Improving green supply chain performance with Operations Research

A thesis submitted to the College of
Graduate and Postdoctoral Studies (CGPS)
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy In the Department of Operations
Management
University of Saskatchewan
Saskatoon, Saskatchewan, Canada

By

Hossein Mirzaee

Permission to Use

In presenting this thesis/dissertation in partial fulfillment of the requirements for a Postgraduate degree from the University of Saskatchewan, I agree that the Libraries of this University may make it freely available for inspection. I further agree that permission for copying of this thesis/dissertation in any manner, in whole or in part, for scholarly purposes may be granted by the professor or professors who supervised my thesis/dissertation work or, in their absence, by the Head of the Department or the Dean of the College in which my thesis work was done. It is understood that any copying or publication or use of this thesis/dissertation or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to the University of Saskatchewan in any scholarly use which may be made of any material in my thesis/dissertation.

Disclaimer

Reference in this thesis to any specific commercial products, process, or service by trade name, trademark, manufacturer, or otherwise, does not constitute or imply its endorsement, recommendation, or favoring by the University of Saskatchewan. The views and opinions of the author expressed herein do not state or reflect those of the University of Saskatchewan, and shall not be used for advertising or product endorsement purposes.

Request for permission to copy or to make any other use of the material in this thesis in whole or in part should be addressed to:

Head of the Department of Finance and Management Science
25 Campus Drive
University of Saskatchewan
Saskatoon, Saskatchewan, Canada
S7N 5A7

OR

Dean
College of Graduate and Postdoctoral Studies
University of Saskatchewan
116 Thorvaldson Building, 110 Science Place
Saskatoon, Saskatchewan S7N 5C9 Canada

Abstract

Due to increasing greenhouse gas emission as a consequence of the production activities in various industries, managing the supply chain has been a big concern between both scholars and practitioners. Green supplier selection and order allocation is among important topics that managers should pay attention to as the majority of the supply chain costs and emission level during production process depends on the procured material by suppliers. Also, investigating the emission abatement regulations, and interactions between regulator and manufacturers is one of the main concerns of supply chain managers that should be figured out.

In the present study, green supply chain problems are taken into account for more investigations. First, a green supplier selection and order allocation model in a closed-loop supply chain considering both environmental and economical criteria, is studied. In this study, one of the carbon emission abatement schemes, cap-and-trade mechanism is proposed. The described problem is modeled as a multi-objective robust optimization (RO) model. Second, the cap-and-trade (C&T) mechanism is further investigated. The goal of this investigation is to find the best strategy for supply chain parties to maximize their utility as well as minimize the carbon emission. To model the described problem, a stochastic three-player game theoretical model is developed.

The results show that the developed models can effectively help decision makers select the most appropriate suppliers, allocate the proper amount of order to each selected supplier, and find optimal strategy of C&T players. Also, the results show that the uncertainty control approaches used in the presented models are capable of handling the model uncertainties from different sources. Furthermore, this study shows that C&T outperforms the penalty based systems in terms of the total utility of the supply chain. Moreover, the robustness of the results is proved by sensitivity analyses.

Another area that is investigated in this study is the disruption effects on supply chain. Disasters and pandemics like COVID-19 can destroy industries by causing huge disruptions in their supply chains. To control these disruptions, decision-makers need to design resilient supply chains. This study proposes a multi-stage, multi-period resilient green supply chain design model considering six resilient strategies. Disruptions are taken into account in both downstream and upstream directions, causing the ripple effect and bullwhip effect, respectively. To control the mentioned disruptions, and handle uncertainties of parameter estimations, a two-stage stochastic optimization approach is applied. The objectives are to minimize the total cost of disruption and CO_2 emission considering the cap-and-trade mechanism as a government-issued emission regulation. The proposed decision-making framework and solution approach are validated using a numerical experiment followed by a sensitivity analysis. The results show the optimal structure of the supply chain and the best resilient strategies to mitigate the ripple effect. Moreover, the effect of a decrease in capacity of facilities on the optimal solution and the applied resilient strategies is investigated. This study provides managerial insights to help governments set the proper amount of cap and supply chain managers to predict the demand behaviour of essential and non-essential products in the event of disruptions.

Acknowledgments

I would like to express my gratitude to my supervisors, Dr. Hamed Samarghandi and Dr. Keith Willoughby, for their support and guidance throughout my Ph.D. program. It would have been impossible to write this dissertation without their encouragement.

Table of Contents

List of Abbreviations

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANP	Analytic Network Process
C&T	Cap-and-trade
FO	Fuzzy Optimization
GHG	Greenhouse Gases
GSC	Green Supplier Chain
GSCM	Green Supplier Chain Management
GSS	Green Supplier Selection
MCDM	Multi-criteria Decision Making
MP	Mathematical Programming
RGSCD	Resilient Green Supply Chain Design
RO	Robust Optimization
SO	Stochastic Optimization
SP	Stochastic Programming

List of Tables

List of Figures

1. Introduction

Environmental considerations have been receiving more attention in various industries across the world. Greenhouse gas (GHG) emission is considered one of the most important environmental concerns caused by economic activities and production, threatens human health, and imposes a cost on governments (Gao et al., 2018). Climate change, which is a consequence of the elevation of GHG emissions leads to challenges that must be addressed by manufacturers and governments. In the following thesis, novel mathematical models to provide an environmental-friendly supply chain and appropriate methods to solve these models are presented. In this chapter, after discussing the problem objectives, motivations behind the following thesis, followed by a summary of the contributions of this thesis is provided. Then, the publications and submissions during Ph.D. studies are presented.

1.1 Research problem and objectives

Supply chains can be assigned an important role in reducing the harmful effects of the product manufacturing process such as CO_2 emission to avoid climate change. Consequently, the concept of green supply chain (GSC) has been widely studied to find better ways of controlling GHG emissions (Haeri and Rezaei, 2019). Due to the increasing environmental issues that have arisen recently, GSCM has become an important topic for both practitioners and researchers (Sang and Liu, 2016). According to Srivastava (2007), GSCM brings environmental considerations to supply chain management; this includes product design, raw material and parts sourcing, production processes, and transportation of finished products to customers. One of the most critical topics in GSCM is supplier selection since about 70% of the cost of the final product arises from component parts and raw material (Ghodsypour and O'brien, 2001). Thus, procuring the raw materials from proper suppliers significantly impacts both the characteristics and the costs of the final product. Accordingly, companies involved in GSCM seek partners that score the highest on environmental criteria (Rao and Holt, 2005).

Supplier selection is the process of evaluating various suppliers to select the best one(s) according to the high-priority criteria for the manufacturers (Ding et al., 2015). In case of multiple sourcing, where more than one partner can be selected for outsourcing, a solution must encompass the selected suppliers and the size of the order to be placed with each of them. To evaluate the suppliers, the manufacturers should first specify their appraisal criteria. According to the literature of GSCM, there are two general types of measures in supplier selection: non-green and green.

Non-green criteria ascertain a company's competitiveness compared to other firms in the market. The most common non-green measures used in the selection process are cost, quality, and lead time (Mirzaee et al., 2018). On the other hand, green criteria consider those company activities that have an adverse impact on the quality of water, air, and soil. The most utilized measures in evaluating the green criteria are the toxicity level of the materials used in products, recyclability, green production, and environmental management systems (Rezaei et al., 2016), as well as pollution production (i.e., the amount of carbon emission) (Yu et al., 2018).

Considering green criteria mentioned above by manufacturers is caused by some incentives that government makes for them to reduce the pollution level. Within the supply chain, there are incentives for manufacturers to apply GSC management. One of the main goals of the manufacturers is satisfying the environmental preferences of the customers given the positive correlation between product greenness and customers' demand (Nouira et al., 2014). Governmental incentives designed to encourage pollution rate reduction exemplify another factor impacting the manufacturers' decision on adopting green technology. These incentives generally reward green economic activities (Li et al., 2018a), or penalize extensive polluting to reduce GHG emissions. In other words, manufacturing emission level is restricted by charging for extra emission (Rout et al., 2021). Two common systems exist for implementing such restrictions: penalty-based system and cap-and-trade (C&T) (Du et al., 2015). A penalty-based system is usually used to force companies to apply environmentally friendly production approaches. Based on this concept, manufacturers will have to pay a penalty based on their GHG emission amounts. Various methods are devised to achieve the mentioned objective. For instance, some governments impose a carbon tax on economical activities. As a result, manufacturers must reduce their carbon emission levels to minimize their carbon tax. Another popular pollution reduction scheme is cap-and-trade (C&T).

C&T is a market-based approach in which the government provides economic incentives to reduce the overall carbon emission level in a geographical area (Knoope et al., 2015). This approach features carbon emission quotas determined by the government for each manufacturer. This quota is calculated based on various factors, including the amount of the manufacturer's annual production. If a manufacturer emits more carbon than its quota, it is required to purchase the extra quota from other manufacturers in the C&T market. In reverse, manufacturers can sell their allowance if they produce less carbon than determined in their quota (Xu et al., 2021a). Cap-and-trade system is one of the most effective mechanisms of controlling GHG emission levels (Xu et al., 2021b). Also, based on Yu et al. (2021), C&T reduces GHG emissions more effectively than the carbon tax system due to making more profit for the manufacturers and producing a higher social welfare. Social welfare can be measured by an indicator called consumer surplus. According to Sinayi and Rasti-Barzoki (2018) consumer surplus can be modeled based on variables such as price and greening level of the product. C&T aims to keep the GHG emissions of an entire geographical area below a predetermined amount. In this system, the policy-maker assigns a combined GHG emission limit to all of the industries that operate in a jurisdiction or the C&T market. Obviously, enforcing a C&T market creates unique challenges. For instance, assessing the amount of carbon emission of the manufacturers or investigating the interactions between active parties in the C&T market. The mentioned complications are one of the main concerns of this thesis.

Given these circumstances, each player in the C&T market must make important decisions, which are often complicated with conflicts of interest among different parties. Each group needs to select the best option among all the available alternatives. In other words, while each party strives to select the option that maximizes its utility, these decisions will undoubtedly impact the utility functions of the other parties. Consequently, an effective solution approach is required to scrutinize the described conflicts and find an equilibrium that maximizes the benefits of all the involved parties. Thus, an appropriate optimization method is required to find the equilibrium.

According to Rao (2019), optimization methods are used to find the maximum or minimum amount of a function while examining different values of its parameters. In our described environment, the goal of each different party is optimizing its own objective function against other parties. One of the main techniques to find the best decision for each party considering their conflicts and the mutual impact of their decisions on the other parties is game theory (GT) (Chavoshlou et al., 2019). GT is a useful tool for decision making when the utility function of different players is affected not only by their own decisions, but also the other players' strategies (Xing et al., 2020). GT is a way to control the uncertainty of predicting other parties' decisions in a supply chain. In other words, GT optimizes a combination of strategies for players with conflicting objectives in a competitive and uncertain environment. GT's appropriateness in dealing with problems with such characteristics has been shown in various studies in the literature (Mahmoudi et al., 2021). It should be noted that various game strategies are devised to deal with different practical conditions. In certain games, players look for a combination of strategies that maximizes everyone's payoff. In other words, if any of the players choose a different strategy, their utility will not increase. This point is called the Nash equilibrium (Axelsson, 2019). Furthermore, games can be categorized based on the players' tendency to cooperate with each other, which results in cooperative and non-cooperative games (Agi and Hazir, 2019). In cooperative games players forge an alliance and all the players know about other parties' decisions. In non-cooperative games, a player is not aware of other players' strategies and needs to select its best strategy based on all the possible outcomes of the other parties' decisions. In this case, a Nash equilibrium shows the best possible strategy, where the players do not change their decision since they will not gain more profit by doing so (Jiang et al., 2021). Agi and Hazir (2019) provide more information about the possible game classifications, especially in the supply chain management context.

In a supply chain, the amount of production, and consequently, the decisions related to raw material outsourcing are highly impacted by market demand and procurement costs. Typically, these factors are not under the company's control. Although firms can impact these parameters by marketing and product pricing, they cannot predict their exact values because of unpredictable factors such as rivals' strategies. This uncertainty prevents the manufacturer from forecasting precise values for demand and procurement cost. Moreover, in a closed-loop supply chain, the quantity of returns consisting of used or rejected products is not easy to predict and is therefore uncertain (Pishvaee et al., 2011). Consequently, decision-makers need to consider appropriately the uncertainty of the parameters, while simultaneously generating models that adequately represent realistic scenarios. In the context of the supply chain, there are three common ways to control the uncertainty of the input data include: stochastic optimization, fuzzy set theory, and robust optimization (RO) (Tordecilla et al., 2021).

In the green supplier selection literature, the majority of studies have focused on dealing with uncertain parameters using stochastic or fuzzy programming. However, correctly estimating the probability distribution of uncertain parameters is one of the challenges of using stochastic programming (Gorissen et al., 2015). Accurate estimation of probability distributions can be particularly difficult when there is a lack of historical data on these parameters, which can lead to unreliable results (Vahdani et al., 2012a). While stochastic programming approach can provide estimated parameter values that are likely to be correct, there is still a small probability that these parameter estimates are wrong; in rare cases, this could cause the solution to be infeasible, which can lead to a significant cost increase. In other words, despite the high accuracy of stochastic programming, there is still some risk involved, and this risk must be carefully considered when making decisions in a supply chain context. (Pishvaee et al., 2011). Similarly, the fuzzy set theory presents challenges as it requires exhaustive knowledge and comprehension of the parameters to generate an accurate membership function. Undoubtedly, obtaining such comprehensive awareness about the market and its dynamics poses an enormous challenge for decision-makers, and is considered to be one of the obstacles for effectively employing the fuzzy set theory for real-world problem optimization (Memon et al., 2015a).

Robust optimization is an analytical technique to address uncertainty in decision-making and has fewer drawbacks compared to the methods mentioned above (Jabbarzadeh et al., 2019). In particular, both robust and stochastic optimization rely on historical data to predict the scenarios and probability distributions, which, once correctly identified, can accurately reflect the uncertain characteristics of random variables (Chen et al., 2022). However, the precision of the probability distribution information is dependent on the number of data samples and the accuracy of the prediction methods; lack of accuracy leads to increased complexity and reduced confidence (Firouzmakan et al., 2019). In the robust optimization approach, the uncertain parameters are typically modeled as belonging to a given uncertainty set, which can be defined in a variety of ways including as a bounded set or as a set of scenarios. The goal of robust optimization is to find a decision or solution that performs well under the worst-case scenario within the given uncertainty set. Accordingly, after realizing any uncertain parameters, the optimal solution is achieved with decent generalization and does not have the mentioned complexity(Lu et al., 2020).

Another important aspect of supply chain management is disruption management. Disruptions caused by natural or human-made disasters affect supply chains in different aspects including transportation delays, labor unavailability, and supply-side shortage. A supply chain disruption announcement decreases a firm's stock returns by 20% on average after six months (Hendricks and Singhal, 2005). Various examples demonstrate the challenges the firms face when trying to recover from a disruption: six months after Japan's tsunami in 2011, Toyota faced disruption in its supply network, and due to a shortage of parts, idled some of its plants in North America (Kim et al., 2015). More recently, the COVID-19 pandemic outbreak caused long-term negative impacts on supply chains and revealed their vulnerabilities (Liu et al., 2022a). These examples showcase the importance of adaptability and resiliency of supply chains in surviving new conditions in case of a sizeable disruption, which has recently gained attention among scholars and practitioners (Ivanov and Dolgui, 2022).

One type of interruption to scrutinize for improving supply chain adaptability is the ripple effect, which is described as the propagation of disturbances that arise from the disruption of supply chain elements (Ivanov et al., 2016). The adverse impacts of the ripple effect spread downstream in the supply chain (Monostori, 2021). Real-world examples emphasize that controlling the ripple effect is crucial for supply chain managers. For instance, in June 2020, Mercedes-Benz ceased production of an off-road vehicle in Alabama as a result of a shortage in components imported from its European suppliers during the global COVID-19 pandemic (Reuters, 2020).

The desirable approach for efficient recovery from the impact of ripple effect is constructing intrinsic supply chain resiliency. Having contingency plans such as backup suppliers or temporary facilities at the supply chain design stage is helpful in controlling the ripple effect (Ivanov et al., 2015). In other words, appropriate strategies must be considered during the design stage to mitigate the crunch in the aftermath of inadmissible events such as supply delay, demand hike, or capacity contraction (Sharma et al., 2022). The auspicious design strategies include, but are not limited to, considering backup suppliers, capacity expansion and multiple assignments (Gholami-Zanjani et al., 2021).

1.2 Motivations

Although there exist numerous studies in the area of supplier selection, only a few papers have considered both green and non-green criteria at the same time. Also, to the best of our knowledge, this chapter is the first study that employs robust optimization to handle uncertainties of the green supplier selection (GSS) problem and cap-and-trade mechanism for carbon emission. Based on the literature, RO is one of the best options to solve various problems in supply chain. In other words, as confirmed by the literature, RO is an efficient approach to deal with uncertainty. However, this approach has not been applied to the green supplier selection problem.

In other words, in this thesis, a GSS model which is embedded in a closed-loop supply chain framework is presented. The model regards both green and non-green measurements in the presence of distinct quantitative and qualitative factors. Moreover, it is assumed that the market operates under the cap-and-trade regulations imposed by the government. To deal with the described problem, an RO approach is employed. It will be demonstrated that the proposed RO model can generate solutions that closely approximate the optimal strategy among all possible strategies. Furthermore, in order to solve the conflicts between different players in the C&T mechanism, a non-cooperative game maximizing the welfare in a cap-and-trade market, in which the players have conflicting interests and objectives is developed. The considered game is decentralized and non-sequential: a) each of the considered three players tries to optimize their own objective function, while being unaware of the other players' strategies; b) decisions are made simultaneously and based on all the possible strategies of the other players. In other words, the mentioned model develops a decision support system (DSS) for the players involved in a C&T mechanism to select the best strategy considering their rivals' moves. The developed DSS also helps the government lower the re-verification costs and the probability of collusion between the manufacturers and verifiers. To achieve a solution which best represents the real world, the supplier lead time and customer preferences are considered to be stochastic. It is assumed that the values of the parameters such as demand, carbon price, amount of lost sales, and manufacturer's quota are dependent on lead time and customer preferences. Additionally, the impact of product greenness on demand is investigated.

This study aims to address the following research questions:

- The impact of cap-and-trade, as an environmental mandate, on the supply chain;
- Finding an effective approach for controlling the intrinsic uncertainty of the model's parameters;
- Selecting the best supplier among all candidates in a supply chain considering economic and environmental criteria;
- Determining clear cause-and-effect relationships between various factors to help government entities with their decision making efforts.

- How the interactions between C&T players impact their decisions?
- Which strategies best help the manufacturers reduce their emission level?
- How C&T players can make effective decisions in presence of uncertainty in other players' strategies and stochastic model parameters?
- How the customers' sensitivity to product greenness versus price impacts the manufacturers' decisions regarding reducing carbon emission levels?
- Which strategic and operational decisions should be made to design a sustainable, resilient green supply chain?
- Which strategies are best to mitigate the ripple effect?

1.3 Contributions of the Thesis

Although there are numerous studies on the supplier selection problem, we know of only a small group of papers addressing both green and non-green factors in the process of supplier evaluation while considering a closed-loop structure with uncertain parameters. Furthermore, as the literature shows, there is no paper that considers RO for green supplier evaluation as well as the cap-and-trade mechanism. Moreover, to the best of our knowledge, previous studies have not considered the role of suppliers in the C&T mechanism as a profit maximizing strategy, or the correlation between sensitivity to product greenness and the demand. Also, a limited number of studies have analyzed C&T as a three-player stochastic game. The present research is an attempt to fill these gaps by fostering the contributions presented below.

- A multi-objective mathematical model for a closed-loop supplier selection and order allocation evaluating the candidates in terms of both environmental and economical criteria is presented. The developed model helps firms achieve a more environmentally friendly manufacturing system. Model realism is enhanced by developing an approach that considers two groups of conflicting criteria (green and non-green).

- The cap-and-trade mechanism, as a method to manage air pollution, is employed in the model. Analyses on the cap and market prices of carbon are performed to help firms and governments determine the values of the parameters to achieve better results. These analyses can subsequently translate to lower cost and carbon emission, as well as more environmentally friendly products. Moreover, based on the analysis conducted on the cap-and-trade approach, this mechanism is demonstrated as a proper approach for carbon emission reduction.

- The generalized model is solved by the RO approach to handle the uncertainty embedded in the problem. Sensitivity analysis has been conducted on two parameters to illustrate the trade-off between model robustness and solution robustness, and solution deviation. This can inform decision-makers of the best parameter values.

- A three-player game is modeled to analyze the interactions between cap-and-trade parties. In this game, a third-party verifier acts a mediator between manufacturer and government. The goal of modeling this problem is to construct a decision support system for cap-and-trade players to maximize their utility and minimize the emission level.

- All possible strategies of the manufacturer to reduce the emission levels are predicted. Upgrading production technology, and outsourcing are two such options. Also, to make the model more realistic, possible bribing actions between the verifier and manufacturer is taken into account, and the government intervention to prevent bribery through a re-verification is analyzed as one of the main variables of the problem.

- The actions of the customer as a vital link in the supply chain are studied with more scrutiny. The correlation between customer sensitivity to product greenness and its impact on upgrading to green technology is investigated. Also, the relationship between product greenness and customer demand is taken into consideration. Furthermore, the linkage between the demand level and the price of purchasing extra carbon emission allowance in the C&T market is formulated.

- The uncertainty of the cap-and-trade players' interactions is controlled in two ways.

First, the uncertainty of the C&T players' decisions, which impacts the other players' utility is handled by applying a game theory model. Second, the uncertainty of the values of the parameters of the problem is handled by stochastic optimization.

- The ways to mitigate the ripple effect and demand uncertainty are investigated by developing a multi-period, multi-stage green resilient supply chain considering 6 resilient strategies.
- A two-stage stochastic optimization approach as an efficient way to control the parameter estimation uncertainty and the ripple effect is deployed for the RGSCD problem.

1.4 Publications and Submissions During Ph.D. Study

1.4.1 Preprints

1. Mirzaee, H., Samarghandi, H., Willoughby, K. (2023). Resilient green supply chain design to mitigate the ripple effect: A two-stage stochastic optimization model. Journal of Cleaner Production (under review).
   A major portion of this paper is included in Chapter 5.

1.4.2 Publications

1. Mirzaee, H., Samarghandi, H., Willoughby, K. (2022). A robust optimization model for green supplier selection and order allocation in a closed-loop supply chain considering cap-and-trade mechanism. Expert Systems with Applications (accepted).
   A major portion of this paper is included in Chapter 3.

2. Mirzaee, H., Samarghandi, H., Willoughby, K. (2022). A three-player game theory model for carbon cap-and-trade mechanism with stochastic parameters. Computers Industrial Engineering, 108285.
   A major portion of this paper is included in Chapter 4.

1.5 Organization of the Thesis

The thesis is organized as follows:

- **Chapter 1: Introduction** gives a clear view of the problem and encountered challenges. In this chapter, we also explained the motivations behind this research, followed by the contributions of this thesis are presented. Then, publications and submissions during the Ph.D. program are listed.

- **Chapter 2: Literature Review** provides a review of previous works regarding the green supplier selection as well as the C&T mechanism. The latest advancements in the uncertainty methods to solve GSCM problems are also addressed.

- **Chapter 3: A robust optimization model for green supplier selection and order allocation in a closed-loop supply chain considering cap-and-trade mechanism** proposes a framework based on the RO approach to model and solve a green supplier selection problem under uncertainty. Then, different analyzes are employed to assess the model and approach performance under uncertainty.

- **Chapter 4: A three-player game theory model for carbon cap-and-trade mechanism with stochastic parameters** explains the procedure of solving conflict between C&T parties using a stochastic game theory model. The robustness of the model is tested under different conditions in presence of uncertainty.

- **Chapter 5: Resilient green supply chain design to mitigate the ripple effect: A two-stage stochastic optimization model** proposes the best resilient strategies to overcome disruptions and mitigate the ripple effect efficiently.

- **Chapter 6: Conclusions and Future work** summarizes this thesis, remaining challenges, and discusses potential future works.

2. Literature Review

In the past few years, GSCM has received considerable attention in both theoretical and empirical studies. GSC researchers have focused on how firms maximize their utility while decreasing their carbon footprint and abiding by the regulations. One of the important topics in the GSCM field, which is relatively recent, is C&T. This mechanism is proven to be one of the most effective approaches of reducing pollutant emissions (Li et al., 2018b).

2.1 Cap-and-trade

Applied research invariably involves the development of methods to more closely align decisions to real-life situations. One such approach to augment applicability involves considering the supply chain as a closed-loop system. Firms in the supply chain can collect used or rejected products and deploy them again in the production system, thus contributing to reduced environmentally harmful waste (Cao et al., 2020a). Moreover, pollution control systems can also provide enhanced applicability for solutions. Cap-and-trade is an interesting mechanism that is becoming more popular in today's consumer market. The emission of greenhouse gas was restricted by the Kyoto Protocol (Oberthür and Ott, 1999) for the first time. The Kyoto Protocol is an international treaty developed within the United Nations Framework Convention on Climate Change (UNFCCC). It was adopted in Kyoto, Japan in 1997 and came into effect in 2005. The Protocol proposes cap-and-trade, which is a flexible framework for reducing air pollution. The existing literature regards cap-and-trade as one of the most effective ways to control the carbon emission (Golpîra and Javanmardan, 2022). Furthermore, based on Yu et al. (2021), cap-and-trade is more effective than the carbon tax system on reducing GHG emissions because it produces a higher social welfare and maximizes utility of the manufacturers. Another research supporting the effectiveness of C&T is conducted by Chen et al. (2020), which further compared emission reduction effects of carbon tax and C&T schemes. They showed that both mechanisms stimulate clean innovation, but C&T is more efficient. They stated that government can control air pollution by assigning the proper carbon cap for manufacturers in a trade-off between environmental and economical objectives.

The C&T approach has been studied from different perspectives in the literature. Gong and Zhou (2013) developed a model to investigate the impacts of creating an emission trading market on single-product production planning problem with stochastic allowance prices and found the optimal production policy as well as emission trading policy under this regulation. They considered the usage of green production technology to decrease emissions. Zhang and Xu (2013) extended the work of Gong and Zhou (2013) by presenting a multi-product production planning model under the C&T system and proposed a profit-maximization model to achieve the firm's optimal policy. In their analyzes, they showed that C&T curbs the emission level better than carbon tax system. Also, they showed that in the C&T system, there is more tendency to produce carbon efficient products. Shen et al. (2014) studied California's cap-and-trade scheme with the goal of implementing it as China's carbon reduction program. Li et al. (2018b) studied the impact of cap-and-trade system on manufacturers' optimal operational decision and showed that customers' green preferences act as an incentive for greening the production technology. Zhang et al. (2019a) considered two scenarios for carbon allowance prices: dynamic and static. They investigated the effects of cap-and-trade market on manufacturers' decisions under both scenarios and showed that upgrading the production technology is positively correlated with penalties imposed for extra emissions.

In the context of supply chain management, cap-and-trade is a relatively new topic. Thus, the need for more research in this area is deeply felt. To the best of the authors' knowledge cap-and-trade regulations have not been addressed in the research body related to green supplier selection. Moreover, although studying the interaction between the verifier and other parties in the C&T market is of consequential importance, the above studies have not considered the role of verifier. To fill this gap, this study involves the third-party emission verifier as a building block of the described network of players in the game. Also, the possibility of using suppliers as a carbon sustainable emission reduction strategy is not considered in the cap-and-trade literature; this option is contemplated in this research as well.

2.2 Game Theory

When investigating the interactions between C&T parties, compromising between conflicting objectives becomes important. Game theory properly deals with the mentioned goal by accounting for the uncertainty of game players' strategies. As such, several articles investigate the interactions between the parties involved in the C&T mechanism from a game theoretical standpoint. The effect of government interventions to make the supply chain greener was studied by Sheu and Chen (2012), who applied a three-stage game theory model to show that government incentives are needed to reduce the adverse environmental effects of supply chain operations. Their results indicate that by using game theory and finding the Nash equilibrium, both supply chain utility and social welfare are increased compared to the case when government intervention is not present.

Zhang et al. (2019a) studied the impact of government intervention on supply chain using game theory. They applied an evolutionary game analysis on manufacturers' behavior under cap-and-trade regulation to investigate the impact of government strategies on manufacturers' decisions under dynamic and static carbon price scenarios. In the two-player game model, they showed that implementing dynamic allowance prices for cap-and-trade system results in a stable strategy; however, with static allowance prices, their evolutionary game was unable to find a stable strategy. Also, they indicated that the manufacturer's probability of implementing a greener technology increases when government penalty for firms' speculations increases, and decreases when the cost of government intervention elevates.

