A SUPPLY CHAIN NETWORK DESIGN CONSIDERING DISRUPTION AT DISTRIBUTION CENTERS WITH CAPACITY CONSTRAINT

by

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AUTHOR'S DECLARATION

I, Pongpanot Karat, the author of this research work, would like to confirm that this thesis follows the Asian Institute of Technology regulations. I would like to emphasize that this is a true copy of the thesis summited to AIT to obtain a master's degree in engineering. The works presented in this thesis has been generated from my own thought. Some external sources were used in my initial idea phase, and all were already cited.

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ABSTRACT

In this research, a supply chain network design (SCN) considering transportation and shortage costs was developed and solved via CPLEX. In general cases, some input parameters have been considered as constant values. However, in real-world problems, most input parameters are not always constant due to the fluctuation of many factors, e.g., time constraints, seasonal demand, and weather conditions. Therefore, an input parameter of the developed model in this research, i.e., the capacity of unreliable distribution centers (unreliable DCs) was considered as random variable and analyzed via a stochastic programming approach which is the scenario-based technique. The result obtained from the scenario-based technique provides decision-makers a more precise value of the model's total cost and made it easier to make strategic decisions and long-term plans.

Keywords: Supply chain network, Supply chain network design, Stochastic programming, Scenario-based technique, Unreliable distribution centers.

CONTENTS

CONTENTS

LIST OF TABLES

LIST OF TABLES

LIST OF ABBREVIATIONS

DC	= Distribution Center
DCs	= Distribution Centers
SCN	= Supply Chain Network
SCND	= Supply Chain Network Design

CHAPTER 1
INTRODUCTION

1.1 Background of the Study

Several organization goals, e.g., cost reduction in locating DCs' locations, determining DC capacity, and sourcing shipments between DCs and customers can be achieved by A well-designed supply chain network. Because of fast technological advancement, organizations with a fundamental supply chain can expand the structure of a supply chain to be more complex involving a higher level of interdependence and connectivity between organizations; this results in a supply chain network. Businesses are mostly part of a more extensive network of organizations; a supply-chain network can be used to highlight interactions between organizations. The flow of information and materials across organizations can be seen using a supply chain network. SCNs are now more worldwide than ever and commonly consist of five key areas: external suppliers, production centers, distributors, demand zones, and transportation assets.

Many companies nowadays have been directed to modify their primary supply chain, analyzing the tools and resources to develop an improved SCN design that considers taxation regulations, new entrants into their industry, and availability of resources, resulting in more complex and appropriate network designs. A supply chain network can be strategically designed to relieve the cost of the supply chain. Specialists have recommended that 80% of supply chain costs are defined by the location of facilities and the flow of products between the facilities. Supply chain network design can also be referred to as Network Modelling. A mathematical model can be developed to optimize the supply chain network. For example, transportation, fixed cost of opening DCs, and shortage costs can be written in a mathematical form and solved by some software to reach optimal solutions.

Designing a SCN relates to constructing a network which contains all the facilities, production approaches, products, and transportation properties owned by the organization or those not owned by the organization, but which support the supply chain operations and product flow. The SCND should also consists of details of the number and location of facilities: plants, warehouses, and suppliers. Therefore, a SCN can be illustrated as the integration of nodes with capability and capacity, connected by various ways to help products move between facilities. As data accessibility keeps improving, it is getting growingly essential for organizations to create data-driven SCND decisions regarding transportation based on accurate transportation data.

There is no definitive way to design a SCN as the network footprint, the capability and capacity, and product flow. All of these intertwine and are interdependent. There exists no single optimal SCN design. There is an apparent trade-off between responsiveness, risk tolerance, and efficiency in designing the network. Costs in an organization can be relieved by effective designing of SCN. It is necessary to be noted that the supply chain is a consistently improved system and adjust in response, is not stable. A crucial component of designing the SCN is to ensure that the network is multipurpose and robust adequate to deal with future uncertainties. Although there is inherent uncertainty related to the future, the use of information available can conduct the analysis of a SCN risk.

There are two categories of SCN related to uncertainty which are endogenous uncertainty and exogenous uncertainty. Uncertainty can be classified as 'endogenous' when the source of the risk is in the SCN itself, e.g., market fluctuation or technological turbulence. Experts classified uncertainty as exogenous when the risk comes from external sources. Exogenous uncertainties can be further classified, e.g., economic fluctuation can be addressed as a 'continuous risk' while 'discrete' risks represent the events that could rarely disrupt the supply-chain process, e.g., natural catastrophes.

1.2 Statement of the Problem

The models related to supply chain network design consist of many mathematical formulations with different objective functions and constraints. Generally, the purpose of developing a mathematical optimization model is to minimize the total costs of the supply chain network.

Researchers have spent many efforts for decades developing models that suit various practical situations. Related to the disruption problem at distribution centers, an assumption considered in the past research was "when a DC is disrupted, its capacity will be completely lost, and it cannot serve any demand. In other words, it fully fails when disruption occurs". However, a disrupted DC might lose only some of its capacity. Some other research works also considered that the capacity of a DC is unlimited. Therefore, a new model is needed to be developed to address these issues.

In summary, supply chain network design needs to be considered because it helps determine strategic decisions, e.g., defining the suitable number of facilities in the model, determining the facility locations, determining the facility sizes (facility capacity), and determining the allocation of retailers to distribution centers (distribution strategies). Once a strategic decision is derived, it always lasts for a long time, e.g., more than five years. In this current research, the focus will be on the distribution strategies in which the problem of allocation of retailers to distribution centers will be addressed under the existence of disruption at distribution centers.

1.3 Objectives of the Study

The focus of this research is as follows.

1. Developing a model to help allocate retailers to distribution centers considering disruption at DCs.
2. Satisfying the demand of all customers to the maximum extent under disruption.
3. Minimizing the transportation cost and the shortage cost in the network.

1.4 Scope and Limitations of the Study

This research will be conducted under the following assumptions.

1. There are multiple DCs and multiple retailers in the model.
2. There are reliable DCs and unreliable DCs with known maximum capacities.
3. DCs in the model are fixed, which means we know which DCs are open, reliable, not reliable and know DCs' location and DCs' capacities.
4. A retailer will be assigned to a primary DC and/or a secondary DC. If the retailer is assigned to a reliable DC as a primary DC, there is no need to assign a secondary DC. But if the primary DC is an unreliable DC, the retailer will also be assigned to a reliable DC as a secondary one.

5. There is no transportation disruption.
6. When disruption occurs at an unreliable DC, the DC does not entirely fail. The capacity on that DC will change following a discrete distribution with known capacity.
7. No product will be transferred between reliable DCs and unreliable DCs. The product is always transferred directly from DCs to retailers.
8. Any open facility may serve any customer (there are no connectivity restrictions).
9. A single product is considered in the model.

1.5 Organization of the Thesis

This thesis is organized into 6 chapters and the rest are organized as follows

- Chapter 2 presents related literature review.
- Chapter 3 presents the model developed in this study.
- Chapter 4 presents various cases of input parameters of the model tested and analyzed via sensitivity analyses.
- Chapter 5 presents the conclusion and recommendations obtained from this research results.

CHAPTER 2
LITERATURE REVIEW

This research aims to develop a model that effectively helps allocate retailers to distribution centers considering disruption risk at DCs. As such, this literature review covers previous studies related to supply chain network design, disruption in SCND, and mitigation strategies used in SCND.

2.1 Connectivity Between Disruption and SCND

Once a strategy of SCND is launched, it will be very costly and tough to apply a new strategy. When a SCND is in use, the parameters used in the model will not be constant. It will fluctuate due to many factors, such as disruption. As such, models developed to deal with this problem have been explicated by many researchers (Snyder [3]).

A structure related to mental concepts and initial outcome for the emerging area of disruption risk management in SCNs was introduced by Paul et al. [30]. Operational risks such as equipment malfunction, unexpected discontinuities in supply, human-centered issues from strikes to fraud, and risks emerging from natural catastrophes, terrorism attack, and instability of politicization are the focus of the paper.

Snyder et al. [15], Qin and Tang [16], and Klibi et al. [17] reviewed many SCND models which are flexible to all kinds of disruptions. The network reliability theory [18, 19, 20] considers maximizing the probability of a network that a connectivity is still connected after a random disruption occurs. Maximizing demand coverage is another objective of a reliable network. According to classical facility location problems, SCND under random disruptions, in which disruption can disrupt DCs with a given probability, was guided by Snyder and Daskin [23].

Hakimi (1964) introduced the classical p-median problem. He assumed that customers always get service from the facility that minimizes their “travel cost” (that can also serve as a representative for many other costs). Berman et al. [6] introduced a reliability aspect which is, considering the likelihood possibility that a facility might suffer by disruption and lack of serving any demand for the purposed that he tried to conclude the classical p-median problem. In other words, a p-median problem was proposed by Berman et al. [6] and minimizing the demand weighted transportation cost was the objective function. Different facilities were allowed to have different probabilities of failure.

The random disruption in the DCs' locations has been considered in many literatures, but in the real world, disruption can also disrupt the connectivity between DCs and customers. Azad et al. [2] considered that the transportation modes between DCs and customers can be disrupted as well as the DCs' locations.

2.2 Approaches to Mitigate the Effect of Disruption to SCN

Gurnani et al. [31] showed a conclusion of strategies which relieve the probability disruption of a supply chain or alleviate disruption impact. A scrupulous review of the literature on supply chain disruption was presented as the objective.

A stochastic programming model and solution approaches for correcting supply chain network design problems were proposed by Santoso et al. [36]. They presented the importance of the stochastic model via a computing study related to two existing supply chain networks.

Adegoke et al. [32] categorized the types of risks, investigated mitigation strategies to deal with risks, and identified generic strategies which cope most kinds of risk and particular strategies for coping risks. The summary table of the authors' findings, which includes risk category, risk type, classification, and mitigation strategies, is shown in the paper.

Peidro et al. [33] presented a review of literature related to supply chain planning approaches under uncertainty. They identified a taxonomy to classify models from many references. Some of the strengths and weaknesses of the approaches recently used in the review have been addressed and shown in table form.

Baghalian et al. [37] developed a stochastic model for planning a network framework for a supply chain, which consists of several capacitated production facilities, DCs, and retailing facilities regarding both demand-side and supply-side uncertainties. This model assures to provide a predetermined service level for its customers regarding extra and shortage costs in retailing facilities.

The so-called hardening strategy can strengthen selected DCs in SCND under random disruption Lim et al. [1]. This approach considers the random disruption in the location of DCs. Types of DCs are categorized to be two types which are reliable and unreliable DC. The random disruption can occur only in unreliable DCs. When a random disruption occurs, the capacity of disrupted DC fails entirely, and the customers assigned to this DC must be reassigned to a reliable DC. By investment, a reliable DC exists on the system.

