Stochastic models for analysis and optimization of unmanned aerial vehicle delivery on last-mile logistics

by

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B.S., Mazandaran University of Science and Technology, 2010
M.S., University Technology Malaysia, 2015

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Industrial and Manufacturing Systems Engineering
Carl R. Ice College of Engineering

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2022

Abstract

Land transportation is generally considered one of the most expensive, polluting and least efficient parts of the logistics chain. Due to these issues, using unmanned aerial vehicles such as drones for package delivery in last-mile logistics becomes increasingly attractive. However, there are several significant obstacles in terms of technical aspects and performance capabilities of drones like limited flight coverage. In addition, supply chains are exposed to a broad range of uncertainties some of which may cause disruptions in the whole supply chain system. To hedge against these issues, a well-designed reliable network is a top priority. Most existing models for optimization within logistics chain are deterministic, lack reliability, or they are not computationally efficient for larger problems. This dissertation aims to improve the reliability and efficiency of the supply chain network through the development of stochastic optimization models and methods to help address important problems related to delivery of products using drones. To achieve this goal, this study has developed a generalized optimization model that captures the dynamic and stochastic nature of problems by using stochastic optimization and stochastic control.

At first, this study addresses issues bordering on capacitated supply chain problems, specifically on how reliable supply chain networks can be designed in the face of random facility disruptions and uncertain demand. The proposed multi-period capacitated facility location and allocation problem is modeled as a two-stage stochastic mixed-integer formulation that minimizes the total establishing and transportation cost. To overcome the complexity of the model, the L-shaped method of stochastic linear programming is applied by integrating two types of optimality and feasibility cuts for solving the stochastic model. This research improves the proposed algorithm in two ways: replacing the single-cut approach with a multi-cut and showing relatively complete recourse in the stochastic model by reformulating the original model. According to

computational results, the proposed solution algorithm solves large-scale problems while avoiding long run times as well. It is also demonstrated that substantial improvements in reliability of the system can often be possible with minimal increases in facility cost. Next, this research aims to construct a feasible delivery network consisting of warehouses and recharging stations through the development of a stochastic mixed-integer model, resulting in improving the coverage and reliability of the supply chain network. Due to the computational complexity of the scenario-based mixed-integer model, this research improves the performance of the genetic algorithm by considering each scenario independently in one of the steps of the algorithm to significantly improve the computational time need to find the solutions. Computational results demonstrate that the proposed algorithm is efficiently capable of solving large-scale problems. Finally, this dissertation analyzes tradeoffs related to charging strategies for recharging stations which can be viewed as warehouses in last-mile logistics with capacity constraints and stochastic lead times. To enhance delivery time, this research assumes that extra batteries are available at the recharging station where individual drones land when they run out of power and swap empty batteries with fully charged ones. Stochastic Markov decision models are formulated to handle stochasticity in the problem and determine the optimal policy for decision-makers by applying a policy iteration algorithm. To overcome of computational challenges, a novel approximation method called the decomposition-based approach is proposed to split the original Markov decision problem for the system with N states into N independent Markov chain processes. Through numerical studies, this dissertation demonstrates that the proposed solution algorithm is not only capable of solving large-scale problems, but also avoids long run times. It is also demonstrated how different stochastic rate like flight or demand, and inventory and backorder costs can affect the optimal decisions.

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Dedication

To my wife, parents, and sister, for their unconditional love and support.

Chapter 1 - Introduction

A supply chain is formed by a network of entities such as manufacturers, suppliers, and distributors who work together to provide finished products to the end user. Figure 1.1 illustrates a supply chain network consisting of product flow, information, and cash flow links with supplier, producer, and customer.

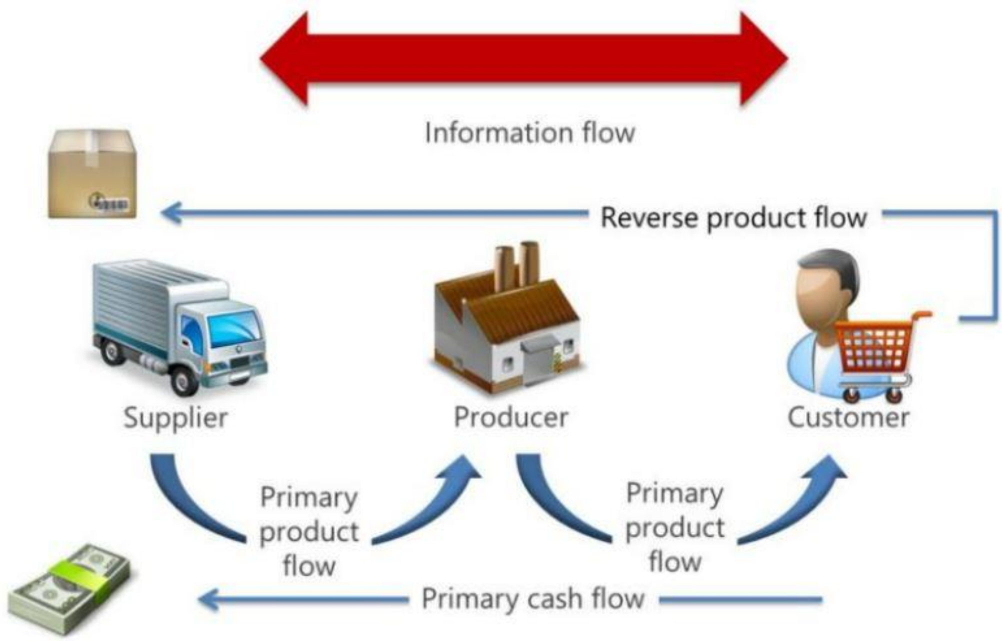


Figure 1.1 An illustration of a company's supply chain

The supply chain management concept emerged in the 1990s to express the need to integrate key business processes. Supply chain management aims to produce and distribute the product in the right quantity, to the right place, and at the right time, in order to minimize system wide costs (or maximize profits) while meeting service levels. According to Melo et al. (2009) supply chain management has three planning levels, namely strategic, tactical, and operational. Strategic planning involves determining the number, location, capacity, and technology of facilities, while tactical/operational planning involves determining the quantities of purchasing, production, distribution, product handling, and inventory holding. Supply chain activities focus on identifying customer demands, improving customer service, controlling production processes, and aligning the goals of supply chain partners (Drezner, 1987). To achieve this aim, logistics management as a part of supply chain management plays a critical role. It ensures a smooth and efficient flow of goods, services, and related information from the point of origin to the point of consumption. The "last mile" of delivery is the final stage in a product's journey from a warehouse shelf to a customer's doorstep in the fastest way possible. This has been driven by the continuously evolving market and customer demands across the industries (e-commerce, food, retail, etc.).

Package delivery has become a significant function of logistics businesses due to the rise of e-commerce and customer preferences for online shopping. Traditionally, packages are delivered to the customer using land transportation (trucks, cars, and motorcycles). However, these means of transportation are considered to be one of the most expensive, less efficient, and most polluting entities of the logistics chain (Gevaers, Van de Vo- orde, & Vanelslander, 2014). In recent years, the use of unmanned aerial vehicles such as drones as an alternative transportation mode has become a promising solution for delivering packages in last-mile logistics. There are several advantages of using drones in package delivery. Firstly, drone delivery is much faster than land transportation since drones do not encounter congestion and road traffic jams. Secondly, drones are not restricted by specific paths, like roads, making them applicable to deliver parcels to areas that difficult to access by other methods. The drone delivery has drawn significant attention, and several companies and government agencies have deployed drones in small amounts to deliver small packages (Hern, 2014; Murray, & Chu, 2015; Ha et al., 2015; Ha et al., 2018). A number of companies have used drones to deliver packages and merchandise items to their customers, including Amazon, DHL, and Google. Unmanned arial vehicles (UAVs) have been identified by

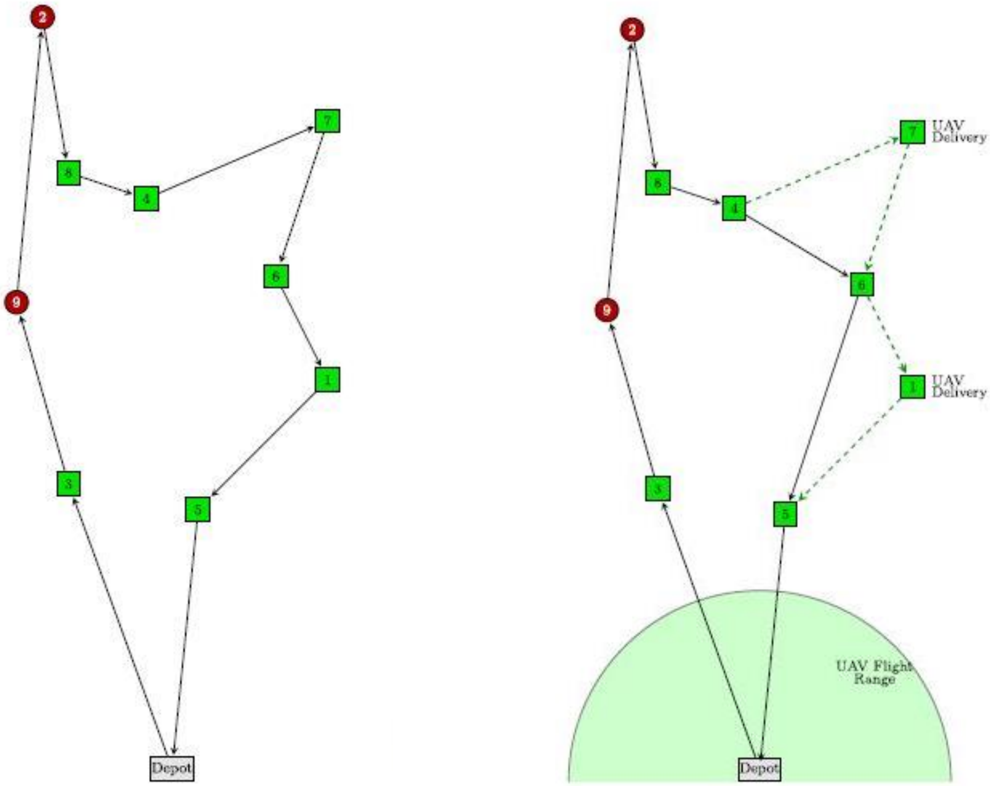
DHL for having potential benefits such as higher last-mile efficiency, lower accidents, and swifter deliveries (Koiwanit, 2018). A subscription service called Amazon Prime Air is being considered by Amazon to rapidly deliver packages within 30 minutes of an online order (Hong, Kuby, & Murray, 2018). Later in June 2022, Amazon announced that customers in Lockeford, California, will be among the first to receive Prime Air drone deliveries in the U.S.

Even though drones are cheaper and faster than traditional methods of parcel delivery, they should be reliable enough for customers and companies to consider them seriously. Prior to drones being widely adopted in supply chain networks, several technical aspects and performance limitations need to be overcome. These, along with the unplanned and unanticipated events that disrupt the normal flow of products and materials within a supply chain, have escalated the necessity of developing a well-designed resilient and reliable network.

1.1 Research motivation and objectives

Logistics chains typically include land transportation, which has been criticized for being costly, inefficient, and polluting. Unmanned aerial vehicles (UAVs) are becoming increasingly attractive as an alternative transportation mode for parcel delivery in last-mile logistics due to these issues. Before drones can be widely adopted in package delivery, several technical and performance obstacles must be overcome. In addition, supply chains face a variety of uncertainties that may create disruptions throughout the entire process. These uncertainties could further increase if drones are included to the supply chain as an alternative mode of transportation. In order to hedge against these issues, a well-designed reliable network should be one of the top priorities.

One of the substantial operational challenges in using drones in the supply chain network is the limited flight coverage since they have limited flight range. Currently, a drone's coverage is limited to a radius of 20 miles, reducing the access for a significant segment of customers, and leading to the use of land transportation delivery processes (Scott, & Scott, 2017). While several research have addressed technological barriers for introducing drones in daily logistics operation, only a few studies have considered operational challenges. Murray and Chu (2015) considered the direct depot-to-customer operation inspired by Amazon. The Prime Air UAV has a range of 10 miles. Thus, UAV deliveries must originate from distribution centers located in close proximity to the customers. Several logistical strategies can address the range limitation of a drone delivery system. A multi-modal approach would combine drones with trucks, using the advantages of one to offset the disadvantages of the other by launching drones from trucks for the "last-mile" only (Murray, & Chu, 2015; Agatz, Bouman, & Schmidt, 2018; Ha et al., 2018). As it is shown in the Figure 1.2 (b), an UAV/truck tandem may be a good option when UAV delivery can't be carried out directly by the distribution center (depot). All customer parcels and a UAV are transported from the DC on a delivery truck. From the truck, the UAV carries parcels for individual customers as the driver makes deliveries. The circular nodes indicate that customers 2 and 9 are ineligible for UAV delivery. Another technique is the installation of charging stations within the existing logistics infrastructure to facilitate batteries recharging (Sundar, & Rathinam, 2013; Dorling et al., 2016; Yu, Budhiraja, & Tokekar, 2018). This is considered as a single-mode (drone only) door-to-door drone delivery system from warehouse to customers would have to rely on single or multiple stops at battery recharging, battery-replacing, or hydrogen-refueling stations.



a) Truck Delivery system. b) Drone/Truck delivery system.

Figure 1.2 Comparison of the delivery system without the aid of drones (a) and system which drone is launched from delivery tuck (b)

For a drone delivery service to be developed within an existing logistics network, a coverage location model is needed. A typical facility location model locates a given number of facilities in order to maximize the volume of origin-destination flow that can travel without running out of fuel. It is, however, more difficult to solve the drone-recharging problem. Drone flight range determines the potential service area of facilities. As a result, it is necessary to have a coverage location model in order to optimize the location of drone delivery stations. In comparison to the usual network design problem, drone-based transportation poses a number of unique challenges. (1) There are fundamental limitations to the flight duration and load capacity of drones, so they cannot transport goods over an extended period of time without replenishing consumables, such as fuel (battery charge) and the products they deliver. (2) UAVs' flight times depend delicately on how much loaded product they carry; therefore, the problem must address the relationship between the weight of the loaded product and the flight time. In this study, warehouses and recharging stations are used to build a logistical network for delivering goods. For recharging station system design, the delivery service coverage should be based on drone flight range in continuous two-dimensional space under different conditions, such as flying with or without a package.

Supply chain is designed by utilizing facility location (optimization) models that find the optimal number, location, and allocation of facilities, which minimize fixed facility and operating costs. Traditional models are based on the assumption that the entire supply chain is completely reliable, and no disruption is anticipated in the supply chain network. However, this assumption is far from reality. Every day, supply chain systems have become more complex and dynamic with wide geographical coverage. Hence, supply chains are exposed to a broad range of uncertainties, some of which may cause disruptions in the supply chain (Rezapour, Farahani, & Pourakbar, 2017). Accidental disruption due to large-scale natural disasters, manufacturing fires, terrorist attacks, wide-spread electrical shutdowns, and financial or political tension is among several other uncertainties that are likely to occur (Govindan, Fattahi, & Keyvanshokooh, 2017). A recent example of Colonial pipeline cyberattack and the widespread transmission of the novel COVID-19, which created grave uncertainties in the global supply chain. In this study, facilities failure and demand fluctuation are considered as two types of uncertainty might cause disruptions in supply chain network.

Supply chain disruptions have been a challenging issue for many companies worldwide (Rezapour, Farahani, & Pourakbar, 2017). The disruption at one level of a supply chain can significantly impact the entire chain: for instance, any failure of a distribution center could cost a company additional transportation cost to satisfy customer demand (Tolooie, Maity, & Sinha, 2020). Hendricks and Singhal (2003) reported on some of the severe impacts of supply chain disruptions on market share, which in some cases fell lower than 11% from just the announcement of disruptions alone. For example, in 2008, the Boeing Company was forced to pay massive amounts in compensation for postponing the delivery of the Dreamliner 787 due to delays the in supply of critical components (Peng et al., 2011). This is one of many real-world examples in which a single catastrophic event has significantly degraded the capabilities of several suppliers. Given the increase in the frequency of occurrence of supply chain disruptions in recent times, more and more researchers are beginning to give precedence to this very important area of research. Another example is evident from the transitional effect caused by the disruptions in a quarter of the world's silicon production as a result of the March 11, 2011 earthquake and tsunami in Japan, forcing more than 130 plants (mainly in the auto and electronics industries) to close down (Lim et al., 2010). The supply chains of many international companies were also influenced dramatically, particularly those in the steel, electronics, and automotive industries. General Motors, for example, had to stop its vehicle production at multiple plants due to parts shortages from Japanese suppliers. Also, Toyota in Japan halted the production of parts initially meant for other markets beyond its shores. The resulting slowdowns and pause of operations by many companies and have raised several questions on supply chain disruption and how to manage these situations. Adding recharging station to supply chain could increase the complexity of the network even more, and any disruptions could lead enormous financial impacts and, in some cases, cause a permanent loss of market share. For example, as shown in Figure 1.3, failure of one recharging station in the last part of the network could cut the network, which results in lost sales or backordering costs.

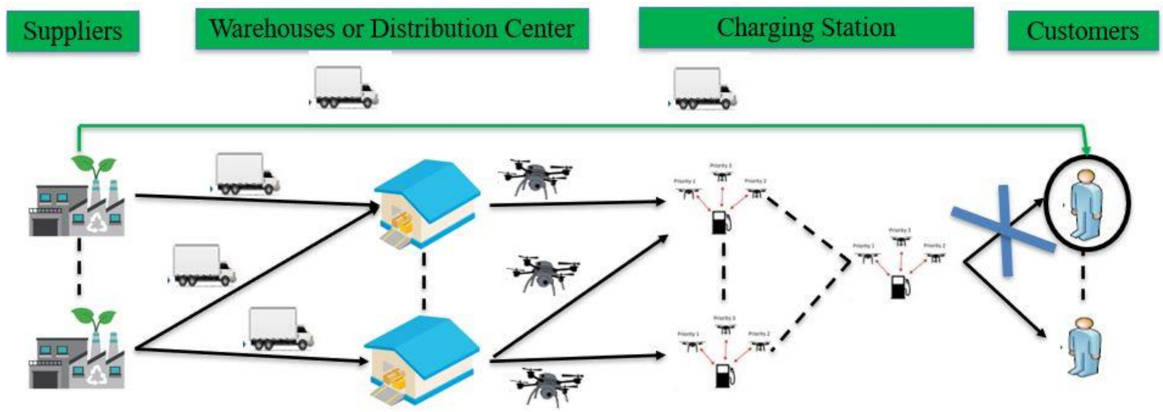


Figure 1.3 Supply chain network under using drones in last-mile delivery under disruption

The COVID-19 crisis with its unexpected global impact, it is a good example to illustrate how demand uncertainty can cause disruption in the whole supply chain system. The infamous toilet paper crisis of early March 2020, when the U.S. states began announcing quarantines, people panic-bought more toilet paper than suppliers had planned for. This was a demand surge. On the other side of this surge is the demand drop in commercial-use toilet paper. People were not at the office, out at restaurants, or in airports using the restroom so the need for large-roll, commercial toilet paper practically ceased. This is an example of a both a drop and a surge for the same product, but for different types of the product.

Therefore, supply chain disruptions have been a challenging issue for companies globally. They are unplanned and unanticipated events that disrupt the normal flow of products and materials within a supply chain. The disruption at one part of the supply chain can significantly impact the entire chain. This is best illustrated in Figure 1.2, where the failure of one facility costs the company additional transportation costs to satisfy the demand of customers by providing another most available facility as a penalty. The uncertainty of natural disasters (occurrence and intensity) and the amount of demand during each time period has a significant effect on designing the supply chain network using drones in last-mile delivery. To hedge against supply chain disruptions, a well-designed and reliable network is a top priority. Consider an example of a lean supply chain that had reached the goal of zero waste, i.e., a supply chain that utilizes single sourcing with absolutely no inventory. This supply chain would be highly efficient under stable conditions but would be highly vulnerable to any supply disruption risk (Peck 2006). The key to managing disruption risks in supply chains is not by eliminating cost reduction, or efficiency thinking but by creating supply chains that are both efficient in stable conditions and capable of handling hazards in unstable conditions (Abrahamsson, Aldin, & Stahre, 2003). Hence, reliable and flexible supply chain designs become a significant consideration to the decision maker.

The objective of this research is to develop stochastic models to address important problems related to the delivery of products on last-mile logistics using drone. There are a lot of uncertainties associated with this logistics network like demand arrival, charging rate, flight rate, and disruptions due to the cyberattack, natural disasters or any other disaster. Yet most current models use simplified deterministic models to address this problem. Instead of using deterministic techniques, this proposed research develops a stochastic model to design a reliable supply chain network. The stochasticity in each problem is handled by different optimization methods to improve supply chain performance and better reflect the true supply chain dynamics and complexity. To overcome computational challenges, different novel approaches are proposed for each problem to provide an exact analysis of the logistics network. The decision options considered in these supply chains could include the location and number of facilities, number of products channeled through the network, location, and number of drones, number of extra batteries in the system, transportation modes, and charging mode. This research includes three main research tasks as follows:

Task 1, Designing reliable supply chains under uncertainties: This research aims to develop a general stochastic model for designing reliable and efficient supply chain networks under random facility disruptions and uncertain demand. This research also aims to develop theories to reduce the algorithm run times while solving large-scale problems. The solution approach utilizes novel decomposition-based techniques under unique last-mile logistics constraints that have never been addressed.

Task 2, Exploring location and efficiency of charging station to extend the coverage of drone delivery system: This research aims to develop a location model for recharging station system design by considering: (1) the flight range of drones under different conditions; (2) delivery service coverage of recharging stations; and (3) development of a feasible delivery network consisting of warehouses and recharging stations. In a stochastic environment, most of the decisions and constraints are scenario-dependent, and their numbers grow exponentially with the number of scenarios. Additionally, increasing the number of charging stations in the system can also exponentially increase the number of allocation variables. As a result of this growth, traditional algorithms cannot be efficiently applied to solve very large size problem. This research aims to develop and modify the genetic algorithm for solving large scale problems with complicated variables to significantly improve the computational time need to find the solutions.

Task 3, Managing drones and battery inventories on last-mile logistics under uncertainty: In this phase of research, it is assumed availability of extra batteries at the recharging station where the individual drone swaps the empty batteries with the full-charged batteries. This research aims to develop Markov decision process models to analyze different charging strategies in recharging stations to improve the delivery time in last-mile logistics. To overcome computational challenges, a novel approximation method is proposed to decompose the original Markov decision problem for the system with N states into N independent Markov chain processes. This research also considers logistics systems when some of the sensors of drones are corrupted by an attacker.

1.2 Proposed methods and research contributions

This dissertation focuses on modeling and solution methodologies applied to solve the stochastic supply chain and logistics network. Solution and modeling methods are broken into two major categories: stochastic optimization (Prescriptive method) and stochastic control (Descriptive method).

At first, this research addresses issues bordering on supply chain network design problems, specifically on how reliable supply chain networks can be designed in the face of random facility disruptions and uncertain demand. The proposed problem is formulated as a two-stage stochastic mixed-integer programming model. The Benders decomposition algorithm is applied to optimize the system as a prescriptive method. This research aims to improve the proposed algorithm in three different ways: replacing the single-cut approach with a multi-cut, improving feasibility and optimality area, and showing relatively complete recourse in the stochastic model by reformulating the original model. The performance of the Benders decomposition algorithm is enhanced by developing a novel feasibility area of the model and introducing valid constraints to the original model. As a result, there is significant improvement in the algorithm's run time through reduction in the number of cuts required to add the problem. Next, this research examines stochasticity in a multi-period stochastic supply chain network design problem while considering charging stations to extend the coverage of drones in last-mile logistics. Our stochastic model is unique due to two conditions: (i) it simultaneously considers delivery service coverage of recharging stations and distribution centers based on the flight range of drones under different conditions, capacities for supply and distribution centers and drone's utilization cost using Euclidian shortest path distance under demand and disaster uncertainty in multiple time periods. (ii) it adopts a combination of the two types of strategies simultaneously to design a reliable network using charging station as one of the levels under two different uncertain parameters in multi-time periods. Additionally, the heuristic algorithm is modified by considering a novel method for generating independent scenarios in order to create a new population. This significantly improves the efficiency of the algorithm due to the decrease in the number of infeasible solutions and allows us to efficiently solve real large-scale problems. Finally, this research evaluates the tradeoffs between the number of batteries and the drones in the last-mile logistics system. For improving the delivery time, this research assumes the availability of extra batteries in the system located at each recharging stations where drones swap their empty batteries with the full-charged batteries. Stochastic Markov decision models are developed to handle stochasticity in the problem and to analyze different charging strategies in recharging stations. The similarities in the transition probabilities for states belonging to a particular set within each state space is exploited to provide an exact analysis for logistics network with three different rate of charging batteries. To overcome difficulties computationally due to the increasing the size of the problem, a novel approximation method called decomposition-based approach is proposed. In addition, the research examines a resilience model in order to protect against cyber threats associated with drones used in last-mile logistics.

The merit of this research is to design reliable models for the supply chain using drones for last-mile delivery. The models are designed to efficiently handle randomness in the system and serve as a framework for several future problems in supply chains using unmanned arial vehicle as a means of transportation. Another merit is the development of the novel decomposition-based algorithm to overcome curse of dimensionality due to the increase in the complexity of the problem.

1.3 Dissertation outline

This dissertation is organized in 6 chapters. Chapter 2 reviews the challenges of using drones in last-mile logistics and discusses modelling, and solution methodologies applied to solve the stochastic supply chain and logistics network. Chapter 3 is a published research paper (Tolooie. Maity, & Sinha, 2020), which discusses the application of stochastic optimization in designing reliable supply chain network. Chapter 4 is an under-review research paper, which provides the stochastic model to extend the coverage of drone delivery system by adding charging station. Chapter 5 is an under-review research paper, that analyzes stochastic control problem in evaluating the number of battery and drones and examines different charging strategies in recharging stations to improve drone delivery time in last-mile logistics. Finally, Chapter 6 summarizes the main conclusion and contributions of this dissertation and discusses the potential future works.

Chapter 2 - Literature Review

There has been an increase in the focus on supply chain and logistics over the past few decades. Using supply chain design, one can estimate how long and how much time it will take to bring goods to market by analyzing the structure and network of a supply chain. Facility location, inventory management, and allocation problems are among the most studied issues in supply chain design (Leiras et al., 2014). Supply chain design can create competitive advantages and customer satisfaction through immediate response to specific customer needs. The activities associated with supply chain design are identifying customer demands, improving companies' ability to meet customer needs, controlling production processes, and aligning goals with supply chain partners. Several factors need to be considered when designing a supply chain network: the location of facilities, the allocation of customers to facilities, and the selection of suppliers (Ivanov, Tsipoulanidis, & Schönberger, 2019).

In the following, in section 2.1, a literature of the most crucial studies that have directly addressed the issue of reliability in supply chain network problems will be introduced. Then, in section 2.2 challenges of using drones in last mile logistics will be discussed and a literature of studies in addressing these challenges will be introduced. Finally, in section 2.3 two stochastic approaches, namely stochastic optimization and stochastic control, applied to solve the stochastic supply chain and logistics network will be introduced.

2.1 Supply chain network design and reliability

Chopra and Meindl (2007) identified three major components of the design of a supply chain: the distribution system, the facility network, and the transportation system. In the supply chain, designing a distribution system determines how and where inventory will be stored. During the design of the transportation system, inventory will be transported physically throughout the supply chain. Designing supply chain networks is perhaps the most important element of supply chain design. Typically, supply chain networks involve the design of facilities, the assignment of capacities, and the allocation of customers. It is a highly strategic decision to design a supply chain network. A new facility can be very expensive to locate, so the organization cannot easily modify its location after it has been decided and implemented. Thus, it is imperative to take extreme care when designing supply chains. In most studies, facility locations and allocations under stochastic parameters, like demand or cost, are considered. However, only a few studies take into account the impact of facility disruptions, as well as other unknown parameters. Drezner (1987) is one of the first to present mathematical models to address issues in facility locations that have unreliable suppliers. The paper investigates the unreliable p-median and (p, q)-center location problems in which a facility has a given probability of becoming inactive. The goal of this paper is to locate p unreliable facilities that minimize expected travel distances between customers and facilities. A heuristic method was developed for solving this problem based on random facility failures. Snyder and Daskin (2005) developed reliable versions of the uncapacitated fixed-charge location problem and the p-median problem, both of which aim to minimize a weighted sum of the nominal cost (when disruptions do not occur) and the expected cost (when disruptions occur). To ensure tractability, they assumed that each facility would fail at the same rate. For tractability, they used the assumption that all facilities have the same probability of failure. Many other scholars considered models similar to Snyder and Daskin's model, but relaxed the uniform disruption-probability assumption using a variety of modeling approaches (Berman, Krass, & Menezes, 2007; Meepetchdee, & Shah, 2007; Cui, Ouyang, & Shen, 2010; Li, & Ouyang, 2010; Lim, Daskin, Bassamboo, & Chopra, 2010; Drezner, & Wesolowsky, 2003). More recently, Zokaee et al. (2017) have developed a model that enables designing a reliable supply chain network using a finite set of scenarios for data costs, supply parameters, or demand factors. Afterwards, Farrokh et al. (2018) designed a close-loop supply chain network under a hybrid uncertainty by considering two sources of uncertainty as parameters. The first source is 'uncertainty of future scenarios' and the second source is 'value of parameters in each scenario with an imprecise nature'.

Other studies that have looked into reliable supply chain modelling include Snyder (2003) proposed a model to minimize the maximal failure cost versus expected failure costs, while Qi, Shen, and Snyder (2010) proposed a model for locating retailers as well as assigning customers to those retailers during cases of disruptions. Using heuristics and approximation algorithms with heterogeneous failure probabilities, Shen, Zhan, and Zhang (2011) proposed a stochastic program using different scenarios along with a nonlinear integer program. During their study, they assumed that in the event of a failure in the current facility, a second facility would be assigned to meet the customer's demand. Klibi and Martel (2012) proposed the use of several models for designing resilient supply chains that have the ability to accommodate disruptions and other types of uncertainties. They formulated the disruption's optimal response strategy and estimated the solution to the supply chain problem based on sample average approximation. Hatefi et al. (2015) presented fuzzy optimization models to design a reliable forward-reverse logistics network to deal with facility disruptions. The proposed model deals with the epistemic uncertainties in the parameters by using credibility constrained programming. To design a resilient closed-loop supply chain network, Jabbarzadeh, Haughton, and Khosrojerdi (2018) developed a stochastic robust optimization model. To deal with random disruption risks, the proposed model uses lateral transhipment. By minimizing the total cost across all disruption scenarios, their model determines the location of facilities and quantities of lateral transhipment. To address the uncapacitated hub location problem when hubs are disrupted, Azizi et al. (2016) proposed a mathematical formulation. In the event that a specific hub is disrupted, the entire demand of that hub is reassigned to the nearest facility using a reassignment strategy. The study was extended by Azizi (2019) by incorporating backup hub nodes as backup assignments for every demand point. According to all these studies, once a disruption occurs, the demand for the failed facility is served by a remaining facility that has not failed, enabling the model to make additional assignment decisions so as to minimize additional assignment costs. For the purpose of designing an efficient and reliable supply chain network, this research focuses on two strategies: reassignment strategies, which are used when disruptions take place, and hardening strategies, which are used when there are no disruptions. This study also determines the optimal facility location and allocation while jointly considering the randomness in the demand and facility failures.

2.2 Application of drones in last-mile delivery

The purpose of this section is to provide a background to the problem that has been addressed in the drone delivery system. To this end, Section 2.2.1 provides an overview of drone-based delivery models, while Section 2.2.2 discusses charging stations as a means of extending the coverage of drones. Lastly, this study compares its main contributions to existing work.

2.2.1 Using drones in package delivery

Logistics companies have already considered the potential advantages and disadvantages of UAVs. Logistics services company DHL, for instance, identifies lower accident rates, faster deliveries, and higher last-mile efficiency as key potential UAV benefits. Key UAV challenges include rules and regulations, limited capacity, and limited coverage ranges. As a result of announcements made by large corporations such as Amazon about potential application of UAVs, UAVs have become more prominent in the media but less so in the academic literature on logistics.

There has been a rapid increase in the utility of UAVs such as drones, particularly in the civilian sector (Finn, & Wright, 2012; Clarke, 2014; Mohammed et al., 2014). There are a number of small-scale applications for drones, thanks to their low operating costs (Zhang, & Kovacs, 2012; Sundar, & Rathinam, 2013). It has been reported that UAVs are being used to collect data on disease propagation (Fornace et al., 2014), agricultural applications (Zhang, & Kovacs, 2012; Pérez-Ortiz et al., 2015), vegetation analysis (Paneque-Gálvez et al., 2014), wildlife monitoring and conservation (Linchant et al., 2015; Sandbrook, 2015), and nighttime lighting assessment (Murray, & Feng, 2016). The use of drones can also be found in disaster relief (Adams, & Friedland, 2011), disease control (Amenyo et al., 2014), traffic monitoring (Kanistras et al., 2013), urban planning (Mohammed et al., 2014), map-making (Tahar et al., 2012), and law enforcement (Finn, & Wright, 2012; Clarke, 2014). Several academics have focused their attention on drone delivery systems because of their growing commercial interest and e-commerce exposure. It has been possible to develop numerous research directions in this area: reliability (Schenkelberg, 2016; Torabbeigi, Lim, & Kim, 2018), security (Seo et al., 2016), optimal routing and scheduling (Murray, & Chu, 2015; Wang, Poikonen, & Golden, 2017), energy efficiency and battery ageing (Park, Zhang, & Chakraborty, 2016), and inventory management (Xu, Kamat, & Menassa, 2018).

