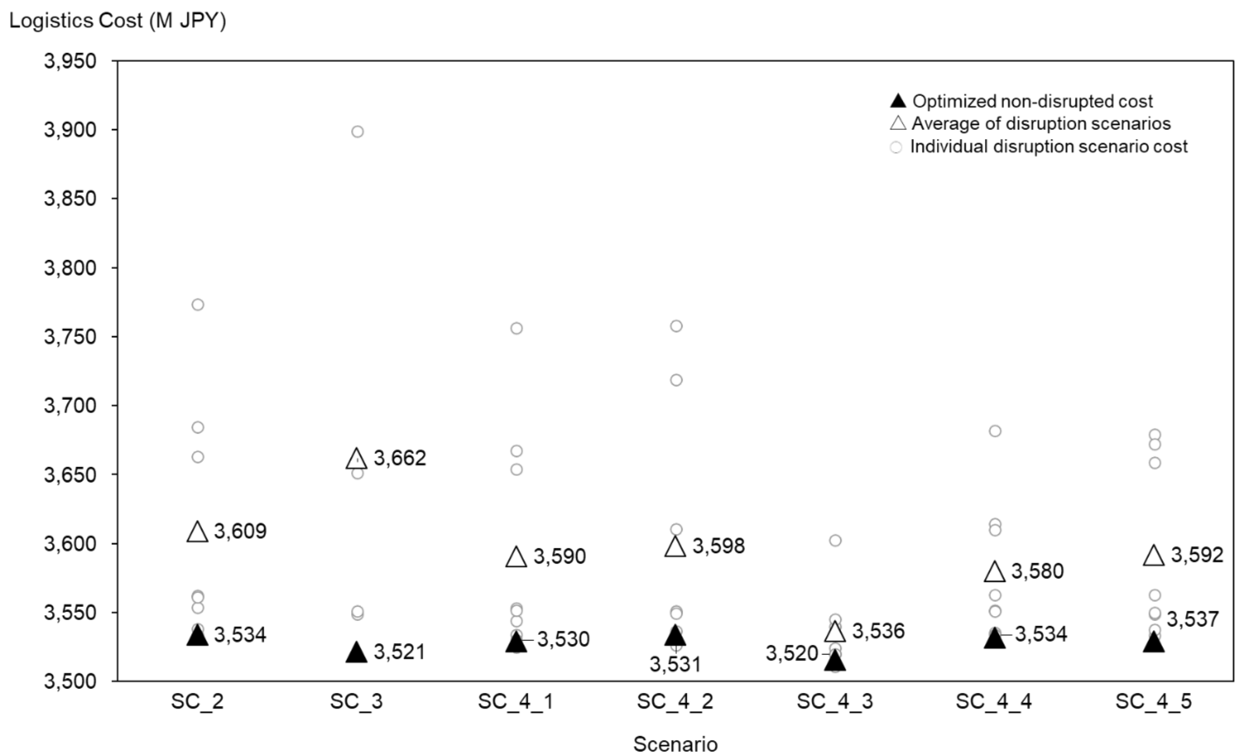
4.3. Research Question 3 (Q.3)

Answering Q.3 evaluates the resiliency of the networks generated from the scenarios presented in Section 4.2. To address this question, we developed Scenario 2’_j, Scenario 3’_j, and Scenario 4’_i_j, which represent the disrupted versions of Scenario 2, Scenario 3, and Scenario 4_i from Section 4.2. Each disruption scenario contains a number of sub-scenarios representing each DC contained within. The letter *j* represents the single DC that is disrupted in the sub-scenario, and the total number of *j’s* equals the number of DCs present in the corresponding undisrupted scenarios. For example, Scenario 2 has seven DCs, so Scenario 2’_j has seven sub-scenarios: Scenario 2’_1 through Scenario 2’_7.