Azad et al. [2] developed a SCN considering both first- and second-order moments to formulate the problem. Also, they applied the concept of a well-known risk measure known as conditional value-a-risk (CVaR) into their model to manage the monetary risk.

Many strategies to relive the effect of disruptions in the supply chain have been reviewed by Wallace J. et al. [29]

A reliable p-median problem was considered, and a heuristic method for solving it was developed by Drezner [21]. Lee [22] also developed a practical approach to solve the reliable p-median problem. In their model, there existed two customer assignments: primary and secondary assignment. Their assumption was that a disrupted DC cannot serve any product of its capacity, and there will be reassignment for customers, who are assigned to the disrupted DC, from the disrupted DC to a non-disrupted DC. Minimizing the cost of a normal situation and a disruption situation was the objective function.

Snyder and Daskin [24] extended their previous work from [23] and the concept of stochastic p-robustness was introduced. They considered facility location models which combine the advantages of both the stochastic and robust facility location models.

Ahmadi Javid A and Azad N [25] developed a novel model to optimize a stochastic supply chain system's location, allocation, capacity, inventory, and routing decisions simultaneously. The demand of each customer is uncertain following a normal distribution, and each distribution center maintains a certain amount of safety stock. They solved the model by an exact solution approach by considering the problem as a mixed-integer convex program and a heuristic method based on a hybridization of Tabu Search and Simulated Annealing.

Chopra et al. [26] showed that bundling the two uncertainties, decoupling recurrent supply risk and disruption risk, can guide a manager to underutilize a reliable source while overutilize a cheaper but less reliable supplier. They presented that increasing quantity from a cheaper but less reliable source is a capable risk mitigation strategy if most supply risk comes from an increase in repeated uncertainty.

Some general concepts for modeling stochastic optimization problems were reviewed by Ruszczyński et al. [39]. Also, the reader can refer to this approach (stochastic programming) by reviewing the tutorial of Alexander Shapiro and Andy Philpott [40].

The summary of the literature review is shown in table1. Table1 shows the existing gap that the author tries to fulfill.

Table 1.1

Literature Review Table

Author	Facility disruption	Transporta-tion disruption	Transporta-tion mode	Site-dependent probability of disruption	Capacitated-facility location problem	Reliable model	Hardening strategy	Soft-hardening strategy	Correlated-probability of disruption
Drezner [21]	✓								
Lee [22]	✓								
Snyder and Daskin [24]	✓			✓		✓			
Berman et al. [34]	✓			✓					
Tang et al. [34]	✓								
Gade and Pohl [5]	✓			✓	✓				
Cui et al. [14]	✓			✓					
Li and Ouyang [35]	✓			✓					✓
Lim et al. [1]	✓			✓			✓		
Azad et al. [2]	✓	✓	✓	✓	✓	✓		✓	
This research	✓			✓	Modified from [2]	✓		Simplified from [2]	

Each criterion and each part can be described as follows.

1. Facility disruption

   The problem considered in the research is mainly about unavailability in distribution centers due to disruption.

2. Transportation disruption

   A disruptive event can occur while a DC is transporting goods to retailers.

3. Transportation Mode

   There is more than one transportation mode in the model, e.g., truck, airplane, and sea shipment.

4. Site-dependent probability of disruption

   The probability of disruption depends on the location of DC.

5. Capacitated-facility location problem (CFLP)

   This concept is about opening facilities with a finite capacity to serve the demands of retailers.

6. Hardening strategy

   The concept of hardening strategy was presented by Lim et al. [1]. The types of DCs are categorized into two: reliable and unreliable DC. When a random disruption occurs at an unreliable DC, the unreliable DC completely fails (not working), and the customers assigned to this DC must be reassigned to a reliable DC. They also assumed that a fully reliable DC appears in the system by investment, and there is no need to consider partial disruption at unreliable DCs.

7. Soft-hardening strategy

   This comprehensive strategy considers the investment level in the model. It is an extended version of the hardening strategy. It assumes that the impact of disruption in unreliable DCs depends on the amount of investment. The impact of disruption can be reduced by additional investment. Because of additional investment, a disrupted unreliable DC does not entirely fail all of its capacity but may lose only just some capacity. The fraction of the capacity loss of a DC depends on the amount of investment for operating and opening.

8. Correlated probability of disruption

   Li and Ouyang [35] introduce this concept. There are strong correlations among facilities because neighboring facilities have a high probability of facing similar hazards. They assumed that neighboring facilities were more likely to fail simultaneously. For instance, the probability of a DC being disrupted is relative to the disruption probability of its near facilities.

9. Reliable model

   Reliability of a model is the ability to perform well even some parts of the system fail due to disruption. There are many ways to enhance the model to perform well under disruption, such as considering primary and secondary assignments in the system.

10. Simplification of soft-hardening strategy

    As mentioned in the table above, this research will simplify the concept of the soft-hardening strategy of Azad et al. [2]. The simplification is that the author will not consider the investment concept in this research, and the rest will be the same as the original.

11. Modification of Capacitated-facility location problem (CFLP)

    The author will modify an unrealistic assumption from the work of Azad et al. [2], which is that the capacities of reliable DCs are unlimited. In this research, the capacities of reliable DCs become limited, which is more realistic to practical situations.

CHAPTER 3
MODEL FORMULATION

3.1 Overview

To reach the desired supply chain network providing the minimization in transportation cost and shortage cost, a mathematical model related to SCN must be developed. Also, sensitivity analyses will be conducted in many scenarios where the input parameters change to prove the model's efficiency and correctness. Therefore, this chapter will address the model formulation in detail as follows.

3.2 Case 1: A General Model without Disruption (No Capacity Changing)

These notations will be used for derivation of mathematical model.

Indices and sets

I	Set of retailers ; $i \in I$
J	Set of reliable DCs ; $j \in J$
K	Set of unreliable DCs ; $k \in K$

Parameters

c_{ij}	Unit transportation cost from reliable DC_j to retailer i
c_{ik}	Unit transportation cost from unreliable DC_k to retailer i
d_i	Demand of retailer i
Cau_k	Capacity of unreliable DC_k, (Note that this value will change because of the unreliability due to disruption, so the concept of stochastic programming will be introduced in the next phase)
Car_j	Capacity of reliable DC_j
π	Penalty cost per unit of shortage
M	A very large value, e.g., 1,000,000
T	Transportation cost
S	Shortage cost
O	Objective function cost

Decision variables

X_{ij} 1, if retailer i is assigned to reliable DC_j as a primary DC

0, otherwise

Y_{ik} 1, if retailer i is assigned to unreliable DC_k as a primary DC

0, otherwise

Z_{ij} 1, if retailer i is assigned to reliable DC_j as a secondary DC

0, otherwise

qx_{ij} Quantities of goods transported from reliable DC_j to retailer i in the primary assignment

qy_{ik} Quantities of goods transported from unreliable DC_k to retailer i in the primary assignment

qz_{ij} Quantities of goods transported from reliable DC_j to retailer i in the secondary assignment

3.2.1 Objective Function

The objective function is the minimum sum of all transportation costs from each DC to each retailer, and all shortage costs, happen at each retailer if the retailer's demand cannot be fulfilled in the whole system.

$$Min \sum_{i\in I}\sum_{j\in J} c_{ij}qx_{ij} + \sum_{i\in I}\sum_{k\in K} c_{ik}qy_{ik} + \sum_{i\in I}\sum_{j\in J} c_{ij}qz_{ij} + \sum_{i\in I}[\, d_i - (\sum_{j\in J} qx_{ij} + \sum_{k\in K} qy_{ik} + \sum_{j\in J} qz_{ij})] * Pen \qquad (1)$$

The objective function's first, second, and third terms represent the transportation costs from DCs to retailers. The last term represents the total shortage costs that happened at all retailers, in which the shortage amount can be calculated from the summation of the gaps between the demand of a retailer and the total amount of goods a retailer received.

Subject to

$$\sum_{j\in J} qx_{ij} + \sum_{k\in K} qy_{ik} + \sum_{j\in J} qz_{ij} \le d_i \quad ; \forall i \in I \qquad (2)$$

The first constraint states that the total amount a retailer receives does not exceed its demand.

$$\sum_{i \in I} (qx_{ij} + qz_{ij}) \leq Car_j \quad ; \forall j \in J \qquad (3)$$

The second constraint prevents a reliable DC from supplying more than its capacity to retailers.

$$\sum_{i \in I} qy_{ik} \leq Cau_k \quad ; \forall k \in K \qquad (4)$$

Similar to constraint 3, this constraint ensures that the total supplies of an unreliable DC delivered to retailers cannot exceed its capacity.

$$\sum_{k \in K} Y_{ik} + \sum_{j \in J} Z_{ij} = 2\left(1 - \sum_{j \in J} X_{ij}\right) \quad ; \forall i \in I \qquad (5)$$

Constraint (5) means that if a retailer is assigned to a reliable DC as a primary DC, it will not be assigned to any unreliable DC as primary DC, and also, there will be no secondary DC for that retailer. However, when a retailer is assigned to an unreliable DC as a primary DC, it will also be assigned to a reliable DC as a secondary DC.

$$X_{ij} \in \{0,1\} \quad ; \forall i \in I, \forall j \in J \qquad (6)$$

$$Y_{ik} \in \{0,1\} \quad ; \forall i \in I, \forall k \in K \qquad (7)$$

$$Z_{ij} \in \{0,1\} \quad ; \forall i \in I, \forall j \in J \qquad (8)$$

Constraints (6) to (8) enforce that these decision variables must be binary.

$$qx_{ij} \geq 0; \forall i \in I, \forall j \in J \qquad (9)$$

$$qy_{ik} \geq 0; \forall i \in I, \forall k \in K \qquad (10)$$

$$qz_{ij} \geq 0; \forall i \in I, \forall j \in J \qquad (11)$$

Constraints (9) to (11) state that the number of goods shipped from each DC to each retailer cannot be negative.

$$qx_{ij} \leq M * X_{ij} \,; \forall i \in I, \forall j \in J \qquad (12)$$

$$qy_{ik} \leq M * Y_{ik} \,; \forall i \in I, \forall k \in K \qquad (13)$$

$$qz_{ij} \leq M * Z_{ij} \,; \forall i \in I, \forall j \in J \qquad (14)$$

Constraints (12) to (14) ensure that the product will be delivered to a retailer from a DC only when the retailer is assigned to that DC.

$$\sum_{k \in K} Y_{ik} \leq 1; \forall i \in I \qquad (15)$$

$$\sum_{j \in J} Z_{ij} \leq 1; \forall i \in I \qquad (16)$$

Constraints (15) to (16) are used to make sure that constraint 5 works properly as we want, e.g., $X_{11} = 0, X_{12} = 0, Y_{11} = 1, Y_{12} = 1 \; and \; Z_{11} = 0, Z_{12} = 0$ will never happen. Even these values happen, constraint 5 is still valid. However, we do not want a scenario like this because we allow only one allocation for primary assignments. If retailer one is already assigned to unreliable DC1 in the primary assignment in this example, it cannot be assigned again to unreliable DC2 in the same primary assignment.