A number of advances have been made in drone capabilities, such as their endurance, speed, payload, and automated navigation systems (Kuttolamadom, Mehrabi, & Weaver, 2010), which have made their application in the package delivery field more promising (Lee, 2017). In the near future, drones package delivery systems are expected to become financially and technically feasible for the civilian sector (Thiels et al., 2015). A drone's technological advancements make it an ideal delivery vehicle. Now that carbon fiber is less expensive, drones are cheaper (Morgan, 2005), lithium polymer batteries allow for longer flight times, and they are capable of autonomous operation with GPS, localization techniques, obstacle detection and avoidance techniques. As compared to trucks, drones can also reduce carbon dioxide emissions (Goodchild, & Toy, 2018). It has been extensively investigated in the literature how these benefits can be exploited, including low delivery costs, reduced maintenance costs, and reduced labor demands (Dorling et al., 2016). The use of drones to deliver blood and vaccines has been studied by Haidari et al. (2016), Scott and Scott (2017). The simulations indicated a potential increase in vaccine availability and cost savings, particularly when drones were used frequently. Dorling et al. (2016) proposed a cost function based on drone utilization and energy consumption.

In terms of technical considerations, researchers are working to make UAVs more durable and safer. One area of research involves improving battery energy storage for UAVs of the size suitable for small parcel delivery. Flight endurance of these aircraft is affected by limited battery capacity, which can also be affected by flight speed and payload. In addition, the flight endurance of these UAVs is further decreased by the addition of redundant sensors and motors, which may be required for safety and reliability reasons. The GPS used by UAVs also has a lower accuracy of about 10 m without corrective technology (Arnold, & Zandbergen, 2011). In heavy forests and urban canyons, UAVs with GPS signals may lose connection. Therefore, more attention is being drawn to approaches that enable UAVs to function in GPS-deficient environments (Clark, & Bevly, 2008; Marais et al., 2014). Researchers are also investigating how to combat GPS "spoofing," which involves broadcasting false signals to hijack a UAV (Humphreys, 2012; Faughnan et al., 2013). It is still necessary for autonomous UAVs to detect and avoid obstacles even with perfect localization information. In this area of robotics, several methods based on vision, sonar, and laser are being improved (Jiménez, & Naranjo, 2011; Merz, & Kendoul, 2013; Apatean, Rogozan, & Bensrhair, 2013; Pestana et al., 2014, Park, & Kim, 2014).

A number of distribution centers and online retailers are implementing drone-based delivery systems, including Amazon Prime Air and Google Wing, fast-food delivery, Deutch Post, and transportation networks (D'Andrea, 2014). Researchers have begun developing operations research models from an operational perspective to optimize drone delivery systems in response to the growing commercial interest in drone delivery systems. In a number of papers, multimodal drone-truck systems have been proposed, in which delivery trucks serve as moving depots and drones are launched from the trucks [Ha et al., 2015, Ha et al., 2018]. As a result of Murray and Chu (2015), the phrase "flying sidekick traveling salesman problem" was coined, which involved first constructing truck routes for traveling salesmen, then substituting drones that deliver to certain customers and then return to the truck down the road. According to Murray and Chu (2015), drones can serve customers close to the warehouse directly by returning to the warehouse or meeting a truck route. Agatz, Bouman, and Schmidt (2015) identified the problem of following a road network by a drone, which is known as the Traveling Salesman Problem with a drone. A Heterogenous Delivery Problem was modeled by Mathew, Smith, and Waslander (2015), where drones are launched from trucks from a road endpoint, and they deliver their products to isolated customers who are located away from the roadway. To reduce delivery time as much as possible, Grippa et al. (2019) suggested assigning customer requests to drones using a task assignment strategy. In the proposed model, drone delivery requests are generated using Poisson processes based on queueing theory. Job assignment policies can be divided into two types: nearest job first to random vehicles, which chooses jobs according to the customer's location, and first job first to nearest vehicles, which chooses jobs according to the arrival time of the customer. If the load is low, the first to nearest vehicles policy will produce a smaller average delivery time, and even if the load is heavy, it will deliver on time.

2.2.2 Drones charging station

There are a few studies that examine drone-only delivery models. According to Dorling et al. (2016), UAVs can return to a depot several times to pick up additional packages or swap for a fresh battery on the basis of a vehicle routing and travel salesman problem. An extensive literature exists on location models for fueling and charging stations on rail and road networks that evaluate routes given their driving range. Researchers have pioneered building on the flow capturing (or intercepting) models to formulate flow refueling problems (Hodgson, 1990; Berman, Larson, & Fouska, 1992). In this problem, vehicles traveling the shortest path between origin and destination (O-D) must be able to complete the trip without running out of fuel given their driving ranges (Kuby, & Lim, 2005; Upchurch, Kuby, & Lim, 2009). On longer round trips, multiple fuel stops may be necessary because of range restrictions. There has been a formulation of the flow refueling problem with both maximal and complete covering objectives (Wang, & Lin, 2009), and a variety of heuristics and exact approaches have been used to solve these problems (Kuby et al., 2009; MirHassani, & Ebrazi, 2013; Capar et al., 2013) and extended (He, Yin, & Zhou, 2015; Riemann, Wang, & Busch, 2015).

A recharging station location and capability model is required to extend the flight range of the battery-powered drones. Unlike vehicle routing problem and travel salesman problem, Dorling et al. (2016) proposed a solution with a restricted flight range that enables UAVs to return to the depot multiple times to pick up additional packages and swap out batteries for fresh ones. Based on existing recharging facilities that are away from the base, Sundar and Rathinam (2013) optimize routes for the drones. Contrary to the existing research in drone route planning, this thesis extends drone-only approaches to the problem of locating a limited number of stationary recharging stations, in line with Amazon Prime Air's preliminary descriptions but with multiple charging stations to extend the service coverage and multiple charging rate to reduce the service time in the system. Among other issues, Hong, Kuby, and Murray (2017) discussed problems with installing a network of recharging stations in urban areas so that drones can be used for commercial delivery without trucking cooperatives. To minimize average flight distance from depots to recharging stations, the authors constructed a coverage location model. A heuristic approach coupled with the Greedy algorithm was used in the formulation of this approach. As a solution to the drone coverage range issue, Yu, Budhiraja, and Tokekar (2018) deployed stationary or mobile recharging stations along the way where the drone could recharge. As the drone is transported from one place to another, mobile charging stations continue to recharge it. As well as identifying when and where to land at charging stations, the proposed algorithm determines the ideal path for the drone to visit multiple locations. Additionally, it determines the best locations for recharging stations and the paths of unmanned ground vehicles. A heuristic optimization deployment approach was proposed by Huang and Savkin (2020), which addressed the issue of station location by deploying charging stations throughout the city. To increase coverage, the authors suggest moving the charging station from one place to another. According to Shao et al. (2020), an optimization algorithm for drone delivery services, including battery swapping stations and maintenance checkpoints, is implemented to increase flight distance from depot to customer based on the ant colony optimization algorithm. As part of their study, Alyassi et al. (2022) proposed an autonomous drone recharging system and assessed the impact of drone batteries on the performance of the system as well. A spiral-based scanning method was used by Bacanli, Elgeldawi, and Turgut (2021) to deploy charging stations for unmanned aerial vehicles.

It is necessary to develop a coverage location model for drone delivery by installing charging stations within existing logistics networks. It is essential to consider how long drones can carry a package under different conditions, such as when flying with or without the package, when designing a location model for charging stations. Based on the assumption that drones can serve one customer at a time across the Euclidean path and can stop by as many stations as necessary, this study addresses the problem of locating charging stations for drones in a package delivery service. Some aspects of drone charging station location are similar to flow refueling, while others are different. In addition to the limited runtime due to on-board energy storage and use, the use of stationary charging stations and the need to recharge several times on longer round trips are similar characteristics. A major difference is that ground transport refueling is based on roads or railways, while drones operate in a continuous space. Euclidean shortest path properties can be used to extract a network from continuous space, however, its structure depends on the warehouse locations, their demand nodes, and their candidate locations. the other difference is that once a package is delivered, the drone's range changes significantly. This research aims to construct a feasible delivery network that consists of warehouses and charging stations for UAVs like drones. Besides, the majority of the studies have not examined the effects of various decision parameters on drone delivery services, such as recharging station configuration, charging time, battery and drone number, flight time, and demand uncertainty. In terms of charging technology (for example, slow recharging, fast recharging, partial recharging, battery swaps, fixed charging), the main models refer to recharging technologies and routing strategies (Koç et al., 2019; Li-ying, & Yuan-bin, 2015) with a focus on sustainability, energy consumption, and power loss (Pal, Bhattacharya, & Chakraborty, 2021, Moupuri, 2021). This study addresses these gaps by introducing extra batteries in the system located at the recharging station which is considered as warehouses in this study with two different parts for full-charged batteries and empty batteries. The study develops stochastic models to deal with stochasticity in this problem and determine the best decision-making policy for decision makers based on different charging rates, arrival rates, flight rates, and costs associated with them.

2.3 Stochastic approaches for supply chain problems

This section focuses on modelling and solution approaches applied to solve the stochastic supply chain and logistics network. Solution and modeling methods can be broken into two major categories, namely stochastic optimization (Prescriptive method) and stochastic control (Descriptive method). In the following section, some of these key studies are discussed that describe the direction of this research.

2.3.1 Stochastic optimization

The stochastic supply chain network problem is normally expressed as mixed-integer linear programming models in most studies. To capture a large number of scenarios for uncertain parameters in these models, a two-stage stochastic mixed-integer programming normally is used. Louveaux and Peeters (1992) formulated a two-stage stochastic programming problem with uncertainty involving transportation cost, selling prices, production cost, and demand. Laporte, Louveaux, and van Hamme (1994) expanded the amount of uncertainty in the system by adding additional factors, such as the establishment of transportation channels between facilities and customers. Barbarosoglu and Arda (2004) developed a two-stage stochastic programming model to formulate a transportation network problem for emergency responses to disasters. They assumed that the uncertainties arising from the disruption of the transportation system leads to not only random demand, but also stochastic supply and route capacity as well. Govindan and Fattahi (2017) considered supply a chain network design problem that involved determining the location of production plants and warehouses by formulating the problem as a two-stage stochastic model. They used a Latin Hypercube Sampling method to create scenarios for stochastic demand and then, by applying a backwards-scenario reduction method, they decreased the number of scenarios. In the area of humanitarian relief logistics, Bozorgi-Amiri and Khorsi (2016) developed a dynamic multi-objective stochastic model in both pre-disaster and post-disaster conditions. In terms of quick responses to disaster relief, they examined a two-stage stochastic programming model considering the case study of an earthquake in Turkey. More recently, Jeihoonian, Zanjani, and Gendreau (2017) also formulated a two-stage stochastic mixed-integer programming model for designing a closed-loop supply chain network to deal with the uncertain quality status of the return stream. It is worth mentioning that all of these models focus on a single-period context. In the area of blood supply chains, Samani, Torabi, and Hosseini-Motlagh (2018) proposed a multi-objective mixed integer linear program for designing supply chain networks in disaster relief settings. For capturing the uncertainty of certain parameters, they formulated a hybrid two-stage stochastic model to make a trade-off between shortages in specific parameters, such as supply or demand and network cost efficiency. In the two-stage stochastic model, stochastic parameters like demand are considered as random variables with an associated probability function. All variables of the problem are classified into two stages. The first stage includes the variables which are not influenced by randomness. The decisions on variables affected by randomness are determined in the second stage based on the first stage solution and realized uncertainty in each scenario. The expected value of all scenarios in the second stage is added to the first-stage objective value to determine the total objective function. Two-stage stochastic programming can be obtained by reformulating the extensive model in a compact form as follow.

$$min C^T X + E[G(X, \xi)] \tag{2.1}$$

Subject to:

$$AX \leq B \tag{2.2}$$

$$\text{Where } G(X, \xi) = g^T(\xi)y \tag{2.3}$$

Subject to:

$$Wy + T(\xi)X \leq h(\xi) \tag{2.4}$$

The coefficients of fist-stage variables in objective function of first stage are denoted by vector C^T. Matrix A is the resource matrix of the first-stage decision variables X. The right-hand numbers in the first-stage constraints are also represented by vector B. Vector y represents second-stage variables. The coefficients of second-stage variables in objective function of second stage are denoted by vector $g^T(\xi)$. $T(\xi)$ is the technology matrix and W is the fixed recourse matrix. The right-hand numbers in the second-stage constraints are also represented by vector $h(\xi)$.

Moreover, Let $K_1 = \{X | AX \leq B, X \in \{0, 1\}\}$. For given scenario ξ, the elementary feasibility set is defined by: $K_2 = \{X | y \geq 0 \; exists \; s.t. Wy + T(\xi)X \leq h(\xi)\}$. This means all possible values of X that make second stage feasible.

These stochastic models involve computational challenges and other complexities when solved. The extensive form of this model which is a mixed-integer program can become extremely large by increasing in the number of scenarios and the scale of the supply chain system. Thus, normal commercial solvers cannot directly solve these large-scale problems with reasonable computing and memory requirements. Meta-heuristics and heuristics algorithms and several decomposition methods (e.g., the L-shaped method) are mostly used to solve stochastic models. Schütz, Tomasgard, and Ahmed (2009) proposed an approach to solve a two-stage stochastic program based on sample average approximation and dual decomposition. The objective of their paper was to minimize the investment and operating costs of supply chain networks. They assumed that there was operational uncertainty in facilities when making strategic decisions. Aghezzaf (2005) and Pimentel, Mateus, and Almeida (2013) presented Lagrangian relaxation-based approaches to solve a two-stage stochastic model and a multi-stage stochastic model, respectively. Both studies assumed that demand variability was the only source of uncertainty in the supply chain network. Recently, Diabat, Jabbarzadeh, and Khosrojerdi (2019) proposed a robust bi-objective supply chain model considering disaster scenarios. The objective of this model was to minimize the time and cost once the disaster occurred. The Lagrangian relaxation and constraint methods were applied to solve the model by considering a case study. In addition, many other studies presented meta-heuristic or heuristic algorithms in this area (Drezner, 1987; Shen, Zhan, & Zhang, 2011; Berman, Krass, & Menezes, 2007; Govindan, Jafarian, & Nourbakhsh, 2015; Cardona-Valdés, Álvarez, & Pacheco, 2014; Pan & Nagi, 2010; Fattahi et al., 2015). Finally, one of the popular approaches in obtaining an exact solution for the Stochastic supply chain network problem is Benders decomposition and is usually known as L-shaped bender decomposition (Santoso et al., 2005; Kiya, & Davoudpour, 2012; Keyvanshokooh, Ryan, & Kabir, 2016). This study applies L-shaped decomposition algorithm of stochastic linear programming by integrating two types of optimality and feasibility cuts for solving the model. In contrast to other studies, this research tries to improve the performance of the algorithm by replacing the single-cuts method with the multi-cuts version and creating a relatively complete recourse compared to the original stochastic model. This extended solution method allows us to find an optimal solution for large-scale problems of numerous scenarios in a reasonable time frame.

The L-shaped method algorithm is presented by Van Slyke and Wets (1969) for stochastic linear programming. The computation time and memory requirement for solving stochastic linear programming is greatly reduced by the L-shaped method algorithm through the drop in the number of second-stage problems. Whenever the second-stage value function is convex and piecewise linear, this approach integrates the second-stage value function into the master problem by a finite number of feasibility and optimality cuts generated by solving linear programming problems. Deterministic master problem and a recourse subproblem with fixed coefficients of decision variable are the major components of the two-stage stochastic programming problem solved by the L-shaped approach (Birge, & Louveaux, 1997; Kall, Wallace, & Kall, 1994). The master problem has fewer variables but many constraints in comparison to the subproblem. The constraints iteratively add up as Bender cuts to the master problem. This method replaces the expected cost function $E[G(X, \xi)]$ of recourse subproblem in the master problem by a piecewise linear function over all scenarios. The optimal value of the master problem has a lower bound and an upper bound on the expected optimal value of the subproblem. Two-stage stochastic can be reformulated by adding constraints (2.5) and (2.6) based on applying L-shaped method:

$$D_l X \geq d_l \qquad l = 1, \dots, r \tag{2.5}$$

$$E_l X + \theta \geq e_l \qquad l = 1, \dots, s \tag{2.6}$$

If a first-stage decision $X \in K_1$ is not $X \in K_2$, a constraint (called a feasibility cut) of type (2.5) should be generated and add to the master problem. If a first-stage decision $X \in K_1$ is also $X \in K_2$, For all $\xi = 1, \dots,$ k solve the linear program:

$$Min\, w = g^T(\xi) y \tag{2.7}$$

Subject to:

$$Wy + T(\xi) X^v \leq h(\xi) \tag{2.8}$$

$$y \geq 0$$

In this case, let π_ξ^v be the associated simplex multipliers of problem ξ of type (2.8) and define:

$$E_{s+1} = \sum_{\xi=1}^{K} q_\xi . (\pi_\xi^v)^T T(\xi) \,/ e_{s+1} = \sum_{\xi=1}^{K} q_\xi . (\pi_\xi^v)^T h(\xi)$$

Let $w^v = e_{s+1} - E_{s+1}X^v$. If $\theta^v \geq w^v$, then stop algorithm and X^v is an optimal solution. Otherwise, add to the constraint (called an optimality cut) of type (2.6).

2.3.2 Stochastic control

A stochastic control problem deals with uncertainties when making decisions to maximize or minimize an objective function. With a given objective function, decision makers need to determine a strategy, which is the stochastic control, to optimize the objective function in a random environment. The stochastic control can be generally considered as the linear control system given by the equations:

$$x^{(t+1)} = Ax^{(t)} + B(U^{(t)}\big(y^{(0)}, \dots, y^{(t)}\big) + \omega^{(t)} \tag{2.9}$$

In equation (2.9), $x^{(t)}$ represents the state of the system at time t, and $y^{(t)}$ is the output of the system at time t. The control input applied at time t depends on the history through the output feedback map $U^{(t)}$. The $\omega^{(t)}$ represents the uncertainty in the state of the system.

Inventory management includes tactical decisions in supply chains system which can be descried by dynamic linkages of sequential decisions under multiple sources of uncertainty. These include storage condition for drones, batteries, charging rate, flight rate, demand, etc., that can affect the outcomes and therefore impact the optimal control decisions in these supply chains. Markov decision process (MDP) is discrete stochastic process that provide a mathematical framework for modeling decision making in situations where outcomes are probabilistic (Puterman, 2014). MDP is descriptive operation research method and one of the approaches use in stochastic control to describe the system. To optimal control decisions in this problem, it is suggested to use MDP. One of the elements in MDP is Decision Epochs which is action or decisions are taken at epochs corresponding to changes in the state. State Space is another element which is the state of the system needed to make decisions and quantify outcomes like the number of items is inventory. An individual state can be theoretically described as a location within the state-space. The action space is another element that includes all the potential unique actions can be taken at any given state. There is transition model in MDP which is the transition probability from one state to another state under specific action. The transition probability matrix (or transition model) includes all the transition probabilities within the state space. The expected net benefit received for being in one state and taking specific action called rewards in MDP. The total set of rewards can be defined using a function or a matrix. Another important element of MDP is policy π which is defined as a mapping of actions to take given the state. The value function for a policy π is V_π, which can be described recursively as in Equation (2.10) using Bellman's equations, where $\pi(s)$ is the action to take as determined by the policy π and γ is the discount factor that prevents the value function from going to infinity. The optimal policy π^* is defined as the decision policy which maximizes the value function, see Equation (2.11).

$$V_\pi(s) = R\big(s, \pi(s)\big) + \gamma \sum_{s' \in \mathcal{S}} p\big(s' | s, \pi(s)\big) V_\pi(s') \tag{2.10}$$

$$\pi^* = \arg\max{}_{\pi'}(V_{\pi'}) \tag{2.11}$$

Obtaining optimal policy π^* that maximizes the value function at each state is the goal of dynamic programming. There are different approaches of finding optimal policies for MDPs. One of the most popular ways to solve for the optimal policy is by implementing the Policy Iteration algorithm (Bellman, 1995). This algorithm works under a simple premise. Firstly, select an initial policy and then determine the value of each state under the current policy. Next, consider whether the value could be improved by selecting a different action. If it can, change the policy at that state to take this new action. This step-by-step process gradually improves the performance of the policy and when no improvements are possible, then the policy is guaranteed to be optimal.

Another popular method is accomplished by formulating the MDP problem as a Linear Program (Manne, 1960). See below for the formulation of an MDP problem as a LP. This requires knowledge or an assumption of the initial state or its probability distribution μ_0 over S, with $\mu_0 > 0$ for all $s \in S$.

$$\begin{aligned} &\max \ \mu_0(s)V(s) \\ &\text{s.t.} \quad V(s) \geq R(s,a) + \gamma \sum_{s' \in \mathcal{S}} p(s'|s,a)V(s') \ \ \forall\, s \in \mathcal{S}, a \in \mathcal{A} \end{aligned} \tag{2.12}$$

Policy iteration are typically faster than general LP algorithms (Farias, & Roy, 2003). There are several challenges with solving large-scale MDPs, especially in practice. One of the most significant challenges is that the information desired to be captured by the states and actions will grow (often exponentially) based on the problem's complexity. This is why dynamic programming is sometimes avoided for large problems. To overcome this challenge, the original Markov decision problem can be split for the system with *N* states into *N* independent Markov chain processes. Each of this independent system is corresponding as a subsystem which efficiently evaluates one of those *N* states. In terms of accuracy of decomposition technique in each subsystem, the impact of other states needs to be accounted.

Chapter 3 - Stochastic Optimization and Designing Reliable Supply Chain Network

Chapter 3.1 to 3.4 is based on the manuscript "A two-stage stochastic mixed-integer program for reliable supply chain network design under uncertain disruptions and demand" Published in Computers & Industrial Engineering (Tolooie, Maity, & Sinha, 2020). Apart from commercial application of L-shape decomposition algorithm, Chapter 3.5 provides another application for this approach in the security-constrained unit commitment problem. Finally, Chapter 3.6 presents the conclusions.

3.1 Introduction

Nowadays, supply chain systems have become more complex and dynamic with wide geographical coverage. Hence, supply chains are exposed to a broad range of uncertainties, some of which may cause disruptions in the supply chain (Rezapour, Farahani, & Pourakbar, 2017). Accidental disruption of facilities due to large-scale natural disasters, manufacturing fires, terrorist attacks, wide-spread electrical shutdowns, and financial or political tension, is among several other uncertainties that are likely to occur (Govindan, Fattahi, & Keyvanshokooh, 2017). Therefore, supply chain disruptions have been a challenging issue for many companies worldwide. The disruption at one level of a supply chain can significantly impact the entire chain: for instance, any failure of a distribution center could cost company additional transportation costs to satisfy customer demand (Snyder & Daskin, 2007). Disruptions in supply chains have enormous financial impacts and, in some cases, cause a permanent loss of market share. Hendricks and Singhal (2003) reported on some of the severe impacts of supply chain disruptions on market share, which in some cases fell lower than 11% from just the announcement of disruptions alone. To hedge against supply chain disruptions, a well-designed and reliable network is a top priority. The key to managing disruption risks in supply chains is not through the elimination of cost reduction or through efficiency but by creating supply chains that are both efficient in stable conditions and capable of handling hazards in unstable conditions. Hence, reliable and flexible supply chain designs have become a significant consideration to the decision maker.

Unlike classical facility location problems where all facilities are reliable, this study adopts Lim et al. (2010)'s reliability concept in our model formulation and consider two types of facilities: unreliable facilities (influenced by random disruptions) and reliable facilities (resistant to random disruptions due to additional investment). This research also applies a hardening strategy to a set of potential distribution center nodes that helps to hedge against the risk of disruptions in the facility reliability problem. Our model also extends the capacitated facility location problem by making decisions regarding the selection of a supplier, the locations of reliable and unreliable distribution centers, the allocation of suppliers to customers, and the amount of products channeled through the network in a multi-time period.

This research seeks to obtain both the optimal number and the locations of both suppliers and distribution centers in order to minimize the total expected transportation cost for the entire supply chain network across all future scenarios. Therefore, our problem is formulated as a two-stage stochastic mixed-integer programming model in order to design a reliable and efficient supply chain network design under the uncertainty of demand and disruptions. Due to the fact that most of the variables and constraints are scenario-dependent, their numbers grow rapidly as the number of scenarios increases. As a result of this growth, standard solutions cannot be efficiently applied to solve this kind of problem. On the other hand, the two-stage structure of the problem leads us to apply decomposition method to tackle such models more efficiently. There are several developed decomposition-based approaches for solving two-stage stochastic programming: the

Bender decomposition method is one of the more powerful techniques for solving large scale problems with complicated variables (Conejo et al., 2006).

In the two-stage stochastic formulation, the decisions of allocation nodes in the second stage of the problem are decomposed by scenarios once the first-stage variables (location of facilities) are fixed. This observation leads to the development of the efficient solution method for two-stage stochastic problems based on the well-known L-shaped method (Van Slyke & Wets, 1969), which is an adaptation of the Bender decomposition method. The L-shaped method uses the fact that the second-stage value function is convex and piecewise, thus, it may be integrated into the master problem with a finite number of bender cuts, called optimality and feasibility cuts by solving linear programming problems.

Due to the computational complexity of the stochastic mixed-integer model, this method is extended by replacing the single-cuts with multi-cut versions and creating relatively complete recourse in stochastic models by reformulating the original model. This improved algorithm can reduce the significant number of linear programming problems that must be solved in the second-stage for generating bender cuts, leading to improved running times. Computational efficiencies of improved algorithms are presented in the analysis section. The main contributions of this chapter are:

First, this study analyzes stochasticity in a multi-period supply chain network design problem where the reliability of the facilities and the demand of the end customers are random. To the best of our knowledge, no existing studies have analyzed capacitated facility network design while considering these two uncertainties at the same time in multi-time periods. This research aims to determine the optimal locations of both the suppliers and the distribution centers to minimize the total expected transportation cost for the entire supply chain network under uncertainty. In other words, the model adjusts the facility location choice and flow allocation decisions in response to the change in demand and the number of operational facilities. The proposed problem is formulated as a two-stage stochastic mixed-integer programming model to design a reliable and efficient supply chain network.

Second, the research adopts a combination of the two types of supply chain network design strategies simultaneously for designing a reliable network under two different uncertain parameters in multi-time periods. This study considers reassignment strategies once a disruption has happened and hardening strategies when there are no disruptions in the system.

Third, it is theoretically shown that if at least one of the suppliers are selected in the first stage, then our proposed stochastic model falls under the category of complete recourse. In other words, the second stage formulation is always feasible for any first stage feasible solution. This study also extends the L-shape algorithm by replacing the single-cuts method with a multi-cuts version, and then compare the results for the single-cut, multi-cut, and complete recourse versions under a case study presented in Peng, Snyder, Lim, and Liu (2011).

The main contributions of this study in comparison to the existing literature are evident in following points:

- Determining optimal facility locations and allocation while jointly considering randomness in the demand and facility failures.
- Using reassignment strategies once a disruption has happened, and using hardening strategies with both reliable and unreliable facilities once there are no disruptions in the system, in order to design an efficient and reliable supply chain network.
- Formulating two-stage stochastic mixed-integer programming models for multi-period capacitated facility locations and allocation problems.

- Developing an efficient solution method for stochastic mixed-integer programming based on the L-shaped decomposition method.
- Providing a trade-off analysis between optimal locations of facilities, disruption probability, and transportation costs.

Next Chapter 3.2 describes how to formulate the two-stage stochastic mixed-integer programming model for reliable supply chain network. The L-shape decomposition algorithm with different types of cuts and the way of replacing multi-cut with single-cut are described by Chapter 3.3. Although the lack of real-world stochastic parameters is being recognized as a main limitation of this problem, Chapter 3.4 provides numerical examples that show the applicability and efficiency of our model and problem-solving approach.

3.2 Reliable supply chain model

This research studies models for reliable supply chain network problems under stochastic demands and with a disruption probability for facilities. The main decision is to choose a set of locations from a set of potential nodes for facility that are robust under disruptions. Any failure of a distribution center could cost the company additional transportation costs to reassign the customer demand. This is best illustrated in Figure 3.1, where the failure of a distribution center costs the company additional transportation costs to satisfy the demand of customers by providing another most available distribution center as a penalty.

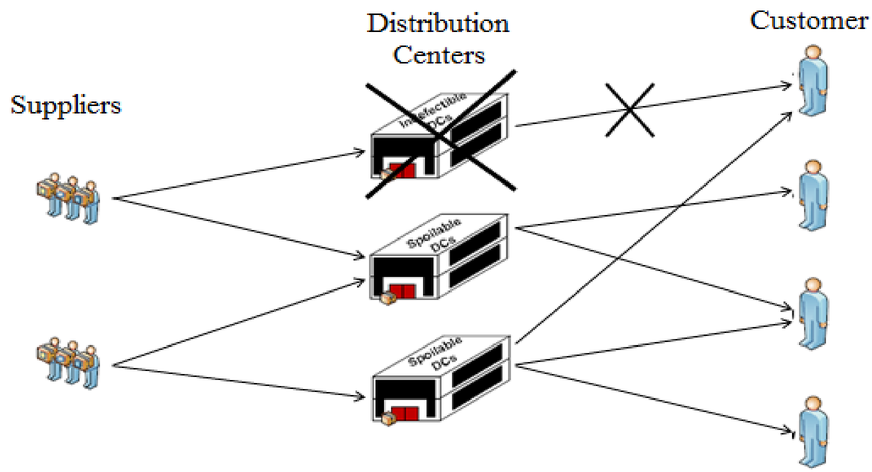


Figure 3.1 Supply chain network under disruption

The proposed supply chain three levels: suppliers, distribution centers, and customer. The customer locations are constant and certain. Each distribution center j ($j \in J$) has either an unreliable facility with fixed cost of f_j^U which may fail with probability q_j ($0 < q_j < 1$) or a reliable facility with fixed cost of f_j^R ($f_j^R \geq f_j^U$) which does not fail. These potential sites are definite and discrete. As Lim et al. (2010) examined, unreliable center hardening cost is presented by a linear function based on failure probability which is calculated by this equation: h=(f_j^R - f_j^U) = (f_j^U*10)*q_j. Consequently, if a site incurs more failure probability, the costs of establishment would augment to compensate for more reliability. Another assumption in the formulated problem is that a single-product that can just move between two different network levels. This implies that no relationships exist among facilities in the same level. This study also assumes that each customer node c($c \in C$) is completely fulfilled either by distribution centers or by suppliers with higher transportation cost as a penalty of not satisfying with distribution center in each period. The objective here is to minimize the fixed cost of facilities and expected transportation cost between facilities by locating a suitable number of reliable facilities among the unreliable facilities, and also to specify the flow volume of products between the facilities within each time period. The demand d_{cp} of customer c ($c \in C$) in period p ($p \in P$) is random with a known distribution. The disruptions occur only in distribution centers with a defined disruption probability and these probabilities and failure occurrence are assumed independent of each other, i.e. when one distribution center fails, it does not have any negative influence on operating other distribution centers.

The extensive form of deterministic equivalent formulation is first derived by extending the capacitated facility location problem for circumstance which a finite set of scenarios can capture uncertainties in the subsequent section, then the two-stage stochastic model is formulated for circumstance which the number of scenarios increase significantly.