Figure 10 presents a comparison of the minimized total logistics costs for Scenario 2, Scenario 3, and Scenario 4_i, alongside the individual total logistics costs of their corresponding resiliency evaluation scenarios—namely, Scenario 2'_j, Scenario 3'_j, and Scenario 4'_i_j. Additionally, Figure 10 also displays the average logistics costs for each of these scenarios.

Figure 10

The Total Logistics Cost of Cost Optimization Scenarios and the Average Total Logistics Cost of Disruption Scenarios



Note. Created from optimization results of all scenarios. The logistics costs are the sum of nine periods.

First, when comparing Scenario 2 and Scenario 3, Scenario 3 exhibits a marginally lower total cost, but the average cost of disruption scenarios is higher than that of Scenario 2. Beyond the average, the maximum loss is also greater for Scenario 3, as one of the dots indicates a logistics cost of 3,900M JPY in the case where DC_24 faces disruption.

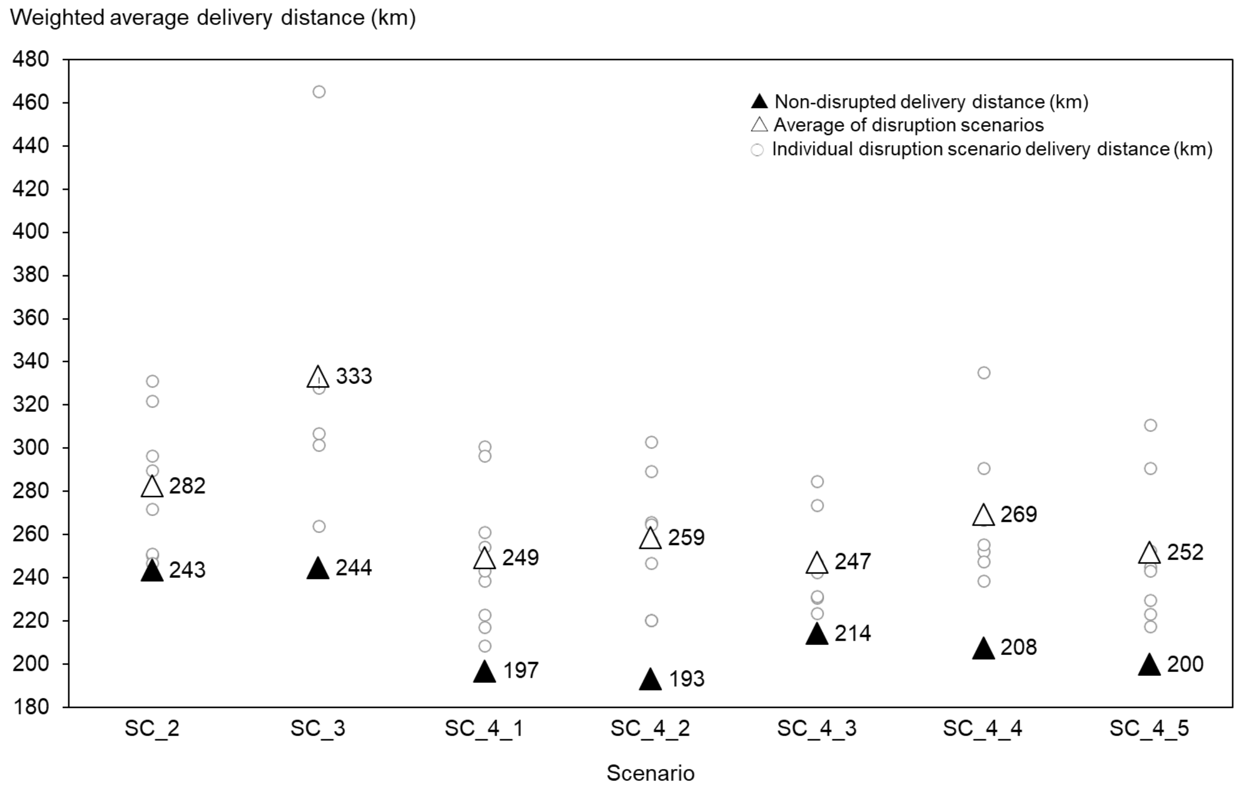
Second, when comparing scenarios from Scenario 4_1 to Scenario 4_5, Scenario 4_3, where a new facility is added in Nagoya, Aichi Prefecture, displays the lowest optimized cost and the lowest average cost of disruption scenarios. The maximum loss is also the smallest in Scenario 4_3.