CHAPTER 4
NUMERICAL EXPERIMENTS AND SENSITIVITY ANALYSES

4.1 Overview

To demonstrate the mathematical model developed in chapter 3, various cases of the proposed model will be presented in this section to prove the correctness and the applicability of the model. Moreover, sensitivity analyses will also be conducted after proving the correctness of the base model. Sensitivity analyses are used to evaluate the impact of input parameters on decision variables and the objective function and analyze the model's trend in various scenarios.

4.1.1 Case 1: Base Case: A General Model Without Disruption (No Capacity Changing)

In this section, input parameters for case 1 are generated and will be used throughout the base case as follows.

Table 4.1

Sets and Indices

Parameters	Value
i	2
j	2
k	2

It is assumed that there are two retailers, two unreliable DCs, and two reliable DCs written as the table 2 above.

Table 4.2

Unit Transportation Cost in Dollars from Reliable DC j to Retailer i (c_{ij}) and from Unreliable DC k to Retailer i (c_{ik})

	j_1	j_2	k_1	k_2
i_1	2.2	2	2.1	2.4
i_2	1.9	3	4.3	1.2

Table 4.3

The Value of Input-Parameters in the Base Case

Parameters	Value	Unit
d_1	100	units
d_2	120	units
Cau_1	90	units
Cau_2	80	units
Car_1	110	units
Car_2	130	units
M	1,000,000	$
π	5	$

The value of each input parameter is generated as shown in the table4 above. Also, these values in table4 will be changed to conduct sensitivity analyses in the next section to help analyze the impact of each input parameter on the value of decision variables and the value of the objective function.

The results run by CPLEX are in table 5 as follows

Table 4.4

The Optimal Value of Decision Variables and the Objective Function Value in the Base Case

	Allocated quantity of goods												T	S	O
	qx_{ij}				qy_{ik}				qz_{ij}						
	qx_{11}	qx_{12}	qx_{21}	qx_{22}	qy_{11}	qy_{12}	qy_{21}	qy_{22}	qz_{11}	qz_{12}	qz_{21}	qz_{22}			
Base case	-	100	-	-	-	-	-	80	-	-	40	-	372	0	372

** Noted that T = transportation cost, S = shortage cost, O = objective function value

The results obtained from the base case are shown in table5, which are

1. The quantity of shipped goods from reliable DC2 to retailer1 in the primary assignment is 100 units (qx_{12}).
2. The quantity of shipped goods from unreliable DC2 to retailer2 in the primary assignment is 80 units (qy_{22}).
3. The quantity of shipped goods from reliable DC1 to retailer2 in the secondary assignment is 100 units (qx_{12}).
4. The transportation cost is 372$.
5. There is no shortage cost.
6. The objective function value is 372$.

Table 4.5

Sensitivity Analyses with Respect to Demand Parameters

Parameter	Parameter value	Allocated quantity of goods												T	S	O (Objective function)
		qx_{ij}				qy_{ik}				qz_{ij}						
		qx_{11}	qx_{12}	qx_{21}	qx_{22}	qy_{11}	qy_{12}	qy_{21}	qy_{22}	qz_{11}	qz_{12}	qz_{21}	qz_{22}			
d_1	25								80		25	40		222	0	222
	50		100						80			40		272	0	272
	75		100						80			40		322	0	322
	100		100						80			40		372	0	372
	125		125						80			40		422	0	422
	150					20			80		130	40		474	0	474
	300					90			80		130	40		621	400	1021
d_2	30								30		100			236	0	236
	60		100						60					272	0	272
	90		100						80			10		315	0	315
	120		100						80			40		372	0	372
	150		100						80			70		429	0	429
	180		100						80			100		486	0	486
	400								80		100	110		505	1050	1555

According to table 6, when $d_1$and d_2 decrease, T also decreases. In contrast, when d_1 and d_2 increase, T also increases as well. This result is understandable because the transportation cost will also increase when the demand increases. There is no shortage cost if the demands are not too high.

Table 4.6

Sensitivity Analyses with Respect to the Capacity of Unreliable DCs

Parameter	Parameter value	Allocated quantity of goods												T	S	O (Objective function)
		qx_{ij}				qy_{ik}				qz_{ij}						
		qx_{11}	qx_{12}	qx_{21}	qx_{22}	qy_{11}	qy_{12}	qy_{21}	qy_{22}	qz_{11}	qz_{12}	qz_{21}	qz_{22}			
Cau_1	0		100						80			40		372	0	372
	45		100						80			40		372	0	372
	67.5		100						80			40		372	0	372
	90		100						80			40		372	0	372
	112.5		100						80			40		372	0	372
	135		100						80			40		372	0	372
	270		100						80			40		372	0	372
Cau_2	20		100						20			100		414	0	414
	40		100						40			80		400	0	400
	60		100						60			60		386	0	386
	80		100						80			40		372	0	372
	100		100						100			20		358	0	358
	120		100						120					344	0	344
	140		100						120					344	0	344

The changes in the capacity of unreliable DC1 (Cau_1) do not affect the result of the model at all. This makes sense because both retailers 1 and 2 have not been assigned to unreliable DC1. In other words, there are no values in qy_{11}row and qy_{21}row when Cau_1 changes.

When the capacity of unreliable DC2 (Cau_2) decreases, the transportation increases. Similarly, when the capacity of unreliable DC2 increases, transportation cost decreases. It happens like this because the transportation cost from unreliable DC2 to retailer2 is less than the transportation cost from reliable DC2 to retailer2 ($c_{ik}\ when\ i = 2, k = 2\ < c_{ij}\ when\ i = 2, j = 1$) or 1.2$ < 2.2$, which can be seen in table1.

Table 4.7

Sensitivity Analyses with Respect to the Capacity of Reliable DCs

Parameter	Parameter value	Allocated quantity of goods												T	S	O (Objective function)
		qx_{ij}				qy_{ik}				qz_{ij}						
		qx_{11}	qx_{12}	qx_{21}	qx_{22}	qy_{11}	qy_{12}	qy_{21}	qy_{22}	qz_{11}	qz_{12}	qz_{21}	qz_{22}			
	27.5								80		100	27.5		348.25	62.5	410.75
	55		100						80			40		372	0	372
	82.5		100						80			40		372	0	372
Car_1	110		100						80			40		372	0	372
	137.5		100						80			40		372	0	372
	165		100						80			40		372	0	372
	192.5		100						80			40		372	0	372
	32.5					68			80		32	40		378.8	0	378.8
	65					35			80		65	40		375.5	0	375.5
	97.5					3			80		97	40		372.3	0	372.3
Car_2	130		100						80			40		372	0	372
	162.5		100						80			40		372	0	372
	195		100						80			40		372	0	372
	227.5		100						80			40		372	0	372

The changes in the capacity of reliable DC1 (Car_1) seem not to affect the model results, but when it is deficient, the shortage will occur, which causes the higher in the objective function value.

When the capacity of reliable DC2 (Car_2) increases, it does not affect the objective function values. On the other hand, when Car_2 decreases, it affects the objective function value. It causes an increase in transportation costs. This is reasonable because when Car_2 decreases, the assignment order will change from $qx_{12}$to $qy_{11} and\ qz_{11}$; and the transportation costs of the new routes are more expensive than the former route. The changes of goods allocation, e.g., from $qx_{12}$to $qy_{11} and\ qz_{11}$, have a relationship with the transportation cost (table1).

CPLEX always tries to minimize the transportation cost and the shortage cost by choosing the cheapest path while satisfying the demands of both retailers as much as possible under input constraints. However, before we confirm that the model and the CPLEX code are correctly generated, we will increase the number of retailers from 2 to 20 in the next section.

4.1.2 Case 2: When the Number of Retailers Increases from 2 to 20

Table 4.8

Unit Transportation Cost in Dollars from Reliable DC j to Retailer i (c_{ij}) and from Unreliable DC k to Retailer i (c_{ik})

	j_1	j_2	k_1	k_2
i_1	3.30	4.49	5.40	4.78
i_2	3.57	3.22	3.59	6.47
i_3	6.84	4.56	6.57	6.17
i_4	5.84	3.06	5.18	3.22
i_5	4.66	4.71	6.29	6.41
i_6	4.52	3.97	4.66	4.78
i_7	3.36	4.75	3.58	3.55
i_8	6.53	5.06	6.40	4.90
i_9	5.73	4.00	4.57	4.50
i_{10}	4.29	6.32	6.21	6.14
i_{11}	6.12	4.85	6.79	6.58
i_{12}	4.74	3.36	3.75	5.42
i_{13}	3.12	3.30	4.67	4.64
i_{14}	6.96	4.04	6.36	6.57
i_{15}	6.11	5.83	3.09	3.24
i_{16}	4.22	3.65	5.37	4.26
i_{17}	6.89	3.90	3.34	5.90
i_{18}	6.61	4.51	6.58	4.84
i_{19}	5.26	5.74	3.52	3.94
i_{20}	4.95	5.39	3.07	6.83

Each unit transportation cost is randomly generated, and most of the costs from c_{ij} are higher than c_{ik} because we assume that most of the transportation costs from reliable DCs are more expensive than unreliable DCs.

Table 4.9

The Value of Input-Parameters for the Case2

Parameter	Value	Unit	Parameter	Value	Unit
d_1	110	units	d_{14}	87	units
d_2	110	units	d_{15}	116	units
d_3	110	units	d_{16}	108	units
d_4	98	units	d_{17}	83	units
d_5	93	units	d_{18}	96	units
d_6	104	units	d_{19}	117	units
d_7	82	units	d_{20}	106	units
d_8	112	units	Cau_1	350	units
d_9	110	units	Cau_2	250	units
d_{10}	89	units	Car_1	800	units
d_{11}	96	units	Car_2	600	units
d_{12}	94	units	M	1,000,000	$
d_{13}	88	units	π	5	$

Every input-parameters above are randomly generated except M and π because M is just an enormous value, and π is the constant penalty cost. The demands vary between 80 to 130.

The results run by CPLEX are in table 11 as follows.