3.2.1 Proposed extensive form model

Table 3.1 Sets, parameters and decision variables for Reliable Supply Chain Model

Sets		
I	The set of candidate sites for suppliers	
J	The set of candidate sites for distribution centers	
C	The set of constant customers	
J_c	The set of candidate sites for distribution centers that can cover each customer $c, c \in C$	
P	The set of time periods	
S_d^C	The set of scenarios for demand	
S_f^D	The set of plausible scenarios for disruptions in distribution centers	
Parameters		
f_i	Fixed cost of established supply nodes i,	$i \in I$
f_j^U	Fixed cost of established unreliable distribution nodes j,	$j \in J$
f_j^R	Fixed cost of established reliable distribution nodes j,	$j \in J$
T_{ij}^S	Transportation cost from supplier i to distribution center j,	$i \in I,\ j \in J$
T_{jc}^D	Transportation cost from distribution center j to customer c,	$j \in J_c,\ c \in C$
T_{ic}^C	Transportation cost from supplier i to customer c,	$i \in I,\ c \in C$
d_{cp}	Demand of customer c in each period p,	$\forall c \in C,\ \forall p \in P$
K_i^S	Capacity at supplier i,	$i \in I$
K_j^D	Capacity at distribution center j,	$j \in J$
q_d^C	Probability of a demand scenario d,	$d \in S_d^C$

q_f^D	Probability of a disruptions scenario f,	$f \in S_f^D$
a_{jf}^D	0–1 indicated parameter if facility j is included in scenario f,	$j \in J, f \in S_f^D$
a_d^C	Percentage variation in demand for each scenario d,	$d \in S_d^C$
Binary Decision variables		
X_i	$\begin{cases} 1 \text{ if supplier } i \text{ is established} \\ \quad 0\ if\ otherwise \end{cases}$	
X_j^U	$\begin{cases} 1\ if\ unreliable\ distribution\ center\ j\ is\ established \\ \quad 0\ if\ otherwise \end{cases}$	
X_j^R	$\begin{cases} 1\ if\ reliable\ distribution\ center\ is\ j\ established \\ \quad 0\ if\ otherwise \end{cases}$	
Continuous Decision variables		
B_{jcpdf}^U	The percentage of demand sent from unreliable distribution center $j(j \in J_c)$ to customer $c(c \in C)$ in each period $p(p \in P)$, demand scenario $d(d \in S_d)$, and disruption scenario $f(f \in S_f)$.	
B_{jcpdf}^R	The percentage of demand sent from reliable distribution center $j(j \in J_c)$ to customer $c(c \in C)$ in each period $p(p \in P)$, demand scenario $d(d \in S_d)$, and disruption scenario $f(f \in S_f)$.	
Z_{icpdf}	The percentage of demand sent from supplier $i(i \in I)$ to customer $c(c \in C)$ in period $p(p \in P)$, demand scenario $d(d \in S_d)$, and disruption scenario $f(f \in S_f)$.	
Y_{ijpdf}^U	The amount of supply sent from supplier $i(i \in I)$ to unreliable distribution center $j(j \in J)$ in period $p(p \in P)$, demand scenario $d(d \in S_d)$, and disruption scenario $f(f \in S_f)$.	
Y_{ijpdf}^R	The amount of supply sent from supplier $i(i \in I)$ to reliable distribution center $j(j \in J)$ in period $p(p \in P)$, demand scenario $d(d \in S_d)$, and disruption scenario $f(f \in S_f)$.	

Table 3.1 presents the necessary sets, parameters and decision variables. The multi-period capacitated facility location and allocation problems under stochastic demand and random disruption can be formulated as mixed-integer programming in extensive form as follow.

$$
\begin{aligned}
Min \quad & \sum_{i \in I} f_i X_i + \sum_{j \in J} f_j^U X_j^U + \sum_{j \in j} f_j^R X_j^R + \sum_{j \in J_c} \sum_{c \in C} \sum_{p \in P} \sum_{d \in S_d^C} \sum_{f \in S_f^D} q_d^C q_f^D a_d^C d_{cp} T_{jc}^D B_{jcpdf}^U \\
& + \sum_{j \in J_c} \sum_{c \in C} \sum_{p \in P} \sum_{d \in S_d^C} \sum_{f \in S_f^D} q_d^C q_f^D a_d^C d_{cp} T_{jc}^D B_{jcpdf}^R + \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{d \in S_d^C} \sum_{f \in S_f^D} q_d^C q_f^D T_{ij}^S Y_{ijpdf}^U \\
& + \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} \sum_{d \in S_d^C} \sum_{f \in S_f^D} q_d^C q_f^D T_{ij}^S Y_{ijpdf}^R + \sum_{i \in I} \sum_{c \in C} \sum_{p \in P} \sum_{d \in S_d^C} \sum_{f \in S_f^D} q_d^C q_f^D a_d^C d_{cp} T_{ic}^C Z_{icpdf} \qquad (3.1)
\end{aligned}
$$

Subject to:

$$X_j^U + X_j^R \leq 1, \qquad \forall j \in J \tag{3.2}$$

$$\sum_{j \in J} X_j^R \geq 1, \tag{3.3}$$

$$\sum_{j \in J_c} B_{jcpdf}^U + \sum_{j \in J_c} B_{jcpdf}^R + \sum_{i \in I} Z_{icpdf} = 1, \qquad \forall c \in C, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D \tag{3.4}$$

$$B_{jcpdf}^U \leq X_j^U a_{jf}^D, \qquad \forall j \in J_c, \forall c \in C, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D \tag{3.5}$$

$$B_{jcpdf}^R \leq X_j^R a_{jf}^D, \qquad \forall j \in J_c, \forall c \in C, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D \tag{3.6}$$

$$Z_{icpdf} \leq X_i, \qquad \forall i \in I, \forall c \in C, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D \tag{3.7}$$

$$\sum_{i \in I} Y_{ijpdf}^U = \sum_{c \in C} a_d^C d_{cp} B_{jcpdf}^U, \qquad \forall j \in J_c, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D \tag{3.8}$$

$$\sum_{i \in I} Y_{ijpdf}^R = \sum_{c \in C} a_d^C d_{cp} B_{jcpdf}^R, \qquad \forall j \in J_c, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D \tag{3.9}$$

$$\sum_{j \in J} Y_{ijpdf}^U + \sum_{j \in J} Y_{ijpdf}^R + \sum_{c \in C} a_d^C d_{cp} Z_{icpdf} \leq X_i K_i^S, \qquad \forall i \in I, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D \tag{3.10}$$

$$\sum_{i \in I} Y_{ijpdf}^U \leq K_j^D X_j^U a_{jf}^D, \qquad \forall j \in J, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D \tag{3.11}$$

$$\sum_{i\in I} Y^R_{ijpdf} \le K^D_j X^R_j a^D_{jf}, \qquad \forall j \in J, \forall p \in P, \forall d \in S^C_d, \forall f \in S^D_f \tag{3.12}$$

$$\sum_{i\in I}\sum_{c\in C} a^C_d d_{cp} Z_{icpdf} + \sum_{i\in I}\sum_{j\in J} Y^U_{ijpdf}$$

$$+\sum_{i\in I}\sum_{j\in J} Y^R_{ijpdf} = \sum_{c\in C} a^C_d d_{cp},$$

$$\forall p \in P, \forall d \in S^C_d, \forall f \in S^D_f \tag{3.13}$$

$$X_i, X^U_j, X^R_j \in \{0,1\}, \qquad \forall i \in I, \forall j \in J \tag{3.14}$$

$$B^U_{jcpdf}, B^R_{jcpdf}, Y^U_{ijpdf}, Y^R_{ijpdf}, Z_{icpdf} \ge 0, \qquad \forall i \in I, \forall j \in J, \forall c \in C, \forall p \in P,$$

$$\forall d \in S^C_d, \forall f \in S^D_f \tag{3.15}$$

Equation (3.1) is the objective function and consists of eight terms. The first three are the fixed costs of establishing supply facilities, unreliable distribution centers, and reliable distribution centers, respectively. The transportation cost from unreliable or reliable distribution center j ($j \in J_c$) to the customer c ($c \in C$) over all plausible scenarios and all periods is calculated by the fourth and fifth terms. The product transportation cost from supplier i ($i \in I$) to unreliable or reliable distribution center j ($j \in J$) is calculated by the sixth and seventh terms. The eighth term calculates the transportation cost from supplier i ($i \in I$) to the customer c ($c \in C$) as a penalty cost for not satisfying the particular customer demand.

For each time period $p, p \in P$, the constraints are described as follow. Constraint (3.2) indicates that for any candidate site we can only locate an unreliable or a reliable distribution center. Constraint (3.3) ensures that there should be at least one reliable distribution center. Constraint (3.4) ensures that each customer must be at least assigned to one of the facilities. Constraints (3.5) and (3.6) indicate that each customer must be assigned to a distribution center which is not failed after disruption for each scenario. Moreover, each customer can only be allocated to the distribution center given that the distribution center is already established. Constraint (3.7) also ensures that each customer can only be assigned to the supplier given that the supplier is already established for each time period and scenario. Constraint (3.8) and (3.9) ensure that the sum of inflow to distribution center j must be equal to the sum of outflow from that distribution. Constraint (3.10) states that a flow occurs if and only if the supplier node is established and the outflow of each supplier node should be less than or equal to its capacity. Constraint (3.11) and (3.12) indicate the inflow to each distribution center node is less than or equal to its capacity, given that the distribution center is established. Constraint (3.13) ensures that all outflows of products from all the suppliers must equal sum of all the customer nodes demands. Constraints (3.14) and (3.15) are non-negative constraints used to represent the binary variables and product-flow variables between the facilities, respectively.

3.2.2 Proposed two-stage stochastic model

To control the large number of scenarios, this study now presents a two-stage stochastic mixed-integer programming with stochastic demand and random disruption while other parameters are deterministic. In two-stage stochastic approach, stochastic parameters are considered as random variables with an associated probability function. In this approach the variables of problem are classified in two stages. The decisions on variables like number and location of facilities which are not affected by randomness are made in first stage. The allocation of customers and amount of supplies which vary regard to randomness are determined in second stage based on facilities location and realized uncertainty in each scenario. The total objective function in this approach consists of the sum of the first-stage objective value and the expected value of all scenarios in the second stage.

In order to make the two-stage stochastic programming formulation for the reliable supply chain network design problem, considering $\xi = (S_d^C, S_f^D)$ as the set of scenarios. For any$A \in \xi$, let $q_A$be the joint probability of S_d^C and S_f^D that scenario A happens. The two-stage stochastic programs can be formulated as:

$$Min \quad \sum_{i \in I} f_i X_i + \sum_{j \in J} f_j^U X_j^U + \sum_{j \in j} f_j^R X_j^R + E[G(X, \xi)] \tag{3.16}$$

Subject to:

$$X_j^U + X_j^R \leq 1, \qquad \forall j \in J \tag{3.17}$$

$$\sum_{j \in J} X_j^R \geq 1, \tag{3.18}$$

$$X_i, X_j^U, X_j^R \in \{0, 1\}, \qquad \forall i \in I, \forall j \in J \tag{3.19}$$

Where $G(X, \xi)$ is the optimal value of the following problem:

$$\begin{aligned} Min \sum_{j \in J_c} \sum_{c \in C} \sum_{p \in P} a^C(\xi) d_{cp} T_{jc}^D B_{jcp}^U(\xi) + \sum_{j \in J_c} \sum_{c \in C} \sum_{p \in P} a^C(\xi) d_{cp} T_{jc}^D B_{jcp}^R(\xi) + \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} T_{ij}^S Y_{ijp}^U(\xi) \\ + \sum_{i \in I} \sum_{j \in J} \sum_{p \in P} T_{ij}^S Y_{ijp}^R(\xi) + \sum_{i \in I} \sum_{c \in C} \sum_{p \in P} a^C(\xi) d_{cp} T_{ic}^C Z_{icp}(\xi) \end{aligned} \tag{3.20}$$

Subject to:

$$\sum_{j \in J_c} B_{jcp}^U(\xi) + \sum_{j \in J_c} B_{jcp}^R(\xi) + \sum_{i \in I} Z_{icp}(\xi) = 1, \qquad \forall c \in C, \forall p \in P \tag{3.21}$$

$$B_{jcp}^U(\xi) \leq X_j^U a_j^D(\xi), \qquad \forall j \in J_c, \forall c \in C, \forall p \in P \tag{3.22}$$

$$B_{jcp}^R(\xi) \leq X_j^R a_j^D(\xi), \qquad \forall j \in J_c, \forall c \in C, \forall p \in P \tag{3.23}$$

$$Z_{icp}(\xi) \leq X_i, \qquad \forall i \in I, \forall c \in C, \forall p \in P \tag{3.24}$$

$$\sum_{i \in I} Y_{ijp}^{U}(\xi) = \sum_{c \in C} a^{C}(\xi) d_{cp} B_{jcp}^{U}(\xi), \qquad \forall j \in J_c, \forall p \in P \tag{3.25}$$

$$\sum_{i \in I} Y_{ijp}^{R}(\xi) = \sum_{c \in C} a^{C}(\xi) d_{cp} B_{jcp}^{R}(\xi), \qquad \forall j \in J_c, \forall p \in P \tag{3.26}$$

$$\sum_{j \in J} Y_{ijp}^{U}(\xi) + \sum_{j \in J} Y_{ijp}^{R}(\xi) + \sum_{c \in C} a^{C}(\xi) d_{cp} T_{ic} Z_{icp}(\xi) \le X_i K_i^{S}, \qquad \forall i \in I, \forall p \in P \tag{3.27}$$

$$\sum_{i \in I} Y_{ijp}^{U}(\xi) \le K_j^{D} X_j^{U} a_j^{D}(\xi), \qquad \forall j \in J, \forall p \in P \tag{3.28}$$

$$\sum_{i \in I} Y_{ijp}^{R}(\xi) \le K_j^{D} X_j^{R} a_j^{D}, \qquad \forall j \in J, \forall p \in P \tag{3.29}$$

$$\sum_{i \in I} \sum_{j \in J} Y_{ijp}^{U}(\xi) + \sum_{i \in I} \sum_{j \in J} Y_{ijp}^{R}(\xi) + \sum_{i \in I} \sum_{c \in C} a^{C}(\xi) d_{cp} Z_{icp}(\xi) = \sum_{c \in C} a^{C}(\xi) d_{cp} \qquad \forall p \in P \tag{3.30}$$

$$B_{jcp}^{U}(\xi), B_{jcp}^{R}(\xi), Y_{ijp}^{U}(\xi), Y_{ijp}^{R}(\xi), Z_{icp}(\xi) \ge 0, \qquad \forall i \in I, \forall j \in J, \forall c \in C, \forall p \in P \tag{3.31}$$

Note that $G(X, \xi)$ the optimal value of the second-stage problem (3.20) – (3.31) is a function of the first-stage decision variable X and realization of uncertain parameters under each scenario ξ. Equation (3.16) is the objective function of first-stage consists of four terms. The first three are the fixed costs of establishing supply facilities, unreliable distribution centers, and reliable distribution centers, respectively. The second term is expected value of all transportation cost between any two level of supply chain over all possible scenarios. This expected value is calculated with respect to the joint probability distribution of uncertain parameters. Equation (3.20) is the objective function of second-stage which minimizes the total transportation cost between any two nodes in different level of supply chain. This equation is a function of the first-stage decision variable and realization of uncertain parameters (demand and disruption) under each scenario ξ. Constraints (3.21) – (3.31) are same as constraints (3.4) – (3.15) except the fact that the decision variables of first stage and uncertain parameters are realized before starting the second stage.

3.3 Solution methodology

3.3.1 Background

The L-shaped method algorithm is presented by Van Slyke and Wets (1969) for stochastic linear programming. The computation time and memory requirement for solving the problem is greatly reduced by this approach through the reduction in the number of second-stage problems. The concept behind this method is that whenever the second-stage value function is convex and piecewise linear on a polyhedral domain, this function can be introduced by a finite number of feasibility and optimality cuts to the main problem. These cuts can be generated by solving linear programming.

The L-shaped method algorithm is developed by Laporte, Louveaux, and van Hamme (1994) to solve mixed-integer stochastic model which the integer variables are always included in the first stage. The whole idea of this extended algorithm is to create a method for obtaining the feasible solutions for first stage integer or non-integer variables and using them in the linear outer approximation of $G(X,\xi)$ for continuous variables. In this method the second-stage problem is linear, thus the duality theory of linear programming can be applied to gain outer approximations of the recourse cost function. Thus base on the concept of decomposition, linearization, and approximation, this study follows the L-shaped method to present the solution approach.

3.3.2 Feasibility and optimality cuts

The two-stage stochastic programming problem is decomposed into deterministic master problem and a recourse subproblem with fixed coefficients of decision variable by the L-shaped approach (Birge, & Louveaux, 1997; Kall, Wallace, & Kall, 1994). The master problem contains fewer variables but a large number of constraints in compare with subproblem. These constraints iteratively added to the master problem are known as benders cuts. In this approach, the recourse subproblem is solved by using optimal solution of master problem to determine the optimality and feasibility cuts over all scenarios. These cuts are iteratively added in the master problem as additional constraints. The purpose of this method is to replace the expected cost function of recourse subproblem over all scenarios in the master problem by a piecewise linear function. The optimal value in the master problem has a lower bound on the optimal value and an upper bound on the expected optimal value of the subproblem. In this study, the L-shaped method is applied into reliable supply chain network design problem with demand and disruption uncertainties. As a result, the master problem determines the facility location plan with piecewise linear function of transportation cost. The reason for formulating the problem in a multi-period setting is that the decision made about the first stage variables depends on the expected cost value of all scenarios which go through all periods in each scenario in the second stage. If the model is not formulated as a multi-period problem, then the decision to open facilities without considering how to allocate the facilities to the customers in later time periods will depend on which one is the cheaper one. However, that may not be optimal in a combined model where each facility has a disruption probability and can fail in later time periods. The disruption is only realized in subsequent time periods which also impacts the allocation (considers transportation costs and demand) to the customers. If the model suggested opening a cheaper facility but later, it failed because of the high disruption probability then the customers allocated to this facility has to be reassigned which might cause huge transportation costs for the system. If we consider the impact of choosing to open a facility in later time periods, then only the decision will be optimal as we also consider the transportation costs and disruptions. Thus, the total expected cost of second stage decisions affects the optimal solution of the first stage. In addition, a different number of periods can result in different total expected costs in the second stage which might result in totally different optimal answers for first stage variables. The reliable supply chain under demand and disruption uncertainties can be reformulated by adding following cuts to the first stage of two-stage stochastic model:

Optimality cut:

$$\sum_{i\in I} X_i E_{i,l} + \sum_{j\in J} X_j^U E_{j,l} + \sum_{j\in j} X_j^R E_{j,l} + E[G(X,\xi)] \geq \omega_l \qquad l = 1, \dots, s \tag{3.32}$$

Feasibility cut:

$$\sum_{i\in I} X_i D_{i,l} + \sum_{j\in J} X_j^U D_{j,l} + \sum_{j\in j} X_j^R D_{j,l} \geq d_l \qquad l = 1, \dots, r \tag{3.33}$$

Let $r = s = v$ is the number of iteration of master problem. Let μ_1 represents a set of all possible values of X_i, X_j^U and X_j^R that make first stage feasible and μ_2 represents a set of all possible values of X_i, X_j^U and X_j^R that make second stage feasible. The constraint (3.32) called optimality cut is added to the master problem whenever first-stage decision $X \in \mu_1$ is also $X \in K\mu_2$. $E_{i,l}$ for $i \in I, E_{j,l}$ for $j \in J$ and ω_l are determined using the duals variables present in constraints (3.21) – (3.30) and calculated by following steps:

For all $\xi = 1, \dots, k$ solve the linear program (3.20) – (3.31):

In this case, let $\pi_\xi^v(m)$ be the associated dual value of problem ξ of constraint of type (m) in iteration v and define:

$$E_{i,l} = \sum_{\xi=1}^{K} (-q_\xi \pi_\xi^v(24) - q_\xi \pi_\xi^v(27)\, K_i^S) \qquad \forall i \in I \tag{3.34}$$

$$E_{j,l} = \sum_{\xi=1}^{K} (-q_\xi \pi_\xi^v(22) a_j^D(\xi) - q_\xi \pi_\xi^v(23) a_j^D(\xi) - q_\xi \pi_\xi^v(28) K_j^D a_j^D(\xi)$$
$$- q_\xi \pi_\xi^v(29) K_j^D a_j^D(\xi)) \qquad \forall j \in J \tag{3.35}$$

$$\omega_{l,p} = \sum_{\xi=1}^{K} (q_\xi \pi_\xi^v(21) + q_\xi \pi_\xi^v(30) \sum_{c \in C} a^C(\xi) d_{cp}) \qquad \forall p \in P \tag{3.36}$$

$$\omega_l = \sum_{p \in P} \omega_{l,p}$$

Let $w^v = \omega_l - \sum_{i \in I} X_i E_{i,l} - \sum_{j \in J} X_j^U E_{j,l} - \sum_{j \in j} X_j^R E_{j,l}$. If $\theta^v \geq w^v$, then stop and X^v is an optimal solution. Otherwise, set $v = v + 1$, add to the constraint (3.32), and solve it again.

The constraint (3.33) called feasibility cut is added to the master problem whenever first-stage decision $X \in \mu_1$ is not also $X \in \mu_2$. $D_{i,l}$ for $i \in I$, $D_{j,l}$ for $j \in J$ and d_l are determined using the duals variables present in constraints (3.38) – (3.47) and calculated by following steps:

Let $\xi = 1, \dots,$ k index its possible realizations and let q_ξ be their probabilities.

For all $\xi = 1, \dots, k$ solve the linear program:

$$min\ v1_{cp}^+ + v1_{cp}^- + v2_{jcp}^+ + v2_{jcp}^- + v3_{jcp}^+ + v3_{jcp}^- + v4_{icp}^+ + v4_{icp}^- + v5_{jp}^+ + v5_{jp}^- + v6_{jp}^+$$
$$+ v6_{jp}^- + v7_{ip}^+ + v7_{ip}^- + v8_{jp}^+ + v8_{jp}^- + v9_{jp}^+ + v9_{jp}^- + v10_p^+ + v10_p^- \tag{3.37}$$

Subject to:

$$\sum_{j \in J_c} B_{jcp}^U(\xi) + \sum_{j \in J_c} B_{jcp}^R(\xi) + \sum_{i \in I} Z_{icp}(\xi) + v1_{cp}^+$$
$$- v1_{cp}^- = 1, \qquad \forall c \in C, \forall p \in P \tag{3.38}$$

$$B_{jcp}^U(\xi) + v2_{jcp}^+ - v2_{jcp}^- \leq X_j^U a_j^D(\xi), \qquad \forall j \in J_c, \forall c \in C, \forall p \in P \tag{3.39}$$

$$B^R_{jcp}(\xi) + v3^+_{jcp} - v3^-_{jcp} \le X^R_j a^D_j(\xi), \qquad \forall j \in J_c, \forall c \in C, \forall p \in P \qquad (3.40)$$

$$Z_{icp}(\xi) + v4^+_{icp} - v4^-_{icp} \le X_i, \qquad \forall i \in I, \forall c \in C, \forall p \in P \qquad (3.41)$$

$$\sum_{i \in I} Y^U_{ijp}(\xi) + v5^+_{jp} - v5^-_{jp} = \sum_{c \in C} a^C(\xi) d_{cp} B^U_{jcp}(\xi), \qquad \forall j \in J_c, \forall p \in P \qquad (3.42)$$

$$\sum_{i \in I} Y^R_{ijp}(\xi) + v6^+_{jp} - v6^-_{jp} = \sum_{c \in C} a^C(\xi) d_{cp} B^R_{jcp}(\xi), \qquad \forall j \in J_c, \forall p \in P \qquad (3.43)$$

$$\sum_{j \in J} Y^U_{ijp}(\xi) + \sum_{j \in J} Y^R_{ijp}(\xi) + \sum_{c \in C} a^C(\xi) d_{cp} T_{ic} Z_{icp}(\xi) + v7^+_{ip} - v7^-_{ip} \le X_i K^S_i, \qquad \forall i \in I, \forall p \in P \qquad (3.44)$$

$$\sum_{i \in I} Y^U_{ijp}(\xi) + v8^+_{jp} - v8^-_{jp} \le K^D_j X^U_j a^D_j(\xi), \qquad \forall j \in J, \forall p \in P \qquad (3.45)$$

$$\sum_{i \in I} Y^R_{ijp}(\xi) + v9^+_{jp} - v9^-_{jp} \le K^D_j X^R_j a^D_j(\xi), \qquad \forall j \in J, \forall p \in P \qquad (3.46)$$

$$\sum_{i \in I} \sum_{j \in J} Y^U_{ijp}(\xi) + \sum_{i \in I} \sum_{j \in J} Y^R_{ijp}(\xi) + \sum_{i \in I} \sum_{c \in C} a^C(\xi) d_{cp} Z_{icp}(\xi) + v10^+_p - v10^-_p = \sum_{c \in C} a^C(\xi) d_{cp} \qquad \forall p \in P \qquad (3.47)$$

$$v^+, v^- \ge 0,$$

Let $\sigma^v(m)$ be the dual value associated with optimal solution of problem ξ of constraint of type (m) in iteration v. Define $D_{i,l}$, $D_{j,l}$ and d_l as following equations:

$$D_{i,l} = -\sigma^v(40) - \sigma^v(43) K^S_i \qquad \forall i \in I \qquad (3.48)$$

$$D_{j,l} = -\sigma^{v}(38)a_j^D(\xi) - \sigma^{v}(39)a_j^D(\xi) - \sigma^{v}(44)K_j^D a_j^D(\xi) - \sigma^{v}(45)K_j^D a_j^D(\xi) \qquad \forall j \in J \qquad (3.49)$$

$$d_{l,p} = \sigma^{v}(37) + \sigma^{v}(46)\sum_{c \in C} a^C(\xi)d_{cp} \qquad \forall p \in P \qquad (3.50)$$

$$d_l = \sum_{p \in P} d_{l,p}$$

3.3.3 Multi-cut L-shape algorithm

This point should be highlighted again that the L-shape algorithm proposed in previous section can directly solve the two-stage stochastic model for reliable supply chain network design with binary variables in first stage. One of the disadvantages of this algorithm is that at each iteration, a mixed-integer programming has to be solved for master problem instead of linear programming. The computation time and memory requirement for solving this kind of problem several times may be challenging for large size problem. To overcome this issue, one way is to extend proposed L-shape algorithm by replacing the single-cuts by multi-cuts.

In the L-shape algorithm, this study adds a single optimality cut for all scenario at each iteration to master problem. The multi-cut L-shaped algorithm disaggregates the optimality cut for all scenario in each iteration into separate cuts which are added individually to master problem for each scenario. The idea behind this approach is that by creating more optimality cuts in each iteration, the optimal solution might be obtained in less iteration because of having more corner points in master problem. In addition to adding multiple optimality cuts for each scenario to master problem in this version, θ is replaced by $\sum_{\xi=1}^{K}\theta(\xi)$ in the objective function of the master problem. So the outer approximations of the recourse cost function can reach to optimal value or lower bound in less iteration. It is worth to mention that adding multi-cuts instead of single-cut does not affect feasibility cut at all. One of limitation of this extension is that multi-cut approach works perfectly when the problem deals with small number of scenarios because the additional optimality cut equations iteratively added to master problem are equal to the number of scenarios which causes complexity in problem with large number of scenarios. According to Birge and Louveaux (1997) multi-cut L-shape algorithm is more effective when the number of scenarios is not noticeably larger than the number of constraints in first-stage. To illustrate the effectiveness of the multi-cut approach, a sample set of results is presented in our numerical study and the computational performances are discussed. The reliable supply chain under demand and disruption uncertainties can be reformulated as follow based on applying L-shaped method:

$$min \sum_{i\in I} f_i X_i + \sum_{j\in J} f_j^U X_j^U + \sum_{j\in j} f_j^R X_j^R + \sum_{\xi=1}^{K} \theta(\xi) \qquad (3.51)$$

Subject to:

$$AX \leq B \qquad (3.52)$$

Feasibility cut:

$$\sum_{i\in I} X_i D_{i,l} + \sum_{j\in J} X_j^U D_{j,l} + \sum_{j\in j} X_j^R D_{j,l} \geq d_l \qquad l = 1, \dots, r \qquad (3.53)$$

Optimality cut:

$$\sum_{i\in I} X_i E_{i,l}(\xi) + \sum_{j\in J} X_j^U E_{j,l}(\xi) + \sum_{j\in j} X_j^R E_{j,l}(\xi) + \theta(\xi) \geq \omega_l(\xi) \qquad l(\xi) = 1, \dots, s(\xi) \qquad (3.54)$$

$$X \in \{0, 1\}, \theta \in \Re$$

Where for each scenario $\xi = 1, \dots,$ k solve the linear program problem (3.20) – (3.31):

$$E_{i,l}(\xi) = -q_\xi \pi_\xi^v(24) - q_\xi \pi_\xi^v(27) K_i^S \qquad \forall i \in I \qquad (3.55)$$

$$E_{j,l}(\xi) = -q_\xi \pi_\xi^v(22) a_j^D(\xi) - q_\xi \pi_\xi^v(23) a_j^D(\xi) - q_\xi \pi_\xi^v(28) K_j^D a_j^D(\xi)$$
$$- q_\xi \pi_\xi^v(29) K_j^D a_j^D(\xi) \qquad \forall j \in J \qquad (3.56)$$

$$\omega_{l,p}(\xi) = q_\xi \pi_\xi^v(21) + q_\xi \pi_\xi^v(30) \sum_{c \in C} a^C(\xi) d_{cp} \qquad \forall p \in P \qquad (3.57)$$

$$\omega_l(\xi) = \sum_{p \in P} \omega_{l,p}$$

Let $w^v(\xi) = \omega_l(\xi) - \sum_{i \in I} X_i E_{i,l}(\xi) - \sum_{j \in J} X_j^U E_{j,l}(\xi) - \sum_{j \in j} X_j^R E_{j,l}(\xi)$. if $\theta^v(\xi) \geq w^v(\xi)$ for any scenario ξ, then stop and X^v is an optimal solution. Otherwise, set $v(\xi) = v(\xi) + 1$, add to the constraint (3.54), and solve the master problem again.

3.3.4 Stochastic program with relatively complete recourse

In addition to the multi-cut version which improves the computational time of algorithm with respect to optimality cuts, it is noted that by adding the additional constraint in first stage and altering one our assumption, the algorithm can be improved in terms of computational time. The feasibility constraint of type (3.33) is iteratively added to the master problem by solving dual subproblem whenever the subproblem is not feasible by using first stage solutions. In other word, whenever first-stage decision variable $X (X \in \mu_1)$ is not inside the μ, feasibility cut must be added. This study shows that, by adding equation $\sum_{\mathrm{i} \in \mathrm{I}} \mathrm{X_i} \geq 1$ to the first stage and assuming each supplier has infinite capacity to supply, the subproblem is always feasible with respect to every solution of first stage. This means that our stochastic program has relatively complete recourse ($\mu_1 \subset \mu_2$). The model is called relatively complete recourse when the second-stage problem is feasible for any feasible first-stage solution. This alternative representation significantly improves the computation time of algorithm by skipping finding dual of subproblem to generate feasibility cut for master problem.

Let $\mu_1 = \{X_i, X_j^U, X_j^R \mid X_j^U + X_j^R \leq 1,\ \sum_{j \in J} X_j^R \geq 1,\ X_i, X_j^U, X_j^R \in \{0, 1\}, i \in I, j \in J\}$ represents a set of all possible values of X_i, X_j^U and X_j^R that make first stage feasible. Let $\mu_2 = \{X_i, X_j^U, X_j^R \mid Constraints\ (3.21)\ to\ (3.31)\}$ be all possible values of X_i, X_j^U and X_j^R that make the second stage formulation given by Equation (3.20) feasible. Using Proposition 1, it is shown that if at least one supplier is selected then the proposed two stage optimization has relatively complete recourse and does not need feasibility cut presented in Equations (3.33).

Proposition 3.1: *If* $\sum_{i \in I} X_i \geq 1$, *then the stochastic optimization model present in Equation (3.16) has a relatively complete recourse, i.e.* $\mu_1 \cap \{X_i | \sum_{i \in I} X_i \geq 1\} \in \mu_2$.

Proof: To prove this proposition, it is required to show that if condition $\sum_{i \in I} X_i \geq 1$ is satisfied then all solutions in the set μ_1 are present in the set μ_2.

If $\sum_{i \in I} X_i \geq 1$, then there exist at least one $X_{i'} = 1, i' \in I$. Rewriting Equation (3.27) for supplier i' and period p as:

$$\sum_{j \in J} Y_{i'jp}^U(\xi) + \sum_{j \in J} Y_{i'jp}^R(\xi) + \sum_{c \in C} a^C(\xi) d_{cp} T_{i'c} Z_{i'cp}(\xi) \leq K_{i'}^S \tag{3.51}$$

If $\sum_{j \in J_c} B_{jcp}^U(\xi) + \sum_{j \in J_c} B_{jcp}^R(\xi) + \sum_{i \in I} Z_{icp}(\xi) = 1, c \in C, p \in P,$ and $\sum_{j \in J} X_j^R \geq 1,$ and Equations (3.22) – (3.26) and Equations (3.28) – (3.31) are satisfied (trivial balance constraints) then from Equation (3.51) there exists a supplier i' for which either $\sum_{j \in J} Y_{i'jp}^U(\xi) \geq 1$ or $\sum_{j \in J} Y_{i'jp}^R(\xi) \geq 1$ or $\sum_{c \in C} a^C(\xi) d_{cp} T_{i'c} Z_{i'cp}(\xi) \geq 1$. This suggests that $\sum_{j \in J} Y_{i'jp}^U(\xi) + \sum_{j \in J} Y_{i'jp}^R(\xi) + \sum_{c \in C} a^C(\xi) d_{cp} T_{i'c} Z_{i'cp}(\xi) \geq 1$. Thus, $\mu_1 \cap \{X_i | \sum_{i \in I} X_i \geq 1\} \in \mu_2$. This concludes the proof.