Pan et al. (2019) expanded the literature on C&T players' conflict resolution through a game which consisted of more players. They employed a model to solve a three-player game of C&T between manufacturer, government, and a third-party verifier, and found the best policy for the players. Furthermore, they established a method on how the government can reduce carbon emissions efficiently. Chapter 4 expands on the work of Pan et al. (2019) by considering parameter uncertainty and supplier's role in carbon emission reduction, relating demand to product greenness, and correlating carbon emission quota to carbon price. Additionally, the cited studies do not explore vertical disintegration or effects of subcontracting and outsourcing parts of the manufacturing process in an effort to reduce the manufacturer's emission penalties. To the best of the authors' knowledge, few research efforts examine the three-player game between C&T players. Henceforth, in this study a three-player game which includes all players involved in a C&T game is developed to fill this gap in the literature.

The next topic to consider is categorizing the proposed model from a centralized—decentralized decision making standpoint. Centralized decision models optimize the entire supply chain's profit instead of maximizing the profit of each member separately (Esmaeili-Najafabadi et al., 2021). On the other hand, where a unified decision system is not an option, decentralized models prove to be useful by optimizing the objective function of each organization in the supply chain separately (Golpîra and Javanmardan, 2021). Decentralized decision systems have been applied in various problems from closed-loop supply chain (Muneeb et al., 2018), to green supply chain (Golpîra et al., 2017), to energy management (Golpîra et al., 2020), among others.

For instance, Golpîra and Javanmardan (2021) developed a decentralized decision support system for a closed-loop supply chain and showed that it is an appropriate approach for a competitive environment including different parties in a supply chain. Muneeb et al. (2018) developed a decentralized decision planning model for a solid waste management system and asserted that a supply chain consisting of different decision makers in different echelons is generally a decentralized system. Feng et al. (2022) investigated the impact of environmental decentralization on green technology innovation, and indicated that there is a positive correlation with improvement of green innovation and environmental decentralization. The effects of fiscal decentralization on ecological sustainability is investigated by Sun et al. (2022), which showed that using a decentralized fiscal system plays an important role in decreasing the ecological footprint.

The proposed scheme in this study is a decentralized decision model because, in the real-world, it is not logical to assume that a manufacturer cooperates with the government in concealing its true carbon emission; such assumptions are not realistic and negate the cause for enacting C&T regulations and GHG emission verification regimes. On the contrary, in the proposed model, each involved party has its own objective function which is optimized without consideration for the other partys' utility or losses.

2.3 Product Greenness and Demand

When designing a game theory model for C&T, it is important to take all external factors that influence the players' objectives into account, including customer preference toward product greenness (Krass et al., 2013). Many authors assert that product greenness is an important factor impacting customer demand (Kundu et al., 2021). For instance, Cao et al. (2020b) designed an agri-food supply chain, where demand is dependent on a product's greenness and price. They demonstrated that increasing green standards can result in greener and higher quality products, yet decrease the supply chain profits, because the product cost rises, which reduces demand. Also, Li et al. (2018b) studied the effects of C&T regulation on manufacturers' operational decisions when customer sensitivity toward product greenness is an incentive for manufacturers to use green production technologies. Their work showed that customer preference for green products is a strong incentive for manufacturers to upgrade their technology. The work of Li et al. (2018b) inspired us to consider similar incentives in the presented model to make the results more representative of the real world.

It should be noted that demand magnitude and its dependence on the employed green technology have not been explored in most of the available C&T literature; only a few research studies exist on the correlation between demand and greenness in the context of carbon reduction regulations. In addition, the classification of customers based on their reaction to environmental issues has not been well studied. In the present study, demand and product greenness are considered to be interrelated. In other words, using environmentally-friendly material in the production process, or upgrading machinery to green technology to decrease carbon emission increases demand. On the other hand, when customer sensitivity toward product greenness is correlated with demand for a product, manufacturers tend to green their processes and products to enhance customer satisfaction, and consequently, increase their market share.

2.4 Uncertainty

Another important factor in designing a game for C&T is accounting for uncertainty of the forecast values of parameters to make the model robust for unforeseen changes in the parameter values, as inaccurate parameter estimation causes higher losses in an uncertain environment (Wang et al., 2021). Therefore, devising an effective approach to handle uncertainty is required. Uncertainty can be categorized based on different criteria. One possible categorization is based on the nature of uncertainty, which includes likelihood, vagueness, missing information, imprecise and messy information. The categorization of uncertainty is essential for selecting the appropriate technique for its effective handling and management. This thesis focuses on controlling the uncertainty caused by missing information. The three common approaches of dealing with such uncertainty are stochastic programming and fuzzy set theory, and robust optimization (Tordecilla et al., 2021). Several studies in the field of supply chain management have utilized robust optimization as a means to manage and mitigate uncertainty (Lamba and Singh, 2019; Thevenin et al., 2022; Xia et al., 2018). According to the literature, stochastic optimization is used to control the uncertainty when historical data is available and predicting the future values of a parameter based on past data and trends is doable (Vahdani et al., 2012b). Although fuzzy set theory is one of the most commonly used methods of tackling uncertainty, it needs a deep knowledge about the parameters to build a membership function, which is not always available (Memon et al., 2015b).

In the context of cap-and-trade, various researchers have included uncertainty in their work. Carmona et al. (2009) formulated an uncertain model for carbon allowance price in the C&T market, and identified the main influencing factors. They applied stochastic method for handling uncertainty, and considered emission reduction cost as the stochastic parameter. Uncertainty control in C&T games was extended by Ludkovski (2011), who applied a combination of two relevant methods: a stochastic game-theoretical model to investigate the optimal strategy for energy producers under a carbon emission reduction program, and a hybrid method to control the uncertainty of the problem. Game theory was employed to control the uncertainty of interaction with other chain parties, and stochastic method was applied to tackle the uncertainty of model parameters. Ludkovski (2011) showed that this hybrid method is proved to be an efficient approach to control a model containing uncertainty in both model parameters and players' decisions in a non-cooperative game. Song et al. (2019) conducted another research which combined more than one uncertainty control method. They considered fuzzy set theory and stochastic modeling, and developed a fuzzy stochastic model to predict the exact price of carbon allowance.

The above papers generally consider demand and carbon price as uncertain parameters but do not discuss their interaction with factors such as customer preference regarding product greenness. This chapter considers the relation between demand and customer preference toward product greenness. Also, carbon price is deemed to be dependent to demand. Furthermore, sensitivity to product greenness, and supplier lead time are two parameters that are assumed to be uncertain. Since stochastic optimization is proven to be an appropriate method of handling uncertainty, and thus, has been a popular method in the literature, it is employed in the present manuscript as well.

2.5 Supplier Selection

Green supply chain management seeks to reduce the harmful effects of the supply chain's activities on the environment. In this regard, firms need to identify the most effective measures for evaluating the environmental performance of their suppliers. Research in green supplier selection, in comparison with traditional supplier selection (which generally deals with the firm's utility and quality of the products) is limited. However, the common environmental criteria used in green supplier selection include:

- Environmental management system: the suppliers' policies for making the production process environmentally friendly (e.g., the ISO 14001 certificate). (Amin and Zhang, 2012; Awasthi et al., 2010; Bai and Sarkis, 2010; Govindan et al., 2013; Gupta and

Barua, 2017; Handfield et al., 2002; Hashemi et al., 2015; Hsu and Hu, 2009; Hu et al., 2015; Kumar et al., 2017; Kuo et al., 2010; Lee et al., 2009; Mafakheri et al., 2011; Qin et al., 2017; Rashidi and Cullinane, 2019; Rezaei et al., 2016; Tseng and Chiu, 2013; Yeh and Chuang, 2011);

- Pollution production: the amount of pollution created by a manufacturer (Amin and Zhang, 2012; Giri et al., 2022; Govindan et al., 2013; Hashemi et al., 2015; Hu et al., 2015; Huang et al., 2016; Kannan et al., 2015; Kumar et al., 2017; Luthra et al., 2017; Qin et al., 2017; Rezaei et al., 2016; Wu et al., 2021);

- Recyclability: the capability of suppliers in using recycled material in their manufacturing process (Amin and Zhang, 2012; Govindan and Sivakumar, 2016; Hu et al., 2015; Kannan et al., 2015; Yeh and Chuang, 2011);

- Green product: the ability of suppliers in using green technology as well as environmentally friendly material (Amin and Zhang, 2012; Giri et al., 2022; Handfield et al., 2002; Lee et al., 2009; Tseng and Chiu, 2013);

- Product toxicity: the level of toxic substance used in suppliers' products (Gupta and Barua, 2017; Hu et al., 2015; Kannan et al., 2015; Rezaei et al., 2016).

Table 2.1 summarizes the findings of the mentioned papers. One of the challenges of the supplier selection problem is that firms tend to maximize their utility while trying to perform proficiently on environmental characteristics. Therefore, companies are required to identify both the non-green and green criteria affecting the firm's performance. Different studies have identified the most important criteria in the traditional supplier selection problems. Dickson (1966), Lehmann and O'shaughnessy (1974), Weber et al. (1991), and Cheraghi et al. (2004) conducted research to identify non-green supplier evaluation measures. Those studies showed that cost, delivery performance, and quality are the three most used and important criteria in this particular problem area.

The next step of the supplier selection and order allocation process is assessing the candidates regarding the criteria mentioned above. Researchers have applied different techniques to solve this problem. Chai et al. (2013) classified these techniques into three main groups: multi-criteria decision-making (MCDM), artificial intelligence (AI), and mathematical programming (MP). A list of the papers that apply these techniques to solve the supplier selection problem is presented in table 2.1. Multi-criteria decision-making is a framework that helps the decision makers find the best alternative between multiple options based on various criteria. To select the best option, MCDM sorts the alternatives based on their scores. Artificial intelligence refers to the science of making computers able to work, learn, and think intelligently.Finally, MP is a useful approach in clearly addressing supply chain management problems. Constraints or equations can implement assumptions to improve model realism. In this research, an MP is presented to model the problem.

The decision to develop a closed-loop supply chain setting instead of an open supply chain environment was made based on the premise that a closed-loop system is more reflective of the real-world situations. This is supported by findings in the problem's literature, which suggest that supply chains tend to collect second-hand products from customers in an effort to reduce costs and improve environmental sustainability. Therefore, we deemed it necessary to create a model that accounts for these realistic factors.

Table 2.1: Literature review summary

References	Criteria		Solving Approach			Uncertainty Approach			Closed-loop	Findings
	Green	Non-green	MCDM	MP	AI	Fuzzy	SO	RO		
Awasthi et al. (2010)	✓	-	✓			✓				A fuzzy multi-criteria approach is presented that consists three steps: finding the best criteria, scoring the suppliers using fuzzy TOPSIS, and sensitivity analysis of criteria weights on suppliers evaluation.
Bai and Sarkis (2010)	✓	✓			✓					A new supplier selection technique using rough set and grey system theory is presented.
Kuo et al. (2010)	✓	✓			✓					A green supplier selection model is generalized using a hybrid method called ANN-MADA.
Mafakheri et al. (2011)	✓	✓	✓	✓						A two-stage multi-criteria dynamic programming approach for supplier selection and order allocation is proposed.
Yeh and Chuang (2011)	✓	✓			✓					A green partner selection model is solved by genetic algorithm to find the set of pareto optimal solutions.
Amin and Zhang (2012)	✓	✓		✓		✓			✓	A framework for supplier evaluation in a closed-loop supply chain is generalized.
Govindan et al. (2013)	✓	✓	✓			✓				Triple Bottom Line approach for supplier selection using a fuzzy multi-criteria model is developed.
Tseng and Chiu (2013)	✓	✓			✓					Environmental and non-environmental criteria for selecting the best partners are identified by evaluating the weight of criteria and using grey relational analysis.
Hu et al. (2015)	✓	✓	✓							A novel evaluation system of green supplier selection under the mode of low carbon economy is investigated.
Hashemi et al. (2015)	✓	✓	✓							A comprehensive green supplier selection model using ANP and Grey relational analysis is proposed.
Kannan et al. (2015)	✓	✓	✓			✓				Fuzzy Axiomatic Design is proposed to to select the best green supplier for a plastic manufacturing company.
Huang et al. (2016)	✓	✓		✓	✓					A game-theoretic model is presented in order to investigate the impacts of supplier selection, transportation mode selection, the product line design, and pricing strategies on profits and greenhouse gases emissions.
Rezaei et al. (2016)	✓	✓	✓							Best worst method is used to find the best suppliers among the qualified suppliers.
Luthra et al. (2017)	✓	✓	✓							An integrated approach of AHP, VIKOR, and multi-criteria optimization is developed to solve evaluate the sustainable supplier selection.
Qin et al. (2017)	✓	-	✓			✓				TOMID approach to solve a green supplier selection problem considering interval type-2 fuzzy sets is extended.
Kumar et al. (2017)	✓	✓	✓			✓				Suppliers' performance is evaluated based on Green Practices using the fuzzy-extended Elimination and Choice Expressing Reality approach.
Gupta and Barua (2017)	✓	-	✓			✓				Supplier evaluation is done using a three-phase methodology including three phases: identifying green criteria, ranking determined criteria using a novel best worst method, and ranking suppliers using fuzzy TOPSIS.
Arabsheybani et al. (2018)	✓	✓		✓		✓				The study presents a novel fuzzy MOORA model using ratio analysis for sustainable supplier selection, coupled with FMEA to assess supplier risks, and demonstrates its effectiveness through a case study on evaporative coolers in the home appliance industry.
Moheb-Alizadeh and Handfield (2018)	✓	✓		✓			✓			A sustainable and efficient supply chain is designed using a multi-objective MINLP model for supplier selection and order allocation with stochastic demand.
Rashidi and Cullinane (2019)	✓	✓	✓			✓				A comparative analysis of TOPSIS and Fuzzy DEA for addressing the sustainable supplier selection problem is presented. Results demonstrate that TOPSIS yields superior results in terms of both computational complexity and responsiveness to turbulence in the number of suppliers.
Wu et al. (2021)	✓	✓	✓			✓				A framework employing multiple methods is introduced for selecting sustainable suppliers in the chemical industry, taking into account economic, social, and environmental criteria.
Liu et al. (2022b)		✓	✓			✓				A novel MCGDM approach considering the bidirectional influence relation among criteria, consensus, decision-makers' psychological factors is proposed. The model is designed to offer effective support for emergency decision-making.
Giri et al. (2022)	✓	✓	✓			✓				The Pythagorean fuzzy set-based DEMATEL method is developed and applied to solve the supplier selection problem in sustainable supply chain management.
Saputro et al. (2023)		✓	✓			✓				A two-phase solution approach based on integrated (MCDM) and multi-objective simulation-optimization is developed to solve an uncertain supplier selection problem.
Our thesis	✓	✓		✓				✓	✓	

2.6 Resilient strategies to mitigate the ripple effect

The literature related to the resilient strategies to mitigate the disruption effects focuses on three aspects. First is the environmental perspective of the supply chain design. The second facet is linked to resilience strategies of mitigating the ripple effect. The third prospect is associated with employing stochastic optimization to deal with parameter uncertainty and ripple effect. Table 2.2 lists the related studies and highlights their opposing views. The rest of this section recaps the corresponding literature, the existing gaps, and the contributions of this paper.

Green supply chain design integrates environmental issues into strategic decisions (Foroozesh et al., 2022). The significance of these issues has attracted the attention of various scholars recently (Bhatia and Gangwani, 2021). The role of environmental investment in the supply chain network configuration phase in making the supply chain greener is the main focus of

Wang et al. (2011). In their study, they considered CO_2 emission as the main indicator of supply chain greenness, which is a mainstream index for environmental issues and can be estimated with more ease. In a similar study O'Brien (2013) considered environmental issues in GSCD by explaining limited goals such as GHG emission. Hasani et al. (2021) take environmental and economic concerns into account in designing a supply chain network. They utilized resilient strategies to mitigate disruptions. Mohebalizadehgashti et al. (2020) formulated a multi-objective MILP for the GSCD problem which aims to minimize CO_2 emissions from transportation and maximize total utilization of facility capacities.

In recent years, especially after the COVID-19 pandemic, supply chain resiliency has received extensive attention. For instance, several researchers published review papers to comprehensively study resilience strategies in supply chains (Hosseini et al., 2019; Ivanov et al., 2019; Snyder et al., 2016). Tomlin (2006) specify that resilience strategies are classified into two main groups: pre-disruption and post-disruption schemes. For instance, accumulating safety stock is a pre-disruption resilience strategy for a situation when the supply side of the supply chain is affected (Foroozesh et al., 2022). Yılmaz et al. (2021) introduced four stages of controlling the ripple effect, namely, preparation, first response, preparation for recovery, and recovery. They suggest employing pre-disruption resilience strategies in the first three stages and utilizing a post-disruption resilient strategy for the last stage. The resilience of a system refers to its ability of recovering from disruptions and continuing to provide the necessary service functions. Based on Hosseini and Ivanov (2022), a measure of this ability is the ratio of recovery to loss in terms of service function. It means that if a system experiences loss of service due to a disruption, its resilience is measured by the amount of time and money it requires to recover and restore the lost service. The higher the ratio of recovery to loss, the more resilient the system is considered to be.

Ni et al. (2018) recommend applying post-disruption strategies such as using contingency supplies furnished by backup suppliers or stockpiling systems to maintain customer satisfaction and responding to unmet demand. Kamalahmadi and Mellat-Parast (2016) develop a two-stage MIP to design a sourcing plan with high flexibility. They combine the transportation channel selection problem and supplier selection and order allocation problem, and devise contingency plans for mitigating the negative effects of disruption to minimize total supply chain cost. They found that contingency plan implementation increases suppliers' flexibility in adapting to manufacturers' capacity, and reduces disruption's severity. Jabbarzadeh et al. (2018) applied and assessed inventory levels and backup suppliers as two resilient strategies. Hosseini et al. (2020) considered segregating suppliers as a resilience strategy in supply chain design.

One way to prevent the spread of the ripple effect and to disallow parameter uncertainty to negatively affect the predictions is utilizing a proper uncertainty control method. Accoding to Rezapour et al. (2017) and Kamalahmadi and Mellat-Parast (2016), robust, stochastic, and fuzzy techniques are more prominent than the deterministic models to cope with uncertainties. Badri et al. (2017) developed a two-stage stochastic optimization model to maximize the total value of a supply chain. Yılmaz et al. (2021) applied a two-stage stochastic technique to design a reverse supply chain in the presence of ripple effect, and showed that, as a result, the emission level increases by 40%. Therefore, emission abatement regulations should be enforced to avoid the upsurge. In chapter 5, a two-stage stochastic optimization approach is utilized to cope with uncertainties. For more information about multi-stage stochastic optimization and implementation of stochastic techniques, the interested reader is referred to Khaloie et al. (2020) and Cui et al. (2020).

Table 2.2 summarizes the recent and relevant studies. According to the literature summary and the above-mentioned papers, one notices that although there is more emphasis on minimizing the GHG emissions in green supply chain management, environmental considerations are not the main focus of supply chain design problems, and governmental emission reduction regulations such as cap-and-trade are considered as a hindrance that work against maximizing the utility. Furthermore, the ripple effect, as one of the main disruption elements, is rarely considered in resilient supply chain design studies.

The papers that have studied the ripple effect have mainly considered resilience strategies in their general form, such as pre-disruption and post-disruption schemes; specific resilience strategies such as safety stock and backup suppliers have rarely been studied. In other words, resilience strategies are more studied based on pre- or post-disruption classification,

Table 2.2: Literature review summary

Authors	Network stages	Multi-period	Green supply chain	The ripple effect	Uncertainty	Resilient strategies	Disruption effects
Kamalahmadi and Mellat-Parast (2016)	2	–	–	–	Others	Contingency plans	Supply disruption
Fattahi et al. (2017)	3	✓	–	–	Two-stage SP	Contingency and mitigation(general)	Facility capacity
Mohammed et al. (2017)	3	–	–	–	SP	–	–
Rezapour et al. (2017)	3	–	–	✓	Deterministic	Emergency stock at retailers, backup capacities at suppliers, multiple sourcing	Supplier disruption
Pavlov et al. (2017)	4	–	–	✓	FO	–	–
Badri et al. (2017)	3	✓	–		Two-stage SP	–	–
Amiri-Aref et al. (2018)	3	✓	–	–	Two-stage SP	–	–
Zahiri et al. (2018)	3	✓	–	–	FO	–	–
John et al. (2018)	1	✓	–	–	Deterministic	–	–
Liao (2018)	2	–	✓	–	Deterministic	–	–
Ni et al. (2018)	1	✓	–	–	Two-stage SP	Backup facilities, safety stock, idle capacity reserve	Demand
Jabbarzadeh et al. (2018)	2	–	✓	–	SP	Backup suppliers, production capacity expansion	Supply disruption
Sawik (2019)	2	✓	–	–	Two-stage SP	–	–
Darestani and Hemmati (2019)	3	✓	✓	–	RO	–	–
Hosseini and Ivanov (2019)	2	–	–	✓	Others	–	–
Hosseini-Motlagh et al. (2019)	3	–	✓	–	Others	–	–
Zhang et al. (2019b)	2	–	–	✓	FO	Backup manufacturer, multiple distributor	Supply disruption
Hosseini et al. (2020)	2	–	–	✓	SP	–	Supplier disruption
Tucker et al. (2020)	3	✓	–	✓	SP	Configuration of suppliers and manufacturers, safety stock	Supply disruption
Mohebalizadehgashti et al. (2020)	3	✓	✓	–	Others	–	–
Özçelik et al. (2021)	2	–	✓	✓	RO	–	–
Hasani et al. (2021)	3	✓	✓	–	RO	Backup suppliers, facility dispersion, facility fortification	Supply disruption
Yılmaz et al. (2021)	3	–	✓	✓	Two-stage SP	Temporary facilities	Supply disruption
Foroozesh et al. (2022)	4	✓	✓	–	FO	Multiple sourcing, horizontal collaboration, coverage radius	Supply disruption
This study	4	✓	✓	✓	Two-stage SP	Backup suppliers, multiple sourcing, temporary facilities, blockchain, safety stock, stockpiling	Supply, demand
SP=Stochastic programming, RO= Robust optimization, FO=Fuzzy optimization							

and the details of particular strategies like temporary facilities and safety stock are neglected. Regarding the uncertainty control approaches, most of the papers have used robust (RO) or fuzzy optimization (FO) and stochastic programming (SP); few studies consider multi-stage stochastic programming to handle uncertainty. The literature related to this study is limited to the general form of disruption and rarely studies the areas of the supply chain affected by disruptions. To the best of our knowledge, there is no study that considers both upstream and downstream propagation of disruptions in a supply chain.

The fifth chapter of this thesis studies the ways to mitigate the ripple effect and demand uncertainty by developing a multi-period, multi-stage green resilient supply chain. We consider six resilience strategies to keep the supply and demand side of the supply chain in control. We deploy a two-stage stochastic optimization approach as an effective way of controlling parameter estimation uncertainty and ripple effect.

3. A robust optimization model for green supplier selection and order allocation in a closed-loop supply chain considering cap-and-trade mechanism

3.1 Background

Due to increasing air pollution, which is a consequence of the environmental effects of production in various industries, green supply chain management (GSCM) has attracted the attention of both scholars and practitioners. Green supplier selection is an important problem in GSCM and seeks to satisfy a firm's environmental goals as well as its economic targets. In this chapter, for the first time, a green supplier selection problem considering both green and non-green evaluation criteria in a closed-loop supply chain is studied, and a cap-and-trade mechanism as a way of controlling the air pollution caused by manufacturers is proposed. To solve this particular problem, we propose a multi-objective robust optimization (RO) model. This specific model is an effective approach to handle uncertainty. A numerical example using randomly generated data, accompanied by subsequent discussion of the proposed approach, is deployed to validate the model. The results prove that the developed model for green supplier selection is able to effectively enhance the decision-making process of the experts. By illustrating the trade-off in robustness between the model and proposed solutions, as well as the effect of the deviation penalty on the closeness of results to the achieved solution, we

Most of the context in this chapter have been published in Mirzaee, H., Samarghandi, H., Willoughby, K. (2022). A robust optimization model for green supplier selection and order allocation in a closed-loop supply chain considering cap-and-trade mechanism. Expert Systems With Applications (under review).

show how firms can make optimal decisions when assigning the parameters. Furthermore, analyses show that decreasing the allowance amount (cap) and increasing the allowance prices in the cap-and-trade system escalate the firms' costs, but lower the amount of carbon released. Finally, we show that the cap-and-trade mechanism results in a better solution in terms of the total utility of the supply chain compared to the penalty-based system for a specific range of carbon allowance.

3.1.1 Robust optimization

We need to consider the intrinsic uncertainty of the parameters, since incorrect estimation of parameter values may lead to colossal losses in an uncertain environment (Wang et al., 2021). Obviously, this requires an effective approach to handling such uncertainty. To the best of our knowledge, RO has been rarely applied to solve the problems in the literature on green supplier evaluation. In this chapter, RO is employed because it handles infeasibility efficiently deals with data uncertainty and efficiently deals with data uncertainty. Moreover, it does not limit uncertain parameter values to point estimates (Jeyakumar et al., 2014), while assigning a cost to infeasibility. Other popular approaches are capable of controlling uncertainty, but may be unable to address the situation of solution infeasibility. The expected cost of infeasibility can be significant and must be considered.

Unlike deterministic methods that feature a specific value for the parameters, RO considers various parameter values and obtains solutions under all possible scenarios. Mulvey et al. (1995) introduced RO as a new approach for uncertain problems. This method performs a trade-off between two kinds of robustness; namely, model robustness (i.e., the obtained solution yields the least infeasibility in all scenarios), and solution robustness (i.e., the solution is as close to the optimal value as possible in all scenarios). Simply put, the goal of RO is to achieve a robust solution that ensures all the real scenarios are nearly optimal and feasible.

Mulvey et al. (1995) assumed x and y as design variables (in which their optimal value is not dependent upon the real value of the uncertain parameters), and control variables (in which their optimal value depends on the value of the uncertain parameters). Correspondingly, there are two groups of constraints: control constraints, and structural constraints.

The former are those that include noisy parameters, while the latter feature the constraints with no uncertain parameters. The basic structure of the RO model is presented below.

$$Min\ \ c^T x + d^T y \tag{3.1}$$

$$Ax = b \tag{3.2}$$

$$Bx + Cy = e \tag{3.3}$$

$$x, y \geq 0 \tag{3.4}$$

where A and b are deterministic parameters, and B and C are uncertain parameters. In other word, equations (3.2) and (3.3) convey the structural and control constraints, respectively. There are a finite set of scenarios s defined for the RO problem with the probability Pr_s for each scenario. Then, the model formulation transforms to the following:

$$Min\ \ \sigma(x, y_1, ..., y_s) + \omega\rho(\delta_1, ..., \delta_s) \tag{3.5}$$

$$Ax = b \tag{3.6}$$

$$B_s x + C_s y + \delta_s = e_s \tag{3.7}$$

$$x, y_s \geq 0 \tag{3.8}$$

in which δ_s indicates the permitted infeasibility in constraint (3.7) under scenario s. The objective function includes two parts. The first part represents the solution robustness, and the second part is a measure of model robustness. As the value of the penalty of infeasibility, ω helps to make a trade-off between model robustness and solution robustness. The first part of the presented objective function can be reformulated as follows:

$$\sigma(x, y_1, ..., y_s) = \sum_s Pr_s \xi_s + \lambda \sum_s Pr_s \left(\xi_s - \sum_{s'} Pr_{s'} \xi_{s'} \right)^2 \tag{3.9}$$

where λ is the penalty for solution variance and takes positive values. ξ_s is the value of the objective function in each scenario. In this equation, the first part shows the average value of the objective in different scenarios, and the second part indicates the objective variance.