Table 4.10

The Optimal Value of Decision Variables and the Objective Function Value in Case 2

	qx_{ij}		qy_{ik}		qz_{ij}		T	S	O
	j_1	j_2	k_1	k_2	j_1	j_2			
i_1	110	0	0	0	0	0			
i_2	0	0	0	0	110	0			
i_3	0	81	0	0	0	0			
i_4	0	0	0	98	0	0			
i_5	93	0	0	0	0	0			
i_6	0	0	0	0	0	104			
i_7	82	0	0	0	0	0			
i_8	0	0	0	0	0	0			
i_9	0	110	0	0	0	0			
i_{10}	89	0	0	0	0	0			
i_{11}	0	0	0	0	0	0			
i_{12}	0	0	44	0	0	50			
i_{13}	88	0	0	0	0	0			
i_{14}	0	87	0	0	0	0			
i_{15}	0	0	0	116	0	0			
i_{16}	0	0	0	0	0	108			
i_{17}	0	0	83	0	0	0			
i_{18}	0	0	0	36	0	60			
i_{19}	0	0	117	0	0	0			
i_{20}	0	0	106	0	0	0			
Value							6572.2	1185	7757.2

Table 4.11

Sensitivity Analyses with Respect to Each Parameter

	Capacity	T	S	O	% Change respect to O
d_{ij}	$d_{ij} - 60$	3066.7	0.0	3066.7	-60.42%
	d_{ij}	6562.7	1185.0	7747.7	0.00%
	$d_{ij} + 60$	6922.9	6045.0	12967.9	67.38%
	$d_{ij} + 100$	6646.2	10045.0	16691.2	115.43%
Cau_1	150	5810.6	2070.0	7880.6	1.72%
	350	6562.7	1185.0	7747.7	0.00%
	600	7247.1	480.0	7727.1	-0.27%
Cau_2	100	5844.1	1935.0	7779.1	0.41%
	250	6562.7	1185.0	7747.7	0.00%
	700	7189.9	545.0	7734.9	0.17%
Car_1	200	4844.1	3045.0	7889.1	1.83%
	800	6562.7	1185.0	7747.7	0.00%
	1400	6562.7	1185.0	7747.7	0.00%
Car_2	150	5646.9	2375.0	8021.9	3.54%
	600	6562.7	1185.0	7747.7	0.00%
	1200	7629.7	0.0	7629.7	-1.52%

For the demand parameters (d_{ij}), there exists a shortage cost which is 1185$. When the demands are decreased, the shortage cost disappears, and, similarly, when the demands increase, the shortage cost is higher, which makes sense because shortage depends on the demands.

For parameters related to capacity (Cau_k and Car_j), the shortage costs tend to increase when the capacities of both reliable and unreliable DCs reduces. Similarly, the transportation costs also tend to increase when the capacities increase because there is still demand waiting to be satisfied, so products should be delivered to retailers, which causes the higher transportation cost.

Related to the objective function, the higher the capacities of DCs, the lower the objective function. This is sensible because the shortage will be reduced when the capacities are high. Furthermore, demand parameter is the most sensitive parameter respect to the total costs in the system. Therefore, demand parameter should be invested the most to reduce the total costs. As a result, we are confidently sure that the developed model and the CPLEX code work properly as we want. Therefore, we will start introducing a stochastic programming approach to help deal with uncertainties in the model, which are the capacities of unreliable DCs.

4.1.3 Case 3: The Model with Disruption at DCs: Scenario-Based Technique

In case 2, we demonstrated the results of the developed model and its sensitivity analyses when Cau_1 and Cau_2 (capacity of unreliable DC1 and DC2) are constant, which are 350 and 250 respectively. However, the capacities of unreliable DCs should not be constant because they are categorized in the low-reliability group. Therefore, a stochastic programming approach, a scenario-based technique, will be applied to help deal with uncertainties of unreliable DCs.

In this section, we assume that the capacities of unreliable DCs are not constant anymore, and we know the capacity of each scenario with known probability because of historical data. The capacities of both unreliable DCs and the probability of occurrence are presented in tables 13 and 14.

Table 4.12

Capacity Scenario of Unreliable DC1

Capacity ratio	Capacity of unreliable DC1	Probability
Constant value	350	1
0%	0	0.010
25%	87.5	0.018
50%	175	0.022
75%	262.5	0.050
100%	350	0.900

Table 4.13

Capacity Scenario of Unreliable DC2

Capacity ratio	Capacity of unreliable DC2	Probability
Constant value	250	1
0%	0	0.013
25%	62.5	0.012
50%	125	0.030
75%	187.5	0.095
100%	250	0.850

Since there are five scenarios of Cau_1 and Cau_2, there will exist twenty-five possible scenarios of unreliable DC capacities, as shown in table 15. Also, each scenario (we got 25 scenarios) can be used to determine allocation decision (X_{ij}, Y_{ik}, Z_{ij}). As a result, we must run the model $25 * 25 = 625$ times to find every expected total cost when allocation decision is determined by every scenario.

Table 4.14

The Expected Total Cost When Allocation Decision is Determined by scenario1

Scenario	Capacity of unreliable DC1	Probability	Capacity of unreliable DC2	Probability	Total capacities of two DCs	Probability to occur	Cost for each scenario	Expected cost
1	0	0.010	0	0.013	0	0.0001	8466.44	1.10
2	0	0.010	62.5	0.012	62.5	0.0001	8466.44	1.02
3	0	0.010	125	0.030	125	0.0003	8466.44	2.54
4	0	0.010	187.5	0.095	187.5	0.0010	8466.44	8.04
5	0	0.010	250	0.850	250	0.0085	8466.44	71.96
6	87.5	0.018	0	0.013	87.5	0.0002	8300.57	1.94
7	87.5	0.018	62.5	0.012	150	0.0002	8300.57	1.79
8	87.5	0.018	125	0.030	212.5	0.0005	8300.57	4.48
9	87.5	0.018	187.5	0.095	275	0.0017	8300.57	14.19
10	87.5	0.018	250	0.850	337.5	0.0153	8300.57	127.00
11	175	0.022	0	0.013	175	0.0003	8133.84	2.33
12	175	0.022	62.5	0.012	237.5	0.0003	8133.84	2.15
13	175	0.022	125	0.030	300	0.0007	8133.84	5.37
14	175	0.022	187.5	0.095	362.5	0.0021	8133.84	17.00
15	175	0.022	250	0.850	425	0.0187	8133.84	152.10

Scenario	Capacity of unreliable DC1	Probability	Capacity of unreliable DC2	Probability	Total capacities of two DCs	Probability to occur	Cost for each scenario	Expected cost
16	262.5	0.050	0	0.013	262.5	0.0007	8041.29	5.23
17	262.5	0.050	62.5	0.012	325	0.0006	8041.29	4.82
18	262.5	0.050	125	0.030	387.5	0.0015	8041.29	12.06
19	262.5	0.050	187.5	0.095	450	0.0048	8041.29	38.20
20	262.5	0.050	250	0.850	512.5	0.0425	8041.29	341.75
21	350	0.900	0	0.013	350	0.0117	8037.13	94.03
22	350	0.900	62.5	0.012	412.5	0.0108	8037.13	86.80
23	350	0.900	125	0.030	475	0.0270	8037.13	217.00
24	350	0.900	187.5	0.095	537.5	0.0855	8037.13	687.17
25	350	0.900	250	0.850	600	0.7650	8037.13	6148.40
			Expected total cost when allocation routes are determined by scenario1					8048.50

Process 1: The steps to find the expected total cost when the allocation decision is determined by scenario1 are as follows.

1. Find the cost for each scenario by generating every possible outcome of capacities of two unreliable DCs, e.g., the capacities of unreliable DC1 and DC2 in scenario 23 are 350 and 125 respectively, then run the model in CPLEX to find out the cost for each scenario.

2. After we get the cost for each scenario, we multiply it by its probability of occurrence. Then we will have the expected cost for each scenario.
3. We take the sum of all expected costs we have found, then we will finally have the expected total cost when allocation routes are determined by scenario1, which is 8048.50.

As we said earlier that each scenario (noted that we got 25 scenarios) could be used to determine allocation decision (X_{ij}, Y_{ik}, Z_{ij}). However, this section only shows the expected total cost when allocation routes are determined by scenario1, which is 8048.50. Therefore, process1 will be repeated 25 times to find the expected total costs when allocation routes are determined from scenarios 1 to 25.

After the twenty-five-time-repeating process, we got all expected total costs when allocation routes are determined from scenarios 1 to 25, shown in table 16 below, and the allocation routes of a scenario with the lowest cost will be selected.

Table 4.15

Expected Total Cost When Allocation Decision is Determined by Each Scenario

Scenario	Expected total cost	Scenario	Expected total cost
1	8048.50	14	7865.43
2	8250.17	15	7859.99
3	8151.20	16	7897.52
4	8151.20	17	7856.04
5	8148.76	18	7823.18
6	8082.56	19	7784.77
7	8069.03	20	7795.78
8	7955.96	21	7856.35
9	7953.65	22	7856.35
10	7951.21	23	7784.83
11	7897.52	24	7779.74
12	7824.94	25	7794.14
13	7879.26		

As we see in table 16, the lowest cost belongs to scenario 24. Therefore, the allocation decision of scenario 24 will be selected, and it is shown in table17 below.

Table 4.16

Allocation Decision of Scenario 24

	X_{ij}		Y_{ik}		Z_{ij}	
	j_1	j_2	k_1	k_2	j_1	j_2
i_1	1	0	0	0	0	0
i_2	0	0	0	1	1	0
i_3	0	1	0	0	0	0
i_4	0	0	0	1	0	1
i_5	1	0	0	0	0	0
i_6	0	0	0	1	0	1
i_7	1	0	0	0	0	0
i_8	1	0	0	0	0	0
i_9	0	1	0	0	0	0
i_{10}	1	0	0	0	0	0
i_{11}	1	0	0	0	0	0
i_{12}	0	0	1	0	0	1

	X_{ij}		Y_{ik}		Z_{ij}	
	j_1	j_2	k_1	k_2	j_1	j_2
i_{13}	1	0	0	0	0	0
i_{14}	0	1	0	0	0	0
i_{15}	0	0	0	1	0	1
i_{16}	0	0	0	1	0	1
i_{17}	0	0	1	0	0	1
i_{18}	0	0	0	1	0	1
i_{19}	0	0	1	0	0	1
i_{20}	0	0	1	0	1	0

Related to table 17, the meaning of allocation routes for some rows are as follows,

1. In row 5, retailer 5 will be supplied by reliable DC 1 as the primary assignment.
2. In row 15, retailer 15 will be supplied by unreliable DC 2 as the primary assignment and also be supplied by reliable DC2 as the secondary assignment because the unreliable DC 2 cannot fulfill customer demand.
3. In row 20, retailer 20 will be supplied by unreliable DC 1 as the primary assignment, and retailer 20 will also be supplied by reliable DC1 as the secondary assignment because there exists a shortage in unreliable DC 1.

Table 4.17

Comparison Results of Cases 2 and 3

	Result of case 2 (the model without disruption)	Result of case 3 (the model with scenario-based technique)
Total cost	7747.700	7779.74

Related to table 11, the results of case 2 when there exists no disruption at DCs, and case 3 when there exists disruption, which is uncertainty at DCs, and scenario-based technique implemented to the model are 7747.700 7779.74 respectively. Even though the cost of case 3 that we applied a stochastic programming approach is more expensive than case 2, which we did not apply any stochastic programming approach, considering a model with uncertainty is still better because the result is computed more precisely and help the supply chain network designers make a decision easier.