3.4 Numerical example and computational experiment

The case study presented in Peng et al. (2011) is adopted to illustrate the decisions from the model. As shown in Figure 3.2, the case study includes three levels of supply chain namely supplier, transshipment node (distribution center), and customer. By solving the reliable model, this research obtains a supply chain network with selected suppliers and distribution centers from a list of potential locations. These models also calculate the volume of products transported between all level of supply chain, while minimizing the fixed cost and transportation cost for each time period under uncertain disruption and demand.

Figure 3.2 Supply chain design problem (Peng, Snyder, Lim, & Liu, 2011)

The cost of establishing an unreliable facility is determined by a fixed cost plus a variable cost which is a function of the population in each node and is denoted by: $f_{i\ or\ j}$= fixed cost + 1.7*Demand. It is assumed the fixed demand for each node based on the worst-case scenario. The hardening cost used is similar to that of Lim et al. (2010) is calculated as follows: $h = (f_j^R - f_j^U) = (f_j^U * 10) * q_j$. Consequently, if a site incurs more failure probability, the costs of establishment would augment to compensate for better reliability. The disruption probability and failure occurrence data are assumed independent of each other and are taken from Federal Emergency Management Agency (FEMA). Google map is used for calculating distances between two sites via the highways. For computing the transportation cost for trucks, the distance is multiplied by $1.25. 20 random datasets of different problem sizes ranging from 50 to 500 for customers' demands are generated based on exponential distribution with the mean ranging from

2/3 to 2. The L-shape algorithm is coded in Python and CPLEX is used as the solver, executed it on a computer with 3.40 GHz processor and 16 GB of RAM.

3.4.1 Comparison between single-cut, multi-cut and relatively complete recourse model

In this subsection, the performance of the multi-cut and single-cut L-shape method is compared, and it is shown that the use of multi-cut instead of single-cut approach significantly improves the efficiency of L-shape algorithm in our case. It is also shown that the performance of the multi-cut approach is improved by converting the stochastic model to relatively complete recourse model.

As it is mentioned before, the multi-cut L-shaped algorithm disaggregates the optimality cut for all scenario in each iteration into separate cuts which are added individually to master problem for each scenario. The idea behind this approach is that by creating more optimality cuts in each iteration, the optimal solution might be obtained in less iteration because of having more corner points in master problem. However, significant amount of time is required in each iteration to generate the additional optimality cuts. Therefore, the time spent to generate the additional optimality cuts in terms of decreasing the total time should be less than the time achieved by reducing the number of total iterations. Furthermore, by converting model to relatively complete recourse, the number of iterations decreases further because of elimination of the feasibility cuts from the master problem.

Table 3.2 presents the comparison of the computational efficiencies between three L-shape algorithms for different values of λ for random demand, and $|S|$ (the total number of scenarios). For each instance, the total numbers of iterations, the total number of optimality and feasibility cuts added to the master problem, and the solution times are reported for three different approaches. The time restriction of five hours is set for our experiments in such that if the optimal solution is not obtained within this time limit, then such a situation is reported as “No Solution (NS)” in the column of solution time for each approach.

Both single and multi-cut algorithms are able to solve our two-stage stochastic problem with up to 1000 scenarios without any memory issues. Multi-cut approach also successfully solves the problem with up to 16000 scenarios. On the other hand, using the single-cut approach does not obtain optimal solution within five hours for the instances with 2000 scenarios.

Multi-cut algorithm has much better performance than single-cut algorithm in terms of the solution time. In average multi-cut perform 11 times better than the single-cut; this rate increases up to 13.16 in some instances. Although the multi-cut algorithm produces much more constraints in each iteration compared to single-cut, so the time spent for solving each iteration in multi-cut approach is higher than single-cut algorithm. In average the time spent on each iteration in multi-cut is 1.5 times more than single-cut method, but multi-cut obtains optimal solution in much less iterations than single-cut. In average the number of iteration for solving the problem by multi-cut algorithm is 17 times less than single-cut. For this problem, single-cut algorithm runs into memory issues for the instances with $|S| \geq 1000$. When the number of scenarios is 1000, for $\lambda = 1$ the single-cut can obtain solution in 4.6 hours which is still 12.43 times more than multi-cut approach. Multi-cut algorithm runs into problems for the instances with $|S| \geq 16000$.

Table 3.2 Comparison between single-cut, multi-cut and complete recourse methods

		Single-cut			Multi-cut			Complete recourse		
|S|	λ	No. of iters	No. of cuts	Sol. time (s)	No. of iters	No. of cuts	Sol. time (s)	No. of iters	No. of cuts	Sol. time (s)
200	0.5	86	285	3440.7586	5	1000	256.437	4	800	161.566
200	0.75	86	285	3438.2346	6	1162	307.8393	4	953	193.723

200	1	86	285	3474.2285	6	1166	307.3650	4	956	199.262
200	1.25	86	285	3591.1809	6	1164	298.7630	4	961	208.621
200	1.5	86	285	3344.3116	5	1000	253.5446	4	958	200.399
400	0.5	86	485	6697.3933	5	1998	533.6637	4	1850	378.441
400	0.75	86	485	6774.1908	5	1999	508.5652	4	1917	399.480
400	1	86	485	6768.9062	5	2000	520.4204	4	1914	393.187
400	1.25	86	485	6621.4133	5	1999	527.7853	4	1920	402.299
400	1.5	86	485	6618.9044	5	1997	529.6119	4	1915	397.761
1000	0.5	86	1085	16668.487	5	4996	1334.043	4	4108	787.311
1000	0.75	85	1084	16730.439	5	4996	1313.702	4	3980	756.681
1000	1	86	1085	16530.462	5	4991	1331.475	4	3998	770.811
1000	1.25	86	1085	17347.315	5	4999	1329.357	4	4108	778.781
1000	1.5	85	1084	16983.451	5	4994	1302.879	4	4110	790.228
2000	0.5	NS	NS	NS	5	9993	2647.595	4	8020	1698.43
2000	0.75	NS	NS	NS	5	9990	2662.467	4	8111	1788.82
2000	1	NS	NS	NS	5	9983	2690.074	4	7987	1620.57
2000	1.25	NS	NS	NS	5	9992	2666.614	4	8100	1799.22
2000	1.5	NS	NS	NS	5	9991	2667.583	4	8100	1772.02

By converting our stochastic model to relatively complete recourse, the performance of algorithm increase even more in terms of solution time. In average, multi-cut algorithm with relatively complete recourse model performs 1.65 times better than the multi-cut without it. The relatively complete recourse model also generates less number of constraints because there is no need to generate feasibility cuts any more. When the number of scenarios is 16000, for $\lambda = 1$ the multi-cut which is not relatively complete recourse can obtain solution in 5.8 hours which is still 1.45 times more than multi-cut approach with relatively complete recourse model.

In Figure 3.3, it is illustrated how the solution times are changed across number of scenarios for multi-cut, single-cut and relatively complete recourse version when the $\lambda = 1$. It can be clearly seen how solution time of single-cut method is sharply increased by growing the number of scenarios in compare with other two and how much the multi-cut approach with relatively complete recourse model performs better than multi-cut approach without relatively complete recourse model. The variation in number of cuts across number of scenarios for relatively complete recourse, multi-cut and single-cut algorithm when the $\lambda = 1$ is shown in Figure 3.4. As you can see in this figure, the multi-cut with and without relatively complete recourse model produces much more cuts in each scenario compared to single-cut, but multi-cut obtains optimal solution in much less iterations than single-cut.

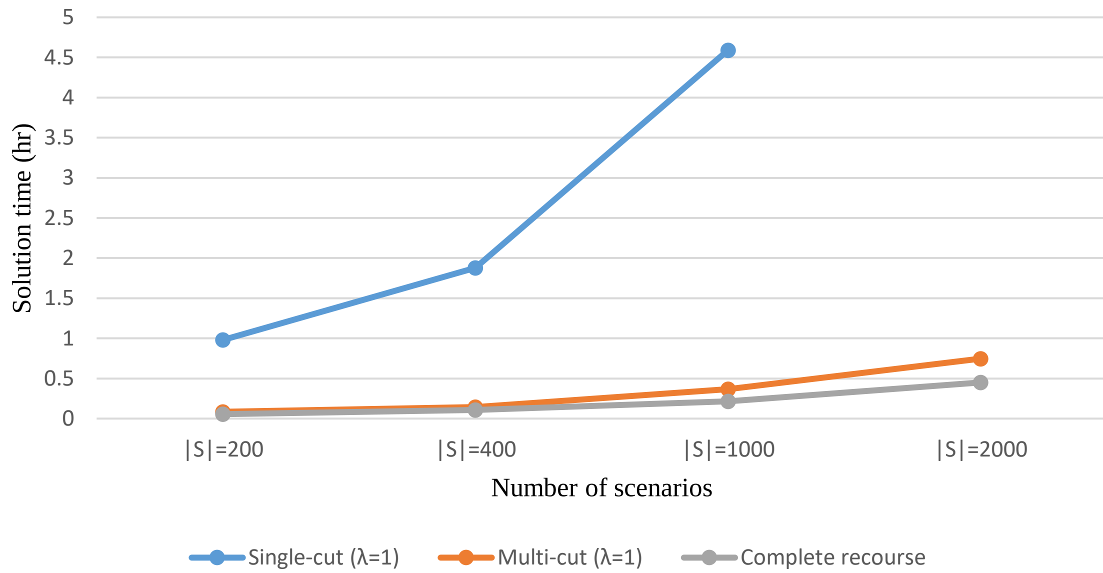


Figure 3.3 Sensitive analysis of different size of scenarios and solution time for different methods

Table 3.3 presents the results for the single-cut algorithm without any restricted time for $|S| = 2000$ instances that this algorithm cannot solve it within five hours. Multi-cut algorithm obtains optimal solution for all of these instances within 0.75 hours. While it almost takes 10 hours for single-cut algorithm to find the optimal solution.

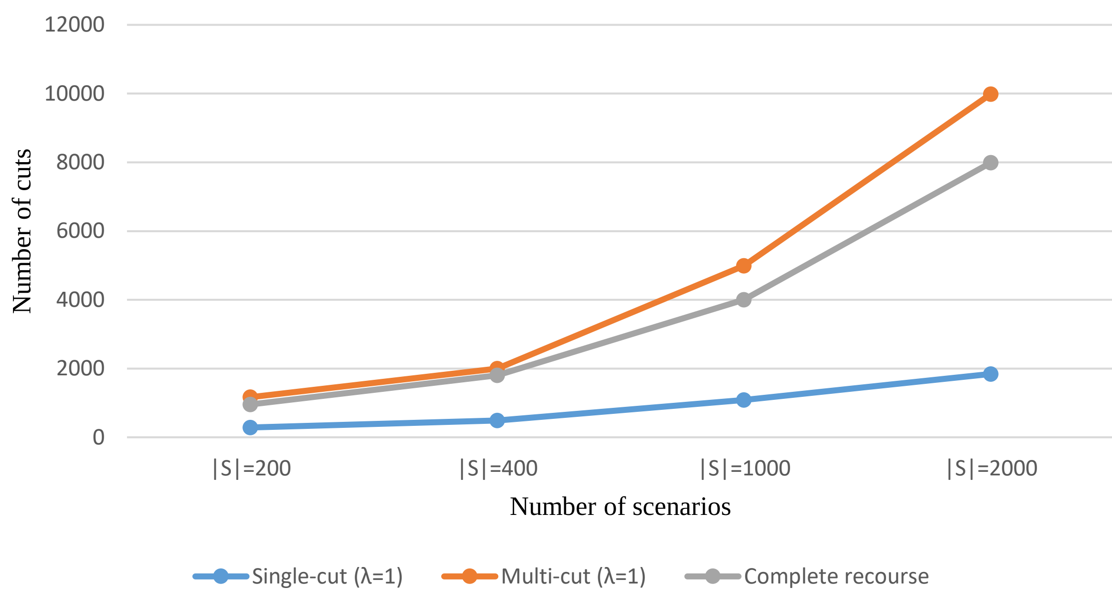


Figure 3.4 Sensitive analysis of different size of scenarios and number of cuts for different methods.

Table 3.3 The results for the single-cut algorithm without any restricted time for $|\boldsymbol{S}| = \mathbf{2000}$

		Single-cut		
|S|	λ	No. of iters	No. of cuts	Sol. Time (s)
2000	0.5	86	1842	35074.734
2000	0.75	86	1842	34996.889
2000	1	86	1842	35005.765
2000	1.25	86	1842	35114.869
2000	1.5	86	1842	35246.116

In summary, the multi-cut algorithms perform much better than single-cut approach on different instances. On average, the multi-cut algorithm performs better yet for instances with a large number of scenarios which cannot be solved within five hours. This results even improve more by converting our stochastic model to relatively complete recourse model.

3.4.2 Benefit of considering disruption risk and applying hardening strategy

In this experiment, this research study the advantages of considering disruption in supply chain network design and applying hardening strategy to face with these disruptions. For fulfilling this purpose, the supply chain network problem is considered from two viewpoints. At first, the problem without any disruption with only one type of distribution center (unreliable distribution center) is considered. Then the increasing rate in total cost for all different disruption scenarios is calculated due to the transportation cost of customer's reassignment in this model. In second perspective, the total cost for our reliable supply chain model for all those disruption scenarios is calculated and compare it with unreliable model.

In both cases first each problem is solved and save the total cost which includes establishing cost and transportation cost. Then the disruption cost of both cases for each scenario takes place in the model is calculated in such way the demands loss in failed distribution center will be satisfied with their closest safe opened distribution centers with higher transportation cost. The optimal costs for designing an unreliable and reliable supply chain network using L-shape algorithm for sample size of 100 are $2967844 and $3046548 respectively and they are break down as it is shown in Table 3.4. It is obvious that with costing more investment about 50% in establishing facility, the total increasing cost for the reliable model is $78704. Thus, the reliable supply chain model can be designed with just about 2.8% additional investment more in total cost.

Table 3.4 The results of two-stage stochastic model for both reliable and unreliable cases

		Unreliable supply chain model		
Component	Number Facilities	Cost of Establishing	Transportation Cost	Total
Facility	9	148800	2819044	2967844
		Reliable supply chain model		
Component	Number Facilities	Cost of Establishing	Transportation Cost	Total

Unreliable Facility	5	84950	1635878	-
Reliable Facility	4	142554	1212316.21	-
All Facilities	9	227504	2848194.21	3046548

There are numerous disruption scenarios which could take place in the network in fact if $|J|$ denote the number of DCs, then disruption scenarios in DCs would be 2^J. Table 5 presents all disruption scenarios in our numerical example and calculates the total cost of each scenario for both cases as well as the percentage of increase in total cost in the first case (designing supply chain network without applying hardening strategy) and compares it with second case cost (designing supply chain network without applying hardening strategy). The average of all total cost is then calculated for easier comparison.

Table 3.5 Analyzing the total cost of each scenario for unreliable model

Scenario	Which DC is disrupted	Damage cost of facility (first case)	Cost of reassignment (first case)	Total cost (first case)	percentage of increase
1	Chino	17040	3382167	3530967	+18.9%
2	Phoenix	13710	3031815	3180615	+7.2%
3	Memphis	19700	3010154	3158954	+6.5%
4	Dallas	13400	2953044	3101844	+4.6%
5	Chi & Pho	30750	4592155	4740955	+59.7%
6	Pho & Mem	33410	3658167	3806967	+28.2%
7	Pho & Dal	27110	3607167	3755967	+26.5%
8	Mems & Chi	36740	3297915	3446715	+16.1%
9	Dal & Chi	30440	3218815	3367615	+13.4%
10	Dal & Mem	33100	3345439	3378500	+14.8%
11	Pho & Chi & Mem	50450	4880655	5029455	+69.4%
12	Pho & Chi & Dal	44150	4887555	5036355	+69.6%
13	Pho & Mem & Dal	46810	4886643	4933453	+61.9%

14	Chi & Mem $ Dal	50140	4887854	4937994	+62.1%
15	All of DCs	63850	18058800	18122650	+500%
16	Average of scenarios (except 15)	-	-	3832400	+29.1%

As shown in the Table 3.5, by applying hardening strategy the reliability of the supply chain network has notably improved. In this table, it can be observed that all damage costs for all scenarios are more than the cost which is spent for making reliable supply chain network. The huge damage cost for reassigning the customer is prevented with specific investments in establishment facilities. For example, in instance number 14 with 2.8 % increase in total cost for applying reliability, we have an expected decrease of 62.1% in total disruption cost. These analyses represent that the reliability of the system can be increased by a slight increase in facility cost.

Comparing total damage cost of each scenario for unreliable model and the cost of making reliable supply chain network is illustrated in Figure 3.5 As shown, all costs for all scenarios are more than the cost which is spent to make a reliable supply chain network. As illustrated in Figure 3.5, scenarios 5, 11, 12, 13, and 14 are significant with 59.7%, 69.4%, 69.6%, 61.9%, and 62.1% increase in total cost respectively. The penalty costs for reassigning customers in these scenarios are huge compared to the cost of making the supply chain network reliable with specified investment.

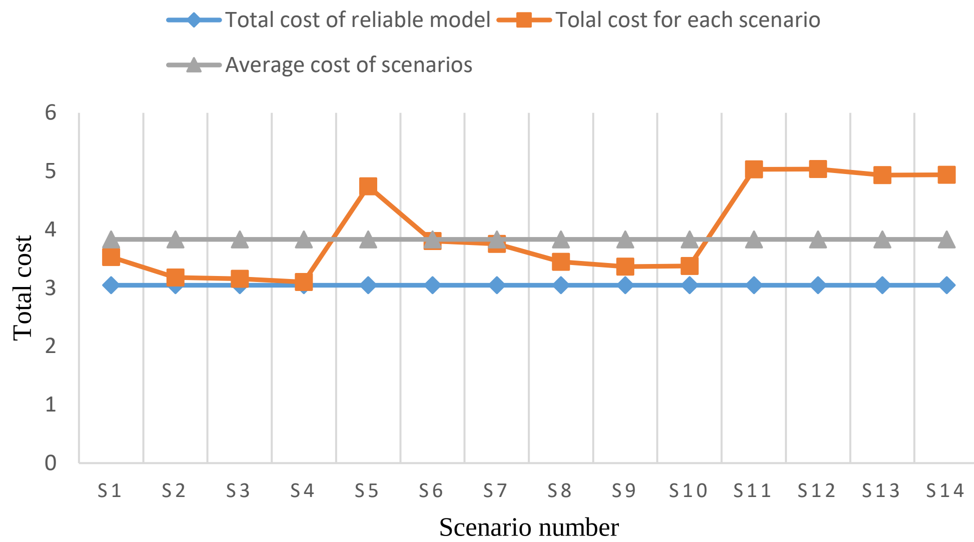


Figure 3.5 Comparing total cost of reliable and unreliable models with all scenarios

3.4.3 Impact of disruption probability and opening fixed cost on number of unreliable and reliable distribution centers

In this part, the impact of changing in disruption probability and fixed opening cost on optimal number of reliable and unreliable distribution centers is studied. Disruption probability is varied from 0.1 to 0.9 under two different hardening fixed costs in distribution centers. Figure 3.6 and Figure 3.7 present the results for size of 200 scenarios for these two different fixed costs. As you can see in these figures, the number of reliable distribution centers increase as disruption probability increases while the number of unreliable distribution centers decrease. In fact, by looking at two figures, it can be observed that the number of reliable distribution centers always dominate the number of unreliable as disruption probability increases, but as you can see in Figure 3.7 the optimal number of reliable distribution centers are less to satisfy customers when the fixed opening cost also grows. Consequently, the optimal number of unreliable distribution centers drop by increasing in disruption probability and increasing in fixed opening costs result in dropping the optimal number of reliable distribution centers.

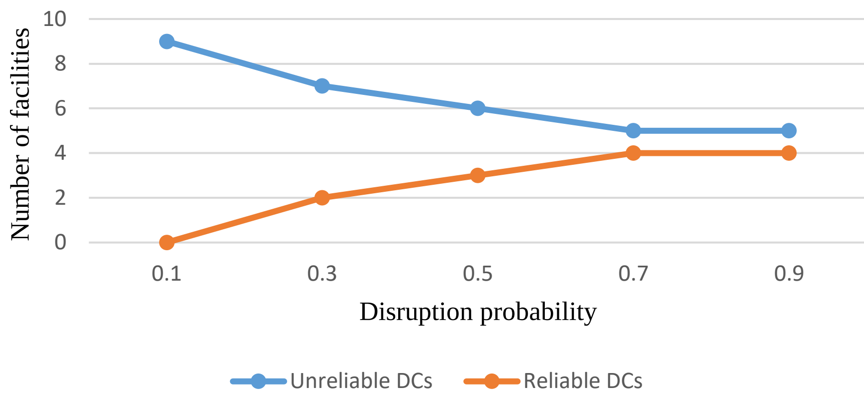


Figure 3.6 Sensitive analysis of disruption probability and lower opening fixed cost on optimal number of unreliable and reliable distribution centers

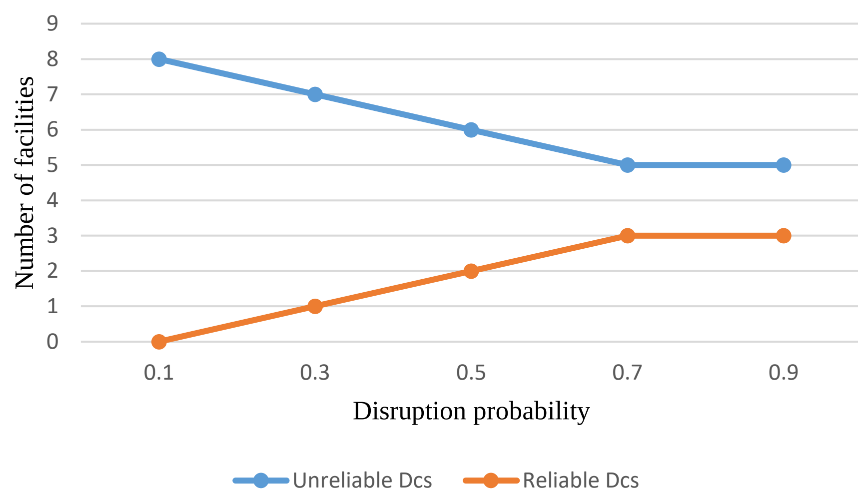


Figure 3.7 Sensitive analysis of disruption probability and higher opening fixed cost on optimal number of unreliable and reliable distribution centers

In summary, the main contribution of this study is to formulate a two-stage stochastic mixed-integer programming model to design a reliable and efficient supply chain network under uncertain parameters, and to develop an algorithm that can solve large-scale problems efficiently. By using numerical experiments, the model can be introduced to larger-sized networks and understand the relationship between optimal locations of facilities, disruption probability, and transportation costs. The computational results are summarized as follows:

- The multi-cut algorithms perform significantly better than the single-cut approach for every scenario, regardless of size. Although the multi-cut approach produced more cuts in each scenario compared to the single-cut, it obtained an optimal solution in fewer iterations than the single-cut approach.
- The result improves even more when converting the stochastic model to a relatively complete recourse model. It can be clearly seen how much the multi-cut approach with relatively complete recourse model performs better than all other models.
- These computational results represent how the reliability of the supply chain system can be improved by a slight increase in facility cost.
- It can be observed that under high disruption probability, the number of reliable distribution centers increased while the number of unreliable distribution centers decreased. In addition, it is clear that by increasing the opening fixed cost of facilities, the optimal number of reliable distribution centers decrease to satisfy customers.
- Increasing the transportation cost results in the model preferring the assignment of reliable distribution centers rather than unreliable distribution centers. Because if one of the unreliable facilities stops working, customers initially allocated to that facility must be reassigned to other operational facilities with very high transportation costs.

3.5 L-shape algorithm application in security-constrained unit commitment

Apart from commercial applications, this method is also applied in another application by Tolooie et al. (2022). In this study, two-stage stochastic security-constrained unit commitment (S-SCUC) has been used by independent system operators to manage the uncertainty attributed to an increasing penetration level of renewable energy. However, computational complexity has been widely regarded as a grand challenge in solving large-scale S-SCUC problems. This study addressed these issues by applying L-shaped decomposition algorithm. It is mathematically proved the S-SCUC problem has relatively complete recourse by leveraging the structural characteristics of the problem and the domain knowledge. A computationally efficient initial solution is proposed to accelerate the proposed L-shaped decomposition algorithm. Comparative results showed that, in the proposed relatively complete recourse L-shaped algorithm, multi-cut with an initial solution performs better than its single-cut counterpart with an initial solution and better than the multi-cut approach without any initial solution. The multi-cut algorithm with an initial solution is significantly superior to the single-cut approach without any initial solution. By using initial solutions in the decomposition algorithm, a significant number of cuts required to add to the master problem based on the L-shaped decomposition algorithm are eliminated. This improved algorithm reduced a significant number of linear programming problems that have to be solved in the second stage for generating Bender cuts, which leaded to improved running times.

3.6 Conclusion

In this research, the reliable facility network design problem under uncertainty conditions in the presence of customer demand and disruptions at distribution centers was analyzed. The problem was formulated as a two-stage stochastic optimization problem and used the L-shape decomposition approach to solve it. It was also theoretically proved that the proposed stochastic formulation has a relatively complete recourse structure when at least one supplier is selected. This improves the performance of the L-shape algorithm by significantly reducing the total number iterations in the L-shape decomposition due to absence of feasibility cuts. To illustrate the applicability of the model and the improved algorithm, a case study was presented based on empirical data sourced from Peng et al. (2011), and those results were then discussed.

In summary, this study potentially offers a number of significant contributions to the literature, and the supply chain industry in general. The main contribution of this study is that, by developing a two-stage stochastic model for reliable supply chain network design with stochastic parameters in multi-time periods and solving it, the relationships between the facility decisions, such as facility location, product assignment and key factors such as transportation cost, hardening investment and disruption probability, were understood. It was observed that under high disruption probability, increasing the transportation cost results in the model preferring the assignment of reliable distribution centers rather than unreliable distribution centers. Furthermore, an efficient solution method was developed for the optimization problem based on the multi-cut L-shaped decomposition method, which allowed us to solve real large-scale problems in shorter time frames. It is shown that multi-cut algorithms perform much better than single-cut algorithms in different instances, and that these results can be improved by converting our model to a relatively complete recourse model.

Chapter 4 - Designing Reliable Supply Chain Network Using Drones in Last-Mile Delivery

Chapter 4 is based on the manuscript "Heuristic approach for optimizing reliable supply chain network using drones in last-mile delivery under uncertainty" Submitted to International Journal of System Assurance Engineering and Management.

4.1 Introduction

The rise of e-commerce and the increase in customer inclination towards online shopping makes package delivery a significant function of logistics businesses. Traditionally, packages are delivered to the customer using land transportation (trucks, cars, and motorcycles). However, these means of transportation are considered one of the most expensive, less efficient, and most polluting entities of the logistics chain (Gevaers, Van de Vo- orde, & Vanelslander, 2014). Due to these issues and infrastructure limitations in remote areas, using unmanned aerial vehicles such as drones for package delivery in last-mile logistics is becoming an increasingly attractive alternative transportation mode. Drones have seen tremendous growth in several fields including surveillance, healthcare, scientific research, photography, emergency response, and wireless communications (Finn, & Wright, 2012; Clarke, 2014; Sandbrook, 2015). Drones have become a promising solution for delivering packages in last-mile logistics because drone technology is efficient in travel, more reliable, and has better energy consumption. Some big companies such as Amazon, DHL, and Google have used drones as a means to deliver packages and merchandise items to their customers. Amazon is considering a premium delivery service called Amazon Prime Air, which rapidly delivers packages within 30 minutes of a customer ordering online (Hong, Kuby, & Murray, 2018). There are several advantages of using drones in package deliver. Firstly, drone delivery is much faster than land transportation since drones do not encounter congestion and road traffic jams.

Secondly, drones are not restricted by specific paths, like roads, making them applicable to deliver parcels to areas that difficult to access by other methods. Although using drones to deliver packages has many advantages over traditional land transportation delivery, there are several significant obstacles in technical aspects and performance capabilities to overcome before drones can have widespread commercial adoption. One of the substantial obstacles in using drones in the commercial sector is the limited flight coverage since drones are battery-operated devices with a limited-service range. Currently, a drone’s coverage is limited to a radius of 20 miles, which reduces access for a significant segment of customers, leading to the use of land transportation delivery processes (Scott, & Scott, 2017). Several logistical strategies can address the range limitation of a drone delivery system. A multi-modal approach would combine drones with trucks, using the advantages of one to offset the disadvantages of the other by launching drones from trucks for the “last-mile” only (Murray, & Chu, 2015; Agatz, Bouman, & Schmidt, 2018; Ha et al., 2018). Another technique is the installation of some stations within the existing logistics infrastructure so that drones can recharge their batteries in these stations after they run out of power (Sundar, & Rathinam, 2013; Dorling et al., 2016; Yu, Budhiraja, & Tokekar, 2018). To develop a drone delivery service by installing charging stations within the existing logistics network, a coverage location model is necessary. A location model for recharging station system design must consider the delivery service coverage of recharging stations based on the flight range of drones in continuous two-dimensional space under different conditions, such as flying with or without the package. This research aims to construct a feasible delivery network consisting of warehouses and recharging stations.

In recent years, supply chain systems have become more complex and dynamic with wide geographical coverage, exposing supply chains to a broad range of uncertainties, some of which may cause disruptions (Rezapour, Farahani, & Pourakbar, 2017). Accidental disruption due to large-scale natural disasters, manufacturing fires, terrorist attacks, wide-spread electrical shutdowns, and financial or political tensions are among several other uncertainties that are likely to occur (Govindan, Fattahi, & Keyvanshokooh, 2017). The recent example of the Colonial pipeline cyberattack or the widespread transmission of the novel COVID-19 developed grave uncertainties in the global supply chain. Supply chain disruptions have been challenging for many companies worldwide (Rezapour, Farahani, & Pourakbar, 2017). A disruption at one level of a supply chain can significantly impact the entire chain: for instance, any failure of a distribution center could cost company additional transportation costs in order to satisfy customer demand (Tolooie, Maity, & Sinha, 2020). Hendricks and Singhal (2003) reported on some of the severe impacts of supply chain disruptions on market share, which in some cases fell lower than 11% from just the announcement of disruptions alone. Adding recharging station to supply chain could increase the complexity of the network even more, and any disruptions could lead enormous financial impacts, and in some cases, cause a permanent loss of market share. For instance, in Figure 4.1, failure of one recharging station in the last part of the network could cut the network which results in losing a lot of orders or cost a lot of money to use backorder to satisfy those orders.

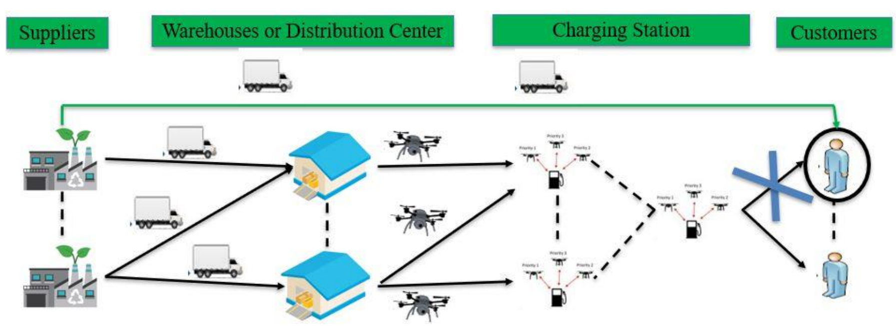


Figure 4.1 Supply chain network under using drones in last-mile delivery under disruption

The uncertainty of natural disasters (occurrence and intensity) and the amount of demand during each time period has a significant effect on designing the supply chain network using drones in last-mile delivery. To provide a well-designed and reliable network, Lim et al. (2010)'s reliability concept is integrated in our model formulation by consider two types of facilities: unreliable facilities (influenced by random disruptions) and reliable facilities (resistant to random disruptions due to additional investment). The concept is known as a hardening strategy that helps to hedge against the risk of disruptions in the facility reliability problem. Our model also extends the capacitated facility location problem by making decisions regarding the selection of a supplier, the locations of reliable and unreliable distribution centers, the number of drones in each distribution centers, the locations of reliable and unreliable recharging stations, the allocation of suppliers to customers, and the amount of products channeled through the network in a multi-time period under different types of scenarios for stochastic demand and disruptions.

The objective of this research is to find the optimal number and the locations of suppliers, distribution centers, charging stations, and number of drones in distribution center in order to minimize the total expected transportation cost and drone's utilization cost for the entire supply chain network across all future scenarios. The stochastic supply chain network problem is normally expressed as mixed-integer linear programming models in most studies (Döyen, Aras, & Barbarosoğlu, 2012; Pradhananga et al., 2016; Manopiniwes, & Irohara, 2017; Alem, Clark, & Moreno, 2016; Mohammadi, Ghomi, & Jolai, 2016). Therefore, our problem is formulated as a mixed-integer programming model in order to design a reliable and efficient supply chain network design under the uncertainty of demand and disruptions. Since, most of the variables and constraints are scenario-dependent, their numbers grow rapidly as the number of scenarios increases. As a result of this growth, standard solutions cannot be efficiently applied to solve this kind of problem. Additionally, facility location problem is NP-hard problem which leads us to apply heuristic algorithm to tackle such models more efficiently. Many other studies presented meta-heuristic or heuristic algorithms in this area (Drezner, 1987; Shen, Zhan, & Zhang, 2011; Berman, Krass, & Menezes, 2007; Govindan, Jafarian, & Nourbakhsh, 2015; Cardona-Valdés, Álvarez, & Pacheco, 2014; Pan & Nagi, 2010; Fattahi et al., 2015). Among several developed heuristic-based approaches for solving this kind of problem, the genetic algorithm is one of the more powerful techniques for solving large scale problems with complicated variables. Due to the computational complexity of the scenario-based mixed-integer model, this method is modified by considering each scenario independently in one of the steps of the algorithm to significantly improve the computational time need to find the solutions. The computational efficiency of improved algorithm is also presented.