Furthermore, equation (3.9) can be written in the following form:

$$\sigma(x, y_1, ..., y_s) = \sum_s Pr_s \xi_s + \lambda \sum_s Pr_s \mid \xi_s - \sum_{s'} Pr_{s'} \xi_{s'} \mid \tag{3.10}$$

Yu and Li (2000) state that, due to non-linearity, this equation is very complicated and time-consuming to solve. To overcome this challenge, they propose the following formulation to linearize the equation.

$$\sigma(x, y_1, ..., y_s) = \sum_s Pr_s \xi_s + \lambda \sum_s Pr_s \left[\left(\xi_s - \sum_{s'} Pr_{s'} \xi_{s'} \right) + 2\theta_s \right] \tag{3.11}$$

$$\left(\xi_s - \sum_{s'} Pr_{s'} \xi_{s'} \right) + \theta_s \geq 0 \qquad \forall s \tag{3.12}$$

$$\theta_s \geq 0 \qquad \forall s \tag{3.13}$$

The variable θ_s is used to prevent $\xi_s - \sum_{s'} P_{s'} \xi_{s'}$ from being negative. According to the above new formulation, the objective function can be written as follows.

$$Min \ \sum_s Pr_s \xi_s + \lambda \sum_s Pr_s \left[\left(\xi_s - \sum_{s'} Pr_{s'} \xi_{s'} \right) + 2\theta_s \right] + \omega \sum_s Pr_s \delta_s \tag{3.14}$$

where ω is defined as the weight of the trade-off between model robustness and solution robustness. The weight ω is a number without a unit, which indicates the penalty assigned to infeasibility; if ω increases, the probability of obtaining an infeasible solution decreases.

3.2 Model Architecture

In this section, a multi-objective, multi-product, multi-supplier, and multi-period robust model for green supplier selection and order allocation in a closed-loop supply chain is presented. Two groups of criteria are presented for supplier evaluation: green and non-green. The non-green criteria are cost, quality, and delivery time, while green criteria are divided into two categories: quantitative (carbon emission amount), and qualitative (environmental management system level, recyclability level, green product level, product toxicity level).

In this closed-loop supply chain, the manufacturer sells its products to the customer, but some products may be rejected due to such problems as low quality. Moreover, the manufacturer tends to use second-hand products in the production process to benefit from their low costs. Second-hand products must be collected from the customers. A percentage of the collected and rejected products are usable. The remainder of the second-hand products are disposed. Therefore, the input material and component parts include products purchased from suppliers, reusable parts or material collected from the final consumer market and usable parts from rejected products (see figure 3.1). Other assumptions of the model are presented below.

Assumptions

- Shortage is allowed and will be back-ordered. A penalty will be charged for each unit of shortage.

- The supply chain operates under cap-and-trade regulations. Accordingly, each manufacturer is allowed to emit a predetermined amount of carbon. Any extra quantity of carbon emission must be purchased from other manufacturers in a trade market. Conversely, manufacturers can sell their unused carbon emission allowance to decrease costs. Note that a carbon tax system allocates a price to carbon emission and puts it on the market to find the emission reduction mechanism. On the other hand, cap-and-trade assigns an emission level to the manufacturers and allows the market to find the allowance price. Therefore, in the cap-and-trade mechanism, the buyers and sellers offer their desired prices, which can be different based on their utility level. The manufacturer considers the maximum offer for selling its allowance and the minimum offer for buying extra allowance.

- Uncertain parameters include demand, cost of products purchased from suppliers, percentage of the returned products, percentage of the collected second-hand products, percentage of reusable collected products, percentage of usable rejected products, and delivery delay.

- Carbon emission is a function of CO_2 released in the production process as well as CO_2

released during material and product transportation. Purchased products from a supplier can be transported by either the manufacturer's trucks (buyer) or the supplier's trucks. The manufacturer is responsible for the carbon emission during the transportation process only if the manufacturer's trucks are employed. Using the manufacturer's truck for transportation is less expensive but increases the amount of carbon released by the manufacturer.

- Different kinds of trucks exist for transporting the procured materials and products according to the weight or volume of the loads.

- A constant interest rate is applied to all of the costs through time.

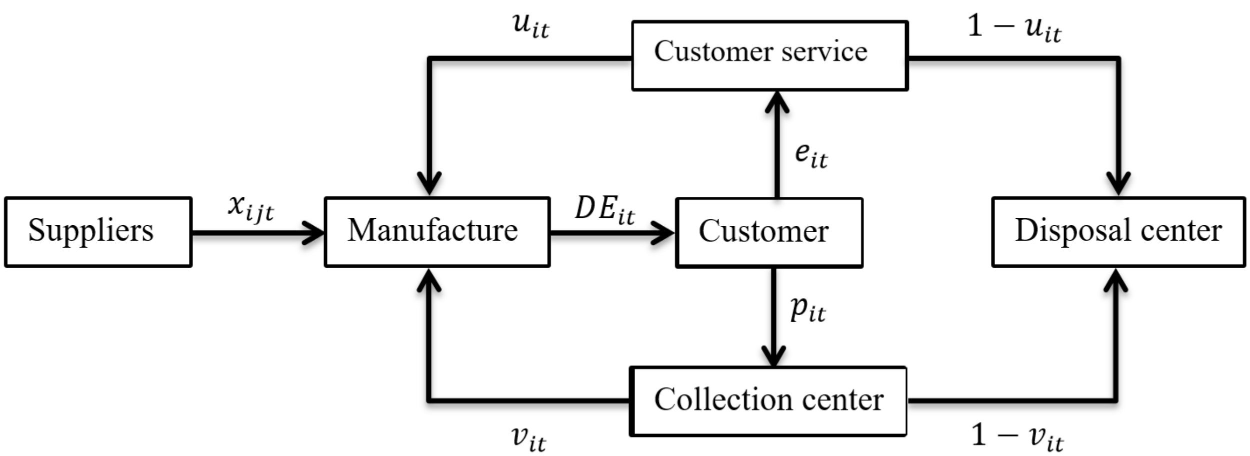


Figure 3.1: Closed-loop supply chain structure

Indices

i: products ($i = 1, \cdots, I$)

j: suppliers ($j = 1, \cdots, J$)

t: periods ($t = 1, \cdots, T$)

k: vehicles ($k = 1, \cdots, K$)

n: echelons in supply chain ($n = 1, 2$) ($n = 1$ and $n = 2$ show the supplier and buyer, respectively).

m: set of prices offered by buyers or sellers at the carbon emission trading market

s: scenarios ($s = 1, \cdots, S$)

Parameters

Pr_s: probability of scenario s

C^s_{ijt}: cost of product i purchased from supplier j in period t under scenario s

ir: interest rate

h_{it}: holding cost of product i in period t

f_{it}: backorder cost of product i in period t

L^s_{jt}: number of days in which products purchased from supplier j in period t under scenario s received after the specified time

G_{ijt}: penalty for each day of late delivery of product i purchased from supplier j in period t

e^s_{it}: percentage of product i rejected in period t under scenario s from the customer due to low quality

u^s_{it}: percentage of usable parts after disassembly of product i rejected by customer in period t under scenario s

p^s_{it}: percentage of used product i collected in period t under scenario s from the customer

v^s_{it}: percentage of reusable parts after disassembly of product i collected as used product in period t under scenario s

O_{ijt}: manufacturer's loss caused by rejected product i purchased from supplier j in period t

SP^m_t: price offered by seller m in the carbon emission allowance market in period t

BP^m_t: price offered by buyer m in the carbon emission allowance market in period t

DC_{it}: disassembly cost for product i in period t

RC_{it}: remanufacturing cost of product i in period t

DP_{it}: disposal cost of product i in period t

TC_{jtkn}: transportation cost of products purchased from supplier j in period t by truck type k belonging to the nth echelon of supply chain

DE^s_{it}: customers' demand for product i in period t under scenario s

d_j: distance of supplier j from the producer

CET_{jtkn}: the amount of carbon emitted per kilometer of transportation from supplier j in period t by truck type k belonging to nth echelon of supply chain

CEP_{ijt}: amount of carbon emitted during production using product i purchased from supplier j in period t

CER_{it}: amount of carbon emitted during remanufacturing or recycling product i in period t

EM_{ijt}: environmental management system score assigned to supplier j from which product i in period t is purchased. This score is determined by experts at the manufacturer's firm evaluating the performance of the suppliers regarding environmental policies (e.g. possession of an ISO 14001 certificate).

GP_{ijt}: green product score of supplier j from which product i in period t is purchased. This is the manufacturer's strategy to purchase products with minimum environmental effects during their life cycle.

RE_{ijt}: recyclability score of product i purchased from supplier j in period t

PT_{ijt}: toxicity score of product i purchased from supplier j in period t

CAP_t: the amount of carbon emission determined by the government as an upper bound for the manufacturer in period t

M_k: breaking point of loads for each kind of truck used for transportation

Decision variables

x_{ijt}: number of product i purchased from supplier j in period t

r_{it}: number of remaining product i at the end of period t

b_{it}: number of back-ordered product i at the end of period t

α_t: allowance of carbon emission the manufacturer needs to buy from the market in period t

β_t: allowance of carbon emission the manufacturer wants to sell to the other manufacturers in period t

τ_t: the best price for the manufacturer to buy carbon allowance in period t

ϕ_t: the best price for the manufacturer to sell carbon allowance in period t

q_{jtkn}: binary variable, equals 1 if the buyer places an order to supplier j in period t transported by truck k belonging to nth echelon; 0 otherwise

W_{jtkn}: auxiliary continuous variable to determine the amount of load from supplier j in period t transported by truck type k belonging to nth echelon

δ_{ijt}^{s+}: under-fulfillment (shortage) of product i purchased from supplier j in period t

δ_{ijt}^{s-}: over-fulfillment (storage) of product i purchased from supplier j in period t

According to the criteria introduced, three objectives are defined. The first objective, ξ_1^s, is cost, which is a measure of non-green criteria. This cost includes uncertain parameters and is formulated as:

$$
\begin{aligned}
\underset{s\in\{1,2,\dots,S\}}{\xi_1^s} &= \sum_j \sum_t L_{jt}^s \sum_i G_{ijt} x_{ijt} + \sum_i \sum_t e_{it}^s \sum_j O_{ijt} x_{ijt} + \sum_i \sum_j \sum_t x_{ijt} C_{ijt}^s \\
&+ \sum_i \sum_t r_{it} h_{it} + \sum_i \sum_t b_{it} f_{it} + \sum_i \sum_t e_{it}^s \sum_j x_{ijt} DC_{it} \\
&+ \sum_i \sum_t p_{it}^s \sum_j x_{ijt} DC_{it} + \sum_i \sum_t e_{it}^s u_{it}^s RC_{it} \sum_j x_{ijt} \\
&+ \sum_i \sum_t p_{it}^s v_{it}^s RC_{it} \sum_j x_{ijt} + \sum_i \sum_t e_{it}^s (1 - u_{it}^s) DP_{it} \sum_j x_{ijt} \\
&+ \sum_i \sum_t p_{it}^s (1 - v_{it}^s) DP_{it} \sum_j x_{ijt} + \sum_j \sum_t \sum_k \sum_n TC_{jtkn} q_{jtkn} \\
&- \sum_t \alpha_t \tau_t + \sum_t \beta_t \phi_t
\end{aligned}
\tag{3.15}
$$

In this equation, the first term calculates the penalty for rejected items. It is an indication of the quality of the products. The second term is the cost of delay. The remaining terms calculate other features including purchasing cost, holding cost, back-order cost, disassembly cost of rejected and collected products, remanufacturing cost for the usable parts obtained from collected and rejected products, disposal cost of the unusable parts, and revenue/cost of selling/buying carbon emission allowance. Of note, three different kinds of criteria (cost, quality, and delivery performance) are included in this objective, all of which are combined in the cost function ξ_1^s.

The second objective is the amount of carbon emission, which is a measure of quantitative green criteria. Due to parameter uncertainty, ξ_2^s is written as:

$$
\begin{aligned}
\underset{s\in\{1,2,\dots,S\}}{\xi_2^s} &= \sum_j d_j \sum_k \sum_t CET_{jtk2} q_{jtk2} + \sum_i \sum_j \sum_t x_{ijt} CEP_{ijt} \\
&+ \sum_i \sum_t (e_{it}^s u_{it}^s + p_{it}^s v_{it}^s) CER_{it} \sum_j x_{ijt}
\end{aligned}
\tag{3.16}
$$

The first term of the equation (3.16) calculates the amount of carbon released during the transportation of purchased products from supplier j by trucks belonging to the manufacturer. The second term measures the carbon emission during the production phase, and the third term calculates the carbon released during the remanufacturing or recycling process fed by components and parts obtained from disassembling the collected and rejected products.

The third objective is a measure of qualitative green criteria. This objective function does not include uncertain parameters, and is defined as:

$$\begin{aligned} z_3 = & \sum_i \sum_j \sum_t LC_{ijt} x_{ijt} + \sum_i \sum_j \sum_t ER_{ijt} x_{ijt} + \sum_i \sum_j \sum_t RE_{ijt} x_{ijt} \\ & + \sum_i \sum_j \sum_t TS_{ijt} x_{ijt} \end{aligned} \tag{3.17}$$

The robust model of the described problem is therefore formulated as:

$$\begin{aligned} Min\ z_1 = & \sum_s Pr_s \xi_1^s + \lambda_1 \sum_s Pr_s \left[\left(\xi_1^s - \sum_{s'} Pr_{s'} \xi_1^{s'} \right) + 2\theta_1^s \right] \\ & + \omega \sum_s Pr_s \left(\sum_i \sum_j \sum_t \left(\delta_{ijt}^{s-} + \delta_{ijt}^{s+} \right) \right) \end{aligned} \tag{3.18}$$

$$\begin{aligned} Min\ z_2 = & \sum_s Pr_s \xi_2^s + \lambda_2 \sum_s Pr_s \left[\left(\xi_2^s - \sum_{s} Pr_{s'} \xi_2^{s'} \right) + 2\theta_2^s \right] \\ & + \omega \sum_s Pr_s \left(\sum_i \sum_j \sum_t \left(\delta_{ijt}^{s-} + \delta_{ijt}^{s+} \right) \right) \end{aligned} \tag{3.19}$$

$$Max\ z_3 \tag{3.20}$$

$$\left(\xi_1^s - \sum_{s'} Pr_{s'} \xi_1^{s'} \right) + \theta_1^s \geq 0 \qquad \forall s \tag{3.21}$$

$$\left(\xi_2^s - \sum_{s'} Pr_{s'} \xi_2^{s'} \right) + \theta_2^s \geq 0 \qquad \forall s \tag{3.22}$$

$$\begin{aligned}\sum_j d_j \sum_k CET_{jtk2} q_{jtk2} + \sum_i \sum_j x_{ijt} CEP_{ijt} \\ + \sum_i (e^s_{it} u^s_{it} + p^s_{it} v^s_{it}) CER_{it} \sum_j x_{ijt} \leq CAP_t - \alpha_t + \beta_t \qquad \forall t, s\end{aligned} \tag{3.23}$$

$$\tau_t = \max_{\forall m} BP^m_t \qquad \forall t \tag{3.24}$$

$$\phi_t = \min_{\forall m} SP^m_t \qquad \forall t \tag{3.25}$$

$$\begin{aligned}u^s_{it} e^s_{it} \sum_j x_{ijt} + v^s_{it} p^s_{it} \sum_j x_{ijt} + \sum_j x_{ijt} + b_{it} + r_{it-1} + \sum_j \delta^{s-}_{ijt} \\ = DE^s_{it} + r_{it} + b_{it-1} + \sum_j \delta^{s+}_{ijt} \qquad \forall i, t, s\end{aligned} \tag{3.26}$$

$$\sum_i x_{ijt} = \sum_k M_k \sum_n W_{jtkn} \qquad \forall j, t \tag{3.27}$$

$$W_{jt1n} \leq q_{jt1n} \qquad \forall j, t, n \tag{3.28}$$

$$W_{jt(k+1)n} \leq q_{jt(k+1)n} + q_{jtkn} \qquad \forall j, t, n; (k = 1, \cdots, (K-1)) \tag{3.29}$$

$$W_{jtKn} \leq q_{jt(K-1)n} \qquad \forall j, t, n \tag{3.30}$$

$$\sum_k q_{jtkn} = 1 \qquad \forall j, t, n \tag{3.31}$$

$$\sum_k W_{jtkn} = 1 \qquad \forall j, t, n \tag{3.32}$$

$$0 \leq W_{jtkn} \leq 1 \qquad \forall j, k, t, n \tag{3.33}$$

$$C^s_{ij(t+1)} = C^s_{ijt}(1 + ir) \qquad \forall i, j, t, s \tag{3.34}$$

$$h_{i(t+1)} = h_{it}(1 + ir) \qquad \forall i, t \tag{3.35}$$

$$f_{i(t+1)} = f_{it}(1 + ir) \qquad \forall i, t \tag{3.36}$$

$$G_{ij(t+1)} = G_{ijt}(1 + ir) \qquad \forall i, j, t \tag{3.37}$$

$$O_{ij(t+1)} = O_{ijt}(1 + ir) \qquad \forall i, j, t \tag{3.38}$$

$$DC_{i(t+1)} = DC_{it}(1 + ir) \qquad \forall i, t \tag{3.39}$$

$$RC_{i(t+1)} = RC_{it}(1 + ir) \qquad \forall i, t \tag{3.40}$$

$$DP_{i(t+1)} = DP_{it}(1 + ir) \qquad \forall i, t \tag{3.41}$$

$$TC_{j(t+1)kn} = TC_{jtkn}(1 + ir) \qquad \forall j, t, k \tag{3.42}$$

Equation (3.18) aims to minimize the costs while trying to obtain the highest utility in the carbon emission trading market. Due to defining different scenarios, this objective is written as a robust objective to obtain the closest solution to all scenarios while keeping infeasibility at the lowest level. Equation (3.19) is another robust objective aiming to minimize carbon emission. Note that equations (3.18) and (3.19) go in opposite directions. In other words, the first and second objectives restrict each other. Therefore, the optimal solution is found through a trade-off between these two objectives. The third objective maximizes quality by choosing the suppliers with the best qualitative performance. Suppliers' qualitative scores are defined by experts on a scale of $0 - 10$.

Equations (3.21) and (3.22) transform the first and second objectives to linear functions. These equations ensure that the deviation of each scenario from the average objective value is a positive amount. Equation (3.23) adheres to the manufacturer's carbon emission allowance, yet makes it possible to buy or sell the allowance. Buying and selling price are defined in equations (3.24) and (3.25), where the maximum and minimum offered price is selected to sell and buy the allowance, respectively. Equation (3.26) balances the inventories.

Equations (3.27) to (3.33) confirm that the purchased products from each supplier are assigned to a specific truck category based on their size. For instance, if three different kinds of trucks are classified by their load size, and the order from a specific supplier fits on the first category, the variable x_{ijt} will be a linear combination of first and second breaking points. Hence, q_{jt1n} will be equal to 1 and variables W_{jt1n} and W_{jt2n} will be positive. Equations

(3.34)-(3.42) refer to the interest rate applied to the prices.

3.2.1 Solution procedure

To solve the proposed RO model, we follow a two-step procedure. In the first step, each of the three objectives is independently solved, i.e., the model is solved three times; each time, one of the objectives is considered and the other two objectives are removed from the model. This way, the optimum value of each objective is found in the absence of the other objectives. Obviously, in multi-objective models, the value of each objective (in the presence of the other objectives) is worse than or equal to their global optimal value. Thus, there is always a deviation between objective function values in multi-objective models and their global optimal values; the goal is to minimize this deviation, which will be done in the second step. In the second step, the model is reformulated as a single objective mathematical model whose objective function is minimizing the normalized deviation of the objectives from their optimal values. Assume that the values of the first, second, and the third objective are demonstrated as z_1, z_2, and z_3, respectively; and the optimal values are illustrated as z_1^*, z_2^*, and z_3^*. Then, the objective function is as follows.

$$Min\ z_{total} = \left[\frac{z_1 - z_1^*}{z_1^*} + \frac{z_2 - z_2^*}{z_2^*} + \frac{z_3^* - z_3}{z_3^*}\right] \tag{3.43}$$

In equation (3.43), z_1 and z_2 are minimization objectives and their values will be greater than or equal to their optimal values, z_1^* and z_2^*, respectively. On the other hand, z_3 is a maximization objective and its value will be smaller than or equal to its optimal value, z_3^*. As the deviation of an objective from its optimal value cannot be negative, equation (3.43) is written such that it remains positive ($z_1 - z_1^* \geq 0; z_2 - z_2^* \geq 0; z_3^* - z_3 \geq 0$).

3.3 Results and Discussions

In order to validate the described RO model for green supplier evaluation, we present results of various instances of the model. The experiments were conducted based on the data set of table 3.1, which was generated randomly using uniform distributions. The data generated to validate the model is not derived from real-world scenarios. Instead, logical values for the parameters have been considered based on the existing literature. Note that the parameters related to price were generated for the first period, and the next periods were calculated according to model constraints. Also, three different scenarios were considered, namely pessimistic, most realistic, and optimistic. The presented data set includes a probability associated with each scenario, whereby the scenario with the highest probability is deemed the most realistic. The pessimistic scenario involves parameters that can potentially lead to a deterioration of optimal utility. For instance, the purchasing cost of a product from the supplier is higher in the pessimistic scenario, which is more expensive for the manufacturer, than in the optimistic scenario. Moreover, the carbon allowance buying price is set higher than its selling price to prevent manufacturers from engaging in brokerage. The pessimistic scenario involves a higher demand than the other two scenarios, posing a challenge for manufacturers to satisfy customer demands. Additionally, the data set includes three truck categories based on their transportation capacity for the purchased loads from suppliers. The presented mathematical model is solved using DICOPT solver of the GAMS software on an 11^{th} generation Intel$^{\text{TM}}$ Core$^{\text{TM}}$ i7-1165G7 CPU with 2.80 GHz clockspeed, and 12 GB of RAM.

3.3.1 Experimental Results

Table 3.2 presents the results obtained by solving the model, which determines the best suppliers and the optimal order allocations. Specifically, the table shows the number of units of each product that the manufacturer should order from each supplier in each period, based on the defined criteria. For instance, the entry $X_{112} = 2617$ indicates that the manufacturer should place an order for 2617 units of product 1 to the first supplier in the second period. In addition, the table provides information on the optimal shortage and storage amounts, which are calculated based on the optimal orders. The over-fulfillment and under-fulfillment values indicate the extent to which the manufacturer's orders exceed or fall short of the actual demand, respectively. These values reflect the trade-off between achieving the best possible solution and meeting customer demand, which is captured in the manufacturer's utility function.

Table 3.1: Data for numerical example

Sets and parameters	**Scenarios**	**Amounts**
i		4
j		5
t		4
k		3
s		3
m		3
ir		0.04
λ_1		15
λ_2		15
ω		50
Pr^s	1, 2, 3	0.2, 0.6, 0.2
C_{ij1}^s	1, 2, 3	$U(10, 23)$, $U(11.5, 26)$, $U(13, 30)$
h_{i1}		$U(28, 35)$
f_{i1}		$U(33, 41)$
L_{jt}^s	$1, 2, 3$	$U(0, 5)$
G_{ijl}		$U(6, 12)$
e_{it}^s	1, 2, 3	$U(0.03, 0.092)$, $U(0.035, 0.126)$, $U(0.04, 0.145)$
p_{it}^s	1, 2, 3	$U(0.02, 0.08)$, $U(0.023, 0.092)$, $U(0.027, 0.105)$
u_{it}^s	1, 2, 3	$U(0.6, 0.9)$, $U(0.62, 0.93)$, $U(0.63, 0.94)$
v_{it}^s	1, 2, 3	$U(0.6, 0.9)$, $U(0.72, 0.93)$, $U(0.73, 0.94)$
O_{ij1}		$U(5, 11)$
SP_t^m		$U(4000, 4020)$
BP_t^m		U(3980,4000)
DC_{i1}		U(4,7)
RC_{i1}		U(10,17)
DP_{i1}		U(3,5)
TC_{j1kn}		$TC_{j111} = U(28, 37)$, $TC_{j112} = U(29, 38)$, $TC_{j121} = U(35, 40)$ $TC_{j122} = U(36, 41)$, $TC_{j131} = U(39, 52)$, $TC_{j132} = U(40, 53)$
DE_{it}^s	$1, 2, 3$	$U(2500, 4600)$, $U(2930, 4760)$, $U(3070, 4990)$
d_j		$U(3, 7)$
CET_jtkn		$CET_{jt1n} = U(0.29, 0.37)$, $CET_{jt2n} = U(0.33, 0.46)$ $CET_{jt3n} = U(0.41, 0.49)$
CEP_{ijt}		$U(0.006, 0.012)$
CER_{ijt}		$U(0.006, 0.012)$
EM_{ijt}		$U(1, 10)$
GP_{ijt}		$U(1, 10)$
RE_{ijt}		$U(1, 10)$
PT_{ijt}		$U(1, 10)$
CAP_t		$U(170, 200)$
M_k		$3000, 6000, 14000$

Furthermore, the table includes information on the optimum carbon trade quantity in each period, which indicates how much carbon allowance the manufacturer should buy or sell. The results indicate that the optimal quantities for purchasing carbon allowance are 96.939, 64.684, 88.764, and 134.056 in periods 1, 2, 3, and 4, respectively. This information is critical for managers in making informed decisions on how much to order from each supplier while considering the defined criteria and the impact of carbon emissions. The values of objective functions 1, 2, and 3 shown in table 3.2 present the score of the selected suppliers based on non-green, quantitative green, and qualitative green criteria, respectively. It should be noted that the importance of an objective value cannot be solely determined by its magnitude. For example, in certain supply chain management scenarios, the second objective may hold greater significance even if its value appears to be the lowest among the three objectives. Therefore, we have normalized the objectives to ensure that their magnitude does not influence reader's perceptions of their relative importance. z_{Total}, represents the overall utility of the manufacturer by taking into account the three aforementioned objectives, and considering the optimal operational decisions made by the decision-makers. These objective functions, along with the total utility function, will be utilized to perform a sensitivity analysis in the subsequent five sections of this chapter.

To analyze the model and check the sensitivity of its objectives to parameters, we performed several analyses. These analyses were chosen based on their relevance to decision-making and their impact on the utility and objective function. Specifically, the parameters λ and ω were analyzed to provide decision-makers with insight into setting the importance level of infeasibility and optimality based on their preferences. Additionally, in view of the significance of carbon emission allowance, and the fact that the optimal solution to the problem is achieved based on the current cap level, an investigation into the effects of cap changes on the utility function and decision variables is warranted to prepare for forthcoming periods. Furthermore, as the allowance price may be uncertain, an examination of its potential impacts on decision-makers' operational decisions is required. The study also compares the applied carbon emission regulation with a penalty-based mechanism to determine which is

Table 3.2: Results of numerical example

Variables	Results
X_{ijt}	$X_{112} = 2,617$ $X_{141} = 1,825$ $X_{142} = 2,506$ $X_{152} = 1,627$ $X_{153} = 4,091$ $X_{211} = 2,558$ $X_{212} = 381$ $X_{214} = 3,121$ $X_{231} = 126$ $X_{243} = 810$ $X_{252} = 2,340$ $X_{253} = 1,908$ $X_{311} = 2,962$ $X_{312} = 2,756$ $X_{343} = 2,813$ $X_{412} = 2,861$ $X_{414} = 2,690$ $X_{421} = 3,382$
r_{it}	0
b_{it}	$b_{14} = 4,243$ $b_{34} = 3,056$ $b_{43} = 3,657$ $b_{44} = 3,937$
α_t	$\alpha_1 = 96.939$ $\alpha_2 = 64.684$ $\alpha_3 = 88.764$ $\alpha_4 = 134.056$
β_t	0
δ^{s+}_{ijt}	$\delta^{s+}_{111} = 178$ $\delta^{s+}_{112} = 159$ $\delta^{s+}_{124} = 202$ $\delta^{s+}_{153} = 147$ $\delta^{s+}_{214} = 123$ $\delta^{s+}_{222} = 101$ $\delta^{s+}_{243} = 106$ $\delta^{s+}_{251} = 92$ $\delta^{s+}_{312} = 97$ $\delta^{s+}_{313} = 113$ $\delta^{s+}_{341} = 126$ $\delta^{s+}_{354} = 145$ $\delta^{s+}_{432} = 103$ $\delta^{s+}_{441} = 143$ $\delta^{s+}_{443} = 174$ $\delta^{s+}_{454} = 105$
δ^{s-}_{ijt}	$\delta^{s-}_{111} = 184$ $\delta^{s-}_{114} = 212$ $\delta^{s-}_{123} = 150$ $\delta^{s-}_{142} = 164$ $\delta^{s-}_{221} = 94$ $\delta^{s-}_{232} = 104$ $\delta^{s-}_{253} = 109$ $\delta^{s-}_{254} = 127$ $\delta^{s-}_{314} = 153$ $\delta^{s-}_{321} = 131$ $\delta^{s-}_{322} = 99$ $\delta^{s-}_{343} = 117$ $\delta^{s-}_{411} = 148$ $\delta^{s-}_{412} = 105$ $\delta^{s-}_{443} = 183$ $\delta^{s-}_{444} = 107$
z_1	$640,743$
z_2	$43,627$
z_3	$1,133,472$
z_{Total}	1.699

more effective in mitigating emissions in this context. It is worth noting that a wide range is selected for the sensitivity analysis to capture extreme situations, and to elucidate trends more clearly, if they exist. The results will be discussed in the following sections.