4.1.4 Case 4: The Model with Disruption at DCs: Scenario-Based Technique

Increase the numbers of reliable and unreliable DCs from 2 to 3 and then use the result of scenario-based technique compared with the result without using the scenario-based technique to find out the difference between the two approaches.

Table 4.18

Unit Transportation Cost in Dollars from Reliable DC j to Retailer i (c_{ij}) and from Unreliable DC k to Retailer i (c_{ik})

	j_1	j_2	j_3	k_1	k_2	k_3
i_1	3.30	4.49	4.40	5.40	4.78	5.27
i_2	3.57	3.22	6.48	3.59	6.47	6.61
i_3	6.84	4.56	3.29	6.57	6.17	4.38
i_4	5.84	3.06	6.13	5.18	3.22	3.32
i_5	4.66	4.71	5.63	6.29	6.41	4.28
i_6	4.52	3.97	4.08	4.66	4.78	3.73
i_7	3.36	4.75	6.45	3.58	3.55	4.22
i_8	6.53	5.06	5.48	6.40	4.90	5.75
i_9	5.73	4.00	4.15	4.57	4.50	5.28
i_{10}	4.29	6.32	3.76	6.21	6.14	4.00
i_{11}	6.12	4.85	4.29	6.79	6.58	6.43
i_{12}	4.74	3.36	3.88	3.75	5.42	4.57
i_{13}	3.12	3.30	5.01	4.67	4.64	3.97
i_{14}	6.96	4.04	5.48	6.36	6.57	6.92
i_{15}	6.11	5.83	5.32	3.09	3.24	3.77
i_{16}	4.22	3.65	5.14	5.37	4.26	3.19
i_{17}	6.89	3.90	3.69	3.34	5.90	6.44
i_{18}	6.61	4.51	4.88	6.58	4.84	5.00
i_{19}	5.26	5.74	6.48	3.52	3.94	3.05
i_{20}	4.95	5.39	5.66	3.07	6.83	4.61

This table, table 19, is similar to table9, but the difference is that, in this table, there are one more number of j and k which are j_3 and k_3 because we decided to increase the numbers of unreliable DCs in this case.

Table 4.19

The Value of Input-Parameters for Case 4

Parameter	Value	Unit	Parameter	Value	Unit
d_1	110	units	d_{15}	116	units
d_2	110	units	d_{16}	108	units
d_3	110	units	d_{17}	83	units
d_4	98	units	d_{18}	96	units
d_5	93	units	d_{19}	117	units
d_6	104	units	d_{20}	106	units
d_7	82	units	Cau_1	350	units
d_8	112	units	Cau_2	250	units
d_9	110	units	Cau_3	300	units
d_{10}	89	units	Car_1	800	units
d_{11}	96	units	Car_2	600	units
d_{12}	94	units	Car_3	700	units
d_{13}	88	units	M	1,000,000	$
d_{14}	87	units	π	5	$

This table, table20, is also similar to table 10, but the difference is that, in this table, Cau_3 and Car_3 are added.

The results run by CPLEX are in table 21 as follows.

Table 4.20

The Optimal Value of Decision Variables and the Objective Function Value in Case 4 (without Using the Scenario-Based Technique)

	qx_{ij}			qy_{ik}			qz_{ij}			T	S	O
	j_1	j_2	j_3	k_1	k_2	k_3	j_1	j_2	j_3			
i_1	110	0	0	0	0	0	0	0	0			
i_2	0	110	0	0	0	0	0	0	0			
i_3	0	0	110	0	0	0	0	0	0			
i_4	0	98	0	0	0	0	0	0	0			
i_5	0	0	0	0	0	75	18	0	0			
i_6	0	0	0	0	0	0	0	0	104			
i_7	82	0	0	0	0	0	0	0	0			
i_8	0	0	0	0	112	0	0	0	0			
i_9	0	110	0	0	0	0	0	0	0			
i_{10}	0	0	0	0	0	0	0	0	89			
i_{11}	0	0	96	0	0	0	0	0	0			
i_{12}	0	94	0	0	0	0	0	0	0			
i_{13}	88	0	0	0	0	0	0	0	0			
i_{14}	0	87	0	0	0	0	0	0	0			
i_{15}	0	0	0	116	0	0	0	0	0			
i_{16}	0	0	0	0	0	108	0	0	0			
i_{17}	0	0	0	83	0	0	0	0	0			
i_{18}	0	96	0	0	0	0	0	0	0			
i_{19}	0	0	0	0	0	117	0	0	0			
i_{20}	0	0	0	106	0	0	0	0	0			
Value										7255.7	0	7255.7

Table 4.21

Capacity Scenario of Unreliable DCs

Capacity ratio	Unreliable DC1		Unreliable DC2		Unreliable DC3	
	Capacity	Probability	Capacity	Probability	Capacity	Probability
Constant value	350	1	250	1	300	1
0%	0	0.01	0	0.01	0	0.02
25%	87.5	0.02	62.5	0.01	75	0.01
50%	175	0.02	125	0.02	150	0.02
75%	262.5	0.05	187.5	0.01	225	0.03
100%	350	0.9	250	0.95	300	0.92

Since there are five capacity possibilities for unreliable DCs, there will be 5*5*5 = 125 possible scenarios. Furthermore, each scenario can be used to determine the allocation decision. As a result, there will exist 125*125 = 15,625 exactly possible scenarios to solve in CPLEX. We must run 15,625 scenarios to find every expected total cost when the allocation decision is determined by every scenario.

The following table will show an example of how to find the expected total cost when the allocation decision is determined by scenario2 (there are 125 scenarios that can be used to determine allocation decision).

Table 4.22

The Expected Total Cost When Allocation Decision is Determined by Scenario2

Scenario	Capacity of unreliable DC1	Capacity of unreliable DC2	Capacity of unreliable DC3	DC1 probability	DC2 probability	DC3 probability	Scenario probability to occur	Total cost for each scenario	Expected cost
1	0	0	0	0.01	0.01	0.02	0.0000017	8039.75	0.01
2	0	0	75	0.01	0.01	0.01	0.0000009	7893.31	0.01
3	0	0	150	0.01	0.01	0.02	0.0000024	7796.13	0.02
4	0	0	225	0.01	0.01	0.03	0.0000030	7761.66	0.02
5	0	0	300	0.01	0.01	0.92	0.0000920	7735.79	0.71
6	0	62.5	0	0.01	0.01	0.02	0.0000014	8039.75	0.01
7	0	62.5	75	0.01	0.01	0.01	0.0000007	7893.31	0.01
8	0	62.5	150	0.01	0.01	0.02	0.0000019	7796.13	0.01
9	0	62.5	225	0.01	0.01	0.03	0.0000024	7761.66	0.02
10	0	62.5	300	0.01	0.01	0.92	0.0000736	7735.79	0.57
11	0	125	0	0.01	0.02	0.02	0.0000034	8039.75	0.03
12	0	125	75	0.01	0.02	0.01	0.0000018	7893.31	0.01
13	0	125	150	0.01	0.02	0.02	0.0000048	7796.13	0.04
14	0	125	225	0.01	0.02	0.03	0.0000060	7761.66	0.05
15	0	125	300	0.01	0.02	0.92	0.0001840	7735.79	1.42
16	0	187.5	0	0.01	0.01	0.02	0.0000020	8039.75	0.02
17	0	187.5	75	0.01	0.01	0.01	0.0000011	7893.31	0.01
18	0	187.5	150	0.01	0.01	0.02	0.0000029	7796.13	0.02
19	0	187.5	225	0.01	0.01	0.03	0.0000036	7761.66	0.03
20	0	187.5	300	0.01	0.01	0.92	0.0001104	7735.79	0.85
21	0	250	0	0.01	0.95	0.02	0.0001615	8039.75	1.30

Scenario	Capacity of unreliable DC1	Capacity of unreliable DC2	Capacity of unreliable DC3	DC1 probability	DC2 probability	DC3 probability	Scenario probability to occur	Total cost for each scenario	Expected cost
22	0	250	75	0.01	0.95	0.01	0.0000855	7893.31	0.67
23	0	250	150	0.01	0.95	0.02	0.0002280	7796.13	1.78
24	0	250	225	0.01	0.95	0.03	0.0002850	7761.66	2.21
25	0	250	300	0.01	0.95	0.92	0.0087400	7735.79	67.61
26	87.5	0	0	0.02	0.01	0.02	0.0000031	8039.75	0.02
27	87.5	0	75	0.02	0.01	0.01	0.0000016	7893.306	0.01
28	87.5	0	150	0.02	0.01	0.02	0.0000043	7796.13	0.03
29	87.5	0	225	0.02	0.01	0.03	0.0000054	7761.659	0.04
30	87.5	0	300	0.02	0.01	0.92	0.0001656	7735.79	1.28
31	87.5	62.5	0	0.02	0.01	0.02	0.0000024	8039.75	0.02
32	87.5	62.5	75	0.02	0.01	0.01	0.0000013	7893.306	0.01
33	87.5	62.5	150	0.02	0.01	0.02	0.0000035	7796.13	0.03
34	87.5	62.5	225	0.02	0.01	0.03	0.0000043	7761.659	0.03
35	87.5	62.5	300	0.02	0.01	0.92	0.0001325	7735.79	1.02
36	87.5	125	0	0.02	0.02	0.02	0.0000061	8039.75	0.05
37	87.5	125	75	0.02	0.02	0.01	0.0000032	7893.306	0.03
38	87.5	125	150	0.02	0.02	0.02	0.0000086	7796.13	0.07
39	87.5	125	225	0.02	0.02	0.03	0.0000108	7761.659	0.08
40	87.5	125	300	0.02	0.02	0.92	0.0003312	7735.79	2.56