There are three main contributions of this study: firstly, stochasticity in a multi-period supply chain network design problem including charging station is examined to extend the coverage of drones in last-mile logistics, where the disaster and the demand are random. The proposed stochastic model is unique because of two conditions: (i) it simultaneously considers delivery service coverage of recharging stations and distribution centers based on the flight range of drones under different conditions, capacities for supply and distribution centers and drone's utilization cost based on calculating Euclidian shortest path distance under demand and disaster uncertainty in multiple time periods. (ii) a combination of the two types of strategies is adopted simultaneously to design a reliable network using charging station as one of the levels under two different uncertain parameters in multi-time periods. The reassignment strategies is considered once a disruption has happened in facilities and hardening strategies when there are no disruptions in the system. The proposed problem is formulated as a stochastic mixed-integer programming model to design an efficient supply chain network. Secondly, the heuristic algorithm is improved by considering a novel method to generate independent scenarios to create a new population. This significantly improves the efficiency of the algorithm due to the decrease in number of infeasible solutions and allows it to efficiently solve real large-scale problems. Thirdly, using numerical experiments, it is shown the relationship between the disruption probability, cost needed to make reliable distribution center and charging station and drone's utilization cost with the number of drones in each distribution center, the number and location of reliable and unreliable distribution center and charging station. Contrary to popular belief, it is observed that by increasing disruption probability, utilization costs of drones and fix cost of establishing reliable and unreliable facilities, the model prefers to lose the demand and pay the penalty cost instead of buying drones and establishing more reliable facilities.

The rest of this chapter is organized as follows: Section 4.2 presents the formulation of a stochastic mixed-integer programming model for designing reliable supply chain network under stochastic demand and disruption. In Section 4.3, the genetic algorithm approach and extensions are described. Section 4.4 provides numerical examples to clarify the applicability and efficiency of the model and problem-solving approach. Finally, Section 4.5 includes concluding remarks and further discussion.

4.2 Reliable supply chain network including charging station

This research studies models for reliable supply chain network problems under stochastic demands and disruption probability for distribution centers and charging stations. The main decision is to determine a set of locations from potential nodes for distribution centers and charging stations that are robust under disruptions. Any failure of a distribution center or charging station could cost the company additional transportation costs to reassign the customer demand. This is best illustrated in Figure 4.2, where the failure of a distribution center costs the company additional transportation costs to satisfy the demand of customers by providing another most available facility as a penalty.

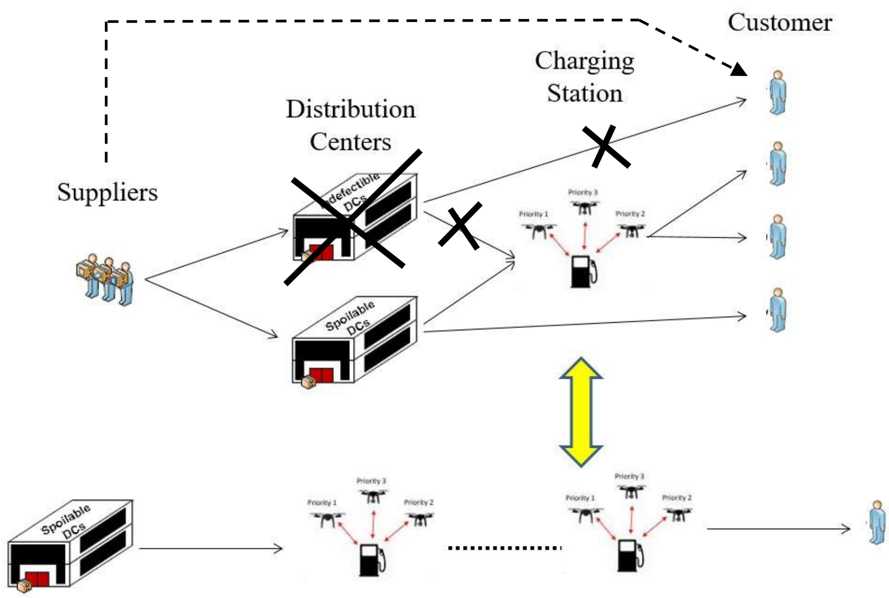


Figure 4.2 Supply chain network under disruption

Charging stations are introduced within the existing logistics to extend the flight range of drone service area. A feasible delivery network consists of the potential locations for distribution centers and charging stations that are covered by calculating the flight range of drones under various conditions. The Euclidean distances determine the set of potential nodes that can be covered by each facility by calculating the maximum coverage range of that facility. Three factors are considered to find this coverage range. First, drones, like all vehicles, can be recharged as many times as needed to reach their destination. If the customer destination is not within the coverage range of a distribution center or charging station, then the drone must be refueled at a station within the facility's coverage range. Second, in the last chain of network, it is not enough to simply arrive at the customer's location within the maximum flying range. A drone must be able to return to a station or the distribution center after delivery of its product without exceeding its remaining fuel range. A third factor is that once the parcel is delivered to customer, the weight of the drone decreases which results in increasing the flight range of drones. Thus, delivery drones do not need to arrive at their destination with at least 50% state of charge to return to the last station, as assumed in standard flow-refueling approaches, because the return trip will use less fuel. It is assumed that the fully loaded trip could require as much as twice the energy for an empty return trip. Under these assumptions, each drone needs to keep at least 1/3 state of charge fuel level for the return trip from the customer. Thus, as it is illustrated in Figure 4.3, the delivery flight range for all step except final step (before customer) would be within the maximum coverage range, but this range would be 2/3 of the normal max-payload flight range for the final delivery step.

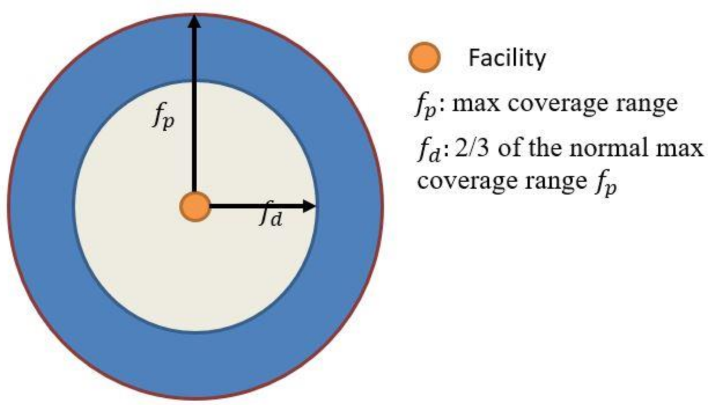


Figure 4.3 Coverage range of each facility

The proposed supply chain consists of four levels: suppliers, distribution centers, charging stations and customer. The customer locations are constant and certain. Each distribution center j ($j \in J$) and charging station l ($L \in J$) has either an unreliable facility with fixed cost of f_j^{UD} and f_l^{UL} which may fail with probability q_j ($0 < q_j < 1$) or a reliable facility with fixed cost of

f_j^{RD} and f_l^{LR} ($f_j^R \geq f_j^U$) which does not fail. These potential sites are definite and discrete. As Lim et al. (2010) examined, unreliable center hardening cost is presented by a linear function based on failure probability which is calculated by this equation: h= (f_j^{RD} - f_j^{UD}) = (f_j^{UD}*10)*q_j. Consequently, if a site incurs more failure probability, the costs of establishment would augment to compensate for more reliability. Another assumption in the formulated problem is that a single-product that can just move between two different network levels except the charging station part which can move between two charging station. It is also assumed that each customer node $c(c \in C)$ is completely fulfilled either by distribution centers directly or through the charging stations or by suppliers with higher transportation cost as a penalty of not satisfying with distribution center in each period. The objective here is to minimize the fixed cost of facilities, cost of buying drones in each facility, depreciation cost and expected transportation cost between facilities by locating a suitable number of reliable facilities among the unreliable facilities, and also to specify the flow volume of products between the facilities within each time period. The demand d_{cp} of customer c ($c \in C$) in period p ($p \in P$) is random with a known distribution. The disruptions occur only in charging stations and distribution centers with a defined disruption probability, and these probabilities and failure occurrence are assumed independent of each other, i.e. when one facility fails, it does not have any negative influence on operating other facilities.

A deterministic equivalent formulation (also known as an extensive form) is derived by extending the capacitated facility location problem for the circumstance which a finite set of demand and disaster scenarios can capture uncertainties in the random parameters.

4.2.1 Proposed extensive form model

Table 4.1 presents the necessary sets, parameters, and decision variables. The multi-period capacitated supply chain network under stochastic demand and random disaster can be formulated as mixed-integer programming in extensive form as follows.

Table 4.1 sets, parameters and decision variables for Reliable Supply Chain Model

Sets		
I	The set of candidate sites for suppliers	
J	The set of candidate sites for distribution centers	
L	The set of candidate sites for Charging Station	
C	The set of constant customers	
J_c	The set of candidate sites for distribution centers within delivery range f_d of customer c ($\forall c \in C$)	
L_c	The set of candidate sites for Charging stations within delivery range f_d of customer c ($\forall c \in C$)	
L_l	The set of candidate sites for Charging stations within Max-payload range f_p of Charging station l ($\forall l \in L$)	
J_l	The set of candidate sites for distribution centers within Max-payload range f_p of charging station l ($\forall l \in L$)	
P	The set of time periods	
S_d^C	The set of scenarios for demand	
S_f^D	The set of plausible scenarios for disruptions in distribution centers	
S_h^L	The set of plausible scenarios for disruptions in charging stations	
Parameters		
f_i	Fixed cost of established supply nodes i,	$\forall i \in I$
f_j^{UD}	Fixed cost of established unreliable distribution nodes j,	$\forall j \in J$
f_j^{RD}	Fixed cost of established reliable distribution nodes j,	$\forall j \in J$
f_l^{UL}	Fixed cost of established unreliable charging station l,	$\forall l \in L$
f_l^{RL}	Fixed cost of established unreliable charging station l,	$\forall l \in L$
C^d	Price of each drone,	
C^u	Usage cost of drones,	
E_{jl}^{DL}	ESP distance from distribution center j to charging station l,	$\forall j \in J, \forall l \in L$
E_{jc}^{DC}	ESP distance from distribution center j to customer c,	$\forall j \in J, \forall c \in C$
E_{lc}^{LC}	ESP distance from charging station l to customer c,	$\forall l \in L, \forall c \in C$

$E_{ll'}^{LL}$	ESP distance from charging station l to charging station l' where $l \neq l'$,	
T_{ij}^{SD}	Transportation cost from supplier i to distribution center j,	$\forall i \in I, \forall j \in J$
T_{jc}^{DC}	Transportation cost from distribution center j to customer c,	$\forall j \in J, \forall c \in C$
T_{jl}^{DL}	Transportation cost from distribution center j to charging station l,	$\forall j \in J, \forall l \in L$
T_{lc}^{LC}	Transportation cost from charging station l to customer c,	$\forall l \in L, \forall c \in C$
$T_{ll'}^{LL}$	Transportation cost from charging station l to charging station l' where $l \neq l'$,	$\forall l \in L, \forall l' \in L$
T_{ic}^{SC}	Transportation cost from supplier i to customer c,	$\forall i \in I, \forall c \in C$
d_{cp}	Demand of customer c in each period p,	$\forall c \in C, \forall p \in P$
K_i^S	Capacity at supplier i,	$\forall i \in I$
K_j^D	Capacity at distribution center j,	$\forall j \in J$
q_d^C	Probability of a demand scenario d,	$\forall d \in S_d^C$
q_f^D	Probability of a disruption scenario f for distribution centers	$\forall f \in S_f^D$
q_h^L	Probability of a disruption scenario h for charging stations	$\forall h \in S_h^L$
a_{jf}^D	0–1 indicated parameter if facility j is included in scenario f,	$\forall j \in J, \forall f \in S_f^D$
a_{lh}^L	0–1 indicated parameter if site l is included in scenario h,	$\forall l \in L, \forall h \in S_h^L$
a_d^C	Percentage variation in demand for each scenario d,	$d \in S_d^C$

Binary Decision variables

X_i	$\begin{cases} 1 \text{ if supplier } i \text{ is established} \\ 0 \; if \; otherwise \end{cases}$
X_j^{UD}	$\begin{cases} 1 \; if \; unreliable \; distribution \; center \; j \; is \; established \\ 0 \; if \; otherwise \end{cases}$
X_j^{RD}	$\begin{cases} 1 \; if \; reliable \; distribution \; center \; j \; is \; established \\ 0 \; if \; otherwise \end{cases}$
X_l^{UL}	$\begin{cases} 1 \; if \; unreliable \; charging \; station \; l \; is \; established \\ 0 \; if \; otherwise \end{cases}$
X_l^{RL}	$\begin{cases} 1 \; if \; reliable \; charging \; station \; l \; is \; established \\ 0 \; if \; otherwise \end{cases}$

Continuous Decision variables

B_{jcpdhf}^{UDC}	The percentage of demand sent from unreliable distribution center $j(j \in J_c)$ to customer $c(c \in C)$ in each period $p(p \in P)$, demand scenario $d(d \in S_d^C)$, and disruption scenarios $f(f \in S_f^D)$ and $h(h \in S_h^L)$.
B_{jcpdhf}^{RDC}	The percentage of demand sent from reliable distribution center $j(j \in J_c)$ to customer $c(c \in C)$ in each period $p(p \in P)$, demand scenario $d(d \in S_d^C)$, and disruption scenarios $f(f \in S_f^D)$ and $h(h \in S_h^L)$.
B_{lcpdhf}^{ULC}	The percentage of demand sent from unreliable charging station $l(l \in L_c)$ to customer $c(c \in C)$ in each period $p(p \in P)$, demand scenario $d(d \in S_d^C)$, and disruption scenarios $f(f \in S_f^D)$ and $h(h \in S_h^L)$.

B^{RLC}_{lcpdhf} The percentage of demand sent from reliable charging station $l(l \in L_c)$ to customer $c(c \in C)$ in each period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

$B^{UJUL}_{jlcpdhf}$ The percentage of demand for customer $c(c \in C)$ sent from unreliable distribution center $j(j \in J_c)$ to unreliable charging station $l(l \in L_c)$ in each period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

$B^{UJRL}_{jlcpdhf}$ The percentage of demand for customer $c(c \in C)$ sent from unreliable distribution center $j(j \in J_c)$ to reliable charging station $l(l \in L_c)$ in each period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

$B^{RJUL}_{jlcpdhf}$ The percentage of demand for customer $c(c \in C)$ sent from reliable distribution center $j(j \in J_c)$ to unreliable charging station $l(l \in L_c)$ in each period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

$B^{RJRL}_{jlcpdhf}$ The percentage of demand for customer $c(c \in C)$ sent from reliable distribution center $j(j \in J_c)$ to reliable charging station $l(l \in L_c)$ in each period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

$B^{ULUL}_{ll'cpdhf}$ The percentage of demand for customer $c(c \in C)$ sent from unreliable charging station $l(l \in L_c)$ to unreliable charging station $l'(l' \in L_c)$ where $l \neq l'$ in each period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

$B^{ULRL}_{ll'cpdhf}$ The percentage of demand for customer $c(c \in C)$ sent from unreliable charging station $l(l \in L_c)$ to reliable charging station $l'(l' \in L_c)$ where $l \neq l'$ in each period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

$B^{RLUL}_{ll'cpdhf}$ The percentage of demand for customer $c(c \in C)$ sent from reliable charging station $l(l \in L_c)$ to unreliable charging station $l'(l' \in L_c)$ where $l \neq l'$ in each period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

$B^{RLRL}_{ll'cpdhf}$ The percentage of demand for customer $c(c \in C)$ sent from reliable charging station $l(l \in L_c)$ to reliable charging station $l'(l' \in L_c)$ where $l \neq l'$ in each period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

N_j Total number of drones in each distribution center $j(j \in J)$.

U^d_{pdhf} Aggregate utilization of drones (total distance travelled by drones) in each period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

Z_{icpdhf} The percentage of demand sent from supplier $i(i \in I)$ to customer $c(c \in C)$ in period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

Y^U_{ijpdhf} The amount of supply sent from supplier $i(i \in I)$ to unreliable distribution center $j(j \in J)$ in period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

Y^R_{ijpdhf} The amount of supply sent from supplier $i(i \in I)$ to reliable distribution center $j(j \in J)$ in period $p(p \in P)$, demand scenario $d(d \in S^C_d)$, and disruption scenarios $f(f \in S^D_f)$ and $h(h \in S^L_h)$.

$$
\begin{aligned}
Min \quad & \sum_{i\in I} f_i X_i + \sum_{j\in J} f_j^{UD} X_j^{UD} + \sum_{j\in j} f_j^{RD} X_j^{RD} + \sum_{l\in L} f_l^{UL} X_l^{UL} + \sum_{l\in L} f_l^{RL} X_l^{RL} + \sum_{j\in J} C^d N_j \\
& + \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D C^u U_{pdhf}^d \\
& + \sum_{j\in J} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{jc}^{DC} B_{jcpdhf}^{UDC} \\
& + \sum_{j\in J} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{jc}^{DC} B_{jcpdhf}^{RDC} \\
& + \sum_{l\in L} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{lc}^{LC} B_{lcpdhf}^{ULC} \\
& + \sum_{l\in L} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{lc}^{LC} B_{lcpdhf}^{RLC} \\
& + \sum_{j\in J} \sum_{l\in L} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{jl}^{DL} B_{jlcpdhf}^{UJUL} \\
& + \sum_{j\in J} \sum_{l\in L} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{jl}^{DL} B_{jlcpdhf}^{UJRL} \\
& + \sum_{j\in J} \sum_{l\in L} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{jl}^{DL} B_{jlcpdhf}^{RJUL} \\
& + \sum_{j\in J} \sum_{l\in L} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{jl}^{DL} B_{jlcpdhf}^{RJRL} \\
& + \sum_{l\in L} \sum_{l'\in L} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{ll'}^{LL} B_{ll'cpdhf}^{ULUL} \\
& + \sum_{l\in L} \sum_{l'\in L} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{ll'}^{LL} B_{ll'cpdhf}^{ULRL} \\
& + \sum_{l\in L} \sum_{l'\in L} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{ll'}^{LL} B_{ll'cpdhf}^{RLUL} \\
& + \sum_{l\in L} \sum_{l'\in L} \sum_{c\in C} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{ll'}^{LL} B_{ll'cpdhf}^{RLRL} \\
& + \sum_{i\in I} \sum_{j\in J} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D T_{ij}^{SC} Y_{ijpdhf}^{U} \\
& + \sum_{i\in I} \sum_{j\in J} \sum_{p\in P} \sum_{d\in S_d^C} \sum_{f\in S_f^D} \sum_{h\in S_h^L} q_d^C q_h^L q_f^D T_{ij}^{SC} Y_{ijpdhf}^{R}
\end{aligned}
$$

$$+\sum_{i\in I}\sum_{c\in C}\sum_{p\in P}\sum_{d\in S_d^C}\sum_{f\in S_f^D}\sum_{h\in S_h^L} q_d^C q_h^L q_f^D a_d^C d_{cp} T_{ic}^{SC} Z_{icpdhf} \tag{4.1}$$

Subject to:

$$X_j^{UD} + X_j^{RD} \le 1, \qquad \forall j \in J \tag{4.2}$$

$$X_l^{UL} + X_l^{RL} \le 1, \qquad \forall l \in L \tag{4.3}$$

$$\sum_{j\in J} X_j^R \ge 1, \tag{4.4}$$

$$\begin{aligned}&\sum_{j\in J_c} B_{jcpdhf}^{UDC} + \sum_{j\in J_c} B_{jcpdhf}^{RDC} + \sum_{l\in L_c} B_{lcpdhf}^{ULC}\\ &+\sum_{l\in L_c} B_{lcpdhf}^{RLC} + \sum_{i\in I} Z_{icpdhf} = 1, \qquad \forall c \in C, \forall p \in P, \forall d \in S_d^C,\ \forall f \in S_f^D, \forall h \in S_h^L\end{aligned} \tag{4.5}$$

$$\begin{aligned}&\sum_{l'\in L_l} B_{ll'cpdhf}^{ULUL} + \sum_{l'\in L_l} B_{ll'cpdhf}^{ULRL} +\\ &B_{lcpdhf}^{ULC} = \sum_{j\in J_l} B_{jlcpdhf}^{UJUL} + \sum_{j\in J_l} B_{jlcpdhf}^{RJUL} \qquad \forall l \in L, \forall c \in C, \forall p \in P,\ \forall d \in S_d^C, \forall f \in S_f^D, \forall h \in S_h^L\\ &+\sum_{l'\in L_l} B_{l'lcpdhf}^{ULUL} + \sum_{l'\in L_l} B_{l'lcpdhf}^{RLUL}\end{aligned} \tag{4.6}$$

$$\begin{aligned}&\sum_{l'\in L_l} B_{ll'cpdhf}^{RLUL} + \sum_{l'\in L_l} B_{ll'cpdhf}^{RLRL} +\\ &B_{lcpdhf}^{RLC} = \sum_{j\in J_l} B_{jlcpdhf}^{UJRL} + \sum_{j\in J_l} B_{jlcpdhf}^{RJRL} \qquad \forall l \in L, \forall c \in C, \forall p \in P,\ \forall d \in S_d^C, \forall f \in S_f^D, \forall h \in S_h^L\\ &+\sum_{l'\in L_l} B_{l'lcpdhf}^{ULRL} + \sum_{l'\in L_l} B_{l'lcpdhf}^{RLRL}\end{aligned} \tag{4.7}$$

$$\begin{aligned}&\sum_{l\in L}\sum_{c\in C} B_{jlcpdhf}^{UJUL} + \sum_{l\in L}\sum_{c\in C} B_{jlcpdhf}^{UJRL} + \sum_{c\in C} B_{jcpdhf}^{UDC} \qquad \forall j \in J, \forall p \in P,\ \forall d \in S_d^C, \forall f \in S_f^D, \forall h \in S_h^L\\ &\le M * X_j^{UD} a_{jf}^D,\end{aligned} \tag{4.8}$$

$$\begin{aligned}&\sum_{l\in L}\sum_{c\in C} B_{jlcpdhf}^{RJUL} + \sum_{l\in L}\sum_{c\in C} B_{jlcpdhf}^{RJRL} + \sum_{c\in C} B_{jcpdhf}^{RDC} \qquad \forall j \in J, \forall p \in P,\ \forall d \in S_d^C, \forall f \in S_f^D, \forall h \in S_h^L\\ &\le M * X_j^{RD} a_{jf}^D,\end{aligned} \tag{4.9}$$

$$\sum_{l' \in L} \sum_{c \in C} B_{ll'cpdhf}^{ULUL} + \sum_{l' \in L} \sum_{c \in C} B_{ll'cpdhf}^{ULRL} + \sum_{c \in C} B_{lcpdhf}^{ULC} \leq M * X_l^{UL} a_{lh}^{L}, \quad \forall l \in L, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D, \forall h \in S_h^L \tag{4.10}$$

$$\sum_{l' \in L} \sum_{c \in C} B_{ll'cpdhf}^{RLUL} + \sum_{l' \in L} \sum_{c \in C} B_{ll'cpdhf}^{RLRL} + \sum_{c \in C} B_{lcpdhf}^{RLC} \leq M * X_l^{RL} a_{lh}^{L}, \quad \forall l \in L, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D, \forall h \in S_h^L \tag{4.11}$$

$$\sum_{c \in C} Z_{icpdhf} \leq M * X_i, \quad \forall i \in I, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D, \forall h \in S_h^L \tag{4.12}$$

$$\begin{aligned} N_j \geq &\sum_{c \in C} a_d^C d_{cp} B_{jcpdhf}^{UDC} + \sum_{c \in C} a_d^C d_{cp} B_{jcpdhf}^{RDC} \\ &+ \sum_{l \in L} \sum_{c \in C} a_d^C d_{cp} B_{jlcpdhf}^{UJUL} + \sum_{l \in L} \sum_{c \in C} a_d^C d_{cp} B_{jlcpdhf}^{RJUL} \\ &+ \sum_{l \in L} \sum_{c \in C} a_d^C d_{cp} B_{jlcpdhf}^{UJRL} + \sum_{l \in L} \sum_{c \in C} a_d^C d_{cp} B_{jlcpdhf}^{RJRL}, \end{aligned} \quad \forall j \in J, \forall p \in P, \forall d \in S_d^C, \forall f \in S_f^D, \forall h \in S_h^L \tag{4.13}$$

$$\begin{aligned} U_{pdhf}^{d} \geq &\sum_{j \in J} \sum_{c \in C} a_d^C d_{cp} E_{jc}^{DC} B_{jcpdhf}^{UDC} \\ &+ \sum_{j \in J} \sum_{c \in C} a_d^C d_{cp} E_{jc}^{DC} B_{jcpdhf}^{RDC} \\ &+ \sum_{j \in J} \sum_{l \in L} \sum_{c \in C} a_d^C d_{cp} E_{jl}^{DL} B_{jlcpdhf}^{UJUL} \\ &+ \sum_{j \in J} \sum_{l \in L} \sum_{c \in C} a_d^C d_{cp} E_{jl}^{DL} B_{jlcpdhf}^{RJUL} \\ &+ \sum_{j \in J} \sum_{l \in L} \sum_{c \in C} a_d^C d_{cp} E_{jl}^{DL} B_{jlcpdhf}^{UJRL} \\ &+ \sum_{j \in J} \sum_{l \in L} \sum_{c \in C} a_d^C d_{cp} E_{jl}^{DL} B_{jlcpdhf}^{RJRL} \\ &+ \sum_{l \in L} \sum_{l' \in L} \sum_{c \in C} a_d^C d_{cp} E_{ll'}^{LL} B_{ll'cpdhf}^{ULUL} \\ &+ \sum_{l \in L} \sum_{l' \in L} \sum_{c \in C} a_d^C d_{cp} E_{ll'}^{LL} B_{ll'cpdhf}^{ULRL} \end{aligned}$$

$$+\sum_{l\in L}\sum_{l'\in L}\sum_{c\in C} a_d^C d_{cp} E_{ll'}^{LL} B_{ll'cpdhf}^{RLUL}$$

$$+\sum_{l\in L}\sum_{l'\in L}\sum_{c\in C} a_d^C d_{cp} E_{ll'}^{LL} B_{ll'cpdhf}^{RLRL}$$

$$+\sum_{l\in L}\sum_{c\in C} a_d^C d_{cp} E_{lc}^{LC} B_{lcpdhf}^{ULC}$$

$$+\sum_{l\in L}\sum_{c\in C} a_d^C d_{cp} E_{lc}^{LC} B_{lcpdhf}^{RLC}, \qquad \forall p\in P, \forall d\in S_d^C, \forall f \in S_f^D, \forall h\in S_h^L \tag{4.14}$$

$$\sum_{i\in I} Y_{ijpdhf}^{U} = \sum_{c\in C} a_d^C d_{cp} B_{jcpdhf}^{UDC} + \sum_{l\in L}\sum_{c\in C} a_d^C d_{cp} B_{jlcpdhf}^{UJUL} + \sum_{l\in L}\sum_{c\in C} a_d^C d_{cp} B_{jlcpdhf}^{UJRL}, \qquad \forall j\in J, \forall p\in P, \forall d\in S_d^C, \forall f\in S_f^D, \forall h\in S_h^L \tag{4.15}$$

$$\sum_{i\in I} Y_{ijpdhf}^{R} = \sum_{c\in C} a_d^C d_{cp} B_{jcpdhf}^{RDC} + \sum_{l\in L}\sum_{c\in C} a_d^C d_{cp} B_{jlcpdhf}^{RJUL} + \sum_{l\in L}\sum_{c\in C} a_d^C d_{cp} B_{jlcpdhf}^{RJRL}, \qquad \forall j\in J, \forall p\in P, \forall d\in S_d^C, \forall f\in S_f^D, \forall h\in S_h^L \tag{4.16}$$

$$\sum_{j\in J} Y_{ijpdhf}^{U} + \sum_{j\in J} Y_{ijpdhf}^{R} + \sum_{c\in C} a_d^C d_{cp} Z_{icpdhf} \le X_i K_i^S, \qquad \forall i\in I, \forall p\in P, \forall d\in S_d^C, \forall f\in S_f^D, \forall h\in S_h^L \tag{4.17}$$

$$\sum_{i\in I} Y_{ijpdhf}^{U} \le K_j^D, \qquad \forall j\in J, \forall p\in P, \forall d\in S_d^C, \forall f\in S_f^D, \forall h\in S_h^L \tag{4.18}$$

$$\sum_{i\in I} Y_{ijpdhf}^{R} \le K_j^D, \qquad \forall j\in J, \forall p\in P, \forall d\in S_d^C, \forall f\in S_f^D, \forall h\in S_h^L \tag{4.19}$$

$$X_i, X_j^{UD}, X_j^{RD}\ X_l^{UL}, X_l^{RL} \in \{0,1\}, \qquad \forall i\in I, \forall j\in J, \forall l\in L \tag{4.20}$$

$$N_j, U_{pdhf}^{d}, B_{jcpdhf}^{UDC}, B_{jcpdhf}^{RDC}, B_{lcpdhf}^{ULC}, B_{lcpdhf}^{RLC}, B_{jlcpdhf}^{UJUL}, B_{jlcpdhf}^{UJRL}, B_{jlcpdhf}^{RJUL}, B_{jlcpdhf}^{RJRL}, Y_{ijpdhf}^{U}, Y_{ijpdhf}^{R}, Z_{icpdhf}, B_{ll'cpdhf}^{ULUL}, B_{ll'cpdhf}^{ULRL}, B_{ll'cpdhf}^{RLUL}, B_{ll'cpdhf}^{RLRL} \ge 0, \qquad \forall i\in I, \forall j\in J, \forall l\in L, \forall c\in C, \forall p\in P, \forall d\in S_d^C, \forall f\in S_f^D, \forall h\in S_h^L, \forall l'\in L \tag{4.21}$$

Equation (4.1) is the objective function and consists of twenty-two terms. The first five are the fixed costs of establishing supply facilities, unreliable distribution centers, reliable distribution centers, unreliable charging station, and reliable charging station, respectively. The cost of buying drones and usage of each one is calculated by sixth and seventh terms. The transportation cost from each node to others over all plausible scenarios and all periods is calculated by terms eight to nineteen. The product transportation cost from supplier i $(i \in I)$ to unreliable or reliable distribution center j $(j \in J)$ is calculated by the 20 and 21 terms. The last term calculates the transportation cost from supplier i $(i \in I)$ to the customer c $(c \in C)$ as a penalty cost for not satisfying the particular customer demand.

For each time period $p, p \in P$, and each scenario $d, f, h, d \in S_d^C, f \in S_f^D, h \in S_h^L$, constraints are described as follow. Constraints (4.2) and (4.3) indicate that for any candidate site we can only locate an unreliable or a reliable facility. Constraint (4.4) ensures that there should be at least one reliable distribution center. Constraint (4.5) ensures that each customer must be completely satisfied by one of the distribution centers with low-rate cost or suppliers with high-rate cost. Constraints (4.6) and (4.7) ensure that for each customer the inflow and out flow of each charging station is equal. Constraints (4.8) to (4.12) indicate that each allocation must be assigned to a facility which is not failed after disruption for each scenario. Moreover, each customer can only be allocated to the supplier given that the supplier is already established. Constraint (4.13) ensures that the number of drones in each facility is greater than number of demands assigned to that facility. Constraint (4.14) is calculated the usage distance of all drones. Constraint (4.15) and (4.16) ensure that the sum of inflow to distribution center j must be equal to the sum of outflow from that station. Constraint (4.17) states that a flow occurs if and only if the supplier node is established and the outflow of each supplier node should be less than or equal to its capacity.

Constraint (4.18) and (4.19) indicate the inflow to each distribution center node is less than or equal to its capacity, given that the distribution center is established. Constraints (4.20) and (4.21) are non-negative constraints used to represent the binary variables and product-flow variables between the facilities, respectively.

4.3 Meta-heuristic algorithm for stochastic location and allocation problem

4.3.1 Background

The computation time and memory requirement for solving stochastic mixed-integer linear programming can be computationally challenging. Decomposition algorithm like Benders decomposition have been proposed to solve network design problems (Kouvelis, Kurawarwala, & Gutierrez, 1992; Gutiérrez, Kouvelis, & Kurawarwala, 1996; Snyder, & Daskin, 2006). However, by increasing the number of scenarios and number of networks in the system, these algorithms even could not solve the problem efficiently. Having near-optimal solutions in short time instead of having optimal solution are often more interesting for managers in real word problem.