Lastly, when comparing Scenario 2 and Scenario 4_3, both the optimized cost and average cost of disruption are lower for Scenario 4_3. It is worth noting that all Scenario 4_i scenarios (three DCs for each manufacturer) exhibit lower average disruption costs compared to Scenario 2 and Scenario 3 (two DCs for each manufacturer).

Figure 11 displays the weighted average distance for DC-Customer shipments instead of costs as depicted in Figure 10. The structure of the Figure 11's graph is consistent with Figure 10.

Figure 11

Weighted Average Delivery Distance from DCs to Customers of Cost Optimization Scenarios and Disruption Scenarios



Note. Created from optimization results of all scenarios. The distance is the weighted average by shipment weight.

First, when Scenario 2 and Scenario 3 are compared, Scenario 2 presents a slightly lower distance for both non-disrupted scenarios and the average of disruption scenarios. In addition to the average, the maximum distance is also smaller for Scenario 2.

Second, when comparing scenarios from Scenario 4_1 to Scenario 4_5, Scenario 4_3, unlike in the total cost comparison, demonstrates the highest average delivery distance. However, the maximum and average increases in the distance for disruption scenarios are the smallest in this scenario.

Lastly, when comparing the two DCs per manufacturer scenarios (Scenario 2 and 3) with the three DCs per manufacturer scenarios (Scenario 4_i), overall, the three DC scenarios exhibit lower average delivery distances, as one would naturally expect.

Chapter 5. Discussion

5.1. Discussion of the Results

In this section, we discuss the results related to each research question and derive practical insights from the findings.

5.1.1. Research Question 1 (Q.1)

As discussed in Section 4.1, Figure 6 illustrates the rapid +7.4% increase in the costs due to the disruption in Period 1, but this decreases to +1.1% in Period 9. Additionally, Figure 7 demonstrates that most of the increased costs result from the rise in DC-Customer transportation costs. This reflects the actual recovery measures implemented by the company.

There are nine manufacturers that the company serves within this network, all of which were affected by the disruption. Each manufacturer had two stock points on the network, except for one which had three, so when the disruption occurred, they were all able to continue shipping products the next day using an alternate DC, albeit with increased transportation costs. The affected DC was located in the Kinki area and served the demand in Kinki and other areas in the western part of Japan. Most manufacturers had another stock point in the Shuto area, which catered to demand in Shuto and other areas in eastern Japan. Due to the disruption, the DCs in the Shuto area needed to cover all parts of Japan, including areas previously served by the disrupted facility in the Kinki area, which led to an increase in transportation costs.

However, the company began opening new temporary facilities to serve demand in the western part of Japan as early as Period 2, which is one month after the disruption. Of the nine manufacturers affected by the disruption, six had stock at the temporary facilities in the Kinki area by Period 9, with two more set utilize the facilities in Period 11, which is outside the model horizon. One manufacturer left the company after the disruption, so by Period 11, the company will have completed preparations for temporary facilities for all affected existing manufacturers. Figure 6 clearly shows the relationship between the increased costs and the opening of temporary facilities. Although we could only collect data until Period 9, it is likely that by Period 11, the company had mitigated the increased costs caused by the disruption.

5.1.2. Research Question 2 (Q.2)

In Section 4.2, we discussed two findings related to Q.2. First, when comparing Scenario 2 (the company's recovery plan) with Scenario 3 (optimizing the allocations of manufacturers to DCs), the cost difference amounts to 13 million JPY over nine months. Second, among the additional DC scenarios (Scenario 4_i), Scenario 4_3, which utilizes the DC in Nagoya, demonstrates the lowest cost at 3,520 million JPY over nine months.