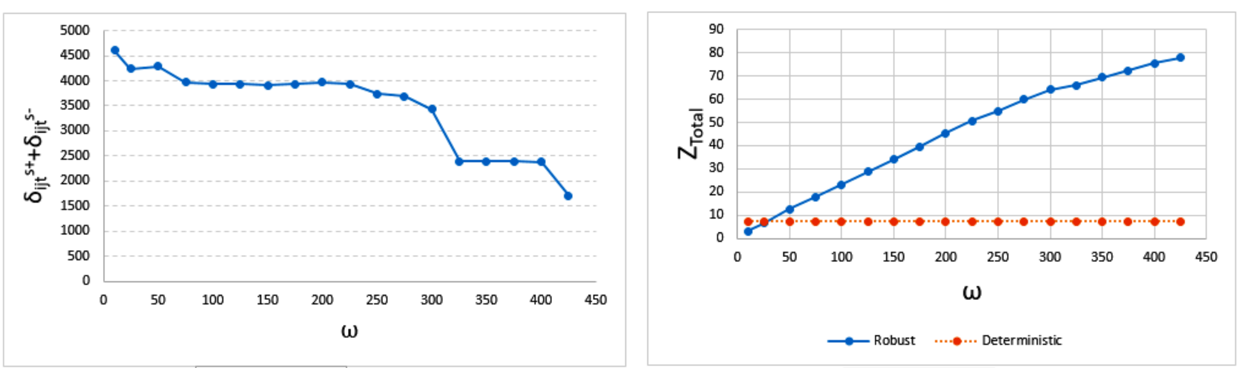
3.3.2 Sensitivity analysis on ω

Robust models rely on the parameter to balance optimality and feasibility, where infeasibility is defined as over- or under-fulfillment. Over-fulfillment increases warehousing costs, while under-fulfillment leads to lower customer satisfaction. Increasing the penalty for infeasible solutions reduces the risk of infeasibility but also decreases model optimality. Therefore, there is always a trade-off between model infeasibility and optimality. Understandably, it is not easy for decision-makers to determine the exact value of ω. Consequently, a suitable way to investigate this issue is to measure different values of the objectives and the amount of model infeasibility when distinct values for ω are considered. Afterward, an analysis of the results enables the decision-makers to manipulate the preferred value of ω.

By increasing the value of ω, due to the imposed penalty, the model tries to decrease the infeasibility. Therefore, as depicted in figure 3.2(a), when ω increases, infeasibility, which is defined as the amount of over-fulfillment and under-fulfillment (this is shown in the y axis), decreases. This shows that by increasing the importance of infeasibility, the model responds well to the changes and tries to decrease the chance of infeasibility. As it is depicted in section b of the mentioned figure this task proves to be costly. As shown in figure 3.2(b), by increasing the value of ω, firms will be penalized more for infeasibility; in this situation, first and second objective functions, which are formulated as robust equations, will deteriorate, and consequently, z_{Total} will become worse.

By scrutinizing these results, decision-makers can assign a precise value to ω based on the goals defined by the firm. For instance, if the objective values are more important, a lower weight for model robustness should be set. On the other hand, if customer satisfaction is more critical, more penalties must be in place for infeasibility (higher values for ω), which leads a worsening of the objective value.

Furthermore, in figure 3.2(b), a comparison is performed between the values of robust and deterministic models. The figure depicts that for a large domain of ω values ($\omega > 25$) the objective function of the deterministic model is better than the robust model. This occurs due to the penalty imposed on the robust model for deviation and infeasibility, i.e., there is more restriction on the objective function. Regardless, by handling uncertainty, robust models are able to achieve solutions that are closer to real-world scenarios. This enhances their applicability.



(a) (b)

Figure 3.2: Sensitivity analysis on ω

3.3.3 Sensitivity analysis on λ

Another crucial aspect includes the impact of the penalty on the deviation of scenarios from the expected value of the objective. Note that the model considers various scenarios, and one cannot be certain which one will happen. Hence, the solution method seeks to achieve a solution that is the closest possible value to the optimum of all scenarios. In this sense, λ is the weight parameter that refers to the importance of solution closeness to all possible scenarios. A larger value for λ implies a higher level of importance for deviation from the average; consequently, the objective value deteriorates due to the increased penalty. This is illustrated in figure 3.3, which demonstrates the impact of varying the importance of deviation of the first and second objectives from their optimal values, represented by λ_1 and λ_2 respectively; both of these objectives are subject to uncertainty. As displayed in figure 3.3(a), by increasing the value of λ_1, the deviation between the objective value in each scenario and the average objective value (y-axis) decreases. On the other hand, according to figure 3.3(b), the value of the first objective function (y-axis) increases. In other words, the first objective function value exacerbates as it is a minimization objective. Consequently, the total objective value deteriorates.

The same occurs for λ_2, but since in this chapter the values of the second objective are significantly smaller than the first objective, λ_2 has a negligible effect on the deviation of the objective function (see table 3.3). It does not mean that the second objective is not important, because the total objective is normalized using equation (3.43) to avoid overestimating the importance of objectives with large values. However, the deviation is fixed on a small amount (11.148) compared to the first objective (486,736), and adding the value of λ_2 does not have an impact on the deviation, although the second objective function worsens (figure 3.3(c)). Therefore, it is recommended to set the value of λ_2 to a small number to avoid deteriorating the second objective, which represents the amount of emission.

In other words, putting more penalty on the diversion of objective values in different scenarios reduces deviation, but worsens the objective values. This provides a road map for the decision-makers to choose values of λ_1 and λ_2 according to their goals.

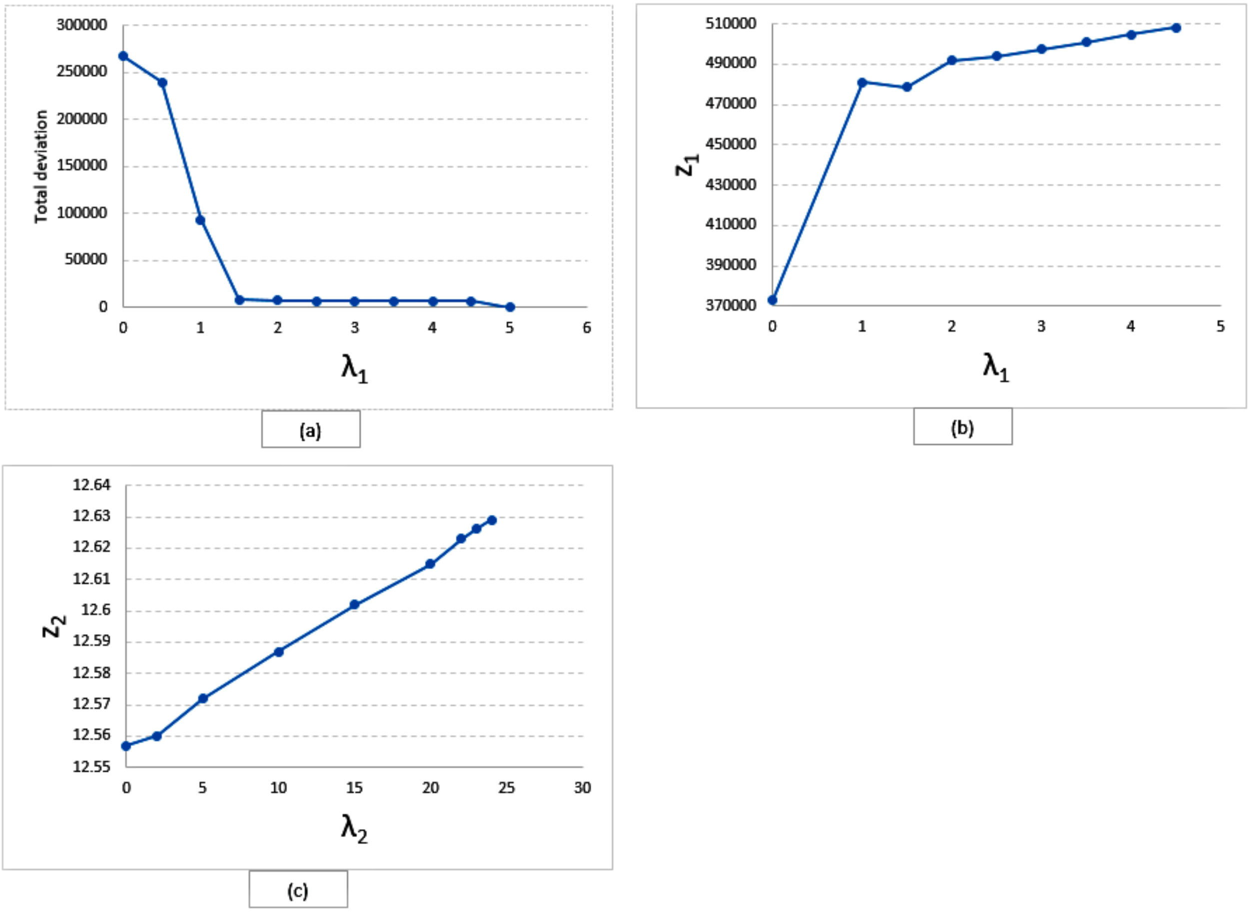


Figure 3.3: Sensitivity analysis on λ

Table 3.3: Effect of λ_2 on Deviation of Second Objective Value

λ_2	z_{Total}	z_1	z_2	z_3	δ	Deviation from Second Objective
0	12.557	486,736	43,182	1,170,111	4,283	11.148
2	12.56	486,736	43,193	1,170,111	4,283	11.148
5	12.572	486,736	43,237	1,170,111	4,283	11.148
10	12.587	486,736	43,291	1,170,111	4,283	11.148
15	12.602	486,736	43,346	1,170,111	4,283	11.148
22	12.623	486,736	43,422	1,170,111	4,283	11.148
23	12.626	486,736	43,433	1,170,111	4,283	11.148
24	12.629	486,736	43,444	1,170,111	4,283	11.148

3.3.4 Sensitivity analysis on CAP

As mentioned in introduction section, governments usually reduce the assigned cap in the cap-and-trade mechanism each year to decrease air pollution[1]. In certain cases, setting a high value for the emission cap by the government may lead to higher greenhouse gas emissions, rendering it an ineffective strategy for controlling emissions. Therefore, an analysis of cap reduction is required to predict the probable effects of this restriction and make the right actions toward the change.

Figure 3.4(a) shows a reverse relationship between objective values and carbon cap. It indicates that by decreasing the carbon allowance cap, the cost objective function ($\times 10^5$) increases, thus worsening the total objective value. This matter can be investigated from different perspectives. From the government's point of view, the total utility decreases by decreasing the cap, but it results in less carbon emission, which can be deemed as a positive result for the government due to health- and environmental-related costs. From the manufacturer's point of view, decreasing the cap is not an ideal option, because they are forced to purchase more allowance, or they will make less money for not being able to sell as much allowance, or they will have to upgrade to more expensive green technologies.

In addition, this restriction affects the amount of allowance to buy or sell. As displayed in figure 3.4(b), while the cap decreases, the amount of total carbon allowance the manufacturer needs to buy (sell), increases (decreases). This is the main driver of the increased cost.

Furthermore, according to figure 3.4(c), changing the cap does not have a discernible impact on the optimal amount of carbon emission (z_2); no trend can be verified in this figure. Based on the parameter values used in this study, reducing the cap does not have a substantial effect on the carbon emissions of manufacturers as they perceive the carbon allowance market as a potential source of profit. Essentially, manufacturers focus on their cost function and attempt to comply with the carbon emission regulations. These findings can assist the regulator in determining the appropriate carbon emission cap and minimizing

[1] As an example, see the cap-and-trade mechanism of Ontario, Canada (accessed March 13, 2020): `https://www.ontario.ca/page/cap-and-trade`.

the impact on manufacturers in terms of emission costs. The lack of a discernible trend in tableau c may be due to defining an inappropriate level of the cap, which only influences the first objective function and has no significant effect on the emission level. Further investigations are required in future research to explore this phenomenon.

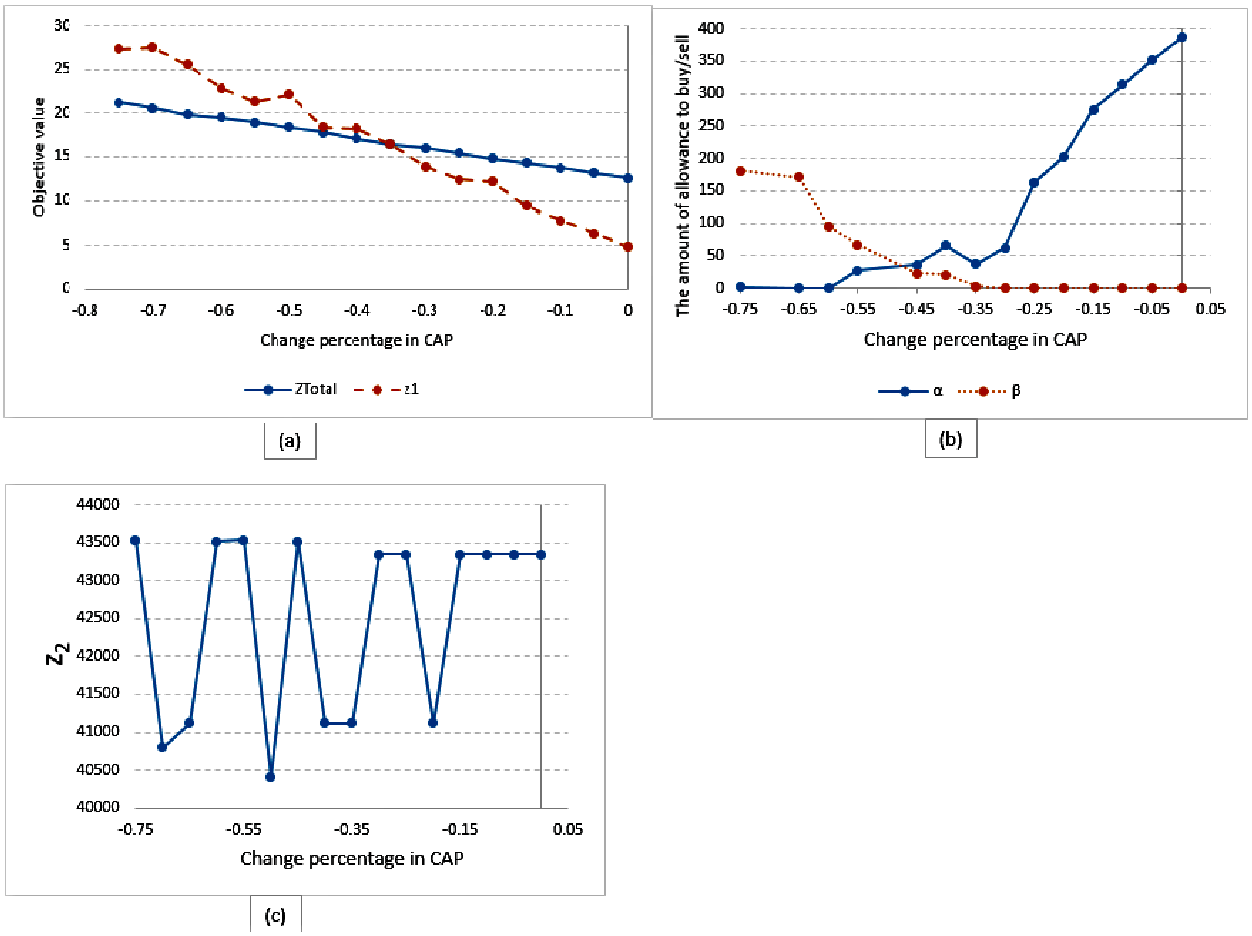


Figure 3.4: Sensitivity analysis on CAP† †Values on the x-axis show cap reduction. For example, -0.1 means cap is decreased by 10%.

†Values on the x-axis show cap reduction. For example, -0.1 means cap is decreased by 10%.

3.3.5 Sensitivity analysis on cap-and-trade market prices

Buying and selling prices are critical parameters in the cap-and-trade system with a direct impact on the amount of carbon allowance being traded by firms. Establishing a low price for emission allowances may lead to a rise in greenhouse gas emissions. Therefore, it is crucial to examine the behavior of manufacturers in response to varying allowance prices. According to table 3.4, by increasing the selling price, the values of the first and total objectives decrease. This can be traced to the growth in the optimal value of the amount of sold allowance.

As shown in table 3.4, when $BP > SP$ the manufacturers turn into brokerages. In this case, firms can buy allowance in the market and sell it at a higher price for a profit. Therefore, the optimal values of variables that control buying and selling allowances in the market will be positive in the same period. To avoid this situation, government can restrict the carbon market price such that BP is always less than SP in carbon trading markets or restrict the companies from buying and selling allowance at the same time.

Table 3.4: Results of sensitivity analysis on carbon market prices

Parameter	Price change (%)	z_{Total}	z_1	z_2	z_3	α	β
BP	-20	13.24	847,973	40,670	1,365,767	296	0
	-10	12.783	728,194	40,670	1,365,767	296	0
	-5	12.9	555,835	43,466	1,147,220	377	0
	0	12.602	486,736	43,346	1,170,111	387	0
	5	10.108	39,832	40,497	1,396,833	5,343	5,085
	10	-0.306	1,363	3,684	5,571,751	3.9×108	3.9×108
SP	-10	-0.307	1,363	3,681	5,568,767	9.9×107	9.9×107
	-5	-0.307	1,363	3,688	5,605,797	135,493	136,376
	0	12.602	486,736	43,346	1,170,111	387	0
	5	12.602	486,736	43,346	1,170,111	385	0
	10	12.602	486,736	43,346	1,170,111	387	0
	20	12.602	486,736	43,346	1,170,111	387	0

3.3.6 Cap-and-trade versus paying penalty to the government

We can also investigate the forcing of manufacturers to pay a penalty to the government for carbon emissions once a certain cap is exceeded. This policy does not allow formation of a carbon emission trading market. As shown in figures 3.5(a)-3.5(c), for the cap changes below 40 percent, the cost of pollution is less in cap-and-trade compared to the penalty-based mechanism. However, the amount of carbon released under the cap-and-trade policy is more than the emissions in the government penalty regulation. Therefore, in case there is a high priority on the carbon reduction objective, government must decrease the cap in the C&T mechanism to a value which is less than 40% of the original amount. Also, z_{Total} in cap-and-trade is lower in the given range. In other words, cap-and-trade performs better than the penalty-based system for manufacturers. Namely, cap-and-trade derives a better total utility; thus, it is preferred to the penalty-based approach.

If the cap is lowered more than 40 percent, no superiority exists between the two mechanisms. This occurs since the cap is decreased below the 40 percent mark, the amount of allowance the manufacturer needs to buy (or the amount of penalty the manufacturer should pay to the government) will be positive; and the quota to sell will gradually tend to zero. In other words, the manufacturer will not be able to generate profit by selling emission allowance. Hence, the gap between the cap-and-trade mechanism and the penalty system will vanish. The above result represents an important insight for the governments when assigning effective values for the cap according to the defined emission targets.

Based on the presented results, cap-and-trade culminates in better outcomes in terms of total model utility, although with higher carbon emission which is the result of assigning equal weights to economic selection criteria, green selection criteria, and carbon emission level. Obviously, assigning more weight to carbon emission levels translates to solutions with less carbon emission.

The cap-and-trade mechanism allocates a constant carbon emission permission to the entire market. Therefore, the manufacturers buy the allowance of the other players in the carbon trading market, while the total allowed carbon emission is a fixed value. As a result, if the firms choose not to sell their allowance in the market, or if they consume all of their own allowances, other firms will no longer be able to place orders.

Conversely, although there is a cap determined by the government in penalty-based systems, the total amount of carbon released can exceed the cap because manufacturers can emit as much carbon as they need by paying the penalty to the government. Therefore, the total carbon released by manufacturers may be more in this system. Note that this argument cannot be confirmed by the results of this chapter because we would require data from all of the manufacturers in the market to audit the total amount of carbon emission. Consequently, this topic is left for study in future research efforts.

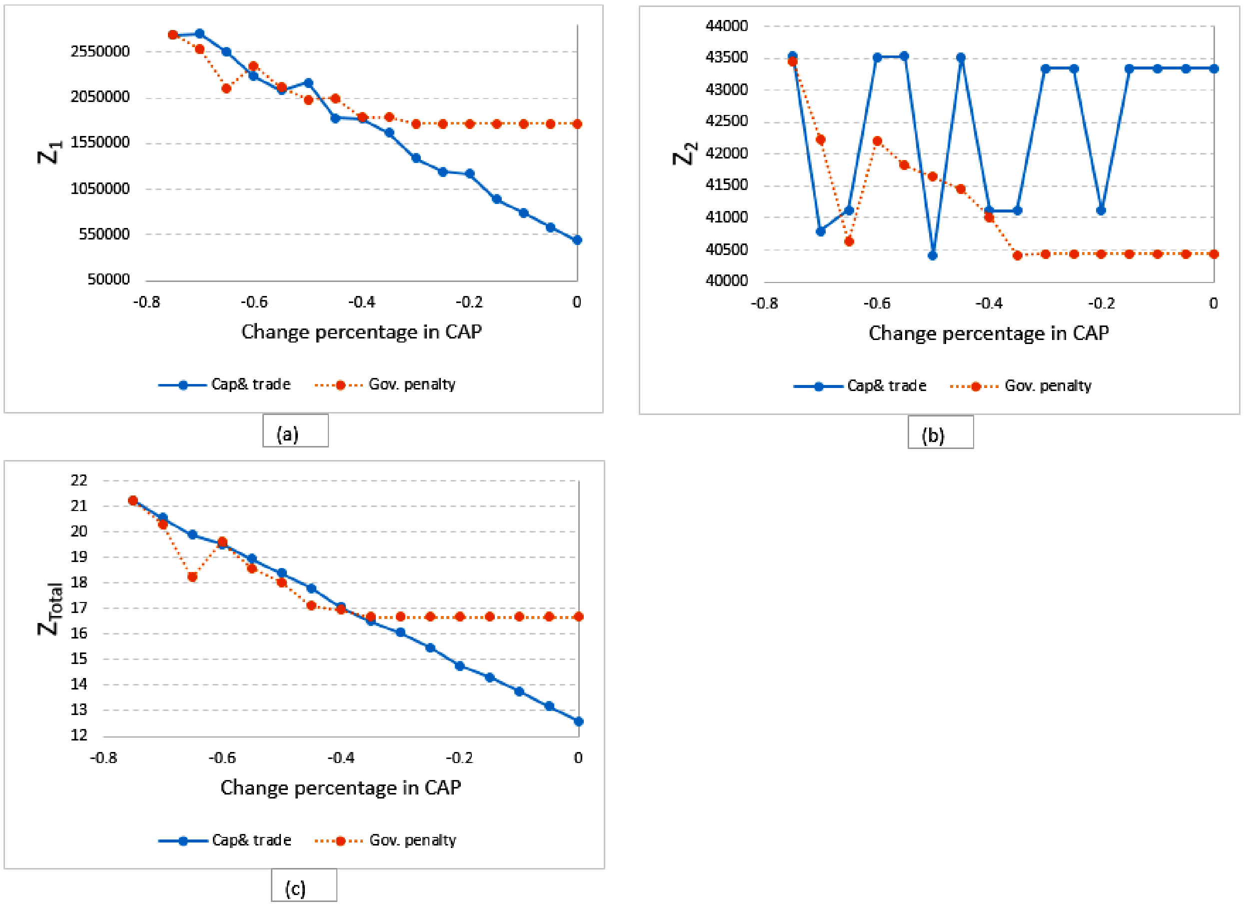


Figure 3.5: Cap-and-trade vs. penalty-based

3.4 Summary

To support decisions related to outsourcing in a green supply chain and to help with procuring the best materials from the best suppliers in an uncertain environment encompassing both green and traditional criteria, a multi-objective robust optimization model is generalized in this chapter. The cap-and-trade mechanism is considered to evaluate the role of this pollution control system. A numerical example is presented to analyze different aspects of the generalized model and the solution approach.

The optimal activity levels of a firm to achieve the maximum utility while meeting the environmental goals are obtained. The proposed model enables the decision makers to work with a more flexible decision support system due to the analysis done on ω and λ. The results show the effect of cap amount and the trade prices on the firm's objective. Therefore, manufacturers will be well-informed about selecting the best suppliers, the amount of orders to place with each of the selected suppliers, and trading in the allowance market to meet their objectives. Additionally, the superiority of cap-and-trade mechanism compared to penalty-based system regarding the total utility of supply chain from a micro-economic perspective is shown in this chapter.

4. A three-player game theory model for carbon cap-and-trade mechanism with stochastic parameters

The cap-and-trade (C&T) mechanism is a widely used tool by governments to reduce the emission of greenhouse gases. Naturally, businesses operating under a C&T scheme adopt strategies to ensure utility maximization and emission minimization. Effectiveness of such strategies depends on mutual interaction of external and internal factors. This chapter develops a stochastic game theoretical model consisting of a manufacturer, a third-party carbon emission verifier, and the government to study the necessary trade-offs to optimize the stated objectives. The proposed model is validated using a numerical example. Furthermore, it is demonstrated that the proposed model maximizes social welfare by finding the best penalty for bribery and violating the assigned carbon emission quota through advising a re-verification strategy to detect possible collusion between the manufacturer and verifier.

The major steps of the proposed model are depicted in Figure 4.1. The following subsections provide a detailed overview of the developed model.

4.1 Background

In the C&T mechanism, governments must assess manufacturers' carbon emissions to allocate the proper amount of allowance and penalize companies in case of excess emissions

Most of the context in this chapter have been published in Mirzaee, H., Samarghandi, H., Willoughby, K. (2022). A three-player game theory model for carbon cap-and-trade mechanism with stochastic parameters. Computers Industrial Engineering, 108285.