This research proposes a metaheuristic algorithm which is an extension of a genetic algorithm. A main improvement of this research to the basic genetic algorithm scheme is that the initial populations are generated in a way that all solutions are feasible across all stochastic scenarios with the highest fitness. In the stochastic facility location and allocation problem, finding feasible solution is challenging because firstly the number of scenario dependent variables are huge which result in long length of string chromosome structure and secondly the allocation networks (scenario dependent variables) highly depend on the location of the nodes. In this approach the algorithm tends to find a better initial population size before the crossover and mutation operation for each individual in each generation. Thus, the average population fitness is improved and the probability of producing higher-quality offspring is increased.

4.3.2 Representation scheme, fitness function and initial population generation

An n-digit string chromosome structure is used that includes binary, integer, and rational parts to represent a solution X. For binary part, the *i*th digit on the string indicates whether the *i*th facility is open (‘‘1’’) or not (‘‘0’’). $X_i, X_j^{UD}, X_j^{RD}, X_l^{UL}, X_l^{RL}$ for $\forall i \in I, \forall j \in J, \forall l \in L$ are the binary variables and the length of the chromosome depends on the size of the potential locations for facilities. For example, in Figure 4.4(a), facilities 2, 3, 4 and 6 out of a total of eight potential sites are open in binary part of solution X. N_j, $\forall j \in J$ are integer part of the chromosome structure and the *i*th digit on the string indicates the number of drones of facility *i*th. Furthermore, in Figure 4.4(b), facility 1 has 214 drones and facility 2 has 103 drones in integer part of solution X. The rest of the string indicates the linear part of the chromosome includes dependent scenario variables like the distance traveled by all drones and the amount of product flowing between each two nodes for each scenario and period. For instance, in Figure 4.4(c), B_{jcpdhf}^{UDC} is the amount of product flowing between unreliable facility 1 to eight demand location for scenarios $d = 1$, $h = 1$, $f = 1$ and periods 1. The total length of chromosome just for variable B_{jcpdhf}^{UDC} is $|J| * |C| * |P| * |S_d^C| * |S_f^D| * |S_h^L|$. This part of the chromosome is combination of the all scenario dependent variables which would be increased by increasing the number of scenarios and periods.

$\forall i \in I$		$\forall j \in J$		$\forall l \in L$			
0	1	1	1	0	1	0	0

(a) Binary part of chromosome structure.

214	103

(b) Integer part of chromosome structure.

30.40	11.20	11.58	90.88	0	00.0	54.69	0

(c) Linear part of chromosome structure.

Figure 4.4 Chromosome structure

As mentioned before, the number of scenario dependent variables are large resulting in long length of string for chromosome structure. Thus, generating the feasible solution and maintaining the feasibility of the solutions after crossover and mutation is challenging in this kind of problem. A novel approach is proposed to deal with these issues. To speed up the generation of initial feasible population with highest fitness, the sequence of the digits in a chromosome is sorted using the following steps:

1- Generate the feasible solutions for scenario independent variables such as location of facility and number of drones in each distribution centers. These solutions are common among all scenarios and periods.

2- Based on the fixed location and number of drones obtained in step 1, the solution is generated for the rest of the string (scenario dependent variables). In this step, for each feasible solution of step one, initial feasible population is generated at specific size for each scenario separately. For example, 20 initial feasible solution would be generated for scenario dependent variable B_{jcpdhf}^{UDC} for scenarios $S_d^C = 1$, $S_f^D = 3$, and $S_h^L = 2$. Then for each scenario the best of these initial solutions will be chosen in terms of fitness score to the number of initial population size. After finding the best initial populations for each scenario, they will be combined and added to the first step solution to generate the complete solution X.

In this approach the algorithm tends to find a better initial population size before the crossover and mutation operation for each iteration, and the objective function value converges within few iterations most of the time. Numerical experiments show that this novel approach has a great impact on the solution time.

For a specific solution X, the problem is solved for each scenario and periods to get the optimal flow assignments. The objective function (4.1) is a commonly used as a fitness function to justify the quality of a solution X. However, unlike most heuristic algorithm in network design-type problems, a given solution X is guaranteed to be feasible since it is generated by considering all constraints.

4.3.3 Genetic algorithm operators (crossover and mutation)

To reiterate, finding the feasible solution for stochastic location and allocation problem with large number of scenarios is challenging. Any switching digits among the solution in performing crossover operation most probably result in infeasible solution. In the proposed method, the crossover on binary and integer parts of the chromosome is separately performed in the way the feasibility of solutions is kept intact. The crossover operation starts with choosing two solutions randomly from the current population. For each pair, the binary and integer part of the solution are taken, and two new solutions are generated by switching some randomly chosen digits at the same position on the chromosomes. In this process it is required to check and make sure all constraints associated with the binary and integer parts of the chromosome are still satisfied or in other words, our solution is still feasible. For example, it is required to be sure there is at least one supplier available or in each potential location for distribution centers only one unreliable or reliable facility can be located. In Figure 4.5, you can see how the unfeasible solution can generate by crossover.

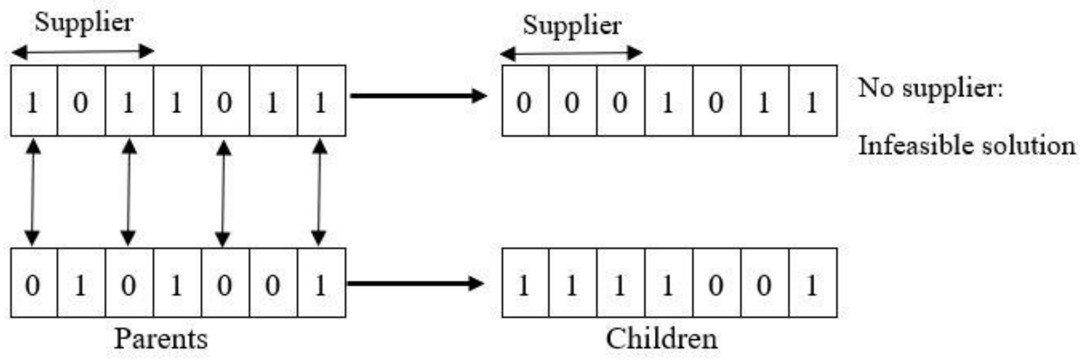


Figure 4.5 Crossover operation

The digit swapping probability is selected uniformly for each pair from the set {0.0, 0.1, 0.2, …, 1.0}. After performing crossover for scenario independent variables, the same process for scenario dependent variables is performed by checking the feasibility of the new network. Next, for crossover and new population generation, mutation is applied to avoid local optimal solution. In each iteration, every solution X has a probability of being chosen for mutation. If selected, one digit from integer part of the chromosome will be randomly selected and changed from 1 to 0 or 0 to 1 as shown in Figure 4.6.

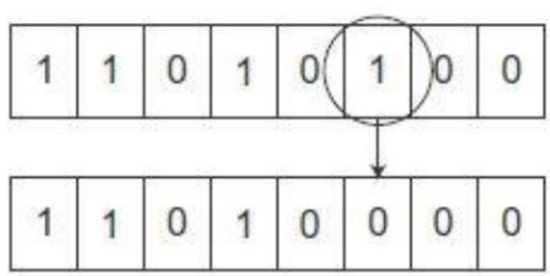


Figure 4.6 Mutation operation

Genetic algorithm normally stops when the best fitness of the population converges, or when the algorithm reaches a pre-specified time limit or iteration limit. In this method, the objective function value converges within few iterations most of the time. Therefore, the algorithm would be stopped after few iterations. It is assumed algorithm will be stopped after 30 iterations, or when the improvement in the best solution is less than 0.01% for 10 consecutive iterations. The heuristic may be summarized algorithmically as follows:

Genetic algorithm for stochastic mixed-integer programming model
1: Initialize I ← 0, k ← 0
2: Generate the feasible initial population based on steps explained in section 4.3.2:
let X_I ← the best solution of generation I;
let X^*← the best solution in record (i.e., $X^* \leftarrow X_0$)
3: If f(X_I) < f(X^*), let $X^* \leftarrow X_I$;
4: Apply the crossover and mutation operators.
compute Δ = (f(X_I) − f(X_{I-1}))/f(X_{I-1})
• If Δ ⩽ 0.01%, let k ← k + 1
• else, let k ← 0
5: If I ⩾ 30 or k ⩾ 10, go to Step 6; else, let I ← I + 1, go to Step 3
6: If f(X_I) < f(X^*), let $X^* \leftarrow X_I$; return the best solution found X^*.

4.4 Numerical example and computational experiment

Several numerical experiments are performed to illustrate the decisions from the model. The case study considers a four-tier supply chain considered in Section 4.2. It is assumed two suppliers with certain capacity; three potential locations for distribution centers, each with a separate capacity; six potential locations for charging stations; and seven demand locations, each of which can be covered by some of the facilities. Next, different scenario sizes ranging from 128 to 4480 are generated for customers' demands based on exponential distribution with the mean of 1 for percentage variation in all demands and facility disruption. For the first part of experiment, the population size is fixed at 15. The genetic algorithm is coded in Python, CPLEX is used as the solver, and the method is executed on a computer with 3.40 GHz processor and 16 GB of RAM.

4.4.1 Comparison between solution time of heuristic method with normal commercial software

In this subsection, the performance of the improved genetic algorithm is compared against commercial software under various scenarios. The genetic algorithm approach significantly improves the solution time of the problem. Genetic algorithm normally terminates when the best fitness of the population converges, or when the algorithm reaches a pre-specified time limit or iteration limit. In the proposed approach, the objective function value typically converges within 5 iterations most of the time. In the computational study, the population size is fixed at 15.

Tables 4.2 presents the comparison of the computational efficiencies between genetic algorithm and commercial software for different values of $|S|$ (the total number of scenarios). For each instance, the difference between objective function value of genetic algorithm and optimal solution, and the solution times are reported. The computation time is restricted to twenty-four hours for all instances; if an optimal solution is not obtained within this time limit, then "No Solution (NS)" is reported in the solution time column.

Table 4.2 Comparison between genetic algorithm and commercial software

|S|	λ	Supplier	DC	C	Periods	Sol. Time	Sol. time (Heuristic)	%Obj
128	1	2	2	7	2	12.8996	87.6327	7%
192	1	2	2	7	2	60.4905	119.2164	6%
256	1	2	2	7	2	104.9837	146.5260	6%
320	1	2	2	7	2	149.4244	184.4826	5%
384	1	2	2	7	2	192.6236	219.9877	7%
448	1	2	2	7	2	248.6868	251.8581	6%
512	1	2	2	7	2	303.4652	282.9916	6%
576	1	2	2	7	2	342.2219	319.6640	7%
640	1	2	2	7	2	403.2904	358.0674	7%
704	1	2	2	7	2	461.3602	396.5483	5%

768	1	2	2	7	2	523.7434	431.3473	5%
832	1	2	2	7	2	597.8175	465.0120	6%
896	1	2	2	7	2	663.8456	509.8795	5%
960	1	2	2	7	2	723.4302	541.6815	4%
1088	1	2	2	7	2	852.3433	595.2275	7%
1216	1	2	2	7	2	979.8793	656.9201	5%
1344	1	2	2	7	2	1102.2947	709.3692	5%
1472	1	2	2	7	2	1236.6621	765.7228	7%
1600	1	2	2	7	2	1362.1032	819.6482	6%
1728	1	2	2	7	2	1498.9123	862.4491	8%
1984	1	2	2	7	2	1868.8712	979.7602	5%
2240	1	2	2	7	2	NS	1095.5643	-
2560	1	2	2	7	2	NS	1253.4565	-
2880	1	2	2	7	2	NS	1446.9037	-
3200	1	2	2	7	2	NS	1685.0081	-
3840	1	2	2	7	2	NS	2102.6981	-
4480	1	2	2	7	2	NS	2595.0043	-

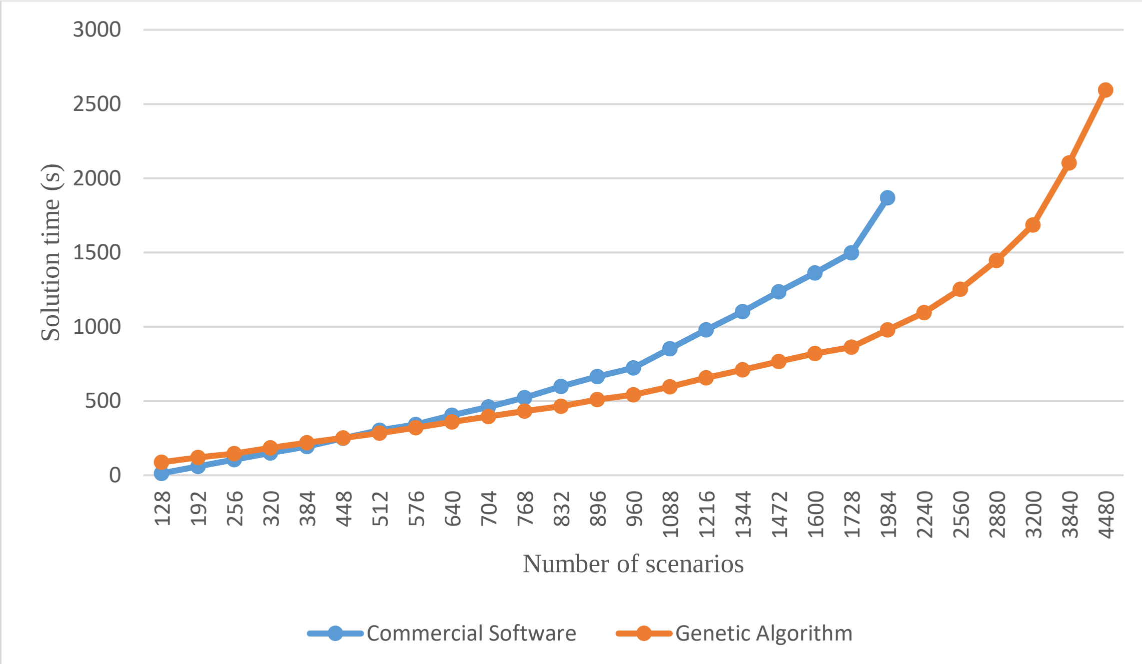


Figure 4.7 Sensitive analysis of different size of scenarios and solution time for genetic algorithm and commercial software

As it is illustrated in Table 4.2 and Figure 4.7, the Genetic algorithm can solve the stochastic problem with up to 4480 scenarios without any memory issues. However commercial software could not obtain an optimal solution within twenty-four hours for instances more than 1984 scenarios. The commercial software can find the optimal solution faster than genetic algorithm for scenario size of 448 or less. Beyond that, the genetic algorithm can find the solution (within range of 5% of optimal solution) much faster. Genetic algorithm has much faster computation times in most cases as shown in Figure 4.7 and performs 40% better on average while this rate increases up to 55% in some instances. The commercial software runs into memory issues for the instances with $|S| \geq 1984$ while for genetic algorithm can easily solve such instances. In summary, the genetic method performs much better in stochastic problem which the size of the problem is exponentially increased by increasing the number of scenarios for uncertain parameters because it can find the near optimal solution in efficient time.

4.4.2 Comparison between objective of heuristic model and number of populations

This section analyzes impact of initial population on the quality of the solution. Table 4.3 presents how objective value is changed by increasing the number of initial population while the size of the problem is |S|=128. It is started with population size of 3 and increase it to 1000. As it is clear, by increasing the size of population from 3 to 1000, the quality of solutions also increases. The solution of instance with population size of 3 is within 7.3% of optimal solution while the solution of instance with population size of 1000 is within 1.6% of optimal solution. However, it is required to consider the fact that the solution time of generating the new population is increased by increasing the size of the population because in this method the feasible solution is always generated which takes time.

Table 4.3 The impact of different size of starting population on objective function value

|S|	λ	Supplier	DC	C	Periods	Optimal Obj	Obj (Heuristic)	Sol. time	|P|	%Obj
128	1	2	2	7	2	33038200	35465235.7856	85.44	3	7.34%
128	1	2	2	7	2	33038200	35254871.3068	157.48	5	6.70%
128	1	2	2	7	2	33038200	35254871.3068	222.98	7	6.70%
128	1	2	2	7	2	33038200	34951946.6136	350.47	10	5.79%
128	1	2	2	7	2	33038200	34917968.1609	540.37	15	5.68%
128	1	2	2	7	2	33038200	34719635.0370	737.46	20	5.08%
128	1	2	2	7	2	33038200	34709896.4992	1584.05	40	5.05%
128	1	2	2	7	2	33038200	34643762.2778	3066.81	80	4.85%
128	1	2	2	7	2	33038200	34414024.4511	5946.56	150	4.16%
128	1	2	2	7	2	33038200	34265179.7640	12394.39	300	3.71%
128	1	2	2	7	2	33038200	33966431.3429	18834.17	500	2.80%
128	1	2	2	7	2	33038200	33573718.7669	36593.47	1000	1.62%

4.4.3 Impact of disruption probability, opening fixed cost, and flight cost on number of drones, number of unreliable and reliable facilities

In this section, the impact of changing in disruption probability, fixed opening cost of facilities and drone flight cost on optimal number of drones, reliable and unreliable facilities is studied. Disruption probability is varied from 0.1 to 0.9 under fixed costs in distribution centers and charging stations. As you can see in Figure 4.8, the number of reliable facilities include charging stations and distribution centers increase as disruption probability increases while the number of unreliable facilities decrease. It is observed that the number of reliable facilities is highest when the disruption probability is high, while the optimal number of unreliable facilities are significantly less to satisfy the demands of the customers.

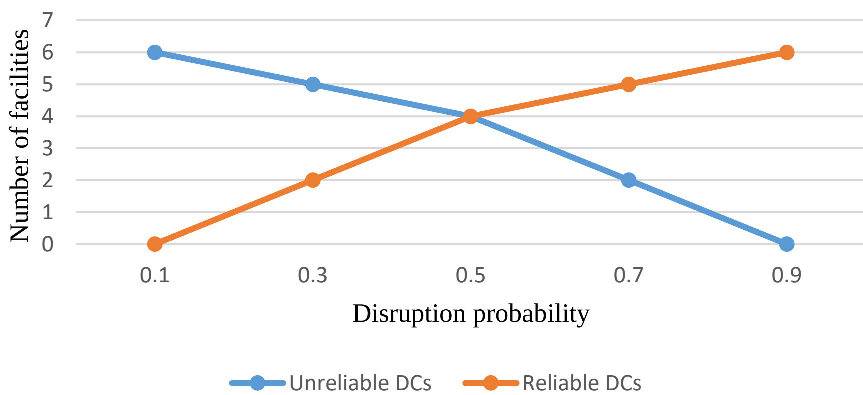


Figure 4.8 Sensitive analysis of disruption probability on optimal number of unreliable and reliable distribution centers and charging stations

To check the effect of fixed opening costs of facilities and flight cost of drones, it is started with 0% increase in fixed opening cost and increase that by 20% six times. Tables 4.4 and 4.5 present the results for size of 512 scenarios for these two experiments. As you can see in Table 4.4, the number of drones and facilities decrease as fixed costs of opening those facilities increase while the probability of disruption remains constant. Contrary to popular belief, it is observed that the system prefers to lose customers instead of having more drones and facilities in the system when the opening fixed cost of facilities increase. The same trend occurs when increasing the flight cost of drones as you it is shown in Table 4.5. By increasing the flight cost of the drones, the system prefers to pay the penalty cost of losing customers than having more drones and facilities in the system.

Table 4.4 Analyzing the impact of opening fixed cost of facilities on optimal number of drones and facilities

The percentage of increasing fixed cost in facilities	Number of drones	Number of DC and battery station
0%	1300	6
20%	1300	6
40%	1230	5
60%	640	3
80%	140	1
100%	140	1
150%	0	0

Table 4.5 Analyzing the impact of flight cost of drones on optimal number of drones and facilities

The percentage of increasing drone flight cost	Number of drones	Number of DC and battery station
0%	1300	6
20%	1230	5
40%	980	4
60%	640	3
80%	640	3
100%	420	2
150%	0	0

4.4.4 Benefit of considering disruption risk and applying hardening strategy

The advantage of having reliable supply chain network in face with random disruptions by applying hardening strategy is studied in this experiment. The disruptions can only happen in distribution centers or charging stations. In this experiment, at first, supply chain network design problem is considered without applying hardening strategy which results in having only unreliable distribution centers and charging stations. Next, the increasing rate in total cost is calculated for all different disruption scenarios due to the transportation cost's reassignment after facility failure in each scenario. Then, after applying hardening strategy, the total cost for the reliable supply chain model is calculated for all those disruption scenarios and compare it with unreliable model.

At first, costs of designing unreliable and reliable supply chain are obtained which include cost of establishing unreliable and reliable facility, transportation, buying drones, and usage. Then the total cost of both cases is calculated after disruption for each scenario takes place in the model in such way the demands loss in failed charging station or distribution center will be satisfied with their closest safe opened charging station, distribution centers or suppliers with higher transportation cost. The optimal costs pf designing an unreliable and reliable supply chain network using drones as a last-mile delivery for scenario sample size of 512 are \$31,525,000 and \$33,038,200 respectively and they are break down as it is shown in Table 4.6. It is obvious that with costing more investment about 70% in establishing more reliable facilities, the total increased cost for the reliable model is \$119000. Thus, the reliable supply chain model can be designed with just about 4.8% additional investment more in total cost.

Table 4.6 The results of stochastic model for both reliable and unreliable cases

	Unreliable supply chain model

Component	Number Facilities	Cost of Establishing	Other Cost	Total
Facility	8	150000	31375000	31525000

Reliable supply chain model

Component	Number Facilities	Cost of Establishing	Other Cost	Total
Unreliable Facility	2	44000	-	-
Reliable Facility	6	225000	-	-
All Facilities	8	269000	32769200	33038200

The total number of disruption scenarios in distribution centers are $2^j, \forall j \in J$, and in charging station are $2^l, \forall l \in L$. Table 4.7 presents total cost of each scenario for reliable and unreliable distribution centers and compares the percentage of increase in total cost in both cases. The average of all total cost is then calculated for better comparison.

Table 4.7 Comparing the total cost of each scenario for unreliable model with cost of having reliable model

Scenario	Which DC is disrupted	Damage cost of facility (first case)	Cost of reassignment (first case)	Total cost (first case)	percentage of increase
1	L1	16500	5,148,032	36673032	+16.33%
2	L2	16500	2,805,725	34330725	+8.90%
3	L3	16500	5,570,467	37095467	+17.67%
4	L4	16500	9,038,217	40563217	+28.67%
5	L1 & L2	33000	13,101,790	44626790	+41.56%
6	L1 & L3	33000	18,158,400	49683400	+57.60%
7	L1 & L4	33000	21,720,725	53245725	+68.90%
8	L2 & L3	33000	12,143,430	43668430	+38.52%
9	L2 & L4	33000	15,340,065	46865065	+48.66%
10	L3 & L4	33000	21,824,757	53349757	+69.23%
11	L1 & L2 & L3	49500	29,107,032	60632032	+92.33%
12	L1 & L2 & L4	49500	29,740,685	61265685	+94.34%
13	L1 & L3 & L4	49500	31,134,090	62659090	+98.76%
14	L2 & L3 $ L4	49500	28,558,497	60083497	+90.59%
15	DC1	20000	19,302,757	50827757	+61.23%

16	DC2	20000	23,006,945	54531945	+72.98%
17	Average of scenarios	-	-		+51.33%

Applying the hardening strategy to design a supply chain network has notably improved system's reliability. As it is shown in Table 4.7, all damage costs from having an unreliable supply chain network for all scenarios are more than the cost spent for making a reliable supply chain network. It is clear that a small investment in establishing facilities can save significant damage costs for reassigning the customer in an unreliable network. For example, in instance number 11, with 4.8% additional investments on establishing reliable facilities, the total disruption cost decreases by 92.33%. The proposed research shows how a slight increase in facility cost can increase the reliability of the system.

The total disruption cost of each scenario for unreliable supply chain model and the cost of having a reliable supply chain network are compared in Figure 4.9. The disruption costs for all scenarios are higher than developing a more reliable supply chain network. In Figure 4.9, scenarios 7, and 10 to 16 have significant damage cost with an average 85.1% increase in total cost. The damage costs for reassigning customers in these scenarios are significant compared to the cost of designing a reliable supply chain network with specified investment.

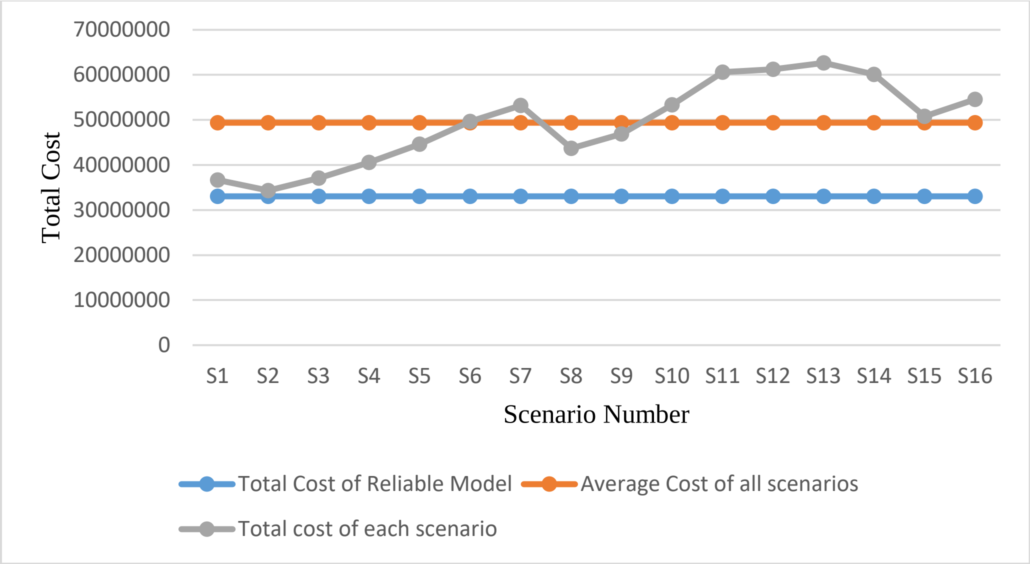


Figure 4.9 Comparing total cost of reliable and unreliable models with all scenarios

To summarize, the main contribution of this study is to formulate a mixed-integer programming model to design a reliable and efficient supply chain network using drones as a last-mile delivery under the uncertainty parameters. The coverage service of the reliable network is extended by introducing extra charging stations in the system. Also, the proposed genetic algorithm can efficiently solve stochastic problems with large number of scenarios. Besides, numerical experiments show the how increasing disruption probability, utilization costs of drones and fix cost of establishing reliable and unreliable facilities can decrease the number of drones and facilities in the system.

4.5 Conclusion

This research analyzes the reliable supply chain network problem that includes charging station to extend the coverage of drones in last-mile logistics under uncertain parameters. The mixed-integer linear programming model is formulated to design a reliable network and a genetic algorithm was applied to solve it. It is shown how a slight increase in facility investment can increase the system's reliability. It is also shown that, by considering each scenario independently to create a new population in the genetic algorithm, the efficiency of algorithm is significantly improved and near optimal solution is obtained in less iterations due to the absence of infeasibility solutions.

In summary, it is shown that the genetic algorithms perform significantly better than the commercial software for most scenario size. Under high disruption probability, the number of reliable distribution centers and charging stations increased while the unreliable facilities decrease. Furthermore, increasing the fixed cost of charging stations and distribution centers and flight cost of drones decreases the optimal number of reliable facilities to satisfy customers.

Chapter 5 - Stochastic Control and Managing Drones and Battery Inventories

Chapter 5 is based on the manuscript "Markov decision process model to evaluate drone and battery inventories in last-mile logistics" and analyzes stochastic control problem in evaluating the number of battery and drones and examines different charging strategies in recharging stations to improve drone delivery time in last-mile logistics.

5.1 Introduction

Logistics networks are often designed in such a way as to reduce costs and delivery times by allowing parcel to be delivered quickly. Land transport such as trucks, cars, motorcycles, and bicycles has been the norm for package delivery for decades since it is inexpensive, reliable, and easy to access. Nonetheless, rising labor costs make unmanned aerial vehicle (UAV) delivery such as drone delivery an increasingly appealing alternative delivery mode. While ground vehicles encounter many obstacles along the delivery route and require assistance crossing otherwise impassable systems, UAVs can fly directly to their destination without any obstacles. Due to drone technology advances, package delivery services are now cheaper and more reliable. In fact, DHL delivers packages on islands and mountains using a UAV called the Parcelcopter. Time, effort, and costs can be saved by using UAVs in these ways. Moreover, UAVs provide quick and precise delivery services in urban areas since they can prevent traffic congestion. Beijing, Shanghai, and Guangzhou were the sites where Alibaba conducted tests to deliver goods using UAVs. To achieve a quick, within-30-minute, delivery (maximum range: 16 km), Amazon developed Amazon Prime Air. In addition, UAVs can provide relief to disaster scenes that can't be reached by ground vehicles or even rescuers walking there. Also, secondary damage cannot affect the disaster relief mission. An example of UAVs used for relief delivery to a Nepal earthquake site can be seen in Figure 5.1.

Figure 5.1 Using drones to deliver relief items in Nepal earthquake 2015

UAVs could revolutionize the logistics industry by using them for 'last-mile' parcel deliveries. Before drones reach widespread adoption in the commercial sector, there are several significant technical and operational obstacles to overcome. A drone is generally faster, more affordable, less labor-intensive, and more environmentally friendly than a ground-based vehicle, like a truck. However, the drone has certain limitations such as reduced delivery capacity and a short flying distance per trip.

From a technical perspective, researchers are working to improve the endurance and safety of UAVs. According to logistics research, researchers are trying to address limitations like limited delivery capacity and limited coverage per trip. Amazon, for instance, proposes a direct warehouse-to-customer operation. Prime Air's UAV can reach a distance of 10 miles (Gross, 2013). It is, therefore, necessary for UAV deliveries to originate from distribution centers located close to the customer. It may also be necessary to relocate existing distribution centers or to build new ones in order to accomplish this. The range of a UAV delivery system can be extended through several logistical strategies. With a multi-modal approach, drones and trucks could be combined, using one's advantages to offset the disadvantages of the other. For example, drones could be launched from trucks in order to deliver the "last mile" to customers (Murray, & Chu, 2015; Agatz, Bouman, & Schmidt, 2015; Ha et al., 2018). Nevertheless, a method to extend the drone's limited flight range would be necessary if a stand-alone drone delivery service was to cover a large area. There may be an answer to this problem by offering drone recharging stations that replace batteries. As it is shown in Figure 5.2, during a single-mode (drone only) door-to-door drone delivery, one or more stops would have to be made for batteries to be recharged, or to be replaced (Sundar, & Rathinam, 2013; Dorling et al., 2016; Yu, Budhiraja, & Tokekar, 2018). By replacing depleted batteries with fully charged ones, the recharging station extends the flight range of the drone. After leaving a warehouse or station, a drone reaches the next station or reaches a destination within a safe return distance. Each recharging station, therefore, serves a particular area's demands.

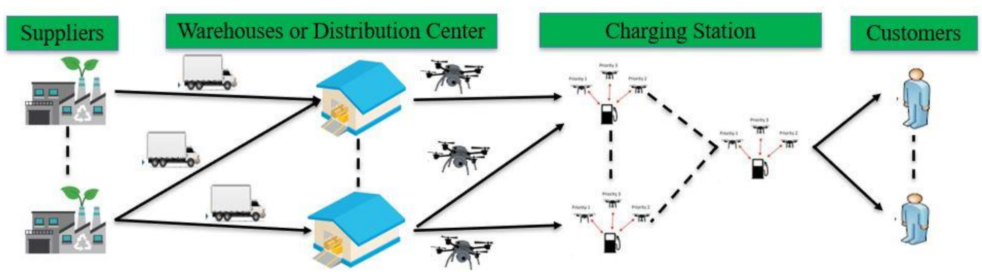


Figure 5.2 Supply chain network includes charging stations to extend the coverage of the drones in last-mile delivery

While research has been conducted to overcome the aforementioned technical and operational issues, no studies have addressed the challenges associated with recharging stations themselves. For example, most of the studies have not examined the effects of various decision parameters on drone delivery services, such as recharging station configuration, charging time, battery and drone number, flight time, and demand uncertainty. In terms of charging technology (for example, slow recharging, fast recharging, partial recharging, battery swaps, fixed charging), the main models refer to recharging technologies and routing strategies (Koç et al., 2019; Li-ying, & Yuan-bin, 2015) with a focus on sustainability, energy consumption, and power loss (Pal, Bhattacharya, & Chakraborty, 2021, Moupuri, 2021). To fill these gaps, this study seeks to improve delivery time by finding the best policy for charging rates inside the charging stations. To enhance delivery time, this research assumes that extra batteries are available at the recharging station where individual drones land when they run out of power and swap empty batteries with fully charged ones. In this logistics network, there are a lot of uncertainties, such as demand arrival, charging rate, and flight rate. The inventory management process as part of the logistics system includes tactical decisions in the supply chain system. These decisions can be described as a dynamic linkage of sequential decisions under these uncertainties. For example, the state of batteries and drones, the rate at which batteries are charged, the rate at which drones are flown, and the demand can all affect the outcomes and thus affect the best control decisions. In this research, different charging strategies are examined for recharging stations, which can be viewed as warehouses in last-mile logistics. There is a difference between these strategies in terms of costs and rates. This research develops stochastic Markov decision models to handle stochasticity in the problem and determine the optimal policy for decision-makers by applying a policy iteration algorithm.