Table 8 displays the percentage of demand served by each DC as part of the solutions for optimization scenarios. When comparing Scenario 3 with Scenario 2, Scenario 3 utilizes fewer DCs and concentrates 46% of the demand in DC_24. In Scenario 2, 27% of the demand was served by DC_41, which is not used in Scenario 3. DC_41 is the DC the company plans to develop as a substitute for DC_01, which was destroyed by the disruption. The optimization results indicate that the network can achieve lower costs by increasing the capacity of DC_24 instead of opening DC_41, although the cost difference is small.

Table 8

Percentage of Demand Served by DCs in Scenarios

DCs	Scenarios								
	BL	SC_1	SC_2	SC_3	SC_4_1	SC_4_2	SC_4_3	SC_4_4	SC_4_5
DC_01		34%							
DC_11	7%	4%	3%		3%	3%	3%	3%	3%
DC_12	9%	6%	2%	23%	3%	3%	2%	3%	3%
DC_13	40%	33%	21%	5%	21%	18%	20%	21%	21%
DC_14	14%	12%	1%		1%				1%
DC_15	10%	9%	9%	10%	9%	9%	9%	8%	
DC_21	1%								
DC_22	2%		10%	16%	10%	10%	7%	8%	8%
DC_23	2%								
DC_24	14%	2%	26%	46%	26%	25%	16%	24%	26%
DC_31					3%				
DC_32						8%			
DC_33							26%		
DC_34								13%	
DC_35									16%
DC_41			27%		23%	24%	16%	19%	21%

Note. The table indicates the percentage of demand served by each DC for different optimization scenarios. The demand is the sum of Periods 1 to 9.

Scenarios 4_1 to 4_5 are the additional DC scenarios, where DC_31 to 35 are added as potential DCs for each scenario. Examining the utilization of the added DCs, DC_33 in Scenario 4_3 is the most utilized (serving 26% of total demand) among the added DCs. The area where DC_33 is located, Nagoya, is the third most populous city in Japan, after Tokyo and Osaka, and is geographically situated between these two cities. This geographical feature enables DC_33 to have the largest throughput and makes Scenario 4_3 the most cost-efficient network, covering the demand that is distant from both DCs in the Tokyo and Osaka areas.

5.1.3. Research Question 3 (Q.3)

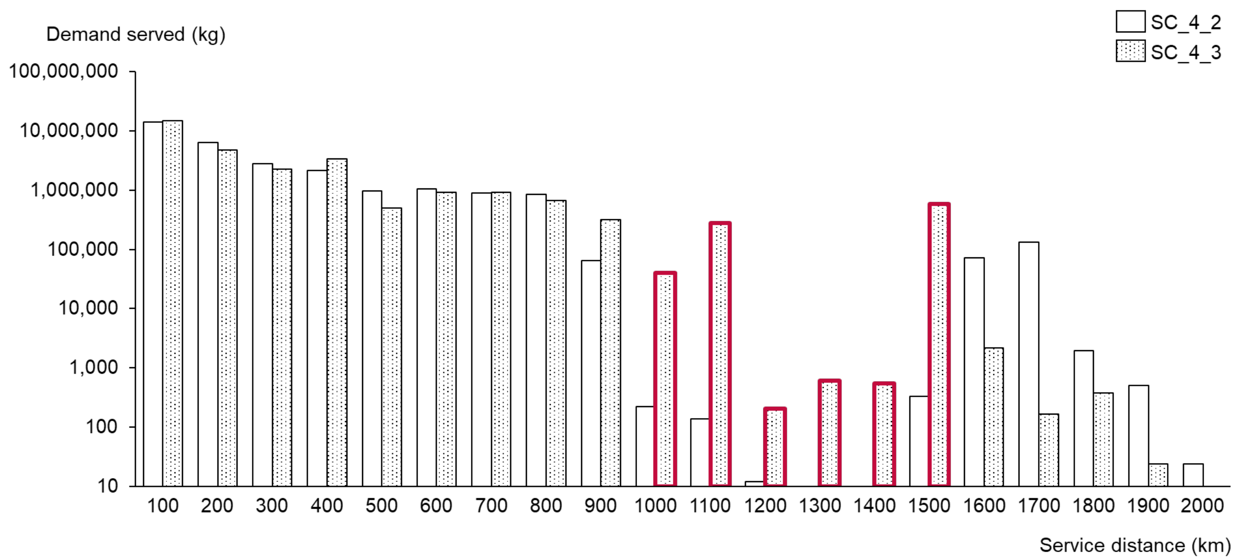
In Section 4.3, the results of the disruption scenarios were discussed. First, we compared the optimization result of Scenarios 2 and 3. While Scenario 3, which removes the constraint of the manufacturer allocation plan and optimizes the allocations, showed a slight improvement in the total cost compared to Scenario 2, which adheres to the allocation plan, it was less resilient in our resiliency evaluation. This is because, in Scenario 3, 46% of the demand is fulfilled by DC_24, as shown in Table 8, leading to a significant impact when this facility is disrupted and bringing up the average cost of disruption scenarios. The total number of DCs used is also less for Scenario 3. Scenario 3 uses five DCs, while Scenario 2 uses eight. Additionally, in Scenario 2, the demand is more evenly distributed among the facilities, which results in a lower maximum loss under the disruption scenarios. We also compared the impact on customer delivery distance in case of disruption. For the same reason, the increase in the average distance was less for Scenario 2.