Scenario	Capacity of unreliable DC1	Capacity of unreliable DC2	Capacity of unreliable DC3	DC1 probability	DC2 probability	DC3 probability	Scenario probability to occur	Total cost for each scenario	Expected cost
41	87.5	187.5	0	0.02	0.01	0.02	0.0000037	8039.75	0.03
42	87.5	187.5	75	0.02	0.01	0.01	0.0000019	7893.306	0.02
43	87.5	187.5	150	0.02	0.01	0.02	0.0000052	7796.13	0.04
44	87.5	187.5	225	0.02	0.01	0.03	0.0000065	7761.659	0.05
45	87.5	187.5	300	0.02	0.01	0.92	0.0001987	7735.79	1.54
46	87.5	250	0	0.02	0.95	0.02	0.0002907	8039.75	2.34
47	87.5	250	75	0.02	0.95	0.01	0.0001539	7893.306	1.21
48	87.5	250	150	0.02	0.95	0.02	0.0004104	7796.13	3.20
49	87.5	250	225	0.02	0.95	0.03	0.0005130	7761.659	3.98
50	87.5	250	300	0.02	0.95	0.92	0.0157320	7735.79	121.70
51	175	0	0	0.02	0.01	0.02	0.0000037	8039.75	0.03
52	175	0	75	0.02	0.01	0.01	0.0000020	7893.306	0.02
53	175	0	150	0.02	0.01	0.02	0.0000053	7796.13	0.04
54	175	0	225	0.02	0.01	0.03	0.0000066	7761.659	0.05
55	175	0	300	0.02	0.01	0.92	0.0002024	7735.79	1.57
56	175	62.5	0	0.02	0.01	0.02	0.0000030	8039.75	0.02
57	175	62.5	75	0.02	0.01	0.01	0.0000016	7893.306	0.01
58	175	62.5	150	0.02	0.01	0.02	0.0000042	7796.13	0.03
59	175	62.5	225	0.02	0.01	0.03	0.0000053	7761.659	0.04
60	175	62.5	300	0.02	0.01	0.92	0.0001619	7735.79	1.25
61	175	125	0	0.02	0.02	0.02	0.0000075	8039.75	0.06
62	175	125	75	0.02	0.02	0.01	0.0000040	7893.306	0.03
63	175	125	150	0.02	0.02	0.02	0.0000106	7796.13	0.08

Scenario	Capacity of unreliable DC1	Capacity of unreliable DC2	Capacity of unreliable DC3	DC1 probability	DC2 probability	DC3 probability	Scenario probability to occur	Total cost for each scenario	Expected cost
64	175	125	225	0.02	0.02	0.03	0.0000132	7761.659	0.10
65	175	125	300	0.02	0.02	0.92	0.0004048	7735.79	3.13
66	175	187.5	0	0.02	0.01	0.02	0.0000045	8039.75	0.04
67	175	187.5	75	0.02	0.01	0.01	0.0000024	7893.306	0.02
68	175	187.5	150	0.02	0.01	0.02	0.0000063	7796.13	0.05
69	175	187.5	225	0.02	0.01	0.03	0.0000079	7761.659	0.06
70	175	187.5	300	0.02	0.01	0.92	0.0002429	7735.79	1.88
71	175	250	0	0.02	0.95	0.02	0.0003553	8039.75	2.86
72	175	250	75	0.02	0.95	0.01	0.0001881	7893.306	1.48
73	175	250	150	0.02	0.95	0.02	0.0005016	7796.13	3.91
74	175	250	225	0.02	0.95	0.03	0.0006270	7761.659	4.87
75	175	250	300	0.02	0.95	0.92	0.0192280	7735.79	148.74
76	262.5	0	0	0.05	0.01	0.02	0.0000085	8039.75	0.07
77	262.5	0	75	0.05	0.01	0.01	0.0000045	7893.306	0.04
78	262.5	0	150	0.05	0.01	0.02	0.0000120	7796.13	0.09
79	262.5	0	225	0.05	0.01	0.03	0.0000150	7761.659	0.12
80	262.5	0	300	0.05	0.01	0.92	0.0004600	7735.79	3.56

Scenario	Capacity of unreliable DC1	Capacity of unreliable DC2	Capacity of unreliable DC3	DC1 probability	DC2 probability	DC3 probability	Scenario probability to occur	Total cost for each scenario	Expected cost
81	262.5	62.5	0	0.05	0.01	0.02	0.0000068	8039.75	0.05
82	262.5	62.5	75	0.05	0.01	0.01	0.0000036	7893.306	0.03
83	262.5	62.5	150	0.05	0.01	0.02	0.0000096	7796.13	0.07
84	262.5	62.5	225	0.05	0.01	0.03	0.0000120	7761.659	0.09
85	262.5	62.5	300	0.05	0.01	0.92	0.0003680	7735.79	2.85
86	262.5	125	0	0.05	0.02	0.02	0.0000170	8039.75	0.14
87	262.5	125	75	0.05	0.02	0.01	0.0000090	7893.306	0.07
88	262.5	125	150	0.05	0.02	0.02	0.0000240	7796.13	0.19
89	262.5	125	225	0.05	0.02	0.03	0.0000300	7761.659	0.23
90	262.5	125	300	0.05	0.02	0.92	0.0009200	7735.79	7.12
91	262.5	187.5	0	0.05	0.01	0.02	0.0000102	8039.75	0.08
92	262.5	187.5	75	0.05	0.01	0.01	0.0000054	7893.306	0.04
93	262.5	187.5	150	0.05	0.01	0.02	0.0000144	7796.13	0.11
94	262.5	187.5	225	0.05	0.01	0.03	0.0000180	7761.659	0.14
95	262.5	187.5	300	0.05	0.01	0.92	0.0005520	7735.79	4.27
96	262.5	250	0	0.05	0.95	0.02	0.0008075	8039.75	6.49
97	262.5	250	75	0.05	0.95	0.01	0.0004275	7893.306	3.37
98	262.5	250	150	0.05	0.95	0.02	0.0011400	7796.13	8.89
99	262.5	250	225	0.05	0.95	0.03	0.0014250	7761.659	11.06
100	262.5	250	300	0.05	0.95	0.92	0.0437000	7735.79	338.05
101	350	0	0	0.90	0.01	0.02	0.0001530	8039.75	1.23
102	350	0	75	0.90	0.01	0.01	0.0000810	7893.306	0.64
103	350	0	150	0.90	0.01	0.02	0.0002160	7796.13	1.68

Scenario	Capacity of unreliable DC1	Capacity of unreliable DC2	Capacity of unreliable DC3	DC1 probability	DC2 probability	DC3 probability	Scenario probability to occur	Total cost for each scenario	Expected cost
104	350	0	225	0.90	0.01	0.03	0.0002700	7761.659	2.10
105	350	0	300	0.90	0.01	0.92	0.0082800	7735.79	64.05
106	350	62.5	0	0.90	0.01	0.02	0.0001224	8039.75	0.98
107	350	62.5	75	0.90	0.01	0.01	0.0000648	7893.306	0.51
108	350	62.5	150	0.90	0.01	0.02	0.0001728	7796.13	1.35
109	350	62.5	225	0.90	0.01	0.03	0.0002160	7761.659	1.68
110	350	62.5	300	0.90	0.01	0.92	0.0066240	7735.79	51.24
111	350	125	0	0.90	0.02	0.02	0.0003060	8039.75	2.46
112	350	125	75	0.90	0.02	0.01	0.0001620	7893.306	1.28
113	350	125	150	0.90	0.02	0.02	0.0004320	7796.13	3.37
114	350	125	225	0.90	0.02	0.03	0.0005400	7761.659	4.19
115	350	125	300	0.90	0.02	0.92	0.0165600	7735.79	128.10
116	350	187.5	0	0.90	0.01	0.02	0.0001836	8039.75	1.48
117	350	187.5	75	0.90	0.01	0.01	0.0000972	7893.306	0.77
118	350	187.5	150	0.90	0.01	0.02	0.0002592	7796.13	2.02
119	350	187.5	225	0.90	0.01	0.03	0.0003240	7761.659	2.51
120	350	187.5	300	0.90	0.01	0.92	0.0099360	7735.79	76.86

Scenario	Capacity of unreliable DC1	Capacity of unreliable DC2	Capacity of unreliable DC3	DC1 probability	DC2 probability	DC3 probability	Scenario probability to occur	Total cost for each scenario	Expected cost
121	350	250	0	0.90	0.95	0.02	0.0145350	8039.75	116.86
122	350	250	75	0.90	0.95	0.01	0.0076950	7893.306	60.74
123	350	250	150	0.90	0.95	0.02	0.0205200	7796.13	159.98
124	350	250	225	0.90	0.95	0.03	0.0256500	7761.659	199.09
125	350	250	300	0.90	0.95	0.92	0.7866000	7735.79	6084.97
Expected total cost when allocation decision is determined by scenario2									7744.60

We must replicate this step 125 times by changing the scenario used to determine allocation decision (in this example, scenario two is used, but we exactly have 125 scenarios. That is why we must replicate this step 125 times). So, there will be tables like this 125 tables.

Table 4.23

Expected Total Cost When Allocation Decision is Determined by Each Scenario

Scenario	Cost	Scenario	Cost	Scenario	Cost	Scenario	Cost	Scenario	Cost
1	7793.67	26	7821.79	51	7629.15	76	7467.36	106	7456.43
2	7744.60	27	7563.61	52	7405.32	77	7345.12	107	7391.77
3	7680.15	28	7454.40	53	7332.04	78	7330.89	108	7321.43
4	7680.15	29	7482.60	54	7318.33	79	7292.94	109	7314.53
5	7651.82	30	7454.27	55	7318.33	80	7290.98	110	7288.32
6	7838.90	31	7641.35	56	7475.11	81	7479.69	111	7456.43
7	7604.45	32	7417.52	57	7394.40	82	7367.49	112	7391.88
8	7567.55	33	7370.00	58	7346.88	83	7319.97	113	7328.24

Scenario	Cost	Scenario	Cost	Scenario	Cost	Scenario	Cost	Scenario	Cost
9	7553.84	34	7345.67	59	7332.73	84	7305.09	114	7314.09
10	7528.08	35	7319.91	60	7307.41	85	7280.49	115	7288.32
11	7719.76	36	7520.61	61	7464.49	86	7437.59	116	7445.23
12	7556.93	37	7406.90	62	7345.41	87	7373.07	117	7380.77
13	7556.93	38	7359.38	63	7331.24	88	7320.08	118	7304.48
14	7542.78	39	7317.03	64	7293.23	89	7282.46	119	7314.09
15	7517.02	40	7319.91	65	7291.27	90	7284.18	120	7288.32
16	7719.76	41	7522.21	66	7464.49	91	7437.59	121	7445.23
17	7556.93	42	7406.90	67	7378.76	92	7373.07	122	7373.14
18	7556.93	43	7359.38	68	7331.24	93	7304.48	123	7304.48
19	7542.78	44	7345.23	69	7317.03	94	7306.26	124	7314.09
20	7516.93	45	7319.91	70	7291.27	95	7280.49	125	7288.32
21	7718.16	46	7520.61	71	7492.47	96	7437.59		
22	7655.58	47	7458.03	72	7428.27	97	7373.07		
23	7556.93	48	7359.38	73	7292.17	98	7304.37		
24	7542.78	49	7345.23	74	7291.27	99	7306.26		
25	7516.93	50	7319.91	75	7291.27	100	7280.49		

After replicating 125 times, we already found out the expected total cost when the allocation decision is determined by each scenario and shown in table 24. The scenario which belongs the lowest cost will be selected. The lowest-cost scenario is scenario 85. As a result, scenario 85 will be used to determine the allocation decision.