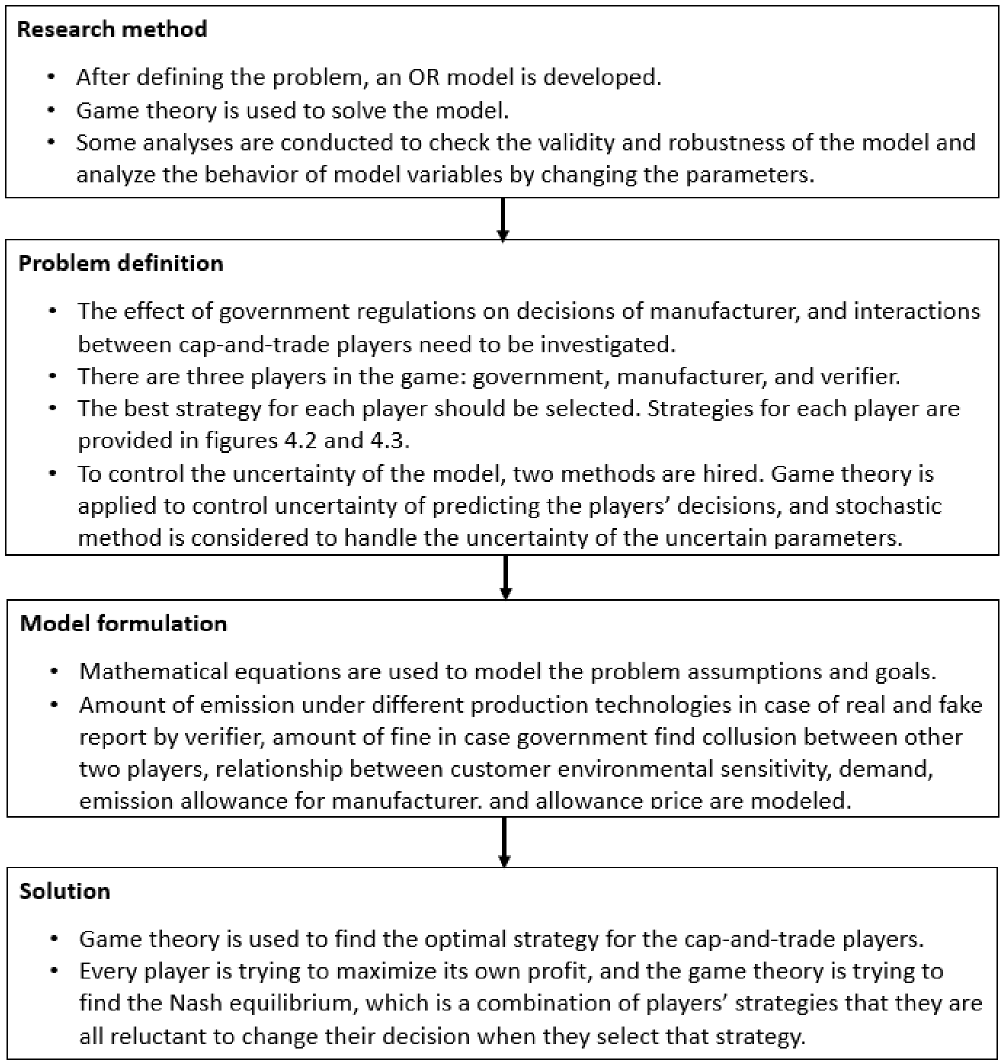


Figure 4.1: The proposed model's major steps

(Pan et al., 2019). Accordingly, a third-party verifier may be deployed to assess and verify the emission data reported to the government by the manufacturers (Bai et al., 2016). However, the manufacturer and verifier may collude to submit a fake report. In this situation, the manufacturer may propose a bribe to conceal the actual carbon emission amount, which the verifier may accept (Khalil and Lawarree, 1995). In other words, bribery is one of the manufacturer's strategies to hide the real GHG emission levels. Other options exist by which the manufacturers can reduce their emissions. One possible alternative involves upgrading to a green production technology. Although technology upgrade can be costly, it decreases the emissions (Xu et al., 2017). Hence, the extra emission allowance can be sold in the C&T market; furthermore, the manufacturer will not have to conceal its emissions to avoid governmental penalties. Another option for reducing carbon emission is subcontracting one or several parts of the manufacturing process to suppliers. Subcontracting lowers the emission for the manufacturer because another company takes the responsibility of a part of the manufacturing process and uses its quota for production. However, this option may prove costly as a result of profit sharing with another company. Therefore, in the present chapter, three possible ways that manufacturers can choose to decrease their reported emission level and make more utility are bribe, green technology upgrade, and outsourcing. On the other hand, there are two strategies for verifier when manufacturer proposes a bribe: accept or decline the bribe. Alternatively, the government may do a random re-verification to detect the probable collusion between the other two parties in the C&T mechanism. However, the re-verification process is costly due to the related human resource expenses; hence, the government needs to decide whether to intervene. In case re-verification confirms collusion between a manufacturer and verifier, the two parties will be charged a penalty. The penalty price ought to be greater than the utility gained from concealing the real emissions (Pan et al., 2019).

The players involved in the game include the manufacturer, verifier, and government. In this game, customer sensitivity to greenness, and supplier's delivery lead time are treated as stochastic parameters. Also, it is assumed that late delivery from the supplier leads to lost sale with its associated costs for the manufacturer. Another assumption of the model is that product demand is a function of its greenness, and impacts the carbon price in the C&T market. Another parameter that is affected by customer preferences is the government's "rigor index" toward carbon generating companies. This index refers to government pressure applied to manufacturers to adopt greener initiatives. In this chapter, the objective of the model is to minimize the overall game costs while maximizing social welfare. The social welfare measure used in this chapter is the product greenness, which can be achieved by minimizing the total emission levels. The strategies that each player can select are presented as follows.

- **Manufacturer:** alternatives to reduce the costs associated with carbon emission and allowance are: 1) outsourcing the products or producing them in-house; 2) upgrading to an environmentally-friendly production technology (there exist different levels of green technology with different costs), or remaining on the current technology and buying more emission allowance in the C&T market, if needed; 3) offering a bribe to the verifier to provide a fake report to government.

Compared to in-house production, outsourcing all or part of the manufacturing process to suppliers usually increases the final product costs. This is referred to as the cost of outsourcing and includes tangible and intangible items such as transportation cost, ordering cost, supplier's profits, loss of control over the manufacturing process, and so on (Arya et al., 2008). On the other hand, outsourcing decreases the cost of purchasing emission allowance or the penalty costs since the suppliers will be responsible for carbon emissions. Also, while upgrading the production technology is costly, it reduces the emission level. Therefore, the upgrade may prove worthwhile.

Furthermore, collusion between the manufacturer and verifier is probable and should be considered. If the firm proposes a bribe and the verifier accepts it, the firm will report lower emissions, and consequently, will benefit from lower allowance costs either by not having to purchase extra emission allowance in the C&T market or by selling unused allowance to other companies. However, if caught by the government, both the manufacturer and the verifier will be fined.

- **Verifier:** The third-party verifier's alternatives are accepting or rejecting the bribe, if one is offered. If the bribe is accepted and not detected by government re-verification, it will generate utility for the verifier. If collusion is confirmed through re-verification, fines will be levied; it will also generate future loss of goodwill for the verifier.

- **Government:** It needs to decide whether to seek re-verification. Re-verification is costly for the government due to the expenses of hiring the experts (Pan et al., 2019). If collusion is detected between the other two players, the government will receive a fine from the manufacturer and the verifier which can cover all or part of the re-verification costs. However, re-verification is not always successful; a probability is assigned to successful detection.

The general procedure and the strategies of each player in the game are described in figures 4.2 and 4.3. Figure 4.2 shows the players' decisions, which are considered as the game variables. Figure 4.3 describes these decisions and their outcomes by showing all the possible decisions for each player and how these decisions impact total game utility. For instance, if government decides on re-verification and detects bribe, it will fine the manufacturer and verifier for their collusion; but if there is no collusion between the manufacturer and verifier, government will have to bear the cost of re-verification. Also, the possible scenarios of the game are illustrated in figure 4.4. The game consists of 16 different scenarios, each requiring a utility function for the players. Note that some of the scenarios are impossible to happen, and hence, will not be analyzed. For instance, if the manufacturer decides the "no bribe" branch, the verifier cannot accept the bribe. Section 4.2.3 describes all the possible scenarios as well as their respective utilities.

The described model has real-world applications as the cap-and-trade system is enforced in some countries. For instance, China has implemented a C&T mechanism (Chen et al., 2021), in which the verification process of emission reports is performed by Shenzhen's cap-and-trade system (Pan et al., 2019). The European Union is another major jurisdiction which has implemented a C&T market (Yang et al., 2021).

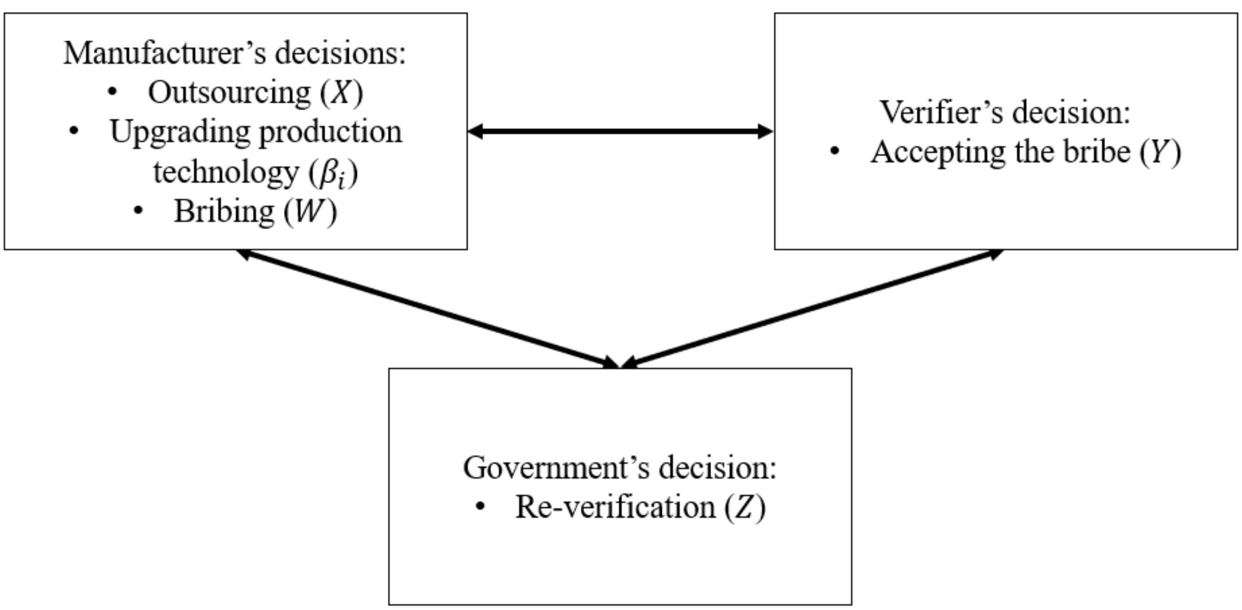


Figure 4.2: The game strategies†

†Note that the described game is non-cooperative and non-sequential.

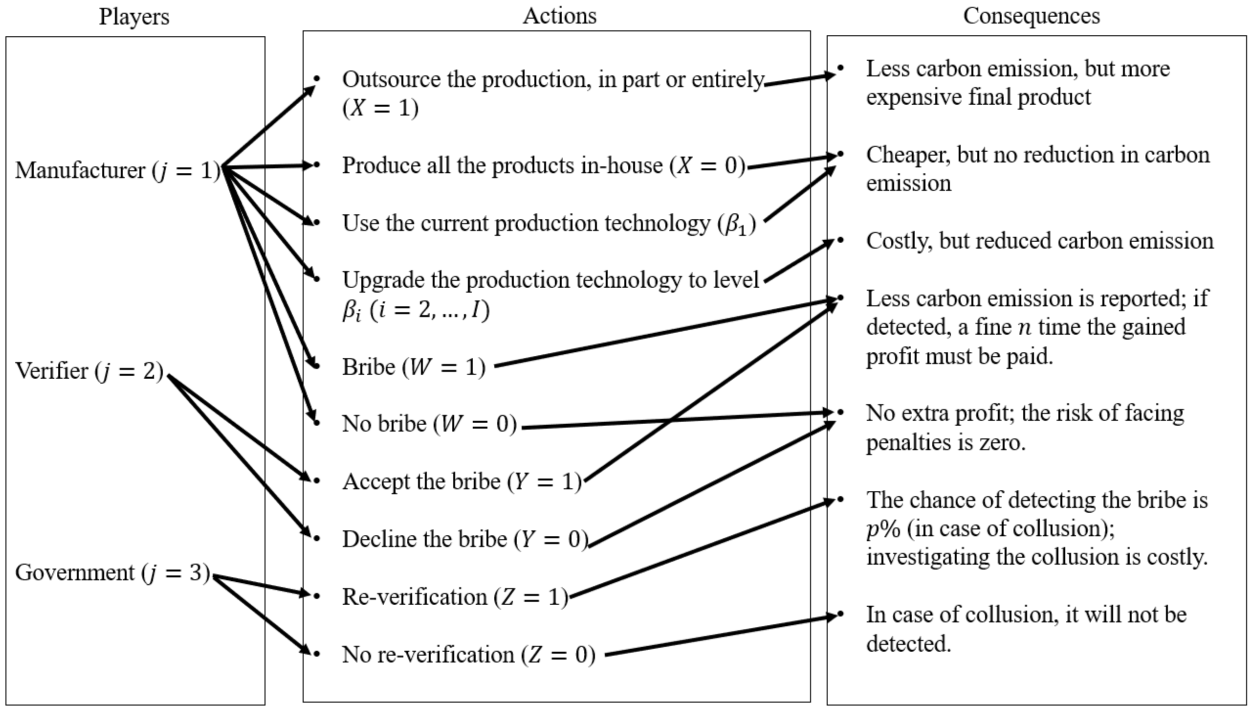


Figure 4.3: The game levels

4.2 Model Architecture

4.2.1 Notations

The following indices are deployed in this model:

$i \in \{1, 2, \ldots, I\}$: the type of technology used in production process; $i = 1$ means that the old technology is used.

$j \in \{1, 2, 3\}$: refers to the manufacturer, verifier, and government, respectively.

$k \in \{1, 2, \ldots, 16\}$: refers to the k^{th} strategy of the players.

The parameters include (all the costs are in thousands of dollars):

U_i: cost of upgrading the manufacturing system to the i^{th} technology level.

Lc: cost of lost sales.

Dd: the duration of time from ordering date to delivery due date for products purchased from the supplier (days).

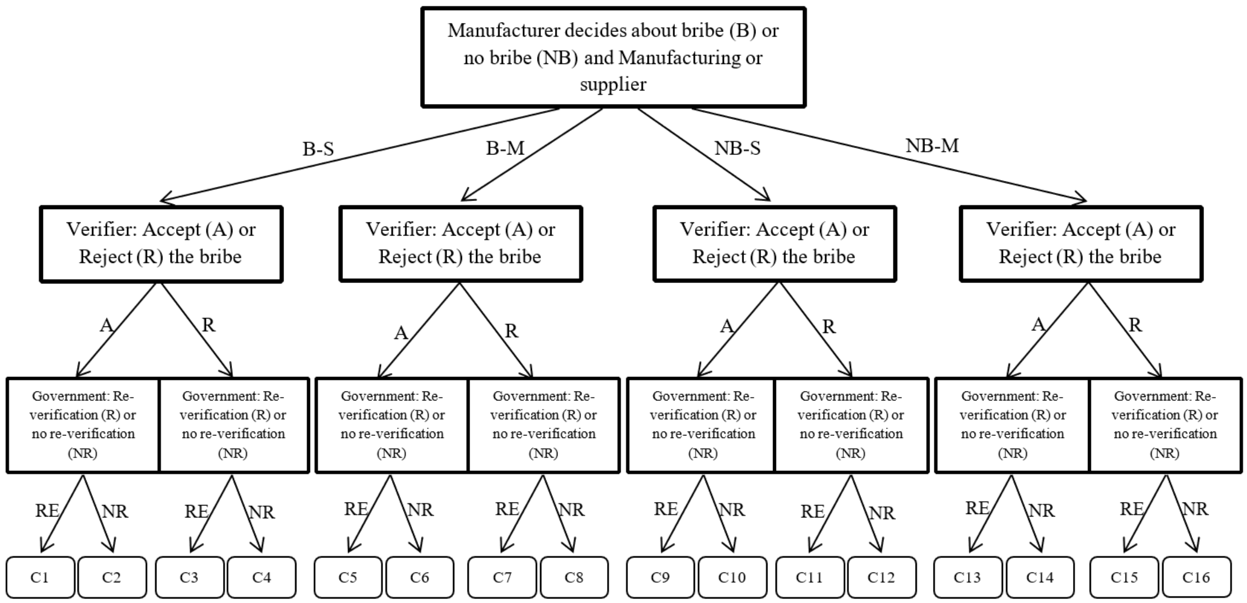


Figure 4.4: Strategies tree

Pr: probability of late order delivery.

μ_{LT}: mean of lead time (days).

σ^2_{LT}: variance of lead time.

μ_{h1_i}: customer sensitivity to the i^{th} technology used in the manufacturing process.

μ_{h2_i}: customer sensitivity to greenness level of the raw material used in the production process when upgrading technology to i^{th} technology level.

σ^2_h: variance of customer sensitivity to greenness.

Dc_i: difference in the final product cost when produced in-house using technology i as opposed to outsourcing.

AE_i: actual emission rate per product when using technology i (kg).

RE_i: reported emission rate per product when using technology i (kg).

a_i: actual emission amount when technology level i is used (kg).

r_i: reported emission amount when technology level i is used (kg).

C_i: concealed emission amount when using i^{th} technology level (kg).

f_{ij}: fine levied to player j for concealing real emissions under the condition that the manufacturer is using technology i.

n_j: penalty coefficient for player j.

b: amount of bribe manufacturer offers to verifier.

Rc: re-verification cost.

$\xi \in [0, 1]$: emission restriction index.

ρ: probability of successful re-verification.

D: demand.

$D1$: demand of customers who are not sensitive to product greenness.

$D2_i$: demand of customers who are sensitive to product greenness, when product is manufactured using technology i.

$x1$: the percentage of customers who are not sensitive to product greenness.

$x2$: the percentage of customers who are sensitive to product greenness.

q: emission quota allocated to the manufacturer (kg).

P: price of emission allowance the C&T trading market.

The following variables are features in the model:

X: a continuous variable showing the decision of the manufacturer to outsource X percent of its production; $X = 1$ means that all the products are procured by the supplier.

W: a binary variable presenting the strategy of the manufacturer for bribery; $W = 1$ means the manufacturer proposes a bribe to the verifier.

β_i: a binary variable showing the level of technology upgrade the manufacturer chooses; $\beta_1 = 1$ means the manufacturer will not upgrade its current technology. Note that $\sum_i \beta_i =$

1.

Y: a binary variable to demonstrate the strategy of the verifier; $Y = 1$ means the verifier accepts the bribe.

Z: a binary variable which highlights the strategy of the government; $Z = 1$ means the government will re-verify.

4.2.2 Mathematical Equations

This section presents the relationships among the parameters.

$$a_i = AE_i D \qquad \forall i \tag{4.1}$$

$$r_i = RE_i D \qquad \forall i \tag{4.2}$$

Equations (4.1) and (4.2) show the actual and reported emission amount, respectively.

$$C_i = a_i - r_i = D\left(AE_i - RE_i\right) \qquad \forall i \tag{4.3}$$

Equation (4.3) indicates the amount of concealed emission in case of collusion between the manufacturer and verifier. Accordingly, equation (4.4) calculates the amount of fine the government charges the players when it detects collusion.

$$f_{ij} = n_j P C_i \qquad \forall i, j \tag{4.4}$$

The government can force carbon-generating companies to reduce their emission by restricting their carbon emission allowance. The overall amount of quota distributed to all companies in the C&T market can be determined by a rigor index. This index represents the pressure the government puts on manufacturers for producing greener products. Equation (4.5) calculates the quota the manufacturer receives according to the emission restriction index.

$$q = \xi D \tag{4.5}$$

As the assigned quota of the manufacturer increases, the carbon allowance price in the C&T decreases. It is assumed that, as shown in equation (5.6), the relationship between allowance price and quota is non-linear.

$$P = Ke^{1/q} = Ke^{\frac{1}{\xi D}}, \tag{4.6}$$

in which K is a constant. Following the work of Nouira et al. (2014) it is assumed that the customers are either "non-sensitive" or "sensitive" to product greenness. If the percentage of non-sensitive and sensitive customers is represented by $x1$ and $x2$, and their demand is denoted by $D1$ and $D2$, respectively, the following equations ensue.

$$D_{total} = D1 + \sum_i \beta_i D2_i \qquad \forall i \tag{4.7}$$

$$D1 = x1.D \tag{4.8}$$

According to Letmathe and Balakrishnan (2005), there is a linear relationship between customers' demand and their sensitivity to greenness. If h_i represents the sensitivity index, equation (4.9) is inferred.

$$D2_i = x2.h_i D \qquad \forall i \tag{4.9}$$

To measure customer sensitivity to product greenness, h_i, two factors are considered: 1) technology used in the manufacturing process ($0 \leq \mu_{h1_i} \leq 1$); and 2) greenness level of the material used in production process ($0 \leq \mu_{h2_i} \leq 1$). Please be advised that the level of sensitivity to greenness can be measured on a spectrum, as opposed to being considered a binary variable. It is assumed that these parameters are equally as important and are both normally distributed. Therefore:

$$h_i = 0.5(\mu_{h1_i} + \mu_{h2_i}) \qquad \forall i \tag{4.10}$$

Furthermore, assume that the lead time of the products purchased from a supplier is normally distributed. Consequently, equations (4.11) and (4.12) calculate the probability of late order delivery, as well as number of lost sales.

$$Pr \leq p\left(z \leq \frac{\mu_{LT} - Dd}{\sigma_{LT}^2}\right) \tag{4.11}$$

$$L = Pr.D \tag{4.12}$$

4.2.3 Game theory model

Table 4.1 shows the utility of the players of the game under each scenario.

Table 4.1: The payoff table

		Re-verification		No re-verification	
		Accept	Reject	Accept	Reject
Bribe	Supplier	C1	C3	C2	C4
	Manufacturer	C5	C7	C6	C8
No bribe	Supplier	C9	C11	C10	C12
	Manufacturer	C13	C15	C14	C16

In this table, the first column displays manufacturer's strategies and the first row shows the combination of verifier and government strategies. Accordingly, table 4.1 determines the payoff values for each combination of all three players' strategies in a two-dimensional table. There are some scenarios that are infeasible to obtain including C9, C10, C13, and C14. Equations below describe players' utilities in each scenario. For instance $C1_M$, $C1_V$, and $C1_G$ represent manufacturer's, verifier's, and government's utility in case 1, respectively.

Manufacturer:

$$\begin{aligned} C1_M = C2_M = C3_M = C4_M = C9_M = C10_M = C11_M = C12_M \\ = \sum_i \left(AE_i.D.P - Dc_i.D\right)\beta_i - Pr.D.Lc \end{aligned} \tag{4.13}$$

$$\begin{aligned} C5_M = \sum_i \left(AE_1 - AE_i\right) D.P.\beta_i - b - \sum_i \rho.f_{i1}.\beta_i - \sum_{i=2}^{I} \beta_i.U_i \\ +(1-\rho)\sum_i \left(AE_i - RE_i\right) D.P.\beta_i \end{aligned} \tag{4.14}$$

$$C6_M = \sum_i (AE_1 - AE_i) D.P.\beta_i - b - \sum_{i=2}^{I} \beta_i.U_i + \sum_i (AE_i - RE_i) D.P.\beta_i \tag{4.15}$$

$$\begin{aligned} C7_M = C8_M = C13_M = C14_M = C15_M = C16_M = \\ \sum_i (AE_1 - AE_i) D.P.\beta_i - \sum_{i=2}^{I} \beta_i.U_i \end{aligned} \tag{4.16}$$

Verifier:

$$C5_V = b - \sum_i \beta_i.\rho.f_{i2} \tag{4.17}$$

$$C6_V = b \tag{4.18}$$

The verifier's utility in all other cases is zero.

Government:

$$C1_G = C3_G = C7_G = C9_G = C11_G = C13_G = C15_G = -Rc \tag{4.19}$$

$$C5_G = -Rc + \rho \sum_i \beta_i (f_{i1} + f_{i2}) - (1-\rho)\left(\sum_i (AE_i - RE_i) D.P.\beta_i\right) \tag{4.20}$$

$$C6_G = \sum_i (AE_i - RE_i) D.P.\beta_i \tag{4.21}$$

The government's utility in all other cases is zero.

The players' goal is to maximize their utility, which is not always attainable due to the conflict between their actions. As such, the second best choice is finding a cell in table 4.1, which optimizes the entire game. In the described game, the optimal point is one from which no player desires to move. In other words, all the other strategies generate less or equal amount of utility for the players. This point is called the Nash equilibrium.

4.2.4 Solution Procedure

After developing the game theory model in section 4.2.3, it is possible to investigate the existence of an optimal solution. In other words, one is tasked to find the best strategy for players considering the conflicts between their utilities. Since the problem is a non-cooperative game, the Nash equilibrium is applied to find the optimal solution, i.e., the cell in the payoff table where the players will not acquire more utility if they select other strategies. Hence, in Nash equilibrium players are not willing to change their chosen strategy.

Assume that S_j^k is the kth strategy of player j, S is the combination of players' strategies ($S = [S_1^k, S_2^k, \ldots, S_J^K]$), and S_{-j} is the combination of the strategies of all players except player j ($S_{-j} = [S_1^k, \ldots, S_{j-1}^k, S_{j+1}^k, \ldots, S_J^k]$). Also, assume that $U_j(S)$ is the utility of player j from its chosen strategy. Also, assume that $U_j(S_j^k, S_{-j})$ is the utility of player j when all other players keep their strategy and player j changes its decision to strategy k. Hence, the following equation can be used to find the Nash equilibrium.

$$U_j(S^*) \geq U_j(S_j^k, S_{-j}) \qquad \forall j \tag{4.22}$$

According to equation (4.22), the optimal strategy for player j is a strategy where, if player j changes its strategy while all other players do not change their decisions, player j's utility function will not improve. Thus, the objective of this model can be written as follows.

$$\text{Max } U_j(S_j^k, S_{-j}) \tag{4.23}$$

To solve this problem, a full enumeration algorithm is performed. In other words, the total utility of players corresponding to the set of all possible combinations of strategies is calculated. The Nash equilibrium is the strategy combination that generates the highest utility.

4.3 Results and Discussion

To validate the proposed game theory model for the C&T mechanism, a numerical experiment is performed in this section, using Python programming language. The experiments were conducted based on the data presented in table 4.2. Since the presented problem in this chapter is an extended version of the problem proposed by Pan et al. (2019), the data set in table 4.2 is simulated according to Shenzhen's cap-and-trade system presented in their paper. Specifically:

- We consider four levels for production technology greenness. Hence, there are three values for the cost of upgrading, plus a zero cost for deciding to not upgrade the current technology.

- Customer environmental sensitivity, a stochastic parameter, has four values for each level of green technology.

  The first three values for μ_{h1_i} and μ_{h2_i} are less than one, meaning that when the production technology is not green, demand for the product declines. The ascending order of μ_{h1_i} and μ_{h2_i} values in this matrix indicates that customers are more willing to buy green products.

- Following the assumption of Pan et al. (2019), Dc_i increases when the employed technology is greener. In other words, in-house production is more expensive after upgrading the technology, which results in a higher difference between in-house and outsourcing production costs.

- The actual emission rate (AE_i) is greater than the reported emission rate (RE_i) in case a bribe is offered.

- n_j values demonstrate that when the government detects collusion, the manufacturer and verifier are fined twice and three times more than their realized utility from collusion.

Table 4.2: Data set

Parameters	Values	Parameters	Values
U_i	[0,80,100,140]	Lc	0.05
Dd	4	μ_{LT}	3.75
σ^2_{LT}	0.05	$x1$	0.6
σ^2_h	0.25	$x2$	0.4
μ_{h1_i}	[0.9, 0.94, 0.99, 1.05]	K	1.2
μ_{h2_i}	[0.85, 0.92, 0.97, 1.04]	Cs	1.1
R	0.5	Dc_i	[1.2, 1.3, 1.45, 1.65]
b	28	AE_i	[4, 3.3, 2.5, 1.5]
Rc	25	RE_i	[3.5, 2.7, 2.1, 1.1]
ξ	0.75	n_j	[2, 3, 0]
ρ	0.8	D	10000

The results of the experiment are shown in table 4.3. According to the results, although there are multiple solutions with the same utility for the problem, it can be inferred that the best strategy for the manufacturer is outsourcing ($X = 1$), which negates the need for proposing a bribe ($W = 0$). When the production is outsourced, the manufacturer will not generate any emission. Hence, a bribe is not offered and the verifier does not have any decisions to make, which is translated as rejecting the bribe ($Y = 0$). Furthermore, the best strategy for the government is no re-verification ($Z = 0$).

All the presented solutions in this section were equal and resulted in the total utility $U = 34,143.81$ for the players. This amount of utility is maximized when $\beta_1 = 1$. That is, the manufacturer is recommended to withhold upgrading its technology since the supplier generates the products. Table 4.3 also shows the utility of the players for the optimal strategy. Notice that, for this special example, the manufacturer's utility is $31,143$, and the other two players' gain is 0 for they do not take an action.

Table 4.3 demonstrates that demand decreases as the customer sensitivity to product greenness increases. Furthermore, as the government strives to lower the carbon emissions, the allowance granted to the manufacturer is less than the required allowance for satisfying the demand, which leads to technology upgrade and using more environmentally friendly material. Ultimately, lowering the quota impacts the price of carbon in the C&T market.

The presented model and solution approach identify the best strategies for the C&T parties and its respective total utility. The optimal strategy for each player can only be detected once the possible decisions of the other players are taken into consideration. Also, the impact of the customer sensitivity on market demand is contemplated. Naturally, the presented model confirms that increasing the market's sensitivity to greenness elevates the demand for green products. In other words, the players must realize market's sensitivity to greenness to maximize their utility; they must also remain under the emission quota determined by the government. Therefore, by leading the C&T players to their best strategies and maximizing their utility while adhering to the emission quota, the presented model results in a more powerful C&T enforcement mechanism while promoting production of more environmentally friendly products. The following sub-sections are devoted to sensitivity analyses to illustrate the impact of uncertainty in parameter values on game utility. Although the employed stochastic optimization method controls parameter uncertainty, deviation between predicted values and the real data is still possible. Hence, h_i and LT, the uncertain parameters in this study, are chosen for sensitivity analysis. Accordingly, decision makers observe the trend in the objective function, and therefore, can devise alternative scenarios in case real data does not follow the predictions. Furthermore, analyzing the emission restriction index, ξ, and re-verification policy provides insight for the government in case intervention in the market is required.