Second, we compared the results for Scenario 4_i, the additional DC scenarios. In these Scenarios, Scenario 4_3, which added DC_33 in Nagoya, performed best in terms of total logistics cost, as elaborated on in Section 5.1.2. Scenario 4_2, which added DC_32 in Sendai (a major city in a northern part of Japan) performed best in terms of average customer delivery distance. It is also important to note that, although the average customer delivery distance of Scenario 4_3 was highest among Scenario 4_i, the increase of the distance in disruption scenarios was lowest in Scenario 4_3.

Figure 12 displays, in log scale, the total demand served by customer distance for Scenario 4_2 and Scenario 4_3. These scenarios were chosen because Scenario 4_2 resulted in the shortest delivery distance, and Scenario 4_3 resulted in the longest delivery distance. The bars highlighted in red show that more demand in the 900 to 1,500 km range is served in Scenario 4_3. This demand is mainly from customers in Hokkaido, a northern island of Japan. Since, in Scenario 4_3, a new facility is added in the central part of Japan, it does not contribute to reducing the delivery distance for customers in Hokkaido. On the other hand, Scenario 4_2 adds a new DC in the northern part of Japan, which reduces the distance for those customers. In the case of disruptions, however, Scenario 4_3 outperforms Scenario 4_2 because the added DC, which is located between Tokyo and Osaka, can efficiently serve customers in those areas when local DCs are disrupted.

Figure 12

Demand by Weight Served by Customer Delivery Distance (Service Distance) Range



Note. The graph indicates the demand (kg) served by all DCs from Period 1 to 9, showing only the results of Scenario 4_2 and 4_3. The demand is divided by the service distance from the DCs to customers. The demand is in log scale.

5.2. Future Opportunities

There are opportunities to expand our model to include several aspects of real-world supply chain dynamics and enhance the model's comprehensiveness and utility. For example, our model, in its present form, does not account for the implications of inventory pooling and economies of scale when assigning manufacturers to multiple DCs. Taking inventory pooling and economies of scale into account increases the costs of additional DCs because the same inventory would be shared by more locations.

Additionally, the model does not factor in regional wage discrepancies, which have implications for labor cost calculations. An approach incorporating these variations could yield a more nuanced understanding of the cost dynamics of DC locations. Similarly, the model remains agnostic to regional rent differentials, which directly impact DC costs. Incorporating these variations could enhance the model's ability to accurately depict the optimal location for additional DCs.