Table 4.24

Allocation Decision of Scenario 85

	X_{ij}			Y_{ik}			Z_{ij}		
	j_1	j_2	j_3	k_1	k_2	k_3	j_1	j_2	j_3
i_1	1	0	0	0	0	0	0	0	0
i_2	0	1	0	0	0	0	0	0	0
i_3	0	0	1	0	0	0	0	0	0
i_4	0	1	0	0	0	0	0	0	0
i_5	0	0	0	0	0	1	1	0	0
i_6	0	0	0	0	1	0	0	0	1
i_7	0	0	0	0	1	0	1	0	0
i_8	0	0	0	0	1	0	1	0	0
i_9	0	0	0	0	1	0	0	1	0
i_{10}	0	0	1	0	0	0	0	0	0
i_{11}	0	0	1	0	0	0	0	0	0
i_{12}	0	1	0	0	0	0	0	0	0
i_{13}	1	0	0	0	0	0	0	0	0
i_{14}	0	1	0	0	0	0	0	0	0
i_{15}	0	0	0	1	0	0	1	0	0
i_{16}	0	0	0	0	0	1	1	0	0
i_{17}	0	0	0	1	0	0	0	0	1
i_{18}	0	1	0	0	0	0	0	0	0
i_{19}	0	0	0	0	0	1	1	0	0
i_{20}	0	0	0	1	0	0	1	0	0

Table 4.25

Comparison Results of Case 4 without and with Scenario-Based Technique

	Result of case 4 (the model without scenario-based technique)	Result of case 4 (the model with scenario-based technique)
Total cost	7255.7	7280.49

Related to table 25, the results of case 4 without and with the scenario-based technique are 7255.7 and 7280.49, respectively. Even though the cost of using the scenario-based technique is more expensive than the model, which we did not apply any stochastic programming approach, considering a model with uncertainty is still better because the result is computed more precisely and helps supply chain network designers make a strategic decision easier.

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This research developed a SCND model considering transportation and shortage costs to help allocate retailers to various distribution centers in which some are not reliable, and hence, disruptions may occur. The developed model is stochastic, and hence, scenario-based technique is employed to help find the optimal solution. The possible scenarios of unreliable DCs are assumed to follow a discrete distribution with known probability. Various scenarios of unreliable DCs and parameters used in the model, such as numbers of reliable DCs, unreliable DCs, and retailers, were tested via sensitivity analyses. From the tested results, it is noticed that the model's total costs when applying the scenario-based technique are higher than those without applying the scenario-based technique. However, the results of the two approaches are not significantly different in some cases because the disruption in the model is not serious. In other words, the probabilities of disruption to occur for many disruption scenarios in the model are very low. If the disruption is so serious, the result of applying the scenario -based technique should be much different compared to the result which is not applied the scenario-based technique.

Considering supply chain networks with a stochastic programming approach is preferable in real-world and practical problems because the scenario-based technique provides expected results regarding the occurrence of disruption for various scenarios. Hence, the stochastic results are considered to be more accurate. As a result, decision-makers or SCN developers can make decisions and long-term plans easier with confidence. In addition, the reason that made the results of the two approaches not significantly different in this research is due to the fact that the possible scenarios of unreliable DCs were generated based on real-world situations which disruption is not so serious; the occurrence probabilities of high ratios of capacity, such as 90% and 100%, are much higher than those of low ratios of capacity. For instance, the probability of 100% ratio of capacity to occur is 0.90, while the probabilities of 0%, 25%, 50%, and 75% ratio of capacity to occur are 0.01, 0.02, 0.02, and 0.05 respectively. In fact, if the occurrence probabilities of low and high-capacity ratios are nearly the same, the results of the two approaches, with and without the scenario-based technique, would be much different.

5.2 Recommendations

The main cost components considered in this research were transportation and shortage costs. Therefore, to be more precise, other cost components such as fixed cost of opening DCs, fixed cost of operating DCs, as well as different transportation modes should be added into consideration in further research. Also, the solution approach to deal with stochastic programming can be altered from scenario-based technique to other stochastic programming techniques such as CVaR. In addition, the disruption considered in this research was considered unreliable DCs, but, in fact, the disruption can also occur at other locations, such as transportation routes and transportation modes. Therefore, extending the consideration of disruption locations of SCN to all possible position is an effective way to adapt the model in this research to real-world problems. Lastly, instead of assuming the capacities of disrupted DCs to follow a discrete distribution, the author would recommend considering that the capacity losses of DCs to follow a continuous distribution to deal with uncertainty nature more accurately.

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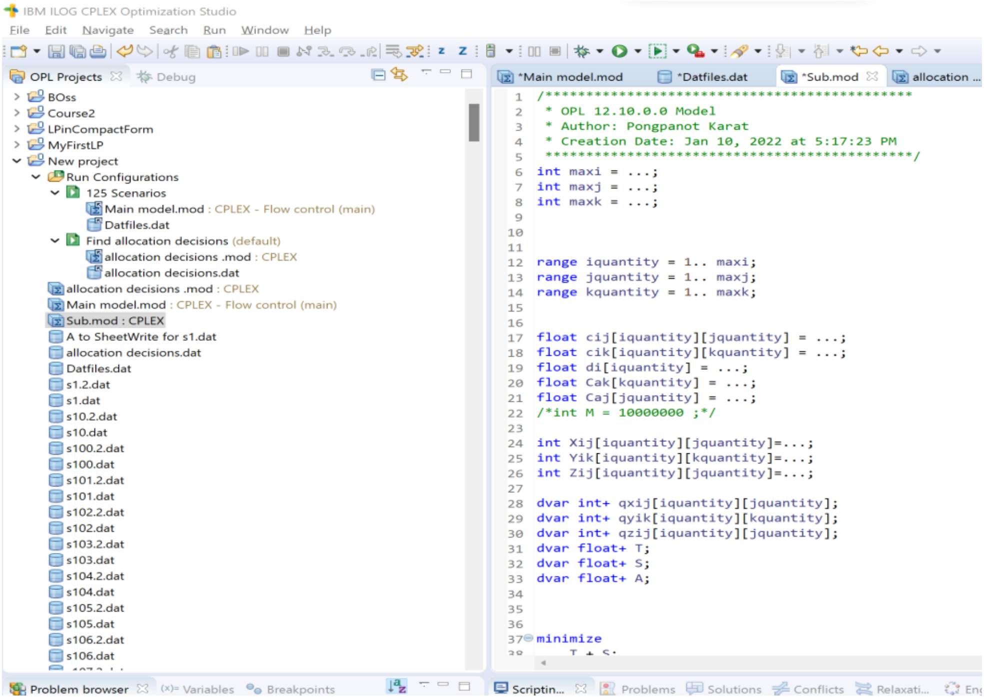
Alexander Shapiro and Andy Philpott. A Tutorial on Stochastic Programming.

APPENDIX

CPLEX OPTIMIZATION PROGRAMMMING CODES

As we mentioned in section 4.1.4 Case 4: The model with disruption at DCs: Scenario-based technique that we must run CPLEX 125*125 = 15625 times, it was very time-consuming. Therefore, the various codes were developed and used to reduce running time via CPLEX.

1. The overview of CPLEX working environment.



2. The based code, referred to as "Sub.mod" in the picture of the number1 above and the picture of number3 below, is used with the code mentioned in number 2 below.

IBM ILOG CPLEX Optimization Studio

File Edit Navigate Search Run Window Help

Data1.dat | Data from e... | Model1.mod | LP for

```
/*********************************************
 * OPL 12.10.0.0 Model
 * Author: Pongpanot Karat
 * Creation Date: Jan 10, 2022 at 5:17:23 PM
 *********************************************/
int maxi = ...;
int maxj = ...;
int maxk = ...;



range iquantity = 1.. maxi;
range jquantity = 1.. maxj;
range kquantity = 1.. maxk;


float cij[iquantity][jquantity] = ...;
float cik[iquantity][kquantity] = ...;
float di[iquantity] = ...;
float Cak[kquantity] = ...;
float Caj[jquantity] = ...;
/*int M = 10000000 ;*/

int Xij[iquantity][jquantity]=...;
int Yik[iquantity][kquantity]=...;
int Zij[iquantity][jquantity]=...;

dvar int+ qxij[iquantity][jquantity];
dvar int+ qyik[iquantity][kquantity];
dvar int+ qzij[iquantity][jquantity];
dvar float+ T;
dvar float+ S;
dvar float+ A;



minimize
    T + S;
```

```

subject to
{
 /*formulation1 */  A == T+S;

   sum(i in iquantity, j in jquantity) cij[i][j]*qxij[i][j]
  +sum(i in iquantity, k in kquantity) cik[i][k]*qyik[i][k]
  +sum(i in iquantity, j in jquantity) cij[i][j]*qzij[i][j] == T;

 sum(i in iquantity) (di[i]- (sum(j in jquantity) Xij[i][j]*qxij[i][j]
                             +sum(k in kquantity) Yik[i][k]*qyik[i][k]
                             +sum(j in jquantity) Zij[i][j]*qzij[i][j]))*5 == S;


 /*formulation2 */ forall(i in iquantity)   (sum(j in jquantity) Xij[i][j]*qxij[i][j]
                                           + sum(k in kquantity) Yik[i][k]*qyik[i][k]
                                           + sum(j in jquantity) Zij[i][j]*qzij[i][j]) <=  di

 /*formulation3 */ forall(j in jquantity) sum(i in iquantity) (Xij[i][j]*qxij[i][j]
                                                             + Zij[i][j]*qzij[i][j]) <= Caj[j

 /*formulation4 */ forall(k in kquantity) sum(i in iquantity) Yik[i][k]*qyik[i][k] <= Cak[k];


 /*formulation9 */ forall(i in iquantity, j in jquantity) qxij[i][j] >= 0;
 /* reduntdant constraint because I already defined float+*/

 /*These 2 constraints indicate that there will be only one assignment for
 primary and secondary assignments, e.g., Y[19][1]=1 and Y[19][2]=1 will never happen!!!! */
/*forall(i in iquantity) sum(j in jquantity) Xij[i][j] <= 1; this one is useless*/
forall(i in iquantity) sum(k in kquantity) Yik[i][k] <= 1;
forall(i in iquantity) sum(j in jquantity) Zij[i][j] <= 1;
}
```