Table 4.3: Results of the numerical experiment

Variables	**Values**
P	1.200168
D_{total}	9500
q	7125
f_{1j}	[11401.6, 17102.4, 0]
f_{2j}	[13681.92, 20522.88, 0]
f_{3j}	[9121.28, 13681.92, 0]
f_{4j}	[9121.28, 13681.92, 0]
Total game utility when β_1=1	34143.81
Utility of players 1, 2, and 3 when β_1=1	[34143.81, 0, 0]
Total game utility when β_2=1	25796.44
Utility of players 1, 2, and 3 when β_2=1	[25.796.44, 0, 0]
Total game utility when β_3=1	17758.4
Utility of players 1, 2, and 3 when β_3=1	[17758.4, 0, 0]
Total game utility when β_4=1	30404.00
Utility of players 1, 2, and 3 when β_4=1	[30404.00, 0, 0]
Optimal solution with reference to table 4.1; all the following result in the same total utility	C2, or C4, or C10, or C12

4.3.1 Sensitivity Analysis on h_i

To analyze the generated model and solution method and check for the robustness of the results, several sensitivity analyses were conducted. First, it was hypothesized that manufacturers may use advertisements to impact customer discretion toward product greenness. For instance, a firm which has upgraded its technology to a greener one may aggressively advertise to inform customers about the upgrade and the importance of purchasing environmentally friendly products. This increases sensitivity to product greenness and elevates the sales of the green products. Hence, the effect perturbing h_i was analyzed. Since h_i is a stochastic parameter, a 95% confidence interval, as per equation (4.24), was used for the analysis.

$$\hat{h_i} \in \left[h_i - \frac{z_{0.05/2} * \sigma_h}{\sqrt{n}}, h_i + \frac{z_{0.05/2} * \sigma_h}{\sqrt{n}}\right] = [h_i - 0.25, h_i + 0.25] \tag{4.24}$$

In this equation, it is assumed that $n = 16$ customers were interviewed and $\sigma_h = 0.51$. Results are displayed in table 4.4.

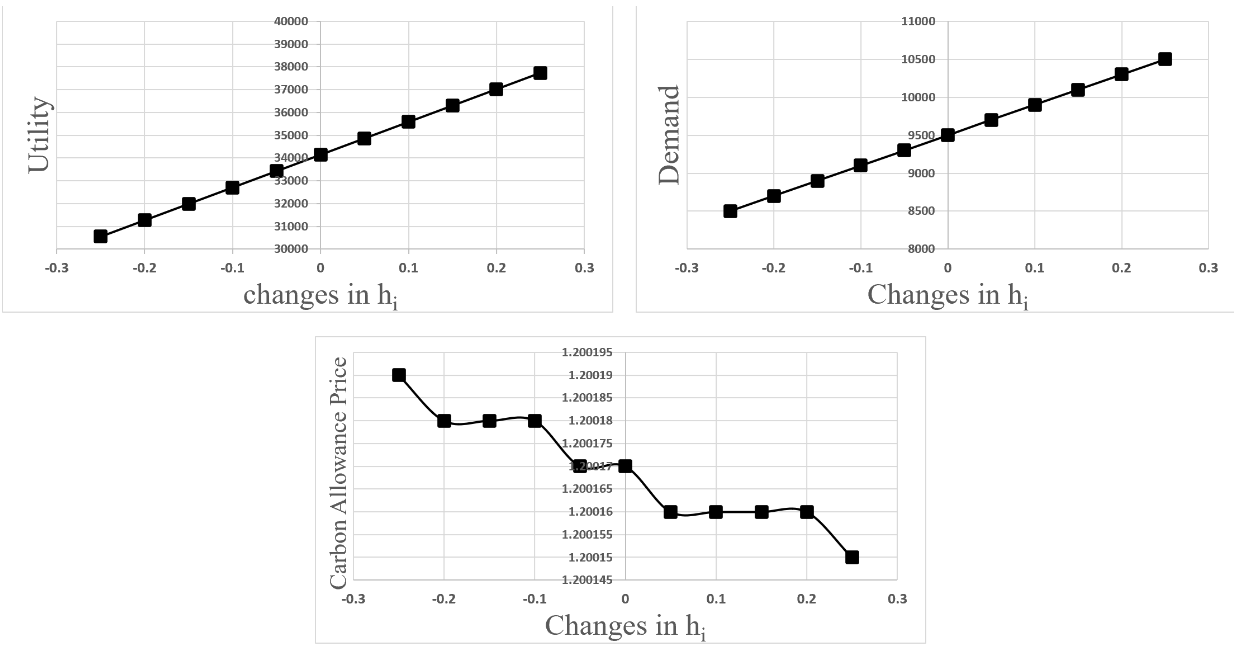


Figure 4.5: Sensitivity analysis on h_i

As shown in table 4.4 and figure 4.5, changes in h_i have a positive correlation with product demand and manufacturer's utility, but they are negatively correlated with carbon allowance price. Since the total utility is positively correlated with h_i, the manufacturer can increase the utility by satisfying the customers who are sensitive to product greenness.

Note that for the studied data set, when h_i increases, demand declines, because it is more profitable to maintain the current production technology. Thus, increasing greenness sensitivity changes demand, and consequently, impacts emission quota and emission allowance

Table 4.4: Sensitivity analysis on h_i

Changes in h_i	Utility	Optimal solution	Demand	Carbon price (P)
-0.25	30550.395	No change	8500	1.20019
-0.2	31269.08	No change	8700	1.20018
-0.15	31987.76	No change	8900	1.20018
-0.1	32706.44	No change	9100	1.20018
-0.05	33425.12	No change	9300	1.20017
0	**34143.81**	**No change**	**9500**	**1.20017**
0.05	34862.49	No change	9700	1.20016
0.1	35581.17	No change	9900	1.20016
0.15	36299.85	No change	10100	1.20016
0.2	37018.53	No change	10300	1.20016
0.25	37737.22	No change	10500	1.20015

The row specified in bold font corresponds with the solution presented in table 4.3

price. When h_i changes are extreme, the optimal solution of the game may change. Note that although the game utility function changes as the value of h_i is altered, the optimal solution remains the same in the interval specified in equation (4.17). Therefore, the optimal solution presented in table 4.3 is robust within the mentioned 95% confidence level.

4.3.2 Sensitivity Analysis on LT

A similar analysis was performed on the supplier's lead time (LT), with a 95% confidence interval for LT presented in equation (4.25).

$$\hat{LT} \in \left[\mu_{LT} - \frac{z_{0.05/2} * \sigma_{LT}}{\sqrt{n}}, \mu_{LT} + \frac{z_{0.05/2} * \sigma_{LT}}{\sqrt{n}}\right] = [3.64, 3.86] \tag{4.25}$$

Table 4.5 and figure 4.6 demonstrate the result of sensitivity analysis on LT. Once again, the optimal solution presented in table 4.3 was proven to be reliable within the created 95% confidence interval for LT. Also, as table 4.5 highlights, although the probability of lost sales due to elongated lead times changed from 5.37% to 26.56%, the effect on utility was marginal. Regardless, effective management of lead times is crucial to prevent shortage and satisfy customers, because as the lost sales probability increases, customer loyalty may decrease, which negatively affects the company's bottom line in the long term. In the proposed model, the manufacturer may enhance the game utility and customer satisfaction by selecting the best suppliers considering the lead time and the rest of the game objectives. Supplier selection, investigating suppliers' impact on the cap-and-trade players' relationships, and how supplier selection increases customer loyalty is an interesting topic for future studies.

Table 4.5: Sensitivity analysis on LT

LT	Probability (%)	Utility
3.64	5.37	34180.89
3.66	6.42	34175.91
3.68	7.62	34170.2
3.7	8.99	34163.72
3.72	10.52	34156.41
3.74	12.25	34148.23
3.75	**13.18**	**34143.81**
3.76	14.16	34139.16
3.78	16.26	34129.17
3.8	18.55	34118.27
3.82	21.04	34106.45
3.84	23.71	34093.76
3.86	26.56	34080.23

The row specified in bold font corresponds with the solution presented in table 4.3

Figure 4.7 reveals that h_i fluctuations have more prominent impacts on the manufacturer utility compared to lead time oscillations. Thus, the manufacturer must control h_i variations more diligently.

4.3.3 The government's impact on the cap-and-trade market

From another perspective, the government is interested in reducing the cost of managing the C&T market and decreasing the overall carbon emission rate of the industries. Analyzing the proposed model specifies guidelines regarding these objectives.

One important factor for the government to determine in this game is n_j, i.e., the penalty

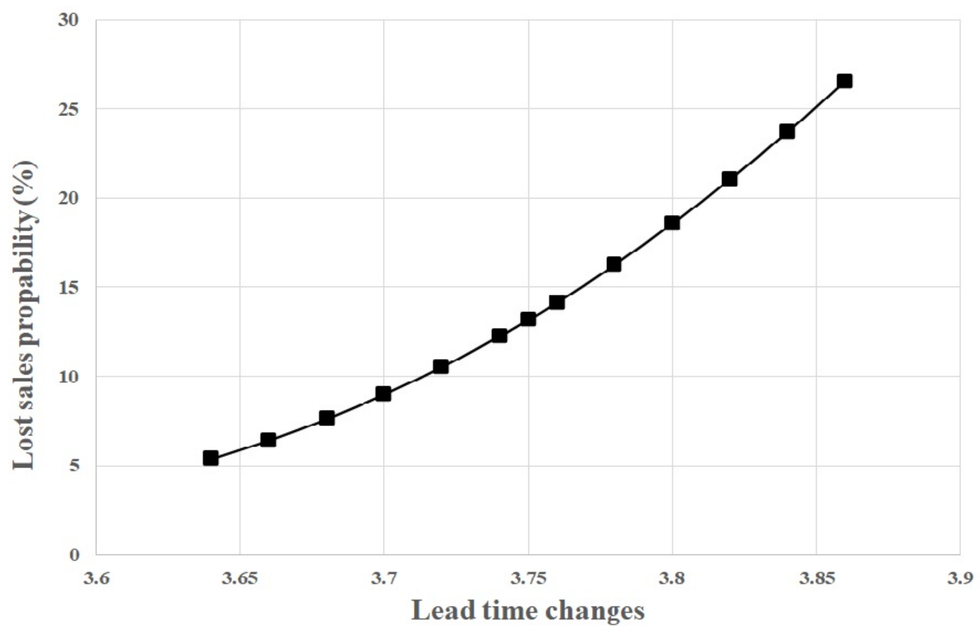


Figure 4.6: Sensitivity analysis on lead time

index on other players in case of a collusion. Although perturbing n_j based on the defined scenarios of table 4.2 has an impact on the total utility, it does not alter the optimal solution. This is due to the fact that the manufacturer outsourced production to suppliers. Consequently, the manufacturer was not seeking to hide its emissions or collusion with the verifier. Knowing this, the government can decrease the frequency of costly re-verifications to detect collusion.

Another lever the government can use to influence the game is ξ or emission restriction index. The emission quota assigned to the manufacturer is determined by the value of ξ. Generally, this value is determined based on customer preference for environmentally friendly products (Li et al., 2018b). In other words, as the customers become more sensitive to environmental issues, the value of ξ is decreased to restrict carbon emission.

As shown in table 4.6 and figure 4.8, ξ and carbon allowance price are negatively correlated. This is an expected result since, according to equation (5.6), decreasing the value of ξ causes the price of carbon allowance in the market to rise exponentially. Higher carbon allowance prices lead to growing total utility for the manufacturer; due to outsourcing, the manufacturer can sell its unused emission quota in the market at higher prices. Figure 4.8

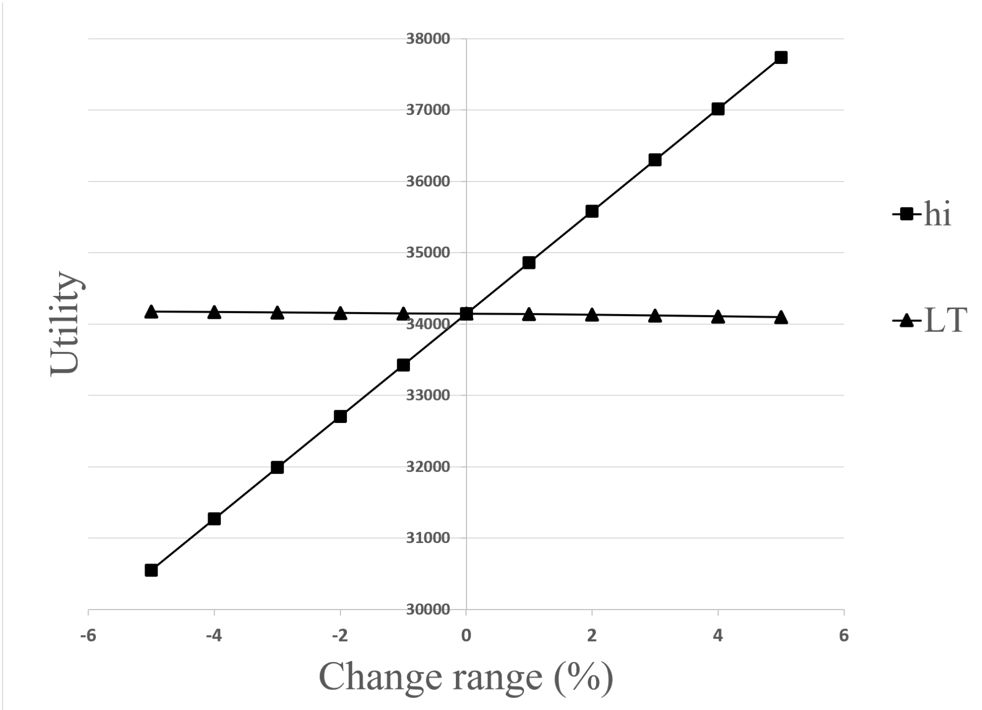


Figure 4.7: Comparing the impact of h_i and lead time perturbations on the manufacturer's utility

depicts that carbon price change curve is almost flat until the value of ξ is decreased to 0.7. In other words, government can influence the manufacturer's decision on technology upgrading in a way that carbon price is not heavily disturbed.

From the game theoretical standpoint, it can be inferred that the government's decision regarding the carbon cap touches all the players, because restricting carbon emission results in less carbon allowance and pollution, yet elevates the allowance price and reduces the game's utility. Hence, the government ought to perform a trade-off between taking customer preferences into account and game utility, i.e., the players' utility.

Table 4.6: Sensitivity analysis on ξ

ξ	Utility	Carbon price (P)
0.05	34233.51	1.202529
0.1	34185.43	1.201264
0.15	34169.42	1.200842
0.2	34161.41	1.200632
0.25	34156.61	1.200505
0.3	34153.41	1.200421
0.35	34151.12	1.200361
0.4	34149.42	1.200316
0.45	34148.07	1.200281
0.5	34147	1.200253
0.55	34146.13	1.20023
0.6	34145.41	1.200211
0.65	34144.79	1.200194
0.7	34144.26	1.20018
0.75	**34143.81**	**1.200168**
0.8	34143.41	1.200158
0.85	34143.05	1.200149
0.9	34142.74	1.20014
0.95	34142.46	1.200133
1	34142.21	1.200126

The row specified in bold font corresponds with the solution presented in table 4.3

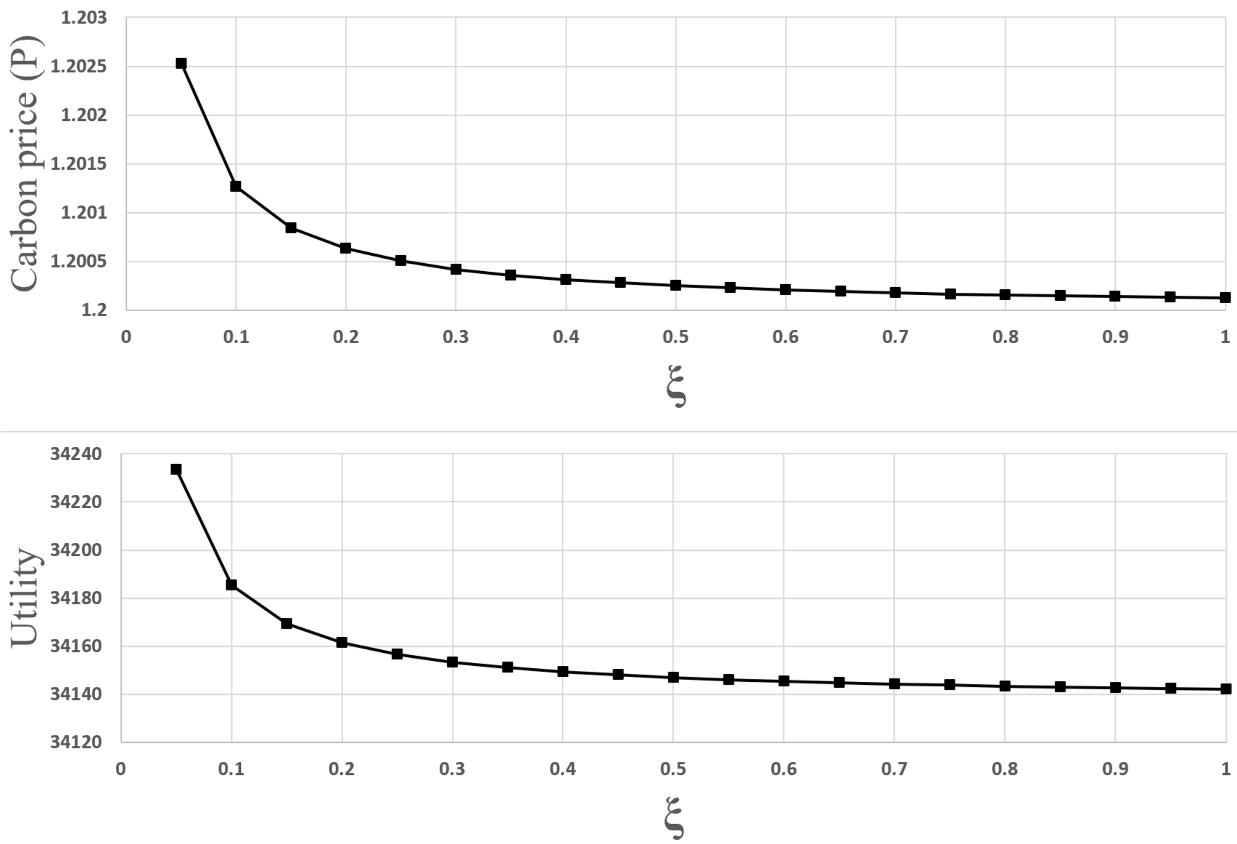


Figure 4.8: Analysis of the impact of the government's intervention/emission restriction index on cap-and-trade market

4.3.4 Re-verification policy

In this study, the re-verification strategy is a decision variable; for the presented data set, the optimal re-verification rate by government is 0%, as depicted in the results table. It is important for government to know the behavior of other cap-and-trade game players before deciding on what re-verification rate should be considered for the market. Therefore, sensitivity analysis is performed on parameter Z to find its impact on collusion, which is demonstrated by the amount of concealed carbon emission, C_i, under each technology level.

When the manufacturer employs the first or second level of technology, the optimal policy is to outsource the entire manufacturing process, which leads to no collusion due to not having any emissions. For the third and fourth level of green technology, the optimal solution changes and the manufacturer chooses in-house production. Therefore, there is a chance of collusion between the manufacturer and verifier, which is shown by the amount of concealed carbon emission.

As shown in figure 4.9, when government increases the re-verification rate, concealed emission decreases, which leads to enhanced social welfare. This reduction is the same in both levels, i.e., the amount of concealed emission in both third and fourth levels is the same. On the other hand, total game utility in both third and fourth green technology levels decreases as re-verification rate increases. As it is evident from figure 4.9, higher re-verification rates reduce total game utility. Hence, generally speaking, smaller values for re-verification are preferred.

In other words, government must perform a trade-off between game utility and environment protection: higher re-verification rates curb concealed emission but reduce total game utility; lower re-verification rates elevate the amount of concealed emission, but lead to increased total game utility.

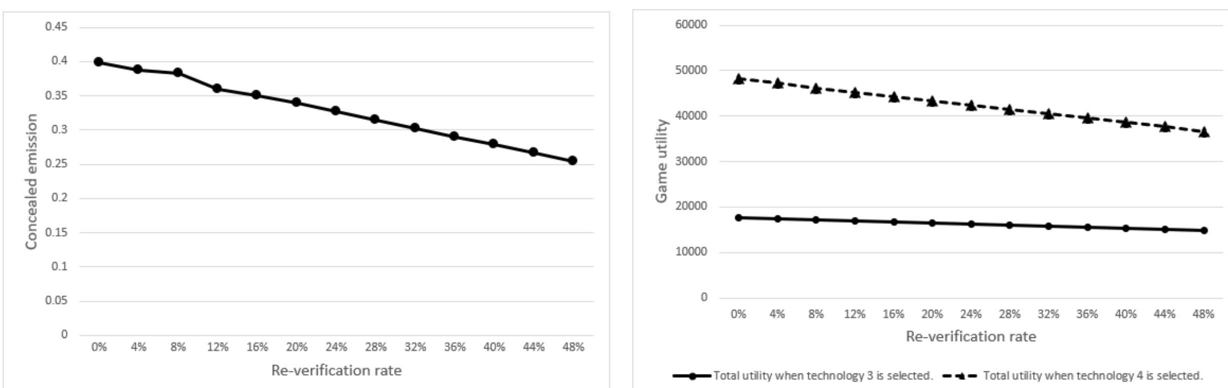


Figure 4.9: Analysis of the impact of re-verification policy on game utility and emission reduction

4.4 Summary

This chapter proposed a model to optimize the strategies of the players who are exposed to the uncertainties of a cap-and-trade market. The uncertainties include carbon allowance price, demand, and customer preference regarding product greenness. The study tends to support government's decisions regarding re-verification strategy, and help the manufacturers develop an effective production process and procurement plan such that all players achieve their best desired utility. The chapter establishes grounds for finding the optimal game strategy for each player to maximize their utility while implementing an effective supervision mechanism.

The developed model's validity and robustness were investigated using a numerical example. The results certified that the proposed model is reliable in the presence of uncertain parameters such as customer sensitivity to product greenness (h_i) and supplier's lead time (LT). Also, sensitivity analysis of government's emission restriction index (ξ), penalty coefficient (n_j), and the impact of government's regulations on the game utility provides helpful information for the legislator in assigning the best values to these parameters and minimizing the chance of collusion.

5. Resilient green supply chain design to mitigate the ripple effect: A two-stage stochastic optimization model

Disasters and disruptions such as the COVID-19 pandemic can significantly interrupt supply chains and industries. To control these disruptions, decision-makers must focus on supply chain resiliency. This chapter proposes a multi-stage, multi-period green supply chain design model and six resilience strategies, with downstream and upstream disruptions taken into account to analyze both the ripple and bullwhip effect, respectively. To control the mentioned disruptions and handle the uncertainties of parameter estimations, a two-stage stochastic optimization approach is devised. The objectives are to minimize the total cost of disruption, and CO_2 emission under the cap-and-trade mechanism as a government-issued emission regulation. The proposed decision-making framework and solution approach are validated using a numerical experiment followed by sensitivity analysis. The results show the optimum structure of the supply chain and the best resilient strategies to mitigate the ripple effect. Moreover, the effect of a decline in capacity of facilities on the optimal solution and the applied resilient strategies is investigated. This study provides managerial insights to help governments set the proper amount of cap, and supply chain managers to predict the demand behavior of essential and non-essential products in the event of disruptions.

Most of the context in this chapter have been published in Mirzaee, H., Samarghandi, H., Willoughby, K. (2022). Resilient green supply chain design to mitigate the ripple effect: A two-stage stochastic optimization model. Journal of Cleaner Production (under review).

5.1 Background

Disruptions caused by natural or human-made disasters affect supply chains in different aspects including transportation delays, labor unavailability, and supply-side shortage. A supply chain disruption announcement decreases a firm's stock returns by 20% on average after six months (Hendricks and Singhal, 2005). Various examples demonstrate the challenges the firms face when trying to recover from a disruption: six months after Japan's tsunami in 2011, Toyota faced disruption in its supply network, and due to a shortage of parts, idled some of its plants in North America (Kim et al., 2015). More recently, the COVID-19 pandemic outbreak caused long-term negative impacts on supply chains and revealed their vulnerabilities (Liu et al., 2022a). These examples showcase the importance of adaptability and resiliency of supply chains in surviving new conditions in case of a sizeable disruption, which has recently gained attention among scholars and practitioners (Ivanov and Dolgui, 2022).

One type of interruption to scrutinize for improving supply chain adaptability is the ripple effect, which is described as the propagation of disturbances that arise from the disruption of supply chain elements (Ivanov et al., 2016). The adverse impacts of the ripple effect spread downstream in the supply chain (Monostori, 2021). Real-world examples emphasize that controlling the ripple effect is crucial for supply chain managers. For instance, in June 2020, Mercedes-Benz ceased production of an off-road vehicle in Alabama as a result of a shortage in components imported from its European suppliers during the global COVID-19 pandemic (Reuters, 2020).

The desirable approach for efficient recovery from the impact of ripple effect is constructing intrinsic supply chain resiliency. Having contingency plans such as backup suppliers or temporary facilities at the supply chain design stage is helpful in controlling the ripple effect (Ivanov et al., 2015). In other words, appropriate strategies must be considered during the design stage to mitigate the crunch in the aftermath of inadmissible events such as supply delay, demand hike, or capacity contraction (Sharma et al., 2022). The auspicious design strategies include, but are not limited to, considering backup suppliers, capacity expansion and multiple assignments (Gholami-Zanjani et al., 2021).

Another important factor in designing a supply chain is attention to the environmental aspects as they bring competitive advantages for the firms (Boskabadi et al., 2022). Devising emission abatement schemes, producing recyclable products, and using green technologies are some of the elements that lead to a greener supply chain (Mirzaee et al., 2022).

On another note, inaccurate estimation of the design parameters may result in colossal losses in uncertain environments (Wang et al., 2021). Ergo, uncertainty in the forecast values of the parameters is another factor that negatively impacts the supply chain performance, which necessitates adopting an appropriate approach. The three most common uncertainty control methods are stochastic optimization, robust optimization, and fuzzy optimization (Tordecilla et al., 2021), among which stochastic optimization is the most popular technique in the ripple effect literature.

Stochastic optimization takes into account disruptions by using scenario-based modeling (Oksuz and Satoglu, 2020), while robust optimization, despite its several advantages, focuses directly on the worst-case scenario, which is not always relevant (Ivanov et al., 2019). Conversely, fuzzy optimization prevents considering some scenarios regarding the ripple effect (Özçelik et al., 2021). Moreover, it requires deep knowledge about the problem's parameters to develop a membership function, which is not always applicable (Memon et al., 2015b). Henceforth, to provide the best strategic and operational decisions, this chapter adopts a two-stage stochastic optimization approach to control uncertainty.

5.1.1 RGSCD model formulation

Problem statement

The resilient green supply chain design problem can be stated as follows: there are four stages represented by sets of I, J, K, and M, i.e., suppliers, manufacturers, warehouses, and retailers, respectively. Raw material is procured to manufacturers by suppliers (X^s_{ijt}). After producing products, they are kept in warehouses (T^s_{jkt}) to be sent to retailers (Z^s_{kmt}). There are L different transportation modes to move the materials and products between the supply chain echelons. T time periods are defined for this problem to make sure the right decisions are made considering long-term planning period. Different levels of the ripple effect are shown by S possible scenarios. Backup suppliers, and temporary manufacturing and warehousing facilities are considered as extra sources in the event of disruption. In order to satisfy a predetermined service level, these backup suppliers and facilities are reserved to be utilized when the ripple effect emerges in the supply chain. The supply chain structure is depicted in figure 5.1. The objective is to minimize the costs of supply chain operational decisions, strategic resilient decisions, and total CO_2 emission during production and transportation process of a product. It is assumed that a cap-and-trade mechanism is in place as an emission abatement mechanism.