In terms of infrastructural investments, our model does not fully encapsulate the fixed costs associated with the establishment of a new facility. Regional costs would also come into play if incorporating fixed costs for new facilities. A more exhaustive analysis of these costs could improve the model's predictive accuracy with respect to investment decisions.

The model also does not account for the capacity constraints of existing DCs. If capacity constraints were incorporated into our models and a DC was determined to be at capacity, then it would result in different demand and manufacturer allocations and cost outcomes.

Our reliance on past transportation costs due to a lack of specific truck vendor tariffs represents another area for potential improvement. Future iterations of the model could strive to integrate accurate vendor tariffs, thereby refining cost predictions and enhancing strategic decision-making.

Lastly, our model employs distance as a surrogate for lead time, not accounting for potential cutoff times that less-than-truckload (LTL) vendors may impose. Incorporating such operational constraints could enhance our model's predictive accuracy with respect to delivery times. For example, LTL facilities enforce shipment cutoff times to ensure next-day delivery to customers. If a shipment from the sponsor company arrives after that cutoff time, then the LTL vendor will not ship to the customer until the second day.

5.3. Supply Chain Resiliency in a 3PL Context

3PL providers often find themselves without the same tools to enhance resilience as their vertically integrated counterparts. For example, a 3PL may not have the ability to increase inventory or safety stock when inventory levels are determined by the client. An interesting dynamic in the 3PL business model is that their "suppliers" are essentially their customers or clients. Further complicating this is the fact that the resilience of these "suppliers" might not be a concern for a 3PL, depending on the specifics of the contractual agreement.

For instance, if a 3PL's contract specifies payment based on a predetermined throughput, a disruption at the supplier's end would not necessarily lead to a reduction in the 3PL's revenue. This is because the immediate impact of a disruption, a scarcity of products on the shelves, primarily tarnishes the client's reputation and sales, leaving the 3PL relatively unscathed. Thus, the concept of "supplier" resiliency takes on a different meaning in the context of 3PLs.

5.4. Recommendations for the Sponsor Company

In this section, we present three recommendations derived from our research. Our first recommendation is for the sponsoring company to continue with their current plan of developing the new facility, DC_41, to replace the disrupted facility. The optimization result of Scenario 2 revealed that the costs of the company's plan for the new facility location and allocation of manufacturers are close to Scenario 3, which optimizes the allocation of manufacturers, while being more resilient to disruptions than Scenario 3. Our research also indicates that, with appropriate demand allocations to each DC, the new network can reduce the total costs compared to the pre-disruption network. The current plan does not include customer allocation to specific facilities, but our optimization results provide a detailed assignment of customers, aggregated at the municipal level, to each DC. This data can be utilized in the detailed planning of the company's future network.

Our second recommendation is for the addition of a new DC in the Nagoya area. In the current configuration, most manufacturers are assigned two DCs to store and ship products, but enforcing three stock points and introducing an additional DC in the Nagoya area may further reduce logistics costs and improve resilience to disruptions. Detailed investigations into customer delivery distance also revealed that adding a further additional DC in the northern part of Japan, (e.g., Sendai), reduces delivery distance, potentially shortening delivery lead times to final destinations.

The delivery distance perspective is important due to the current challenges faced by Japan's trucking industry. Since the 1990s, the Japanese trucking industry has become highly fragmented due to significant regulatory changes. In 1990, the industry transitioned from a difficult license-based application process for new trucking companies to an easier application-based system, allowing numerous trucking companies to enter the market. This has led to increased competition, low profit margins, and low salaries for truck drivers, making it difficult to attract new talent to the industry.

The upcoming "Year 2024" challenge, where regulations to reducing overworked truck drivers' hours will be implemented, is expected to exacerbate the labor shortage. Japan's rapidly aging population and shrinking labor force, combined with the growing e-commerce sector, further strain the already insufficient supply of labor. To cope with this situation and mitigate the burden on the industry and drivers, we recommend that the company considers scenarios with additional DCs to reduce driving distances.