When it comes to solving large-scale MDPs, especially in practice, there are several challenges involved. One of the most significant challenges is that the information desired to be captured by the states and actions will grow (often exponentially) based on the problem's complexity. This is why dynamic programming is sometimes avoided for large problems. As a first step, a transition probability matrix is constructed by taking advantage of the similar transition probabilities among the states belonging to a given set within each state space, which allows us to compute the exact performance estimate for the systems. In large-scale MDPs, finding optimal policy and exact analysis of the system becomes computationally challenging, despite deriving a set of conditions that partition the state space into regions to address dimensionality. To overcome this challenge, a novel approximation method called the decomposition-based approach is proposed to split the original Markov decision problem for the system with N states into N independent Markov chain processes. This independent system corresponds to a subsystem that evaluates one of those N states efficiently. In terms of the accuracy of the decomposition technique in each subsystem, the impact of other states belonging to other subsystems needs to be accounted for constructing the transition probability matrix of that subsystem. Through numerical examples, it is demonstrated that the proposed solution algorithm is not only capable of solving large-scale problems, but also avoids long run times. It is also demonstrated how storage conditions for drones, batteries, charging rate, flight rate, demand, etc. can affect optimal decisions.

The main contributions of this study are: From the tactical and operational side, stochasticity in a logistics network including recharging stations as a warehouse of extra batteries for drones is analyzed where there are a lot of uncertainties associated with this network like demand arrival, charging rate, and flight rate. In the literature, the main models for selecting recharging technology relate to the location of the recharging stations, including recharging technologies and routing strategies with an emphasis on sustainability, energy consumption, and power loss. To the best of our knowledge, no existing studies have analyzed different charging strategies in recharging stations to improve the delivery time in last-mile logistics using drones. This research develops stochastic Markov decision models to handle stochasticity in this problem and determine the best policy for decision-makers based on different charging rates, demand arrival rates, flight rates, and costs associated with them. Methodologically, a novel approximation method called the decomposition-based approach is developed to split the original Markov decision problem for the system into multiple independent Markov chain processes to improve the efficiency of solving the large-scale MDPs. This methodology will create a host of future research topics to advance modeling stochastic systems and mitigate the curse of dimensionality in dynamic programming. To the best of our knowledge, the proposed methodology is novel and has not been published in any relevant reports and venues.

The rest of the study is organized as follows. Section 5.2 describes how to formulate the Markov decision models for proposed system. Using this formulation, stochasticity in the problem is analyzed and the optimal policy is determined. Section 5.3 presents an approximation method to solve large systems. Using this method, Markov chain formulation of the proposed system is developed and the similarities in the transition probabilities for states belonging to a particular set within each state space is exploited. Section 5.4 provides numerical examples that show the applicability and efficiency of our model and problem-solving approach. Finally, some conclusions are discussed in Section 5.5.

5.2 Mathematical model

The logistics network proposed in this study includes three levels: suppliers, recharging station, and the customer (refer Figure 5.3). The recharging comprises of two different segments named as charging station for discharged batteries (I_2) and battery station for full-charged batteries (I_1). Most of the previous studies in this area considered the processing time as an exponential rate. Bradley (2005) analyzed an in-house production and subcontracting model with exponential processing times for orders. Sinha and Krishnamurthy (2020) formulated this problem as continuous-time Markov chain with exponentially distributed interarrival time and production times. This study assumes the empty batteries can be charged in the charging station with three different exponential rates; fast, normal, and slow rate ($\mu_{sb}, \mu_{nb}, \mu_{fb}$) and made to stock in battery station. These rates of charging differ in terms of costs and rates.

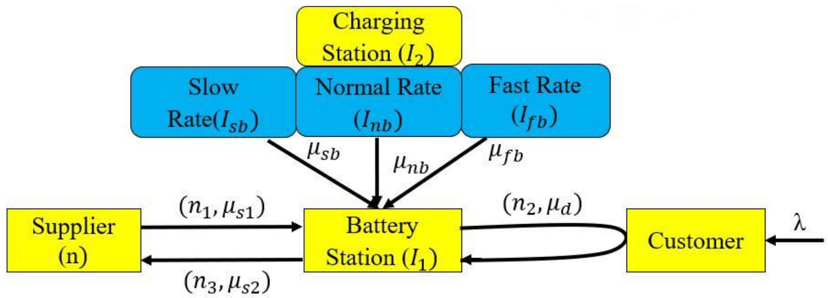


Figure 5.3 Logistics network includes recharging station as warehouses with two different parts

Drones moving between each level of logistics network with different exponential rate ($\mu_{s1}, \mu_{s2}, \mu_d$). Furthermore, customer demands are immediately satisfied if there are full-charged batteries in stock; otherwise, they are considered to be backordered. Customer orders arrive according to a Poisson process λ and are satisfied based on first come-first serve. Only one drone serves each customer, and the order quantity is always less than the drone's capacity. In last-mile logistics, limited and uncertain flight ranges of a large fleet of drones and random demand create complex issues. The selection of full-charged batteries from a slow, normal, or fast rate in a last-mile logistics system with capacity constraints and stochastic lead times can be formulated as a Markov decision process.

Let each state of the system at any time *t* be defined as $\sigma = (I_1, n_1, n_2, n_3)$, where I_1 is the inventory position of full charged batteries and n_k is the total number of drones traveling between each node. n_1 is the total number of drones traveling between the supplier and the recharging station with exponential rate of μ_{s1}. n_2 is the total number of drones traveling back and forth from the recharging station and the customer with exponential rate of μ_d. n_3 is the total number of drones traveling between the recharging station and the supplier with exponential rate of μ_{s2}. Let N be the total number of drones in the system, M be the total number of batteries in the system (includes those installed on drones), and n be the number of drones located in the supplier.

$$\mathrm{n} = N - (n_1 + n_2 + n_3) \quad (5.1)$$

$$I_2 = M - N - I_1 \quad (5.2)$$

Let S_{I1}, denote the possible values of I_1, and *Bmax* denote the finite maximum limit for backorders for full charged batteries which it is assumed is equal to $-N$. Then, the total number of states in S_{I1} is $-N \leq I_1 \leq M - N$. Let S_{nk}, denote the possible values of n_k. Then, the total number of states in S_{nk} is $0 \leq n_k \leq N$.

The state space S can be re-written as $S = \sum S_{I1} * S_{n1} * S_{n2} * S_{n3}$, which should satisfy the following equations:

$$\mathrm{n} = N - n_1 - n_2 - n_3 \quad (5.3)$$

The constraint (5.3) ensures that the total number of drones in the system, N, equals the sum of drones located in the supplier, n, and those flying between levels, n_1, n_2, n_3. Let $a_j = (s, n, f), a_j \in A, j = 1, \dots, 4$ be an action taken at each decision epoch. For any action a_j, s takes the value of 1 if the discharged battery is charging in slow rate station and takes the value 0 if otherwise. Similarly, n and f are defined for normal and fast recharging respectively. Table 1 lists the 4 possible actions available for the decision maker. For instance, action a3 implies that the discharged battery is charging in fast rate station.

Table 5.1 Action space for the system

A	s	n	f
a_1	1	0	0
a_2	0	1	0
a_3	0	0	1

a_4	0	0	0

Then, the system evolution can be modeled as a Markov chain Process. Define $T(\sigma'|\sigma, a_j)$ as the transition probability from state $\sigma = (I_1, n_1, n_2, n_3)$ to state $\sigma' = (I_1', n_1', n_2', n_3')$ under action $a_j \in A$. The model is based on continuous-time Markov chains with exponentially distributed interarrival times, flight times, and charging times, which can be converted to discrete-time Markov chains via uniformization (Lippman 1975). Let $\omega = \lambda + \mu_{s1} + \mu_{s2} + \mu_d + \mu_{sb} + \mu_{nb} + \mu_{fb}$ denote the normalizing factor used for uniformization. Also, let $A_{sj}, A_{nj}\ and\ A_{fj}$ be indicator functions that take the value 1 if slow charging stations, normal charging station, and fast charging station, respectively, are charging battery under action a_j, and 0 otherwise. Transition probabilities are defined as follow:

Demand arrival:

Then $n_1' = n_1 + 1$; and the corresponding $T(\sigma'|\sigma, a_j)$ is given by

$T(\sigma'|\sigma, a_j) = (A_{sj}\lambda + A_{nj}\lambda + A_{fj}\lambda)/\omega$

Drone completes its flight from supplier to recharging station:

Then $n_1' = n_1 - 1$, $n_2' = n_2 + 1$ and $I_1' = I_1 - 1$; and the corresponding $T(\sigma'|\sigma, a_j)$ is given by

$T(\sigma'|\sigma, a_j) = (A_{sj}\mu_{s1} + A_{nj}\mu_{s1} + A_{fj}\mu_{s1})/\omega$

Drone completes its go and back flight from recharging station to customer:

Then $n_2' = n_2 - 1$, $n_3' = n_3 + 1$ and $I_1' = I_1 - 1$; and the corresponding $T(\sigma'|\sigma, a_j)$ is given by

$T(\sigma'|\sigma, a_j) = (A_{sj}\mu_d + A_{nj}\mu_d + A_{fj}\mu_d)/\omega$

Drone completes its flight from recharging station to supplier:

Then $n_3' = n_3 - 1$; and the corresponding $T(\sigma'|\sigma, a_j)$ is given by

$T(\sigma'|\sigma, a_j) = (A_{sj}\mu_{s2} + A_{nj}\mu_{s2} + A_{fj}\mu_{s2})/\omega$

Charging completion:

Then $I_1' = I_1 + 1$; and the corresponding $T(\sigma'|\sigma, a_j)$ is given by

$$T(\sigma'|\sigma, a_j) = (A_{sj}\mu_{sb} + A_{nj}\mu_{nb} + A_{fj}\mu_{fb})/\omega$$

Finally, $\sigma = \sigma'$; and the corresponding $T(\sigma'|\sigma, a_j)$ is given by:

$$T(\sigma'|\sigma, a_j) = \left(\omega - (\lambda + \mu_{s1} + \mu_{s2} + \mu_d + A_{sj}\mu_{sb} + A_{nj}\mu_{nb} + A_{fj}\mu_{fb})\right)/\omega$$

Figure 5.4 presents the simplified transition diagram of our logistics system:

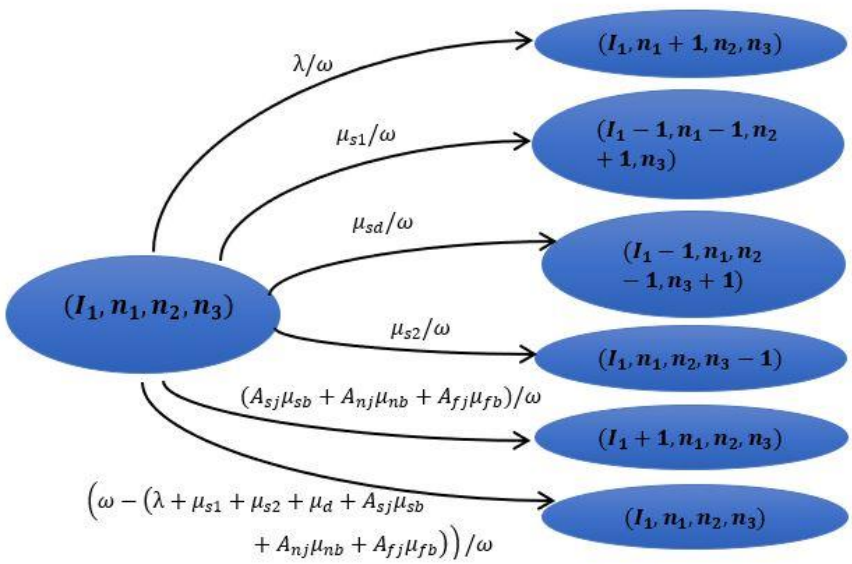


Figure 5.4 All possible transition probability from one state to another for the system

To construct the transition matrix Q, the similarities in the transition probabilities for states belonging to a particular set within each S_z for each action a_j is exploited. Each set $S_z, z = I_1, n_1, n_2, n_3$ can be further partitioned into three mutually exclusive subsets, $S_{z,i} \subset S_z$, $i = 1,2,3$ where $\cup_i S_{z,i} = S_z$. For set S_{I_1}, there are following subsets:

$$S_{I_1,1} = \{I_1 : I_1 = -N\}$$

$$S_{I_1,2} = \{I_1 : -N < I_1 < M - N\}$$

$$S_{I_1,3} = \{I_1 : I_1 = M - N\}$$

For each set $S_z, z = n_1, n_2, n_3$, there are following subsets:

$$S_{z,1} = \{z : z = 0\}$$

$$S_{z,2} = \{z : 0 < z < N\}$$

$$S_{z,3} = \{z : z = N\}$$

The total number of feasible combination of subsets with similarities in the transition probabilities would be 75. This method can significantly simplify the process of constructing transition matrix. Note that to construct the transition matrix you can only use the combination of subsets that can satisfy equation (5.3). For example, the following subset is infeasible:

$$S_{I_1,2} = \{I_1 : -N < I_1 < M - N\}, S_{n_1,1} = \{n_1 : n_1 = 0\}, S_{n_2,2} = \{n_2 : 0 < n_2 < N\}, S_{n_2,3} = \{n_3 : n_3 = N\}$$

The last important element of Markov decision model is the cost function. Define $h(\sigma) = h_{I1}\, max(I_1, 0)$ as the total inventory holding cost rate for full charged batteries and $b(\sigma) = b_{I1}\, max(-I_1, 0)$ as the total backordering cost rate. Let $c(a_j) = A_{sj}c_{sb} + A_{nj}c_{nb} + A_{fj}c_{fb}$ represent the charging cost rate for action a_j. Let $o(\sigma) = o_{n1}n_1 + o_{n2}n_2 + o_{n3}n_3$ represent the total flight cost rate. Let $r(\sigma, a_j)$ denote the immediate cost function at state σ for action a_j, i.e $r(\sigma, a_j) = h(\sigma) + b(\sigma) + o(\sigma) + c(a_j)$.

A policy is defined as a set of actions to take given the state, represented as $\theta = \{a_{(\sigma)}\ for\ all\ \sigma\ in\ S\}$. Let $v_\theta(\sigma)$ denote the value function at state σ for a policy θ. The value function $v_\theta(\sigma)$ can be described in equation (5.4) using Bellman's equations, where $\theta(\sigma)$ is the action to take as determined by the policy θ and γ is the discount factor. The optimal policy is determined by implementing a simple Policy Iteration algorithm (Bellman, 1955) to select an optimal decision policy θ^* that maximizes our value function, see equation (5.5).

$$v_\theta(\sigma) = r(\sigma, \theta(\sigma)) + \gamma \sum_{\sigma' \in S} T(\sigma' | \sigma, \theta(\sigma)) v_\theta(\sigma') \tag{5.4}$$

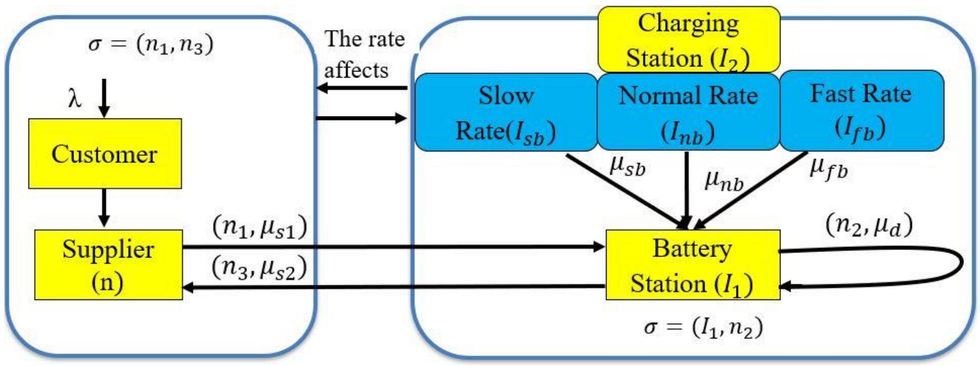
$$\theta^* = argmax_\theta(v_{\theta'}) \tag{5.5}$$

Optimal policies in the above system present challenges when analyzed structurally because the states and actions will grow exponentially based on the problem's complexity. For example, if the number of drones and extra batteries in the system increase from 10 to 20, and 5 to 10, respectively, the number of state increase from 15,000 to 240,000 for 4 actions.

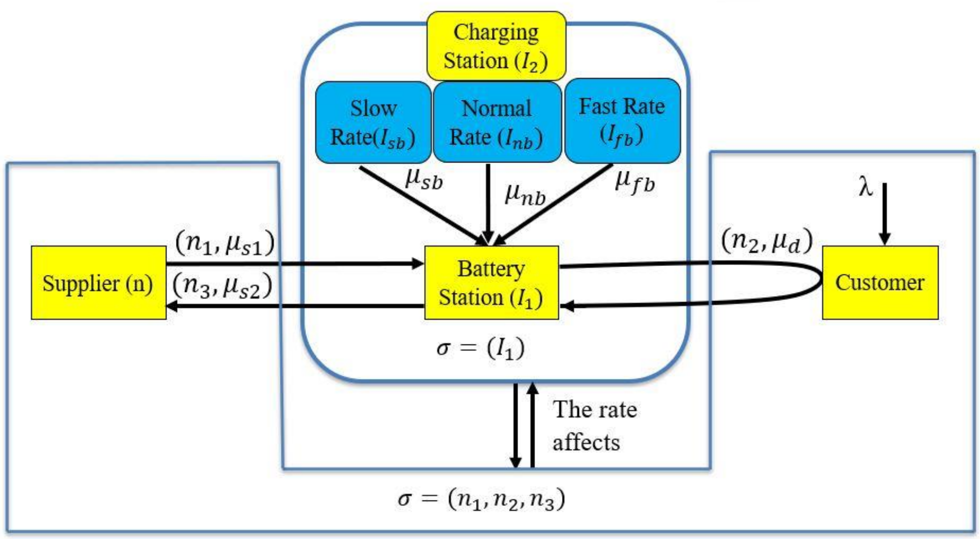
In the next section, a novel approximation method called the decomposition-based approach is described to split the original Markov decision problem for the system into multiple independent Markov chain processes to improve the efficiency of solving the large-scale MDPs.

5.3 Decomposition-based algorithm

The original Markov decision process model described in Section 5.2 has a four-dimensional state space which make the problem computationally challenging. For instance, when I_1 varies from -9 to 5, n_1, n_2, and n_3 are vary from 0 to 9, then we get 15000 states. This issue with dimensionality is addressed by deriving a set of conditions that partitions the state space into regions. Besides, if the number of dimensions or the number of actions increase the size of the system will grow exponentially which make it very difficult for any dynamic programming to analyze the system. To overcome this challenge, a novel approximation method called decomposition-based approach is proposed to split the original Markov decision problem for the system with N states into N independent Markov chain processes. For example, as you can see in Figure 5.5(a) and Figure 5.5(b), the proposed problem in section 2 with four dimensional states defined as $\sigma = (I_1, n_1, n_2, n_3)$ can be split to two problems which both have two dimensional states defined as $\sigma_1 = (n_1, n_3)$ and $\sigma_2 = (I_1, n_2)$, or two problems which one has three dimensional states defined as $\sigma_1 = (n_1, n_2, n_3)$ and another one has one dimensional state defined as $\sigma_2 = (I_1)$. These subsystems are connected to each other through novel probability functions.



(a) First Problem with two dimensional states defined as $\sigma_1 = (n_1, n_3)$ and $\sigma_2 = (I_1, n_2)$



(a) Second problem, one has three dimensional states defined as $\sigma_1 = (n_1, n_2, n_3)$ and another one has one dimensional state defined as $\sigma_2 = (I_1)$

Figure 5.5 Decomposition of the original problem into two subproblems

In terms of accuracy of decomposition technique in each subsystem, the impact of other states needs to be accounted by considering the charging rate, flight rate, and demand arrival rate.

This impact can be applied from one sub-problem to other one by calculating the steady state probability of each system. Sinha and Krishnamurthy (2016) applied the same approach to make the decomposition method more accurate in analyzing the performance of systems with more than two products.

Next, the novel probability functions that interlinks two subsystems together is discussed. In case 2 (shown in Figure 5.5(b)) as an example with two subproblems, X_1 ($\sigma = (n_1, n_2, n_3)$) and X_2 ($\sigma = (I_1)$). Let Π^{X_1} denote the steady-state probability vector and $\pi(n_1, n_2, n_3)$ denote the steady-state probability of state (n_1, n_2, n_3) of the subproblem X_1. Note that, subproblem X_1 is considered as a Markov Chain since it does not include any action. Otherwise, the optimal policy is required to be fixed for Markov decision process before deriving steady-state probability. Using subsets $S_{z,i} \subset S_z$, $i = 1,2,3$ from section 5.3, Chapman–Kolmogorov (C–K) equations can be written. However, in the subproblem X_1, drone completes its flight from supplier to recharging station and between recharging and customer as long as the backorder for the full charged batteries is less than *Bmax* which can be captured by subproblem X_2; i.e., the subsystem X_1 ignores the fact that drones cannot swap the battery due to the possibility that backorders for full charged batteries reach *Bmax*. Therefore, the effective transition probability $T^{X_1}(\sigma'|\sigma)$ for this event in subproblem X_1 needs to be set to recognize this possibility. Let $X_{X_2}^{B}$ denote the event that the backorders at subsystem X_2 is equal to *Bmax* and let $P_{X_2}^{B}$ denote the steady state probability of this event. $\prod(1 - P_{X_2}^{B})$ is the steady state probability that the backorders at all of the states in subsystem X_2 are less than *Bmax*. This implies that the effective transition probability $T^{X_1}(\sigma'|\sigma)$ for drone completes its go and back flight from recharging station to customer in the analysis of subsystem X_1 is given by:

$$T\left(\sigma'\middle|\sigma, a_j\right) = \prod (1 - P_{X_2}^{B}) * \mu_d/\omega$$

By knowing this, for $n_1 \in S_{n_1,1}$, $n_2 \in S_{n_2,1}$, and $n_3 \in S_{n_3}$ the C-K equations are written as follows:

For $n_1 \in S_{n_1,1}$, $n_2 \in S_{n_2,1}$, and $n_3 \in S_{n_3,1}$:

$$\lambda * \pi(n_1, n_2, n_3) = \mu_{s2} * \pi(n_1, n_2, n_3 + 1)$$

For $n_1 \in S_{n_1,1}$, $n_2 \in S_{n_2,1}$, and $n_3 \in S_{n_3,2}$:

$$(\lambda + \mu_{s2}) * \pi(n_1, n_2, n_3) = \left[\prod\left(1 - P_{X_2}^B\right)\right] * \frac{\mu_d}{\omega} * \pi(n_1, n_2 + 1, n_3 - 1) + \mu_{s2} * \pi(n_1, n_2, n_3 + 1)$$

For $n_1 \in S_{n_1,1}$, $n_2 \in S_{n_2,1}$, and $n_3 \in S_{n_3,3}$:

$$\mu_{s2} * \pi(n_1, n_2, n_3) = \left[\prod\left(1 - P_{X_2}^B\right)\right] * \frac{\mu_d}{\omega} * \pi(n_1, n_2 + 1, n_3 - 1)$$

Then the transition matrix Q^{X_1} can be constructed using the subsets explained in section 5.3 and the steady-state probabilities can be calculated using the system of equations (5.6) and (5.7):

$$\Pi^{X_1} Q^{X_1} = 0 \tag{5.6}$$

$$\Pi^{X_1} e^{X_1} = 1 \tag{5.7}$$

Here, $e^{X_1} = [1 \ldots 1]$ of size $S_{n1} * S_{n2} * S_{n3}$. The steady state probability of subsystem X_2 can be calculated by equations (5.8) and (5.9) in a similar way. Note that the optimal policy is required to be fixed for Markov decision process before deriving steady-state probability in the subsystem X_2.

$$\Pi^{X_2} Q^{X_2} = 0 \tag{5.8}$$

$$\Pi^{X_2} e^{X_2} = 1 \tag{5.9}$$

Let $(0, *, *)$ represents a vector with all states having $n_1 = 0$. From the solutions to Equations (5.6) and (5.7), the expected number of drones between supplier and recharging station

$E[N1]$, the expected number of drones flying go and back between recharging station and customer $E[N2]$, and the expected number of drones between recharging station and supplier $E[N3]$ can be calculated using Equations (5.10), (5.11), and (5.12). From the solutions to Equations (5.8) and (5.9), the expected number of on-hand inventory level for full charged battery $E[I1]$ and expected backorders E[B1] can be calculated using Equation (5.13) and (5.14). Besides, let $\theta^*(I1)$ represents the optimal policy in state (I_1) and $A_{s^*,I1}, A_{n^*,I1}$ and $A_{f^*,I1}$ are indicator functions that take the value 1 if slow charging stations, normal charging station, and fast charging station, respectively, are charging battery under optimal action $\theta^*(I1)$, and 0 otherwise. The charge station throughput for fast charging, TH_{FC}, normal charging, TH_{NC}, and slow charging, TH_{SC}, is computed using Equations (5.15), (5.16), and (5.17) respectively.

$$E[N1] = \sum_{n_1} n_1 \pi(n_1,*,*) \tag{5.10}$$

$$E[N2] = \sum_{n_2} n_2 \pi(*, n_2,*) \tag{5.11}$$

$$E[N3] = \sum_{n_3} n_3 \pi(\ *,*\ n_3) \tag{5.12}$$

$$E[I1] = \sum_{I_1} \max\,(I_1, 0)\pi(\ I_1) \tag{5.13}$$

$$E[B1] = \sum_{I_1} \max\,(-I_1, 0)\pi(\ I_1) \tag{5.14}$$

$$TH_{FC} = \sum_{I_1} A_{f,I1}\mu_{fb}\pi(\ I_1) \tag{5.15}$$

$$TH_{NC} = \sum_{I_1} A_{n,I1}\mu_{nb}\pi(\ I_1) \tag{5.16}$$

$$TH_{SC} = \sum_{I_1} A_{s,I1}\mu_{sb}\pi(I_1) \tag{5.17}$$

The decomposition-Based algorithm uses decomposition of the Markov chain to efficiently evaluate the system performance. Note that the performance measures obtained using the above equations use an approximation method. The generalized procedure steps for this iterative decomposition technique are shown below. Let $z = 1, \dots, n$ denote the number of subsystems and $\pi(z)$ is steady state probability, S_z is state space, $T^z(\sigma'|\sigma)$ is transition probability associated with that subproblem z.

Step 0: Initialize $\pi^{itr}(z) = 1/S_z$, $\pi^{itr}(z) = 0$, and $itr = 0$ for $z = 1, \dots, n$.

Step 1: If the subsystem z is Markov chain, calculating the steady-state probabilities $\pi^{itr+1}(z1)$ for each $z1 = 1, \dots, n$, using $\pi^{itr}(z2)$ for $z2 = 1, \dots, n,\ z2 \neq z1$. Then go to step 4.

Else go to step 2

Step 2: If the subsystem z is Markov chain process, using $\pi^{itr}(z2)$ for $z2 = 1, \dots, n, z1 \neq z2$ to calculate the transition probability $T^{z1}(\sigma'|\sigma)$ for the subsystem $z1$.

Step 3: Applying policy iteration using $T^{z1}(\sigma'|\sigma)$ from step 2 to find the optimal policy and then calculate the steady-state probabilities of that subsystem like step 1.

Step 4: Compute $\delta_{itr+1,z} = |\pi^{itr+1}(z) - \pi^{itr}(z)|$, for $z = 1, \dots, n$.

Step 5: if $\delta_{itr+1,z} < \varepsilon$, stop,

Else $itr = itr + 1$, and go to step 1.

To check the effectiveness of the approximation method, the performance and running time of decomposition-based method can be computed and compare with the performance and running time of the original system. The accuracy of these estimates is compared as part of our numerical studies in Section 5.4.

5.4 Numerical example and computational experiment

This section discusses the numerical experiments conducted to test the performance of the developed decomposition-based algorithm. In the first section, the performance of the decomposition algorithm is examined by computing total costs and runtime, while in the second section, insights into the optimal solution for two common scenarios are provided (high and low-rate demand for full charged batteries). The total cost function is defined as $TC = o * (E[N1] + E[N2] + E[N3]) + h * E[I1] + b * E[B1] + c_{sb} * TH_{SC} + c_{nb} * TH_{NC} + c_{fb} * TH_{FC}$ where b is the cost of backordering per unit, h is the holding cost per unit, o is the flight cost, and c is the charging cost per battery for different rate. In all of our experiments, it is observed that the algorithm converges on a personal computer with 11th Gen Intel(R) Core (TM) i7 processor and 12 GB of RAM. The primary system parameters are presented in Table 5.2. These parameters might be different based on the experiment.

Table 5.2 System parameters and costs used in the numerical experiments

Costs and total number of batteries		Rate	
o	10	μ_{s1}	1
h	1	μ_{s2}	2
b	30	μ_d	1.5
c_{sb}	1	μ_{sb}	0.5
c_{nb}	3	μ_{nb}	2
c_{fb}	7	μ_{fb}	8
M	8 ($N = 5$)	λ	1.5

5.4.1 Performance comparison of the decomposition-based approach and normal approach by computing the runtime and total cost

A system is analyzed that includes three levels of supply chain, which are a supplier, a recharging station, and a customer, as shown in Figure 5.3. The original system is decomposed in two different ways: case 1 (Figure 5.5(b)), and case 2 (Figure 5.5(a)). The runtime of applying the decomposed algorithm to cases 1 and 2 and applying the exact algorithm to the original case were compared to make sure the decomposition-based algorithm is efficient. A symmetric case is considered where all of the parameters for case 1 are equal to that of case 2 (see Table 5.2). Table 5.3 compares the computational efficiencies for different state spaces of the original problem for three cases. For each instance, the solution times are reported for three different cases. The time restriction of five hours is set for our experiments such that if the solution is not obtained within this time limit, then such a situation is reported as "No Solution (NS)" in the column of solution time for each approach.

Using a decomposition algorithm in both cases is much more efficient than applying a normal approach in the original case. In both decomposition cases, an optimal policy can be obtained with 1370386 states without a memory issue. However, if the state space exceeded 15000, the original problem encountered a memory issue. In the original problem with 15000 states, the exact algorithm will find the optimal policy in almost 54 minutes, while the decomposition-based algorithm will reach convergence in less than two seconds. To solve the problem with 41743 states, the decomposition algorithm takes less than 5 seconds. By increasing the problem size 13.2 times (from 15000 to 198911 states), the decomposition algorithm still could find the solution in less than 5 minutes. Since case 1 includes a Markov decision process with fewer states, the decomposition algorithm performs slightly better than case 2. The case 1 has only one state ($\sigma =$

(I_1)) on the subsystem includes Markov decision process which decrease the size of the problem for different action and helps policy iteration algorithm to find the solution more efficiently. In average, the decomposition algorithm performs 0.06 times better in case 1.

Table 5.3 Runtime of decomposition-based algorithm in case 1 and 2 and exact algorithm in original case over different state space

Number of Drones	Number of Extra Batteries	Size of the States in Original Problem	Runtime Case 1 (s)	Runtime Case 2 (s)	Runtime Original Case (s)
2	1	108	0.2088	0.27728	0.5895
3	1	320	0.2323	0.3022	1.3826
4	2	875	0.2698	0.3550	3.6089
5	3	1944	0.4354	0.6055	44.6108
6	4	3773	0.5660	0.6854	151.7218
8	4	9477	1.0790	1.1148	1029.6466
9	5	15000	1.4831	1.9112	3221.9349
10	5	21296	1.8084	2.3982	N/A
11	5	29376	2.3344	2.7464	N/A
12	6	41743	3.4561	3.9364	N/A
13	7	57624	5.4676	5.9964	N/A
16	8	122825	28.7554	30.3946	N/A
18	10	198911	262.3887	279.9877	N/A
30	15	1370386	16963.8506	18830.2337	N/A

All three cases are illustrated in Figure 5.6 where solution times change with state space size. As it can be clearly seen, the original case's solution time is sharply increased by increasing the number of states in comparison to the two decomposed cases, and the decomposition-based approach performs better in both cases. The Decomposition algorithm solves problem with 57624 states in less than 6 seconds, whereas exact algorithm cannot solve the problem with more than 15000 states without memory problems.