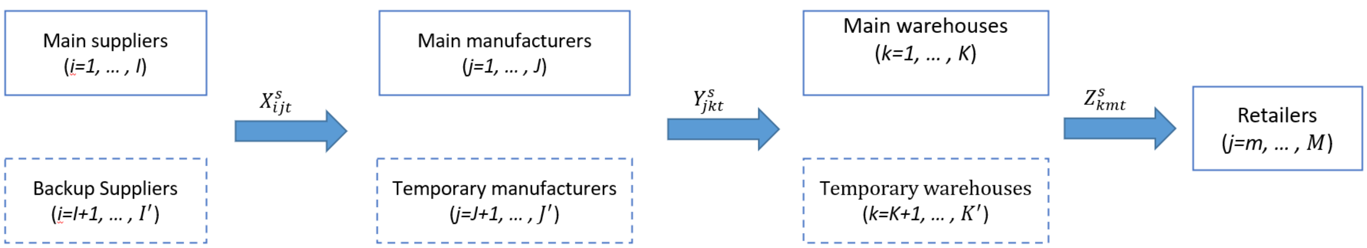


Figure 5.1: Supply chain structure

The developed model in this chapter is formulated based on the following assumptions:

- CO_2 is emitted as a result of transportation as well as production processes in the supply chain.
- The amount of CO_2 emission is restricted by government.
- Different possible scenarios are considered for the uncertain parameters to show the disparate levels of disruptions.
- The manufacturers are allowed to have shortage, which will be back-ordered.
- All temporary manufacturing centers and warehouses are identical in terms of production and storage capacity.

The resilient green supply chain design problem can be stated Ms_j: Setup cost of opening temporary manufacturing center $j \in \{j = J+1, \cdots, J'\}$

Ws_k: Setup cost of opening temporary warehouse $k \in \{K+1, \cdots, K'\}$

So: Setup cost of establishing an information sharing system

$St1_{ijl}$: Saved ordering time due to using the information sharing system for an order placed by manufacturer j to supplier i, per order

$St2_{jkl}$: Saved ordering time due to using the information sharing system for an order placed by warehouse k to manufacturer j, per order

$St3_{kml}$: Saved ordering time due to using the information sharing system for an order placed by retailer m to warehouse k, per order

Dc: Delay cost per order per day

Tr: Training cost of employees to operate the information sharing system

Mic_j^s: Inventory cost per product for manufacturer j under scenario s

Msc_k^s: Shortage cost per product for manufacturer j under scenario s

D_{mt}^s: Demand received by retailer m in period t under scenario s

Mc_j: Production capacity of manufacturer j

Wc_k: Capacity of warehouse k

Spp: Extra cost of stockpiled products

Sm: Minimum number of suppliers

Cep_j: Carbon emission of manufacturer j during production process per product

$Cet1_{ijl}$: Carbon emission of transportation from supplier i to manufacturing center j using transportation mode l, per product

$Cet2_{jkl}$: Carbon emission of transportation from manufacturer j to warehouse k using transportation mode l, per product

$Cet3_{kml}$: Carbon emission of transportation from warehouse k to retailer m using transportation mode l, per product

Rce: Reduced amount of carbon emission per unit of product shipped due to using information sharing system

Cap_t: Maximum allowed carbon emission in period t

r_j^s: Reduced capacity ratio of manufacturer j under scenario s due to the ripple effect

$r_k'^s$: Reduced capacity ratio of warehouse k under scenario s due to the ripple effect

M: A large positive number

Pr^s: Occurrence probability of scenario s

First stage decision variables

XX_{ijtl}: A binary variable showing material flow between manufacturer j and supplier i in period t using transportation mode l; $XX_{ijtl} = 1$ means an order is received by manufacturer j from supplier i

YY_{jktl}: A binary variable showing product flow between manufacturer j and warehouse k using transportation mode l in period t; $YY_{jktl} = 1$ means product flow between manufacturer and warehouse

ZZ_{kmtl}: A binary variable showing product flow between retailer m and warehouse k using transportation mode l in period t; $ZZ_{kmtl} = 1$ means product flow between warehouse and retailer

Second stage decision variables

X_{ijtl}^s: An integer variable showing the number of products transported from supplier i to manufacturer j in period t using transportation mode l under scenario s

Y_{jktl}^s: An integer variable showing the number of products transported from manufacturer j to warehouse k in period t using transportation mode l under scenario s

Z_{kmtl}^s: An integer variable showing the number of products transported from warehouse k

to retailer m in period t using transportation mode l under scenario s

MI_{jt}^{s}: The j^{th} manufacturer's inventory at the end of period t under scenario s

MS_{jt}^{s}: The j^{th} manufacturer's shortage at the end of period t under scenario s

MSS_{jt}^{s}: The amount of j^{th} manufacturer's safety stock in period t under scenario s

SP_{jt}^{s}: The number of ordered stockpiled products by manufacturer j in period t under scenario s

Mathematical formulation

This section presents a two-stage stochastic optimization model with two objectives. The first objective introduces all the supply chain costs; the second objective belongs to the CO_2 emissions. The first stage considers the deterministic variables, which are not dependent to the uncertain parameters. The second stage takes the uncertain variables into account. In this chapter, uncertainty is handled by considering different possible scenarios that may occur due to disruption. The first stage optimizes the channel through which the raw materials transform to the final product. In the second stage, s scenarios are defined for the uncertain variables. The optimal solution of the presented model is obtained based on all possible scenarios in accordance with their occurrence probabilities.

The supply chain costs are as follows:

$$\begin{aligned}C_1 = &\sum_{i,i' \in I} \sum_{j,j' \in J} \sum_{t \in T} \sum_{l \in L} \sum_{s \in S} XX_{ijtl} Dc(Tl1_{ijl}^{s} - St1_{ijl}) \\ &+ \sum_{j,j' \in J} \sum_{k,k' \in K} \sum_{t \in T} \sum_{l \in L} \sum_{s \in S} YY_{jktl} Dc(Tl2_{jkl}^{s} - St2_{jkl}) \\ &+ \sum_{k,k' \in K} \sum_{m \in M} \sum_{t \in T} \sum_{l \in L} \sum_{s \in S} ZZ_{kmtl} Dc(Tl3_{kml}^{s} - St3_{kml})\end{aligned} \tag{5.1}$$

Equation (5.1) shows the cost of transportation delay between different supply chain echelons.

$$
\begin{aligned}
C_2^s = \sum_{i,i' \in I} \sum_{j,j' \in J} \sum_{t \in T} \sum_{l \in L} \sum_{s \in S} X_{ijtl}^s Tc1_{ijl}^s + \sum_{j,j' \in J} \sum_{k,k' \in K} \sum_{t \in T} \sum_{l \in L} \sum_{s \in S} Y_{jktl}^s Tc2_{jkl}^s \\
+ \sum_{k,k' \in K} \sum_{m \in M} \sum_{t \in T} \sum_{l \in L} \sum_{s \in S} Z_{kmtl}^s Tc3_{kml}^s
\end{aligned}
\tag{5.2}
$$

Equation (5.2) refers to the transportation cost throughout the supply chain. Equations (5.3) and (5.4) indicate the cost of holding inventory and the cost of shortage at the end of each period, respectively.

$$
C_3^s = \sum_{j,j' \in J} \sum_{t \in T} \sum_{s \in S} MI_{jt}^s Mic_j^s \tag{5.3}
$$

$$
C_4^s = \sum_{j,j' \in J} \sum_{t \in T} \sum_{s \in S} MS_{jt}^s Msc_j^s \tag{5.4}
$$

The amount of CO_2 emission during the transportation and production processes is calculated by equation (5.5).

$$
\begin{aligned}
E^s = \sum_{j,j' \in J} \sum_{k,k' \in K} \sum_{t \in T} \sum_{l \in L} \sum_{s \in S} Y_{jktl}^s Cep_j + \sum_{i,i' \in I} \sum_{j,j' \in J} \sum_{t \in T} \sum_{l \in L} \sum_{s \in S} X_{ijtl}^s Cet1_{ijl} \\
+ \sum_{j,j' \in J} \sum_{k,k' \in K} \sum_{t \in T} \sum_{l \in L} \sum_{s \in S} Y_{jktl}^s Cet2_{jkl} + \sum_{k,k' \in K} \sum_{m,m' \in M} \sum_{t \in T} \sum_{l \in L} \sum_{s \in S} Z_{kmtl}^s Cet3_{kml}
\end{aligned}
\tag{5.5}
$$

In the two-stage stochastic optimization model, the objective functions are formulated as follows:

$$
Min\, Z_1 = C_1 + \sum_{s \in S} Pr^s (C_2^s + C_3^s + C_4^s) \tag{5.6}
$$

$$
Min\, Z_2 = \sum_{s \in S} Pr^s E^s \tag{5.7}
$$

The first objective function (5.6) minimizes the total cost of supply chain; the second objective (5.7) minimizes total CO_2 emission. In these objective functions the optimal value of uncertain variables are obtained based on all possible scenarios.

Constraints

Constraints (5.8)-(5.10) specify which supply chain partners are used.

$$X^s_{ijtl} \leq XX_{ijtl}M \qquad \forall i, j, t, l, s \tag{5.8}$$

$$Y^s_{jktl} \leq YY_{jktl}M \qquad \forall j, k, t, l, s \tag{5.9}$$

$$Z^s_{kmtl} \leq ZZ_{kmtl}M \qquad \forall k, m, t, l, s \tag{5.10}$$

Constraints (5.11)-(5.13) guarantee that one transportation mode is used to ship a batch of product between different echelons.

$$\sum_{l \in L} XX_{ijtl} \leq 1 \qquad \forall i, j, t \tag{5.11}$$

$$\sum_{l \in L} YY_{jktl} \leq 1 \qquad \forall j, k, t \tag{5.12}$$

$$\sum_{l \in L} ZZ_{jktl} \leq 1 \qquad \forall k, m, t \tag{5.13}$$

Constraints (5.14), (5.15), and (5.16) show the inventory balance of manufacturers, warehouses, and retailers, respectively.

$$\sum_{i,i' \in I} \sum_{l \in L} X^s_{ijtl} + MI^s_{jt-1} + MS^s_{jt} = \sum_{k,k' \in K} \sum_{l \in L} Y^s_{jktl} + MI^s_{jt} + MS^s_{jt-1} \qquad \forall j, t, s \tag{5.14}$$

$$\sum_{j,j' \in J} \sum_{l \in L} Y^s_{jktl} = \sum_{m,m' \in M} \sum_{l \in L} Z^s_{kmtl} \qquad \forall k, t, s \tag{5.15}$$

$$\sum_{k,k' \in K} \sum_{l \in L} Z^s_{kmtl} = D^s_{mt} \qquad \forall m, t, s \tag{5.16}$$

Constraint (5.17) enforces the defined $CO2$ emission cap to the manufacturers.

$$\sum_{j,j' \in J} \sum_{k,k' \in K} \sum_{l \in L} \sum_{s \in S} Y^s_{jktl} Cep_j + \sum_{i,i' \in I} \sum_{j,j' \in J} \sum_{l \in L} \sum_{s \in S} X^s_{ijtl} Cet1_{ijl}$$
$$+ \sum_{j,j' \in J} \sum_{k,k' \in K} \sum_{l \in L} \sum_{s \in S} Y^s_{jktl} Cet2_{jkl} + \sum_{k,k' \in K} \sum_{m,m' \in M} \sum_{l \in L} \sum_{s \in S} Z^s_{kmtl} Cet3_{kml} \leq Cap_t \qquad \forall t \tag{5.17}$$

Constraint (5.18) describes the minimum number of suppliers that must be selected when multiple sourcing strategy is applied.

$$\sum_{i,i' \in J} XX_{ijtl} \geq Sm \qquad \forall j, t, l \tag{5.18}$$

Constraints (5.19) and (5.20) calculate the capacity of manufacturers and warehouses under normal condition as well as under disruption.

$$\sum_{j,j' \in J} Y^s_{jktl} \leq \sum_{j,j' \in J} Mc_j (1 - r^s_j) \qquad \forall j, t, l \tag{5.19}$$

$$\sum_{k,k' \in K} Z^s_{kmtl} \leq \sum_{k,k' \in K} Wc_k (1 - r'^s_k) \qquad \forall j, t, l \tag{5.20}$$

5.1.2 Resilient strategies

Backup suppliers

The backup supplier strategy examines the case of hiring extra possible suppliers. Although hiring extra suppliers imposes higher costs to the supply chain, these suppliers will be available with a higher probability in case of a disruption. By considering this strategy, the range of index i expands to $\{1, 2, \cdots, I, I+1, \cdots, I'\}$, where regular suppliers are represented by $\{1, 2, \cdots, I\}$, and suppliers $\{I+1, I+2, \cdots, I'\}$ portray the backup suppliers. In the event of a disruption, which may cause delay in suppliers' orders or reduction of their capacity, backup suppliers may curtail interruption.

Multiple sourcing

Multiple sourcing diversifies the suppliers, so the supply chain does not heavily rely on a limited number of suppliers, as they may be unavailable when a disruption occurs. Adding constraint (5.21) to the model conduces this resilient strategy to our RGSCD problem. Equation (5.21) ensures that a minimum number of suppliers are selected to procure the required raw material.

$$\sum_{i,i' \in I} XX_{ijtl} \geq Sm \qquad \forall j, t, l \tag{5.21}$$

Safety stock

Bearing safety stock is another risk management strategy that ensures capability of the supply chain in immediately responding to customer requests, even if delays happen while transporting raw material or final products between different supply chain echelons. Keeping safety stock is accomplished via two adjustments to the original model. First, a maintenance cost for the safety stock equal to $\sum_{j,j' \in J} \sum_{t \in T} \sum_{s \in S} MSS_{jt}^{s} Mic_{j}^{s}$ is added to the inventory costs. Furthermore, the extra inventory held as safety stock in form of final product in each time period is added to equation (5.14) to update the manufacturers' inventory balance. After applying this strategic decision to the model, equation 5.14 is updated as follows.

$$\begin{aligned} \sum_{i,i' \in I} \sum_{l \in L} X_{ijtl}^{s} + MI_{jt-1}^{s} + MS_{jt}^{s} + MSS_{jt-1}^{s} = \sum_{k,k' \in K} \sum_{l \in L} Y_{jktl}^{s} + MI_{jt}^{s} \\ + MS_{jt-1}^{s} + MSS_{jt}^{s} \qquad \forall j, t, s \end{aligned} \tag{5.22}$$

Stockpiling

Stockpiling is an undertaking in which, during the disruption, the manufacturers respond to a proportion of demand using the inventory which had been produced and held before the disruption occurred. This strategy lowers the chance of shortage and is extremely valuable, but incurs additional costs including considerably higher holding costs. Generally, stockpiling does not provide measurable benefits prior to disruptions. Using the stockpiling system adds a cost equal to $\sum_{j\in J}\sum_{t\in T}\sum_{s\in S} SP^s_{jt}Spp$ to the cost function. Also, the manufacturers' inventory balance constraint, equation (5.14), changes as follows.

$$\sum_{i,i'\in I}\sum_{l\in L} X^s_{ijtl} + MI^s_{jt-1} + MS^s_{jt} + MSS^s_{jt-1} + SP^s_{jt} = \sum_{k,k'\in K}\sum_{l\in L} Y^s_{jktl} + MI^s_{jt} \\ + MS^s_{jt-1} + MSS^s_{jt} \qquad \forall j,t,s \tag{5.23}$$

Temporary facilities

Temporary facilities expedite the supply chain's recovery from a structural disruption (Yılmaz et al., 2021). When needed, possible temporary facilities including manufacturing centers and warehouses act as emergency response centers. To employ this option, domains of indices i and j expand to $\{1,\cdots,I,I+1,\cdots,I'\}$ and $\{1,\cdots,J,J+1,\cdots,J'\}$, respectively. This strategy is useful when the capacity of facilities is diminished, which is commonly observed during disruption events.

Information sharing system

One of the main consequences of disruptions is delay. Using an efficient system to share the information between all supply chain members is crucial. For instance, a manufacturer can monitor the demand received by retailers to check the possible spikes, and avoid delays by increasing its production capacity and providing more vehicles to transport the final products. Even though using this information sharing system is costly, it helps the supply chain decrease the cost of delay. Applying this system in our model adds $XX_{ijtl}(So+Tr)$ to the cost function, but reduces transportation delay between different echelons in the amounts specified by $St1_{ijl}$, $St2_{jkl}$, and $St3_{kml}$.

5.2 Numerical experiment

Data

To investigate the impact of disruption on supply chain and find the best strategic decisions to control the ripple effect, a numerical experiment was performed using Python programming language and the data extracted from Ghomi-Avili et al. (2018). Note that since some parameters of the proposed model do not exist in the models presented by Ghomi-Avili et al. (2018), their values were simulated as will be discussed below. This table (click on the rectangle) summarizes the data. Four scenarios were considered to represent different levels of disruption in the model. The first scenario belongs to the normal situation; the rest of the scenarios epitomize three disruption levels, from weak to strong. Three backup suppliers, as well as three temporary facilities for the manufacturing stage and warehouses were considered to be used in the event of a disruption, which is destined to increase the transportation costs, delays, inventory and shortage costs, demand for essential products, and decrease the capacity of manufacturers and warehouses. It is assumed that the government gradually decreases the emission cap through time.

Safety stock VS. stockpiling

Stockpiling and safety stock were both used to handle the ripple effect as well as demand spikes. Although from different sources, these two strategies are considered to be identical in controlling disruption effects by procuring the needed products. Thus, they are compared so the managers can choose the best strategy to minimize the costs. Using the presented data set, the developed model was solved considering either the stockpiling or the safety stock strategies under different levels of manufacturers' capacity disruption. The results show that safety stock is a better option when the manufacturers' production capacity drops below 44%. Figure 5.2 depicts the conditions under which each one of the two mentioned strategies are dominant. As it is shown in figure 5.2, by decreasing the manufacturers' capacity, the optimal amount of safety stock the manufacturers should keep increases, which is helpful for decision-makers in their pre-disruption strategy preparations.

Backup supplier VS. Multiple sourcing

Two other beneficial pre-disruption strategies in controlling the ripple effect are using backup suppliers and multiple sourcing. Backup suppliers, though costly, prepare the supply chain for disruption in the supply side, and help with procuring raw material and component parts by lowering the level of risk. Multiple sourcing strategy achieves the same results by

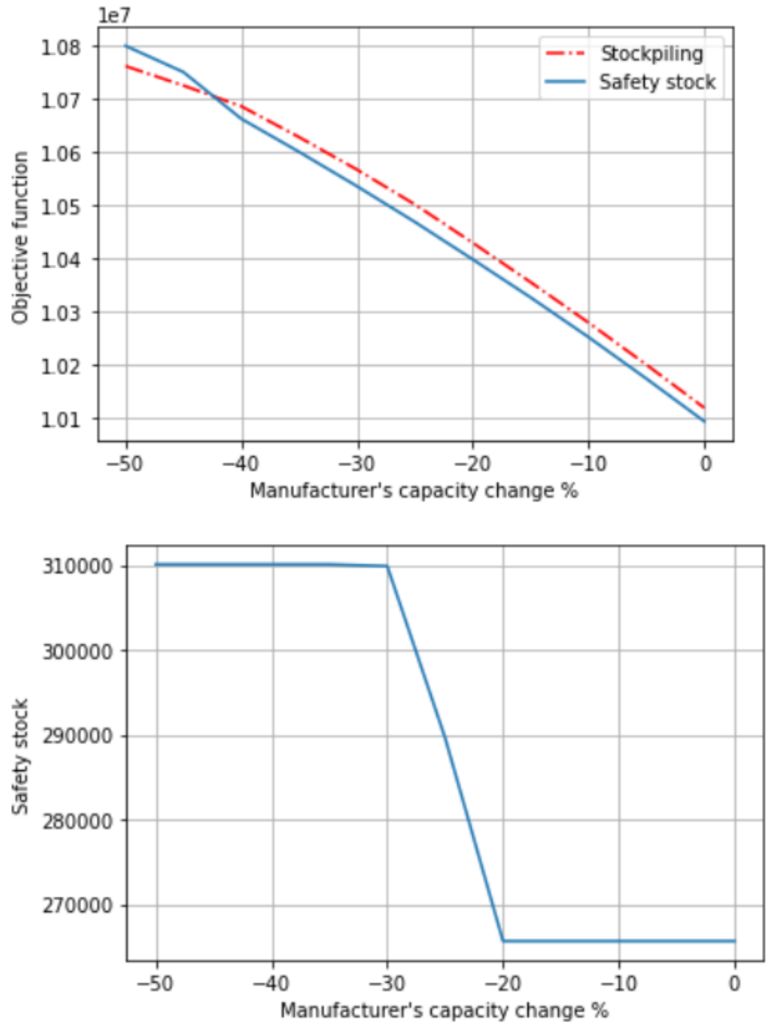


Figure 5.2: Stockpiling vs. safety stockpiling

diversifying the suppliers and avoiding reliance on a limited group of suppliers. The multiple sourcing strategy decreases the supply chain risk, but it has certain disadvantages such as higher costs, lower material quality, and longer lead time due to involvement of secondary suppliers alongside the best selected suppliers in procuring the required material for the manufacturers. In this section, these two strategies are compared to find the optimal and most resilient strategy. Based on figure 5.3, using backup suppliers outperforms multiple sourcing in achieving a higher total utility.

Results of the final model

After comparing similar strategies and determining the dominant game plans using the

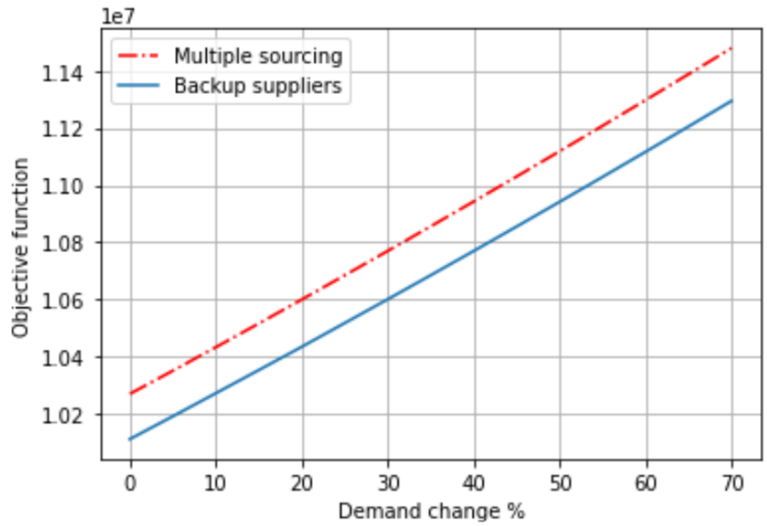


Figure 5.3: Multiple sourcing vs. backup supplier

presented data set, a comprehensive RGSCD model is solved based on four resilient strategies: a) safety stock; b) backup suppliers; c) temporary facilities; and, d) information sharing system. As presented in table 5.2, the best combination of supply chain partners, optimal product flow between different supply chain echelons, and desired amount of manufacturers' safety stock, inventory, and shortage in each period are determined. Z_{Total} shown in table 5.2 is the best total utility obtained under all scenarios. This objective is derived from a combination of strategies that help supply chains recover themselves from disruptions. Manufacturers are allowed to produce extra products as long as they have enough storage space. Also, they are allowed to have shortage and respond to that shortage in the future periods. In this regard, the optimum amount of manufacturer's storage and shortage at the end of each period are achieved. For instance, for the presented test problem, MSS_{31}^{1} indicates that under scenario 1, manufacturer 3 should hold $73,874$ safety stocks to be well prepared for demand fluctuations. Furthermore, the table determines backup suppliers that should be used and temporary facilities that should be opened to maintain the service level during disruptions. The last three rows of the table specify the optimal product flow between suppliers and manufacturers, manufacturers and warehouses, and warehouses and retailers.