Our third recommendation is for the company to utilize digital network models for their planning and operations. The analysis related to Q.1 revealed that the digital network model can accurately grasp the quantitative impact of disruptions and the effectiveness of countermeasures, such as opening temporary facilities. The digital network model can be utilized in two ways:

The first use case is contingency planning after disruptions. In answering Q.1, we utilized past data to quantify the impact of disruptions and countermeasures. However, if during a disruption, the company has the model and necessary data on hand they can develop contingency plans in real-time. With the model and data, it is easy to create and compare scenarios and decide on appropriate measures based on the results.

The second use case is business continuity planning. For answering Q.3, we developed various scenarios anticipating future potential disruptions and estimated the impact of those disruptions on the network. Anticipating disruptions and having a playbook beforehand will significantly reduce the actual impact of disruptions.

To realize these use cases, a sophisticated model and reliable data are necessary. For model sophistication, focusing on the points described in Section 5.2 is essential. In terms of data, different types of data, such as customer demand, existing facility, product information, and relevant costs, must be in a state that can easily be integrated into the model for analysis. A detailed definition of data requirements, such as periods, granularities, keys, attributes, and an appropriate data management process, is required.

Chapter 6. Conclusion

Our project sponsor experienced a severe disruption that destroyed one of their major DCs. This disruption led to increased lead times, degraded service levels, and higher logistics costs, even resulting in the loss of a customer. These consequences prompted the company to focus on supply chain disruptions and resiliency studies. We aimed to answer three fundamental questions: First, what was the quantitative loss caused by the disruption? Second, how should we rebuild the network to recover from the disruption? Third, how can we add resiliency to mitigate potential future disruptions?

To answer these questions, we collected real-world data spanning two years, which included the disruption the company faced, and developed mixed-integer linear programming (MILP) models. Numerous discussions with the sponsor company contributed to our understanding of the specific industry focused on in our research, the fundamental cost structure of their business, and the representation of these elements in our models. Additionally, we developed practical optimization scenarios through these discussions, which were used for further scenario planning analysis.

To answer the first question, we created two scenarios to compare: the actual network and flow after the disruption and an imaginary network and flow where the disruption did not occur. The comparison of these scenarios provided us with the quantitative financial loss caused by the disruption. It also highlighted how the costs evolved over time as the company started to recover from the disruption by implementing temporary facilities near the affected DC. The cost increase caused by the disruption was +7.4% in the first month, but after nine months, it was reduced to +1.1%, demonstrating that their prompt establishment of emergency temporary facilities contributed to rapid recovery. As stated in Section 2.1, the sponsor company utilized all reactive node-based resilience measures; flexible capacity at the facilities, reassigning of customers, and expansion of facility capacity, reflecting their preparedness for the disruption.

Now, the company has a plan to develop an equivalent-sized facility to replace the temporary facilities, which can be considered a true recovery from the disruption. We addressed the second question by evaluating their plan and comparing it to other network configurations, such as changing the allocations of manufacturers to DCs and adding a further additional DC in another region. Our results show that the company's planned location for the new DC is efficient, reducing the total cost by 3.5% compared to the pre-disruption network and would result in an improved post-disruption network. We also optimized the allocation of manufacturers to each DC using the same set of DCs as their plan, but the improvement was merely 0.4% compared to their allocation plan. We created scenarios to add another DC in regions where they currently do not operate a DC. Some additional locations showed a slight improvement in cost compared to their current plan. Among those, an additional DC in Nagoya, located in the central part of Japan, exhibited the best performance, improving the total cost by 0.4%.

To answer the third question, we evaluated the resiliency of the optimized solutions for different network configurations discussed in the previous paragraph, such as the company's recovery plan and additional DC scenarios. One interesting finding was that their current plan for manufacturer allocations was more resilient than the cost-minimized allocations. Considering the slight improvement in the total cost and taking resiliency into account, their current plan may be superior to the cost-minimized solution. Additionally, among the additional DC scenarios, the scenario that adds a Nagoya DC, again, demonstrated the best performance in terms of resiliency. It may be worth considering Nagoya as a future network improvement plan after implementing their recovery strategy.