3. The code was used to reduce time because initially, we must run 15,625 times.

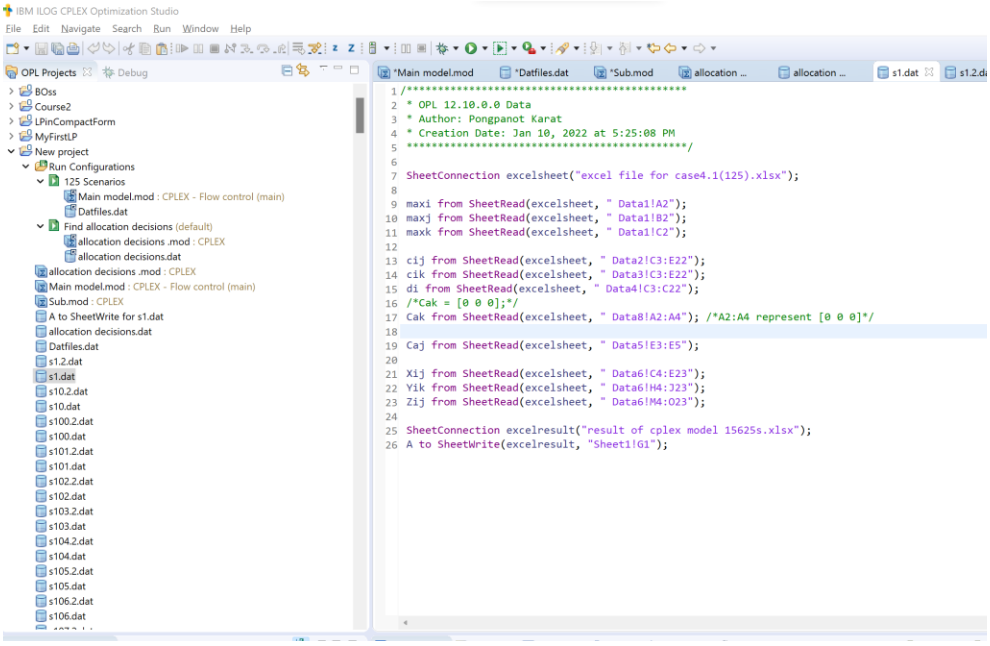
```
{string} datFiles=...;

main {
        var source = new IloOplModelSource("Sub.mod");
        var cplex = new IloCplex();
        var def = new IloOplModelDefinition(source);

        for(var datFile in thisOplModel.datFiles)
        {
        var opl = new IloOplModel(def,cplex);

        var data2= new IloOplDataSource(datFile);

        opl.addDataSource(data2);
        opl.generate();

        if (cplex.solve()) {
           opl.postProcess();
           var o=new IloOplOutputFile("res"+datFile+".txt");
           o.writeln("OBJ = " + cplex.getObjValue());
           o.close();
           writeln("OBJ = " + cplex.getObjValue());
        } else {
           writeln("No solution");
        }
       opl.end();
      }

   }
```

4. "datFiles" contains capacities of unreliable DCs of each scenario, and we have 125 scenarios. Therefore, there are 125 datFiles.

Data1.dat | Data from e... | Model1.mod | *Main model.mod | *Datfiles.dat | *Sub.mod | allocation ... | 99+

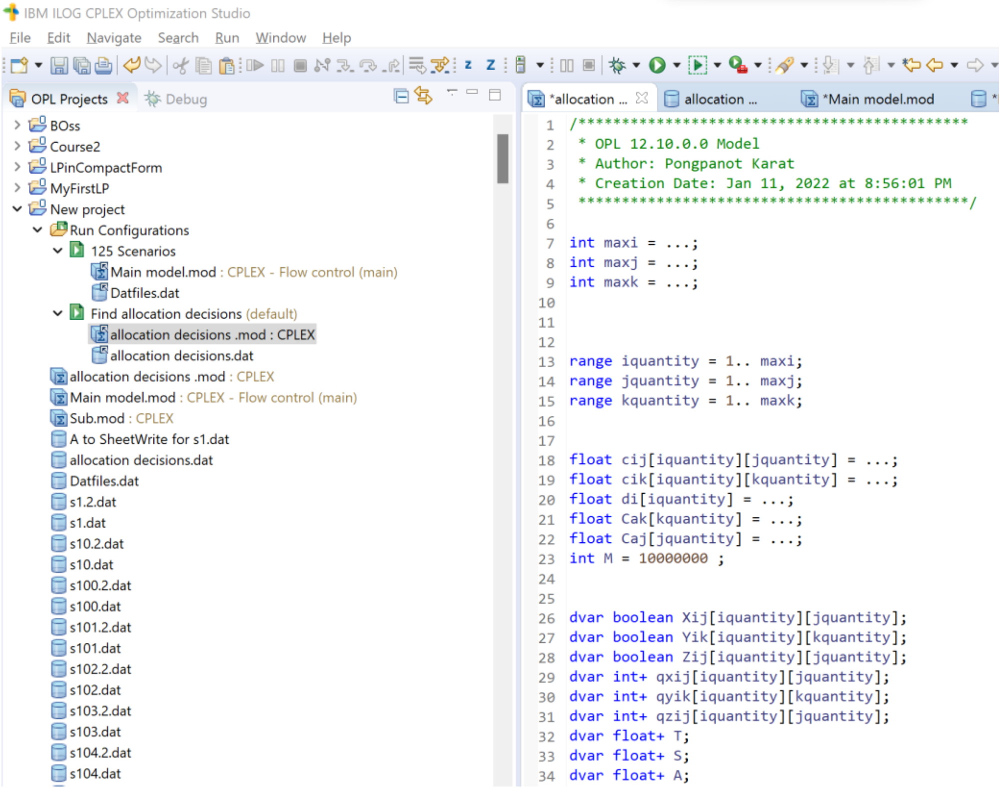
```
/*********************************************
 * OPL 12.10.0.0 Data
 * Author: Pongpanot Karat
 * Creation Date: Jan 10, 2022 at 5:17:36 PM
 *********************************************/

datFiles = {"s1.dat","s2.dat","s3.dat","s4.dat","s5.dat","s6.dat","s7.dat","s8.dat","s9.dat","s10.dat"
,"s11.dat","s12.dat","s13.dat","s14.dat","s15.dat","s16.dat","s17.dat","s18.dat","s19.dat","s20.dat","s21.dat"
,"s22.dat","s23.dat","s24.dat","s25.dat","s26.dat","s27.dat","s28.dat","s29.dat","s30.dat","s31.dat","s32.dat"
,"s33.dat","s34.dat","s35.dat","s36.dat","s37.dat","s38.dat","s39.dat","s40.dat","s41.dat","s42.dat","s43.dat"
,"s44.dat","s45.dat","s46.dat","s47.dat","s48.dat","s49.dat","s50.dat","s51.dat","s52.dat","s53.dat","s54.dat"
,"s55.dat","s56.dat","s57.dat","s58.dat","s59.dat","s60.dat","s61.dat","s62.dat","s63.dat","s64.dat","s65.dat"
,"s66.dat","s67.dat","s68.dat","s69.dat","s70.dat","s71.dat","s72.dat","s73.dat","s74.dat","s75.dat","s76.dat"
,"s77.dat","s78.dat","s79.dat","s80.dat","s81.dat","s82.dat","s83.dat","s84.dat","s85.dat","s86.dat","s87.dat"
,"s88.dat","s89.dat","s90.dat","s91.dat","s92.dat","s93.dat","s94.dat","s95.dat","s96.dat","s97.dat","s98.dat"
,"s99.dat","s100.dat","s101.dat","s102.dat","s103.dat","s104.dat","s105.dat","s106.dat","s107.dat","s108.dat"
,"s109.dat","s110.dat","s111.dat","s112.dat","s113.dat","s114.dat","s115.dat","s116.dat","s117.dat","s118.dat"
,"s119.dat","s120.dat","s121.dat","s122.dat","s123.dat","s124.dat","s125.dat" };
```

5. An example of datFiles, “s1.dat”, the possibility 1 in which the capacity of unreliable DCs 1, 2, and 3 are 0, 0, and 0, respectively.



This section presents the codes used to find the allocation decision for each scenario.

1. The codes were used to find the allocation decision for each scenario.




```
/*********************************************
 * OPL 12.10.0.0 Model
 * Author: Pongpanot Karat
 * Creation Date: Jan 11, 2022 at 8:56:01 PM
 *********************************************/

int maxi = ...;
int maxj = ...;
int maxk = ...;



range iquantity = 1.. maxi;
range jquantity = 1.. maxj;
range kquantity = 1.. maxk;


float cij[iquantity][jquantity] = ...;
float cik[iquantity][kquantity] = ...;
float di[iquantity] = ...;
float Cak[kquantity] = ...;
float Caj[jquantity] = ...;
int M = 10000000 ;


dvar boolean Xij[iquantity][jquantity];
dvar boolean Yik[iquantity][kquantity];
dvar boolean Zij[iquantity][jquantity];
dvar int+ qxij[iquantity][jquantity];
dvar int+ qyik[iquantity][kquantity];
dvar int+ qzij[iquantity][jquantity];
dvar float+ T;
dvar float+ S;
dvar float+ A;
```

```



minimize
      T + S;

subject to
{
```

```
/*formulation1 */  A == T+S;

  sum(i in iquantity, j in jquantity) cij[i][j]*qxij[i][j]
 +sum(i in iquantity, k in kquantity) cik[i][k]*qyik[i][k]
 +sum(i in iquantity, j in jquantity) cij[i][j]*qzij[i][j] == T;

 sum(i in iquantity) (di[i]- (sum(j in jquantity) qxij[i][j]
                              +sum(k in kquantity) qyik[i][k]
                              +sum(j in jquantity) qzij[i][j]))*5 == S;


 /*formulation2 */ forall(i in iquantity)   (sum(j in jquantity) qxij[i][j]
                                           + sum(k in kquantity) qyik[i][k]
                                           + sum(j in jquantity) qzij[i][j]) <=  di[i];

 /*formulation3 */ forall(j in jquantity) sum(i in iquantity) (qxij[i][j]
                                                              + qzij[i][j]) <= Caj[j];

 /*formulation4 */ forall(k in kquantity) sum(i in iquantity) qyik[i][k] <= Cak[k];

 /*formulation5 */ forall(i in iquantity) sum(k in kquantity) Yik[i][k]
                                        + sum(j in jquantity) Zij[i][j] == 2*(1-sum(j in jquantity)Xij[i][j]);

 /*formulation9 */ forall(i in iquantity, j in jquantity) qxij[i][j] >= 0;
 /* reduntdant constraint because I already defined float+*/

 /*formulation10 */ forall(i in iquantity, j in jquantity) qxij[i][j] <= M * Xij[i][j] ;
 /*formulation11 */ forall(i in iquantity, k in kquantity) qyik[i][k] <= M * Yik[i][k] ;
 /*formulation12 */ forall(i in iquantity, j in jquantity) qzij[i][j] <= M * Zij[i][j] ;

 /*These 2 constraints indicate that there will be only one assignment
 for primary and secondary assignments, e.g., Y[19][1]=1 and Y[19][2]=1 will never happen!!!! */
/*forall(i in iquantity) sum(j in jquantity) Xij[i][j] <= 1; this one is useless*/
forall(i in iquantity) sum(k in kquantity) Yik[i][k] <= 1;
forall(i in iquantity) sum(j in jquantity) Zij[i][j] <= 1;
}
```