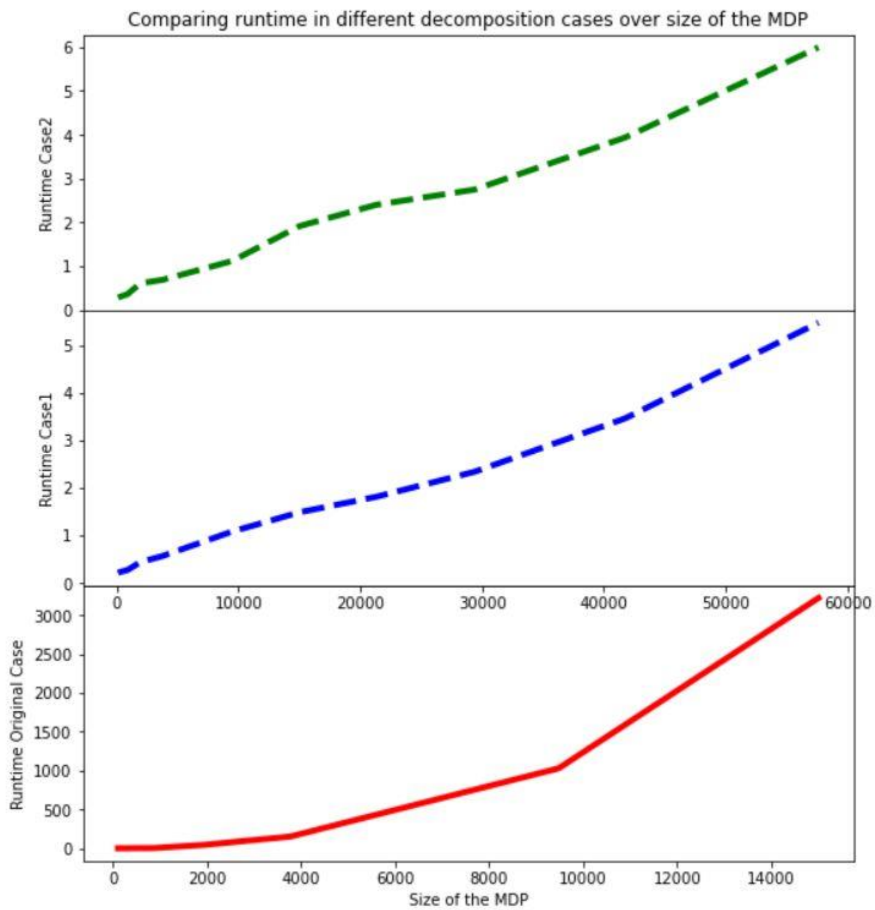


Figure 5.6 Runtime comparison between decomposition-based algorithm in case 1 and 2 and exact algorithm in original case over different state space

The variation in solution time across different scenarios for all three cases is shown in Figure 5.7 to verify the accuracy of the decomposition-based algorithm. Based on different values for flight and customer arrival rates, the scenarios are defined. As an example, it is assumed that in one case, customer arrival rates exceed flying rates between the supplier and the recharging station. these parameters are changed to create different scenarios for each case. Across 54 different scenarios, the variation in solution time is less than 0.25 sec for case 1, 0.4 sec for case 2, and 5 sec for the original case.

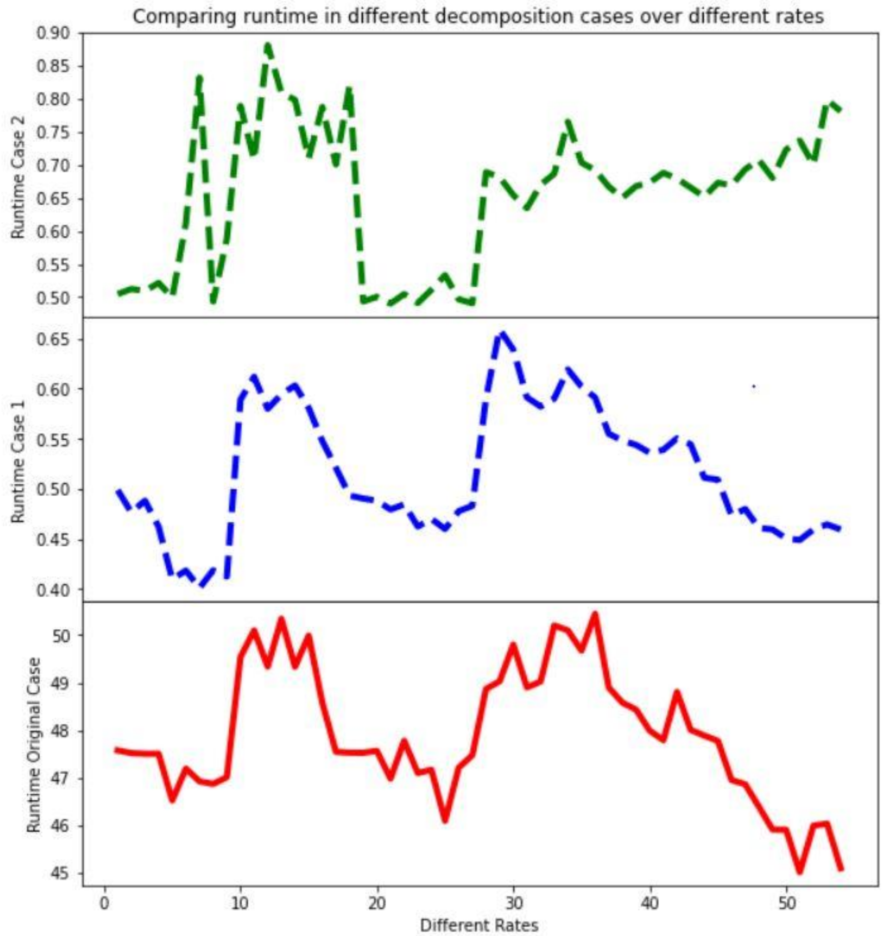


Figure 5.7 Runtime comparison between decomposition-based algorithm in case 1 and 2 and exact algorithm in original case over different flying and customer rates

In order to verify the effectiveness of the decomposition-based method, the difference in total costs between the decomposition cases and the original problem in different scenarios are computed and compared. A decomposition-based algorithm's performance is measured by finding the percent difference between the total cost of decomposition case and the original problem. For example this amount for case 1 is $(TC[original\ case] - TC[case1])/TC[original\ case]$, and for case 2 is $(TC[original\ case] - TC[case2])/TC[original\ case]$.In Figure 5.8, it is shown the percentage variation in total costs between the original case and each of the cases 1 and 2, which represent different scenarios. Clearly, the cost obtained by the decomposition algorithm in case 1 and case 2 differs from the cost obtained by the exact algorithm in the original case by less than 3% in 90 percent of cases. The percentage increases to 95 percent if the cost variation increases by 4%. Three scenarios result in an 8 percent variation in cost, which is still less than 10 percent. It is because the demand rate in all these cases is much lower than other rates related to the problem that this increase occurs. Therefore, it is more likely that drones will not fly between logistics levels, thus undermining the subsystem connections.

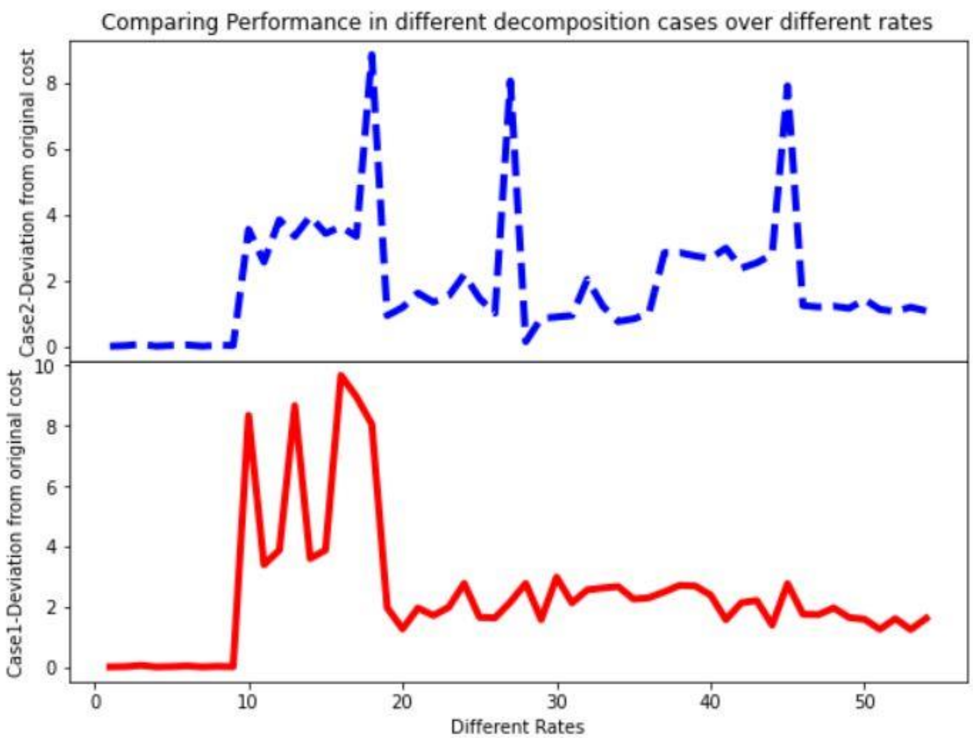


Figure 5.8 Performance comparison between decomposition-based algorithm in case 1 and 2 and exact algorithm in original case over different flying and customer rates

To verify the accuracy of the decomposition-based algorithm, the algorithm performance in cases 1 and 2 is also compared to the exact algorithm in the original case over different state spaces. Figure 5.9 shows the variation in total cost between each decomposition case and the original case as the problem size increases. State spaces range from 108 to 15000. Over 7 different problem sizes, both case 1 and case 2 show less than 0.004 variation in total cost.

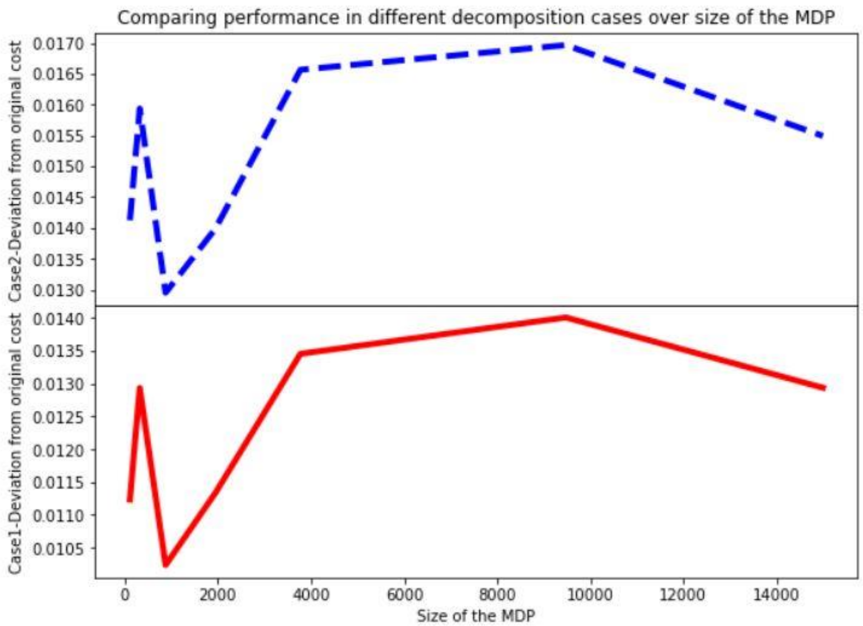


Figure 5.9 Performance comparison between decomposition-based algorithm in case 1 and 2 and exact algorithm in original case over different state space

Our results suggest that the decomposition-based approach is fairly accurate for various choices of flight and customer rate, and the different sizes of the problem. Furthermore, it is noted that the runtime for the decomposition approach ranged from 0 to 30 seconds and did not increase significantly as the size of the states was varied from 108 to 122825. This suggests that the approach can be used to analyze fairly large systems. In contrast, the runtime of the exact approach for the original problem ranged from 0 to 3221 seconds. This increased significantly as the size of the states was varied from 108 to 15000.

5.4.2 Effect of the holding cost and backorder cost on inventory position

In this part, the impact of changing in flying rate, customer arrival time, holding cost and backorder cost on inventory position of full charged batteries is studied. Two different scenarios are considered in this study for a system with 10 drones and 4 extra batteries. So the inventory position of full charged batteries should be varied between 0 and 4, and the backorder level should be varied between 0 to 10. In the first scenario it is assumed the demand rate for full charged batteries is less by reducing the rate of flying and customer arrival. In the second scenario the rate of flying and customer arrival are increased to have a high demand rate for full charged batteries. Table 5.4 presents the flying rates and customer rates used in these two scenarios.

Table 5.4 System Parameters for Sensitivity Analysis

	Scenario 1	Scenario 2
μ_{s1}	1	4
μ_{s2}	0.5	3
μ_d	1	4
λ	1	3

Figure 5.10 shows the impact of increasing holding cost on the inventory position of expected on-hand full charged batteries $E[I1]$ and expected backorders $E[B1]$ for two different scenarios. It is observed that the inventory position of full charged batteries decreases from 3 to 0 for first scenario with increasing inventory cost from 1 to 20. For second scenario with higher demand rate for full charged batteries, inventory position of full charged batteries decreases from 1.5 to 0. On the other hand, the inventory position for backorders increases from 0 to 8 for second scenario with high demand rate for full charged batteries while in the low demand rate scenario, the backorders increase from 0 to 6.5. In fact, by looking at this figure, it can be observed that by increasing the inventory cost, system prefers to have less on-hand full charged specially when the demand rate of full charged batteries is high. It can be also said that by increasing holding cost, system prefers to have more backorders and pay the penalty cost for that than have more on-hand full charged batteries to satisfy the orders.

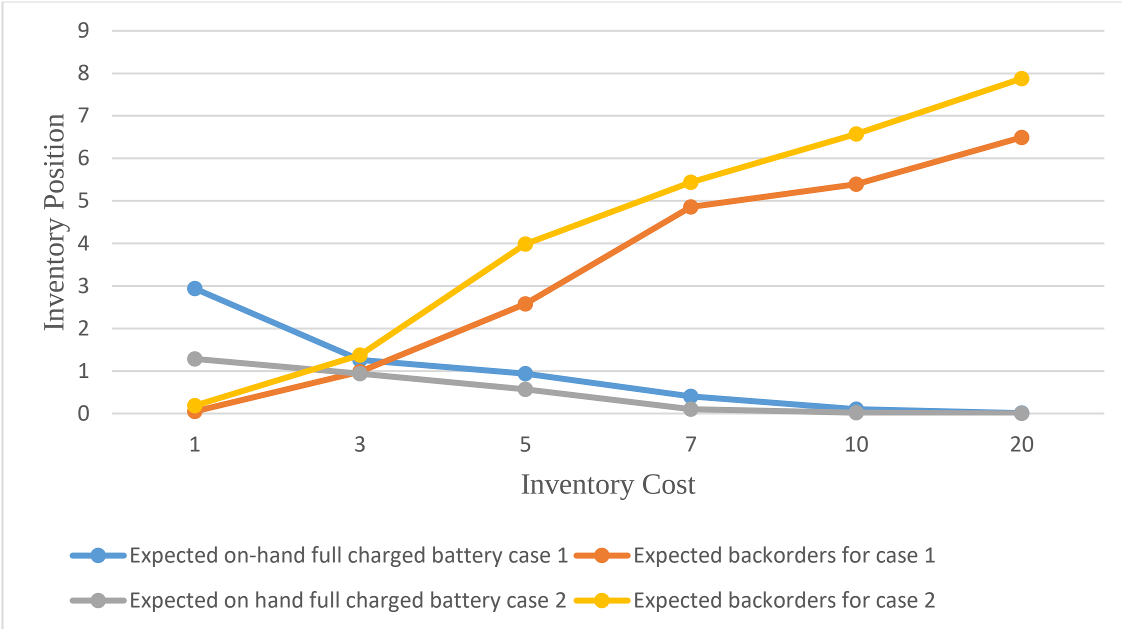


Figure 5.10 Sensitive analysis of increasing holding cost on optimal number of inventory position of full charged batteries in different scenarios

Figure 5.11 shows the impact of increasing backorder cost on the inventory position of on-hand full charged batteries and expected backorders for two different scenarios. As you can see clearly, the inventory position of full charged batteries increases from 0 to 3 for first scenario with increasing backorder cost from 20 to 100. Same situation, inventory position of full charged batteries increases from 0 to 2.5 when the demand rate for full charges batteries increased. In contrast, the inventory position for backorders decreases from 7.2 to 1.5 for scenario with high demand rate for full charged batteries while in the low demand rate scenario, the backorders decrease from 5.5 to 0. It is clear by increasing the backorder cost, the system prefers to have more on-hand full charged specially when the demand rate of full charged batteries is low. It can be also said that by decreasing backorder cost, the system prefers to have more backorders and pay the penalty cost for that than have more on-hand full charged batteries to satisfy the orders.

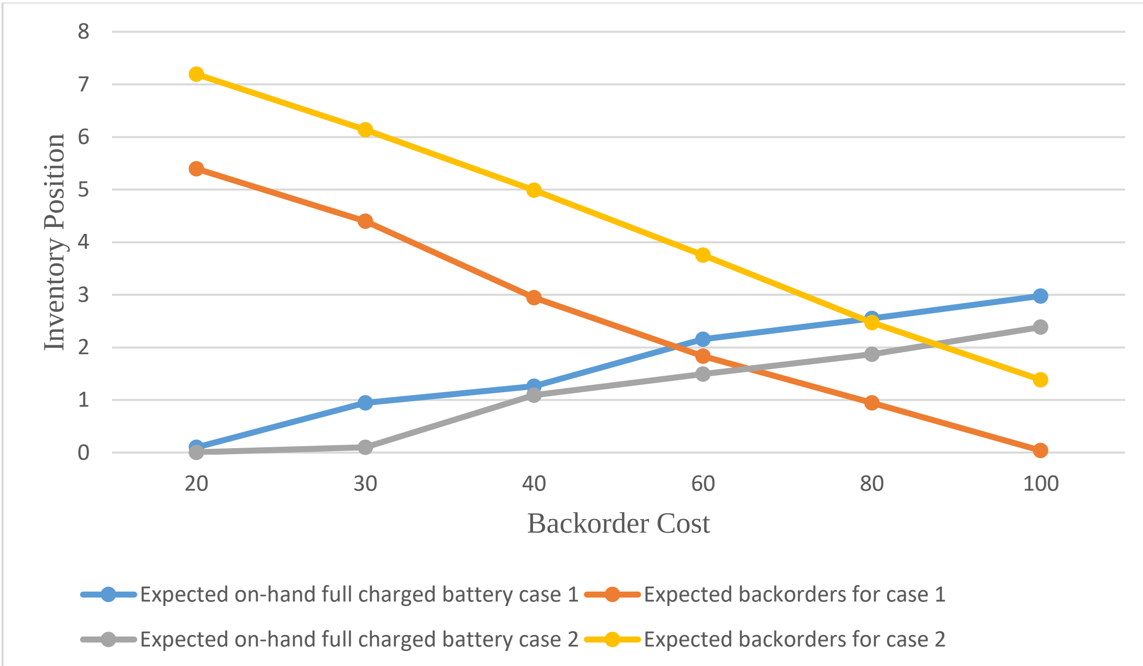


Figure 5.11 Sensitive analysis of increasing backorder cost on optimal number of inventory position of full charged batteries in different scenarios.

5.5 Conclusions

In this study, different charging strategies in recharging stations was examined to improve drone delivery time in last-mile logistics. In order to determine the best policy for decision-makers, stochastic Markov decision models were formulated based on different charging rates, arrival rates, flight rates, and associated costs. To improve the efficiency of solving the large-scale MDPs, a novel approximation method called the decomposition-based approach was developed to decompose the original Markov decision problem for the system into multiple independent Markov chain processes. To demonstrate the capability of this algorithm to efficiently solve the large-scale problems, numerical experiments conducted to check the performance of the algorithm. It was shown that the performance of the decomposition algorithm is significantly high in terms of runtime for large-scale problem. It was also shown that the decomposition-based approach is fairly accurate for various choices of flight and customer rate, and different size of the problem. The approach not only provides reasonably accurate estimates of performance measures for large systems but also scales well in terms of computational effort. The insights on the characteristics of the optimal solution were provided by analyzing inventory position of full charged batteries over different cases. It is observed that under low inventory cost and high backorder cost, the system prefers to have more on-hand full charged batteries.

Chapter 6 - Conclusions and Future Research

This dissertation provides a general methodology for modeling dynamic problems in last-mile logistics using drones under uncertainty. This research also studies different decomposition techniques under unique last-mile logistics constraints that has never been addressed before. The proposed Bender-decomposition algorithm is improved by reducing the feasibility space of the problem and a novel approximation method called decomposition-based approach is developed to split the original Markov decision problem for the system with multiple independent Markov chain processes to increase the efficiency when trying to solve these complex models. It can be seen from the results that these approaches can show a similar result to what we can expect to see in the real-world situation and the proposed solution algorithms is not only capable of solving large-scale problems, but also avoids long run times. This methodology will create a host of future research topics to advance modeling reliable and resilient supply chain system using unmanned aerial vehicles delivery on last-mile logistics. A summary of the main contributions of this work is provided below, along with notes on potential avenues for future research and extensions.

6.1 Conclusions

In chapter 3, the reliable facility network design problem under uncertainty conditions in the presence of customer demand and disruptions at distribution centers was analyzed. The problem was formulated as a two-stage stochastic optimization problem and used the L-shape decomposition approach to solve it. It was also theoretically proved that the proposed stochastic formulation has a relatively complete recourse structure when at least one supplier is selected. This improves the performance of the L-shape algorithm by significantly reducing the total number iterations in the L-shape decomposition due to absence of feasibility cuts. To illustrate the applicability of the model and the improved algorithm, a case study was presented based on empirical data sourced from Peng et al. (2011), and those results were then discussed. L-shaped decomposition algorithm was also applied to solve the S-SCUC problem, and a computationally efficient initial solution is further proposed to accelerate the proposed algorithm.

This study potentially offers a number of significant contributions to the literature, and the supply chain industry in general. The main contribution of this study is that, by developing a two-stage stochastic model for reliable supply chain network design with stochastic parameters in multi-time periods and solving it, the relationships between the facility decisions, such as facility location, product assignment and key factors such as transportation cost, hardening investment and disruption probability, were understood. It was observed that under high disruption probability, increasing the transportation cost results in the model preferring the assignment of reliable distribution centers rather than unreliable distribution centers. Furthermore, an efficient solution method was developed for the optimization problem based on the multi-cut L-shaped decomposition method, which allowed us to solve real large-scale problems in shorter time frames. It is shown that the multi-cut algorithms performed significantly better than the single-cut approach for every scenario, regardless of size. Although the multi-cut approach produced more cuts in each scenario compared to the single-cut, it obtained an optimal solution in fewer iterations than the single-cut approach. The result improved even more when converting the stochastic model to a relatively complete recourse model. It can be clearly seen how much the multi-cut approach with relatively complete recourse model performs better than all other models. These computational results also represented how the reliability of the supply chain system can be improved by a slight increase in facility cost. Moreover, comparative results for the S-SCUC problem show that, in the proposed relatively complete recourse L-shaped algorithm, multi-cut with an initial solution performs much better than its single-cut counterpart with an initial solution and better than the multi-cut approach without any initial solution.

Chapter 4 analyzed the reliable supply chain network problem that includes charging station to extend the coverage of drones in last-mile logistics under uncertain parameters. The mixed-integer linear programming model was formulated to design a reliable network and a genetic algorithm was applied to solve it. It is shown how a slight increase in facility investment can increase the system’s reliability. It was also shown that, by considering each scenario independently to create a new population in the genetic algorithm, the efficiency of algorithm is significantly improved and near optimal solution is obtained in less iterations due to the absence of infeasibility solutions. Computational results showed the genetic algorithm performs significantly better than the commercial software for most scenario size. It was also showed that under high disruption probability, the number of reliable distribution centers and charging stations increased while the number of unreliable facilities decrease. Furthermore, increasing the fixed cost of charging stations and distribution centers and flight cost of drones decreases the optimal number of reliable facilities to satisfy customers.

There are three main contributions of this study: firstly, stochasticity in a multi-period supply chain network design problem including charging station is examined to extend the coverage of drones in last-mile logistics, where the disaster and the demand are random. The proposed stochastic model is unique because of two conditions: (i) it simultaneously considered delivery service coverage of recharging stations and distribution centers based on the flight range of drones under different conditions, capacities for supply and distribution centers and drone’s utilization cost based on calculating Euclidian shortest path distance under demand and disaster uncertainty in multiple time periods. (ii) a combination of the two types of strategies was adopted simultaneously to design a reliable network using charging station as one of the levels under two different uncertain parameters in multi-time periods. The proposed problem was formulated as a stochastic mixed-integer programming model to design an efficient supply chain network. Secondly, the heuristic algorithm was improved by considering a novel method to generate independent scenarios to create a new population. This significantly improved the efficiency of the algorithm due to the decrease in number of infeasible solutions and allowed it to efficiently solve real large-scale problems. Thirdly, based on numerical experiments, the effects of disruption probability, cost needed to build a reliable distribution center and charging station, and drone's utilization cost were analyzed in relation to the number of drones per distribution center, the number and location of reliable and unreliable distribution centers and charging stations. Contrary to popular belief, it was observed that by increasing disruption probability, utilization costs of drones and fix cost of establishing reliable and unreliable facilities, the model prefers to lose the demand and pay the penalty cost instead of buying drones and establishing more reliable facilities.

In the chapter 5, different charging strategies in recharging stations was examined to improve drone delivery time in last-mile logistics. In order to determine the best policy for decision-makers, stochastic Markov decision models were formulated based on different charging rates, arrival rates, flight rates, and associated costs. To improve the efficiency of solving the large-scale MDPs, a novel approximation method called the decomposition-based approach was developed to decompose the original Markov decision problem for the system into multiple independent Markov chain processes.

To demonstrate the capability of this algorithm to efficiently solve the large-scale problems, numerical experiments conducted to check the performance of the algorithm. It was shown that the performance of the decomposition algorithm is significantly high in terms of runtime for large-scale problem. It was also shown that the decomposition-based approach is fairly accurate for various choices of flight and customer rate, and different size of the problem. The approach not only provided reasonably accurate estimates of performance measures for large systems but also scaled well in terms of computational effort. Insights on the characteristics of the optimal solution were provided by analyzing inventory position of full charged batteries over different cases. It is observed that under low inventory cost and high backorder cost, the system prefers to have more on-hand full charged batteries.

The main contributions of this study are: From the tactical and operational side, stochasticity in a logistics network including recharging stations as a warehouse of extra batteries for drones is analyzed where there are a lot of uncertainties associated with this network like demand arrival, charging rate, and flight rate. In the literature, the main models for selecting recharging technology relate to the location of the recharging stations, including recharging technologies and routing strategies with an emphasis on sustainability, energy consumption, and power loss. To the best of our knowledge, no existing studies have analyzed different charging strategies in recharging stations to improve the delivery time in last-mile logistics using drones. This research developed stochastic Markov decision models to handle stochasticity in this problem and determine the best policy for decision-makers based on different charging rates, demand arrival rates, flight rates, and costs associated with them. Methodologically, a novel approximation method called the decomposition-based approach is developed to split the original Markov decision problem for the system into multiple independent Markov chain processes to improve the efficiency of solving the large-scale MDPs. This methodology will create a host of future research topics to advance modeling stochastic systems and mitigate the curse of dimensionality in dynamic programming. To the best of our knowledge, the proposed methodology is novel and has not been published in any relevant reports and venues.

6.2 Future study

One of the important concerns in using drones in commercial sector is drone-related cyber threats. This is a major concern since modern control systems are becoming large and decentralized and thus more vulnerable to attacks. These cyber threats not only make disorder in communications between drones, but also attempt to attack the entire network by injecting or modifying data. Considering logistics system when some of the GPS sensors of drones are corrupted by an attacker create a unique future research topics to advance modeling reliable and resilient supply chain system using unmanned aerial vehicles delivery on last-mile logistics. Stochastic models can be developed to adaptively learn the policy based on what the attackers does, and parameter changes to create the resilient system.

The linear control system structure and the future path of this system are described in follow. This study is concerned with the estimation and control of linear systems when some of the sensors are corrupted by an attacker. The linear control system can be developed to improve the resiliency of the system. The linear control system can be written as following the equations:

$$x^{(t+1)} = Ax^{(t)} + B(u^{(t)}\left(y^{(0)}, \dots, y^{(t)}\right) + \omega^{(t)})$$

$$y^{(t)} = Cx^{(t)} + e^{(t)}$$

Where, $x^{(t)}$ is the state of the system at time *t*, and $y^{(t)}$ is the output of the GPS sensors at time *t*. $u^{(t)}$ is the action, and the control input applied at time *t* depends on the past measurements $\left(y^{(a)}\right)_{0\leq a\leq t}$ through the output feedback map $u^{(t)}$. The vector $e^{(t)}$ indicates the attacks injected by the attacker in the different sensors, and the vector $\omega^{(t)}$ is the other uncertainties in the state of the system. In the absence of an attack on sensor $i \in \{1, \dots, p\}$, neither $e_i^{(t)}$ nor output $y_i^{(t)}$ of sensor *i* are corrupted, otherwise $e_i^{(t)}$(and therefore $y_i^{(t)}$) can have any value. Accordingly, $e^{(t)}$ indicates the set of sensors attacked. It can be assumed that the set of attacked nodes does not change over time. More precisely, if $K \subset \{1, \ldots, p\}$ is the set of attacked sensors, then we have for all *t*, $supp(e^{(t)}) \subset K$ (where $supp(x)$ denotes the support of *x*, i.e., the indices of the nonzero components of *x*). The assumption is reasonable because a model where the set of attacked nodes changes every time step while having a fixed cardinality is not very realistic since it would assume that the attacker abandons from *t* to *t + 1* some of the nodes he had control over. Moreover, if you are dealing with a malicious agent, it cannot be assumed the attacks $e_i^{(t)}$ (for an attacked sensor *i*) to follow any particular model. $e_i^{(t)}$ can simply take any arbitrary real numbers.

For Future research two different directions can be considered. a simple case where the adversaries have complete information of the system and can only influence state and output by action $e^{(t)}$ bounded by lower and upper values. Next, the adversaries have incomplete information of the system and can view the state of the system as $y^{(t)}$. Then, the adversaries take optimal action $e^{(t)}$ while assuming an optimal action $u^{(t)}$ by the system owner.

In both case it is really critical to construct an iterative estimator to estimate the state of a linear dynamical system in the presence of attacks. The estimate of the state is updated by a simple iterative rule each time a new measurement is received. This estimator needs error detector to detect possible errors, i.e. deviations from the normal behavior. The error detector is supposed to be collocated with the controller; therefore, it only has access to $y^{(t)}$ and $u^{(t)}$ to evaluate the behavior of the system. Proper approaches to detecting malfunctions in control systems can help estimator to determine the action which can be adaptively changed based on what the attackers does, and parameter changes. This model will give a new characterization of the maximum resilience of a system to attacks and the possibility of increasing the resilience of a system by secure local feedback.

In the next step, Karush–Kuhn–Tucker (KKT) conditions can be developed to derive the optimal solution for proposed stochastic model. The special case can also be considered when the probability of uncertainty $\omega^{(t)}$comes from the exponential distribution. In this case MDP model can be developed and best policy would be obtained based on the decomposition-based approach proposed in chapter 5. The linear control system can adaptively learn the policy based on these changes. Deep reinforcement learning can be also applied to consider how states change between time periods and optimizes the system over the time.

Another future path could include using machine learning models to predict future scenarios and probabilities of these scenarios for uncertain parameters and adapting these models to L-shape algorithms. Machine learning models can generate much more accurate scenarios for uncertainties associated with the problem like demand which can help decision makers to obtain more accurate solutions based on scenario-based algorithms like bender decomposition. However, the L-shape algorithm works using the duality theory of linear programming. In this method the second-stage problem is linear (convex), thus the duality theory of linear programming can be applied to gain outer approximations of the recourse cost function. The convexity can be lost by applying machine learning models at the second stage of the problem to generate the scenarios or the probability associated with them. Adopting these models in bender decomposition algorithms could be a unique future research topic for this research. Also, most of the reliability strategies are theoretical. In the future, it is better to study the reliable supply chain network in the real world, to make an optimization model that better reflects reality.

Chapter 5 explains how decomposing the MDP in different ways can affect the accuracy of the decomposition-based algorithm. As it is mentioned, for accuracy of the decomposition technique in each subsystem, the impact of stochastic rates in other states needs to be accounted. I believe that developing a theory to construct a structure for decomposing MDPs based on stochastic rates existing in the problem is a promising area for research. Of course, tradeoffs between the accuracy and efficiency of the decomposition algorithm must be considered for generalizing this structure. In addition, another interesting area of research would be characterizing the optimal policies in decomposition-based algorithms and extending them to original problems. In a MDP problem with many dimensions, it is impossible to determine the characteristics of optimal policies and how they change over time. However, the decomposition-based algorithm can provide us with the opportunity to find the characteristics of optimal policies in each subsystem and generalize them to the original system.

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