During our research, we have illuminated the fiscal implications of high-impact, low-probability events for our sponsor company. Yet, it is crucial to acknowledge that our study touches upon merely a fragment of the potential economic aftermath of a supply chain disruption.

For example, this disruption necessitated the redeployment of high-salary office professionals to the remaining and temporary DCs. Our analysis does not account for these additional labor expenditures, nor does it incorporate the financial impact of these individuals being diverted from their customary roles.

Additionally, there are potential ripple effects from such a disruption. Potential initiatives could be shelved, insurance premiums may soar, a valuable reputation could be tarnished, and loyal clients could be lost to the competition. Our study does not venture into quantifying these potential losses, yet they are undeniably critical considerations.

As an organization deliberates over the financial feasibility of investing in supply chain resilience, it is important that it grasps the full spectrum of potential costs associated with the alternatives. It is not merely about weighing the immediate costs against benefits; it is about understanding the depth and breadth of the consequences, seen and unseen, that can emanate from an unanticipated disruption. This understanding requires a lens of wisdom, foresight, and a deep appreciation for the intricate interconnectivity of today's global supply chains.

Our research revealed the quantitative loss caused by the disruption, evaluated and justified their recovery plan, and presented the possibility of adding an additional DC in a new region to reduce total logistics costs and increase the resiliency of their network. We hope this research serves as an opportunity for the sponsor company to begin fully utilizing optimization models of their 3PL networks to understand the complex trade-offs of their supply chain and support strategic decision-making that balances efficiency and resiliency.

References

Center for Spatial Information Science. (n.d.). *CSV Address Matching Service*. The University of Tokyo. Retrieved May 7, 2023, from https://geocode.csis.u-tokyo.ac.jp/geocode-cgi/geocode.cgi?action=start

Govindan, K., Fattahi, M., & Keyvanshokooh, E. (2017). Supply chain network design under uncertainty: A comprehensive review and future research directions. *European Journal of Operational Research*, *263*(1), 108–141. https://doi.org/10.1016/j.ejor.2017.04.009

Janić, M. (2019). Modeling the resilience of an airline cargo transport network affected by a large scale disruptive event. *Transportation Research Part D: Transport and Environment*, *77*, 425–448. https://doi.org/10.1016/j.trd.2019.02.011

Janjevic, M., Valderrama, C., Bucci, M., & Klibi, W. (2022). *The New Competitive Edge: Analytics Driven Supply Chain Design, An Executive Guide*. MIT Center for Transportation & Logistics and Coupa Software.

Krikke, H. R., & Gknatsas, E. (2020). Towards a Pro-Silience Framework: A Literature Review on Quantitative Modelling of Resilient 3PL Supply Chain Network Designs. *Sustainability (Basel, Switzerland)*, *12*(10), 4323-. https://doi.org/10.3390/su12104323

Maharjan, R., & Kato, H. (2022). Resilient supply chain network design: A systematic literature review. *Transport Reviews*, *42*(6), 739–761. https://doi.org/10.1080/01441647.2022.2080773

Martel, A., & Klibi, W. (2016). *Designing Value-Creating Supply Chain Networks*. Springer International Publishing. https://doi.org/10.1007/978-3-319-28146-9

Rice, J. B. (2021, August 25). The 7 Core Capacities of Supply Chain Resilience. *MITSupplyChain*. https://medium.com/mitsupplychain/the-7-core-capacities-of-supply-chain-resilience-dde24c96908b

Saragih, A. (n.d.). *Value of Information (VOI) Analysis in Supply Chain Network Design Under Uncertainty*.

Winkenbach, M., & Janjevic, M. (2023). *Session 07: Last-mile Logistics Network Design*. SCM.293 / 11.263 / 1.263 Urban Last-Mile Logistics.