Table 5.1: Optimal results of the proposed model

Decision variable	Optimal Value
Objective functions	$Z_{Total} = 8,005,492.07$ $Z_1 = 4,451,676.10$ $Z_2 = 3,553,815.97$
Manufacturers' inventory	$MI^1_{32} = 36,822$
Manufacturers' shortage	$MS^1_{14} = 14,807$ $MS^1_{15} = 29,665$ $MS^1_{16} = 44,465$ $MS^1_{34} = 36,857$ $MS^1_{35} = 73,779$ $MS^1_{36} = 110,633$
Safety stock	$MSS_{111} = 29,604$ $MSS_{112} = 14,780$ $MSS_{131} = 73,874$
Selected suppliers and facilities	$XX_{4321} = 1, XX_{4331} = 1, XX_{4341} = 1, XX_{4351} = 1, XX_{4361} = 1, XX_{5121} = 1, XX_{5131} = 1, XX_{5141} = 1, XX_{5151} = 1, XX_{5161} = 1$ $YY_{1521} = 1, YY_{1531} = 1, YY_{1541} =, YY_{1551} = 1, YY_{1561} = 1, YY_{3421} = 1, YY_{3431} = 1, YY_{3441} = 1, YY_{3451} = 1, YY_{3461} = 1, YY_{3721} = 1, YY_{3731} = 1, YY_{3741} = 1, YY_{3751} = 1, YY_{3761} = 1, YY_{3821} = 1, YY_{3831} = 1, YY_{3841} = 1,$ $YY_{3851} = 1, YY_{3861} = 1$ $ZZ_{4321} = 1, ZZ_{4331} = 1, ZZ_{4341} = 1, ZZ_{4351} = 1, ZZ_{4361} = 1, ZZ_{4721} = 1, ZZ_{4731} = 1, ZZ_{4741} = 1, ZZ_{4751} = 1, ZZ_{4761} = 1, ZZ_{5421} = 1, ZZ_{5431} = 1, ZZ_{5441} = 1, ZZ_{5451} = 1, ZZ_{5461} = 1, ZZ_{5621} = 1, ZZ_{5631} = 1, ZZ_{5641} = 1,$ $ZZ_{5651} = 1, ZZ_{5661} = 1, ZZ_{7121} = 1, ZZ_{7131} = 1, ZZ_{7141} = 1, ZZ_{7151} = 1, ZZ_{7161} = 1, ZZ_{8221} = 1, ZZ_{8231} = 1, ZZ_{8241} = 1, ZZ_{8251} = 1, ZZ_{8261} = 1, ZZ_{9121} = 1, ZZ_{9131} = 1, ZZ_{9141} = 1, ZZ_{9151} = 1, ZZ_{9161} = 1, ZZ_{9421} = 1,$ $ZZ_{9431} = 1, ZZ_{9441} = 1, ZZ_{9451} = 1, ZZ_{9461} = 1, ZZ_{9621} = 1, ZZ_{9631} = 1, ZZ_{9641} = 1, ZZ_{9651} = 1, ZZ_{9661} = 1, ZZ_{10721} = 1, ZZ_{10731} = 1, ZZ_{10741} = 1, ZZ_{10751} = 1, ZZ_{10761} = 1$
Product flow from suppliers to manufacturers	$X^2_{4321} = 38,643, X^2_{24331} = 38,643, X^2_{4341} = 39,189, X^2_{4351} = 38025, X^2_{4361} = 38,632, X^2_{5121} = 15,671, X^2_{5131} = 15,477, X^2_{5141} = 15,682, X^2_{5151} = 15,720, X^2_{5161} = 15,822, X^3_{4321} = 41,134, X^3_{4331} = 41,717, X^3_{4341} = 41,464,$ $X^3_{4351} = 41,259, X^3_{4361} = 41,127, X^3_{5121} = 16,578, X^3_{5131} = 16,439, X^3_{5141} = 16,428, X^3_{5151} = 16,909, X^3_{5161} = 16,495, X^4_{4321} = 48,711, X^4_{4331} = 46,704, X^4_{4341} = 48,284, X^4_{4351} = 46,340, X^4_{4361} = 47,417, X^4_{5121} = 19,510,$ $X^4_{5131} = 18,789, X^4_{5141} = 18,27, X^4_{5151} = 18,550, X^4_{5161} = 18,305$
Product flow from manufacturers to warehouses	$Y^1_{1521} = 14,824, Y^1_{1531} = 14,780, Y^1_{1541} = 14,807, Y^1_{1551} = 14,858, Y^1_{1561} = 14,800, Y^1_{3421} = 14,871, Y^1_{3431} = 14,743, Y^1_{3441} = 14,715, Y^1_{3451} = 14,794, Y^1_{3461} = 14,825, Y^1_{3721} = 7,311, Y^1_{3731} = 7,405, Y^1_{3741} = 7,336, Y^1_{3751} = 7,395,$ $Y^1_{3761} = 7.310, Y^1_{3821} = 14,870, Y^1_{3831} = 14,674, Y^1_{3841} = 14,806, Y^1_{3851} = 14,733, Y^1_{3861} = 14,719, Y^2_{1521} = 15,671, Y^2_{1531} = 15,477, Y^2_{1541} = 15,682, Y^2_{1551} = 15,720, Y^2_{1561} = 15,822, Y^2_{3421} = 15,721, Y^2_{3431} = 15,599, Y^2_{3441} = 15,825,$ $Y^2_{3451} = 15,218, Y^2_{3461} = 15,216, Y^2_{3721} = 7,500, Y^2_{3731} = 7,835, Y^2_{3741} = 7,795, Y^2_{3751} = 7,639, Y^2_{3761} = 7,893, Y^2_{3821} = 15,486, Y^2_{3831} = 15,209, Y^2_{3841} = 15,569, Y^2_{3851} = 15,168, Y^2_{3861} = 15,523, Y^3_{1521} = 16,578, Y^3_{1531} = 16,439,$ $Y^3_{1541} = 16,428, Y^3_{1551} = 16,909, Y^3_{1561} = 16,495, Y^3_{3421} = 16,550, Y^3_{3431} = 16,523, Y^3_{3441} = 16,716, Y^3_{3451} = 16,718, Y^3_{3461} = 16,492, Y^3_{3721} = 8,736, Y^3_{3731} = 8,357, Y^3_{3741} = 8,220, Y^3_{3751} = 8,340, Y^3_{3761} = 8,298, Y^3_{3821} = 16,388,$ $Y^3_{3831} = 16,837, Y^3_{3841} = 16,528, Y^3_{3851} = 16,201, Y^3_{3861} = 16,337, Y^4_{1521} = 19,510, Y^4_{1531} = 18,789, Y^4_{1541} = 18,227, Y^4_{1551} = 18,550, Y^4_{1561} = 18,305, Y^4_{3421} = 19,509, Y^4_{3431} = 18,802, Y^4_{3441} = 18,969, Y^4_{3451} = 16,918, Y^4_{3461} = 19,166$ $Y^4_{3721} = 10,234, Y^4_{3731} = 9,111, Y^4_{3741} = 10,121, Y^4_{3751} = 10,303, Y^4_{3761} = 10,225, Y^4_{3821} = 18,968, Y^4_{3831} = 18,791, Y^4_{3841} = 19,194, Y^4_{3851} = 19,119, Y^4_{3861} = 18,026$
Product flow from warehouses to retailers	$Z^1_{4321} = 7,439, Z^1_{4331} = 7,317, Z^1_{4341} = 7,378, Z^1_{4351} = 7,311, Z^1_{4361} = 7,417, Z^1_{4721} = 7,432, Z^1_{4731} = 7,426, Z^1_{4741} = 7,337, Z^1_{4751} = 7,483, Z^1_{4761} = 7,408, Z^1_{5421} = 7,492, Z^1_{5431} = 7,421, Z^1_{5441} = 7,364, Z^1_{5451} = 7,378, Z^1_{5461} = 7,453$ $Z^1_{5621} = 7,332, Z^1_{5631} = 7,359, Z^1_{5641} = 7,443, Z^1_{5651} = 7,480, Z^1_{5661} = 7,347, Z^1_{7121} = 7,311, Z^1_{7131} = 7,405, Z^1_{7141} = 7,336, Z^1_{7151} = 7,395, Z^1_{7161} = 7,310, Z^1_{8221} = 7,411, Z^1_{8231} = 7,318,$ $Z^1_{8241} = 7,393, Z^1_{8251} = 7,335, Z^1_{8261} = 7,400, Z^1_{8521} = 7,459, Z^1_{8531} = 7,356, Z^1_{8541} = 7,413, Z^1_{8551} = 7,398, Z^1_{8561} = 7,319, Z^2_{4321} = 7,806, Z^2_{4331} = 7,871, Z^2_{4341} = 7,957, Z^2_{4351} = 7,701, Z^2_{4361} = 7,608, Z^2_{4721} = 7,915, Z^2_{4731} = 7,728,$ $Z^2_{4741} = 7,868, Z^2_{4751} = 7,517, Z^2_{4761} = 7,608, Z^2_{5421} = 7,975, Z^2_{5431} = 7,622, Z^2_{5441} = 7,740, Z^2_{5451} = 7,983, Z^2_{5461} = 7,907, Z^2_{5621} = 7,696, Z^2_{5631} = 7,855, Z^2_{5641} = 7,942, Z^2_{5651} = 7,737, Z^2_{5661} = 7,915, Z^2_{7121} = 7,500, Z^2_{7131} = 7,835,$ $Z^2_{7141} = 7,795, Z^2_{7151} = 7,639, Z^2_{7161} = 7,893, Z^2_{8221} = 7,904, Z^2_{8231} = 7,507, Z^2_{8241} = 7,677, Z^2_{8251} = 7,612, Z^2_{8261} = 7,758, Z^2_{8521} = 7,582, Z^2_{8531} = 7,702, Z^2_{8541} = 7,892, Z^2_{8551} = 7,556, Z^2_{8561} = 7,765, Z^3_{4321} = 8,365, Z^3_{4331} = 8,489,$ $Z^3_{4341} = 8,279, Z^3_{4351} = 8,461, Z^3_{4361} = 8,335, Z^3_{4721} = 8,185, Z^3_{4731} = 8,034, Z^3_{4741} = 8,437, Z^3_{4751} = 8,257, Z^3_{4761} = 8,157, Z^3_{5421} = 8,220, Z^3_{5431} = 8,173, Z^3_{5441} = 8,108, Z^3_{5451} = 8,428, Z^3_{5461} = 8,213, Z^3_{5621} = 8,358, Z^3_{5631} = 8,266,$ $Z^3_{5641} = 8,320, Z^3_{5651} = 8,481, Z^3_{5661} = 8,282, Z^3_{7121} = 8,376, Z^3_{7131} = 8,357, Z^3_{7141} = 8,220, Z^3_{7151} = 8,340, Z^3_{7161} = 8,298, Z^3_{8221} = 8,096, Z^3_{8231} = 8,380, Z^3_{8241} = 8,377, Z^3_{8251} = 8,133, Z^3_{8261} = 8,041, Z^3_{8521} = 8,292, Z^3_{8531} = 8,457,$ $Z^3_{8541} = 8,151, Z^3_{8551} = 8,068, Z^3_{8561} = 8,296, Z^4_{4321} = 9,283, Z^4_{4331} = 9,653, Z^4_{4341} = 10,209, Z^4_{4351} = 6,849, Z^4_{4361} = 8,975, Z^4_{4721} = 10,226, Z^4_{4731} = 9,149, Z^4_{4741} = 8,760, Z^4_{4751} = 10,069, Z^4_{4761} = 10,191$ $Z^4_{5421} = 10,002, Z^4_{5431} = 9,902, Z^4_{5441} = 8,760, Z^4_{5451} = 8,953, Z^4_{5461} = 9,047, Z^4_{5621} = 9,508, Z^4_{5631} = 8,887, Z^4_{5641} = 9,467, Z^4_{5651} = 9,597, Z^4_{5661} = 9,258, Z^4_{7121} = 10,234, Z^4_{7131} = 9,111,$ $Z^4_{7141} = 10,121, Z^4_{7151} = 10,303, Z^4_{7161} = 10,225, Z^4_{8221} = 10,300, Z^4_{8231} = 8,898, Z^4_{8241} = 9,872, Z^4_{8251} = 8,748, Z^4_{8261} = 9,256, Z^4_{8521} = 8,668, Z^4_{8531} = 9,893, Z^4_{8541} = 9,322, Z^4_{8551} = 10,371, Z^4_{8561} = 8,770$

To validate the proposed model and solution approach, and to investigate the supply chain behavior, further analyses are conducted as follows.

Behaviour of essential and non-essential products

Distinguishing the supply chain's products between essential and non-essential is crucial for the managers. As it was evident during the COVID-19 pandemic, essential products experienced a large spike in demand, which was mostly non-present for non-essential products. To measure the impact of demand change on the optimal solution of the designed model a sensitivity analysis was designed. For this purpose, different rates of demand fluctuation were considered and the results were analyzed. Demand increases can be interpreted as the fluctuation of demand for essential products; demand decrease represents the market uncertainties for non-essential products. Figure 5.4 demonstrates that demand intensification calls for expanding the adoption of temporary facilities for manufacturers and warehouses. Also, based on figure 5.4, elevation of demand induces higher need for product flow between temporary facilities, which indicates a desired response to disruptions via activation of the temporary facilities.

The effects of carbon abatement regulation

An array of carbon emission regulations are employed in various countries to restrict supply chains from harming the environment. One way to restrict the emission levels is to place a cap on the manufacturers' emission. Accordingly, the proposed model assumes that a cap-and-trade regulation is enforced, where the cap is gradually decreased by governments to reduce total CO_2 emissions and to allow manufacturers to adapt to the regulation requirements. Hence, we analyze the impact of cap modifications on the supply chain in this section. As it is shown in figure 5.5, reducing the cap imposes enormous costs to the supply chain for CO_2 emissions; the model reacts by reducing the emission level, which results in total utility contraction. After reducing the cap to 76% of its original amount, the model becomes infeasible. In other words, reducing the cap beyond a certain threshold makes it impossible to respond to customers' demand, while adhering to the maximum emission requirements. Therefore, the government is advised to recognize supply chain limitations before setting

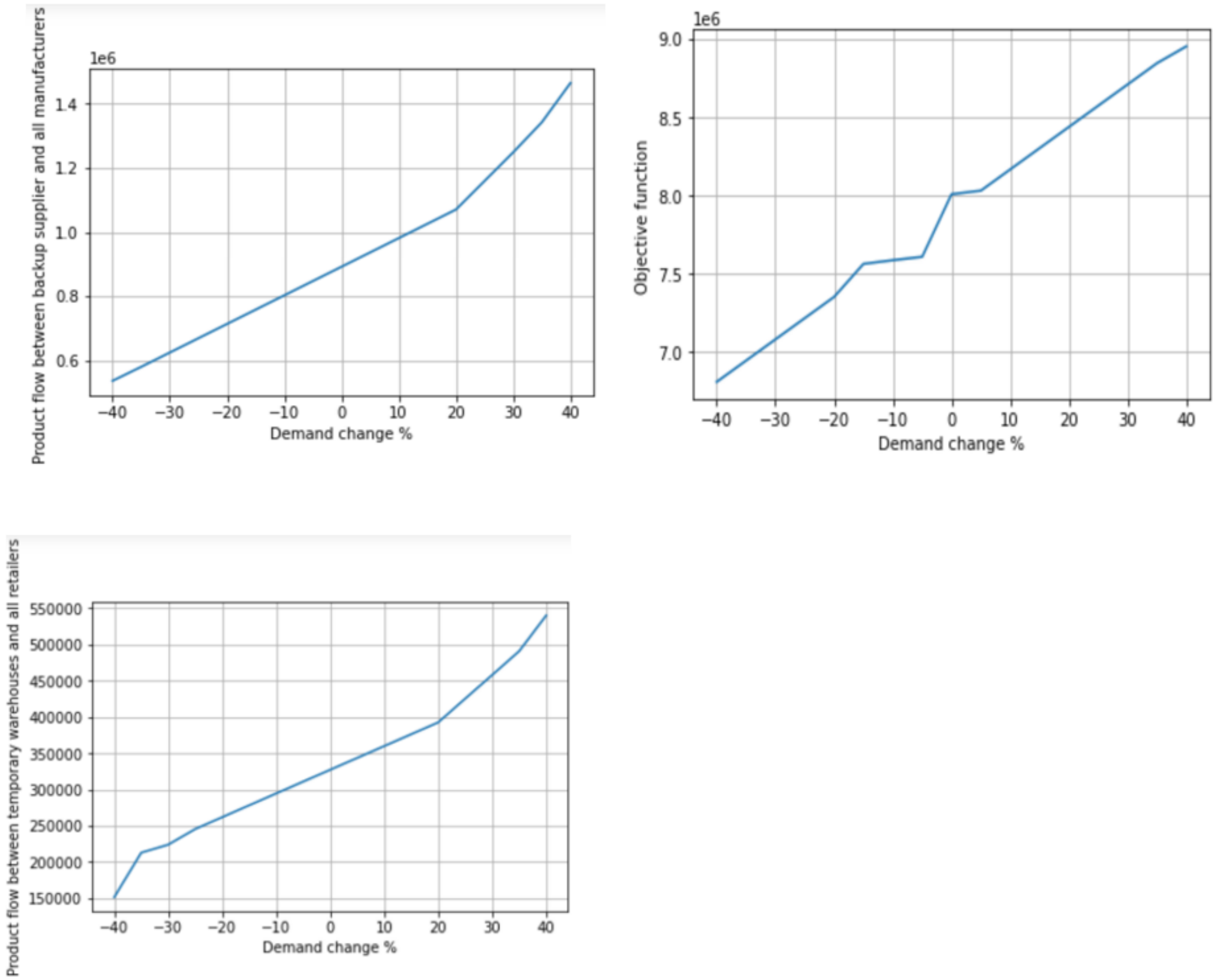


Figure 5.4: Sensitivity analysis on demand fluctuation for essential and non-essential products

the cap amounts. The other methods of reducing the emission levels without decreasing the production level is discussed in Mirzaee et al. (2022).

Capacity decrease effect

Ripple effect usually impacts the capacities of manufacturers and warehouses (Monostori, 2021), which calls for an appropriate risk management strategy, such as responding to customers' demand by keeping more safety stock. A sensitivity analysis is conducted to assess the correct strategies when the capacities are decreased. As figure 5.6 illustrates, decreasing the capacity of the supply chain facilities deteriorates the objective function value for it forces the model to responds to demand by keeping more safety stock, which is more

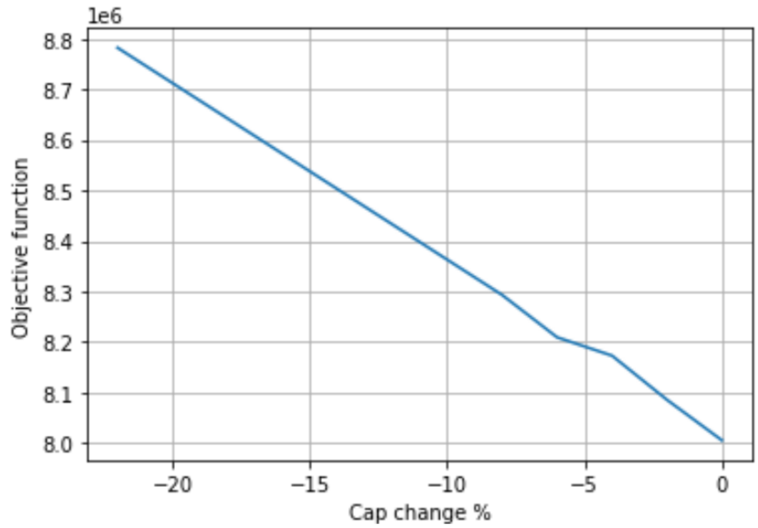


Figure 5.5: The effect of carbon abatement regulations

expensive to carry. Decreasing the capacity beyond a certain threshold causes infeasibility as the limited capacity makes it impossible to handle the realized demand. Consequently, the supply chain managers must consider keeping an appropriate amount of temporary facilities available to prevent service level degradation.

5.3 Summary

This chapter proposes a resilient green supply chain design to mitigate the ripple effect of pandemic disruptions such as COVID-19. The study tends to find the best strategies in designing a supply chain to alleviate the ripple effect. There are six resilient strategies applied in the designed supply chain to minimize the risk of a decrease in service level. Also, a two-stage stochastic optimization approach is applied to control the ripple effect and parameter estimation uncertainty. This study provides a decision making framework for supply chain managers to use the best transportation channel for the materials and final products, enhance service level, and control uncertainty of estimated model parameters and disruptions.

To check the validity of the designed model and proposed solution approach, a numerical example was presented. The results confirm the selected resilient strategies help the supply chain mitigate the ripple effect in the presence of stochastic parameters and possi-

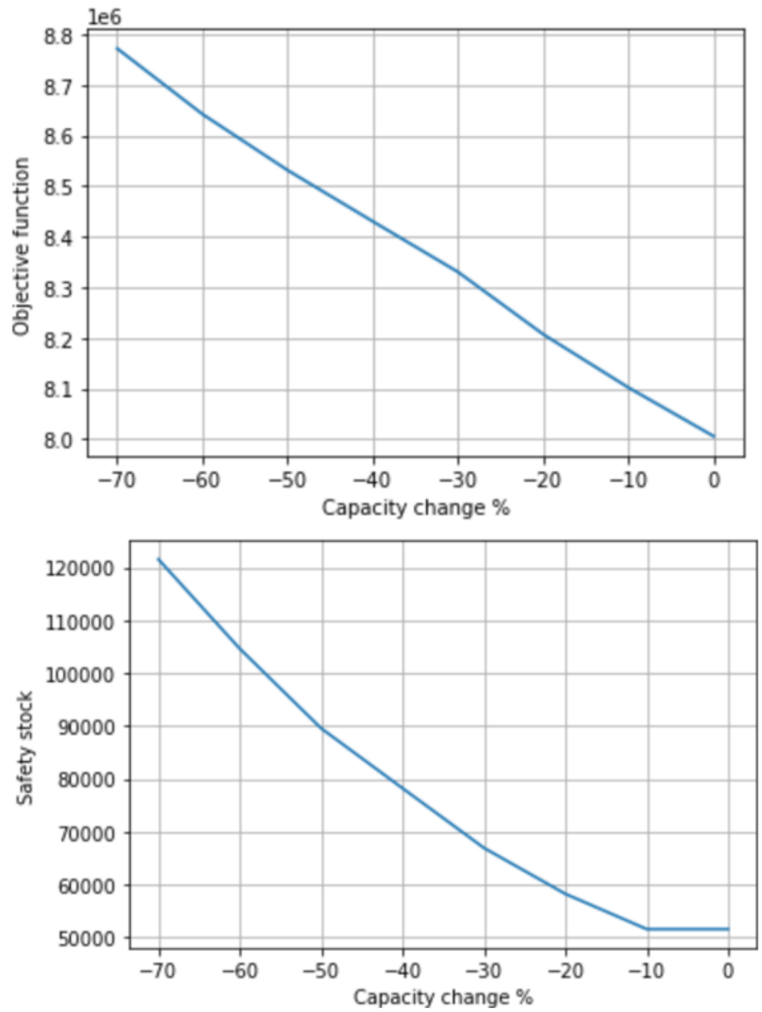


Figure 5.6: Capacity effect

ble disruptions. Demand and facilities' capacity analysis helps the supply chain managers make the best possible strategic decision for their procurement and production plans before facing disruptions. Moreover, the sensitivity analysis of the carbon cap reveals that governments should provide a proper amount of carbon allowance for manufacturers, and shows the optimal interval for the cap.

6. Conclusion and Future Works

6.1 Conclusion

To decrease the harmful effects of the production process, it is vital to control manufacturers' environmental behavior by encouraging them to update their technologies to a greener alternative, and use environmentally friendly materials. One of the activities manufacturers can do to decrease their emission level is selecting the most proper suppliers. To optimize the manufacturer's objectives while considering governmental-issued restrictions such as C&T, this research proposed a multi-objective robust optimization. Also, in order to optimize the interactions between C&T parties, a three-player stochastic game theory model is developed. A numerical example is presented to analyze different aspects of the generalized model and the solution approach.

The present study grants optimal actions a firm can take to minimizes its cost while meeting environmental guidelines. The GSS problem is modeled and makes a flexible decision support system for decision makers. The analysis done on the RO model parameters indicates that cap amount and the trade prices affect the firm's objective. Therefore, manufacturers will find the best suppliers to select, and a proper amount of orders to place with each of the selected suppliers.

Based on the results and sensitivity analyses presented in chapter 3, manufacturers can make informed decisions about the appropriate weighting of their model infeasibility and deviation from various scenarios. Moreover, the managerial insights derived from the analyses of emission cap and allowance prices can assist governments in selecting an appropriate cap for the cap-and-trade scheme, resulting in reduced emissions. Additionally, the study demonstrates that the cap-and-trade mechanism is superior to the penalty-based system in terms of the overall supply chain utility from a micro-economic perspective.

Also, an analysis to validate the developed model on the interactions between C&T players is done. The results indicated that the developed model is reliable in the presence of uncertain parameters. The sensitivity analyses conducted on the game utility offer valuable insights to governments in determining the optimal values for the rigor index and assigning the appropriate emission quota to manufacturers. Additionally, the analyses provide guidance on setting the re-verification rate to minimize the risk of collusion. For supply chain managers, a sensitivity analysis is performed on lead time and customer sensitivity to greenness to prepare them for potential fluctuations in the uncertain parameters of the model and forecast the impact on objective functions. Armed with this information, they can develop a contingency plan to manage the potential uncertainties.

This study also proposes a resilient green supply chain design to decrease the disruption effects of pandemics by finding the best strategies in designing a supply chain to alleviate the ripple effect. A two-stage stochastic optimization approach is applied to control the ripple effect and parameter estimation uncertainty. This model provides a decision-making framework for supply chain managers to use the best transportation channel for the materials and final products, enhance service level, and control uncertainty of estimated model parameters and disruptions.

Chapter 5's sensitivity analyses offer insights for supply chain managers to anticipate the performance of essential and non-essential products during a disruption, enabling them to create contingency plans to meet the demand for essential products while reducing non-essential product inventory to free up storage space and decrease holding costs. Furthermore, this chapter recommends that the government relax its regulations during disruption periods to aid the supply chain in its recovery.

6.2 Future works

Since this study is one of the first to consider cap-and-trade mechanisms in the green supplier selection, more research in this area can be pursued. For instance, this research analyzes the cap changes and their effects on the objectives from the manufacturer's point of view. Accordingly, a motivating topic for future research is finding the optimal value of the cap assigned by the government to reduce the adverse environmental effects of production industries, while remaining business friendly. One could explore a pricing study to find a reasonable range for the allowance prices according to different factors. Specifically, decreasing the cap will leave all of the manufacturers with less allowance for carbon emission. Therefore, the manufacturers will have less allowance to offer in the trade market, resulting in elevated trading prices. In this case, some manufacturers may decide to simply sell their allowance to generate utility. This presents a challenge from the existing problem's perspective.

In this study, we explored the difference between the cap-and-trade system and the penalty-based mechanism to control air pollution from the manufacturer's point of view. If one has access to data about the total amount of carbon released by all manufacturers in the market, one could study the differences between the two particular pollution control regimes from the government's perspective.

This work pioneers the analysis of a three-player game with the interaction between players' decisions in a stochastic environment under cap-and-trade regulations. Given the emerging nature of this field, more research is required. One interesting topic for future work is including all the manufacturers that operate in a C&T market in the analysis. In this case, striving for customer satisfaction leads to competition between these rivals, and may impact their technology upgrade decisions or usage of environmentally friendly materials in the production process.

Also, given that the carbon allowance price is affected by various factors, it is worthwhile to predict the exact value of this parameter. Hence, researching the price of carbon allowance is another inspiring topic for future work. Furthermore, investigating the effect of customer sensitivity to product greenness on the government restriction index represents another interesting topic for future studies. Such analysis enhances the model's ability in governmental and industrial decision-making.

Furthermore, this research employs game theoretical analysis to find the best strategy for the cap-and-trade players as a single decision. However, players' strategies may be dynamic, i.e., the players update their selected strategy for the next periods by analyzing the consequences of their decisions. Evolutionary game theory is a method to find a stable strategy for all the players by considering the dynamic environment of decision-making. Since two players hide their bribery-related actions from the government, the data that lead to the government's best strategy based on the costs and benefits of the re-verification decisions will be scarce. As a result, developing an approach to overcome this issue by redesigning the cap-and-trade mechanism is an interesting topic for future research efforts.

References

Agi, M. A. and Hazir, Ö. (2019). Game theory-based research in green supply chain management: a review. *IFAC-PapersOnLine*, 52(13):2267–2272.

Amin, S. H. and Zhang, G. (2012). An integrated model for closed-loop supply chain configuration and supplier selection: Multi-objective approach. *Expert Systems with Applications*, 39(8):6782–6791.

Amiri-Aref, M., Klibi, W., and Babai, M. Z. (2018). The multi-sourcing location inventory problem with stochastic demand. *European Journal of Operational Research*, 266(1):72–87.

Arabsheybani, A., Paydar, M. M., and Safaei, A. S. (2018). An integrated fuzzy moora method and fmea technique for sustainable supplier selection considering quantity discounts and supplier's risk. *Journal of cleaner production*, 190:577–591.

Arya, A., Mittendorf, B., and Sappington, D. E. (2008). Outsourcing, vertical integration, and price vs. quantity competition. *International Journal of Industrial Organization*, 26(1):1–16.

Awasthi, A., Chauhan, S. S., and Goyal, S. K. (2010). A fuzzy multicriteria approach for evaluating environmental performance of suppliers. *International Journal of Production Economics*, 126(2):370–378.

Axelsson, J. (2019). Game theory applications in systems-of-systems engineering: A literature review and synthesis. *Procedia Computer Science*, 153:154–165.

Badri, H., Ghomi, S. F., and Hejazi, T.-H. (2017). A two-stage stochastic programming approach for value-based closed-loop supply chain network design. *Transportation Research Part E: Logistics and Transportation Review*, 105:1–17.

Bai, C. and Sarkis, J. (2010). Integrating sustainability into supplier selection with grey system and rough set methodologies. *International Journal of Production Economics*, 124(1):252–264.

Bai, W., Wang, J., Yao, Q., Li, Y., Li, J., and Cheng, W. (2016). Investigation of international carbon verification policy-systems. *Journal of Engineering Studies*, 8(3):322–331.

Bhatia, M. S. and Gangwani, K. K. (2021). Green supply chain management: Scientometric review and analysis of empirical research. *Journal of cleaner production*, 284:124722.

Boskabadi, A., Mirmozaffari, M., Yazdani, R., and Farahani, A. (2022). Design of a distribution network in a multi-product, multi-period green supply chain system under demand uncertainty. *Sustainable Operations and Computers*, 3:226–237.

Cao, He, P., and Liu, Z. (2020a). Production and pricing decisions in a dual-channel supply chain under remanufacturing subsidy policy and carbon tax policy. *Journal of the Operational Research Society*, 71(8):1199–1215.

Cao, Tao, L., Wu, K., and Wan, G. (2020b). Coordinating joint greening efforts in an agri-food supply chain with environmentally sensitive demand. *Journal of Cleaner Production*, 277:123883.

Carmona, R., Fehr, M., and Hinz, J. (2009). Optimal stochastic control and carbon price formation. *SIAM Journal on Control and Optimization*, 48(4):2168–2190.

Chai, J., Liu, J. N., and Ngai, E. W. (2013). Application of decision-making techniques in supplier selection: A systematic review of literature. *Expert Systems with Applications*, 40(10):3872–3885.

Chavoshlou, A. S., Khamseh, A. A., and Naderi, B. (2019). An optimization model of three-player payoff based on fuzzy game theory in green supply chain. *Computers & Industrial Engineering*, 128:782–794.

Chen, Tang, H., Wu, J., Li, C., and Wang, Y. (2022). A robust optimization framework for energy management of cchp users with integrated demand response in electricity market. *International Journal of Electrical Power & Energy Systems*, 141:108181.

Chen, Tang, Q., et al. (2021). Modeling carbon emission allowance trading in china's ets.

Chen, Wang, C., Nie, P.-y., and Chen, Z.-r. (2020). A clean innovation comparison between carbon tax and cap-and-trade system. *Energy Strategy Reviews*, 29:100483.

Cheraghi, S. H., Dadashzadeh, M., and Subramanian, M. (2004). Critical success factors for supplier selection: an update. *Journal of Applied Business Research*, 20(2):91–108.

Cui, L., Deng, J., Liu, R., Xu, D., Zhang, Y., and Xu, M. (2020). A stochastic multi-item replenishment and delivery problem with lead-time reduction initiatives and the solving methodologies. *Applied mathematics and computation*, 374:125055.

Darestani, S. A. and Hemmati, M. (2019). Robust optimization of a bi-objective closed-loop supply chain network for perishable goods considering queue system. *Computers & industrial engineering*, 136:277–292.

Dickson, G. W. (1966). An analysis of vendor selection systems and decisions. *Journal of Purchasing*, 2(1):5–17.

Ding, J., Dong, W., Bi, G., and Liang, L. (2015). A decision model for supplier selection in the presence of dual-role factors. *Journal of the Operational Research Society*, 66(5):737–746.

Du, H., Li, B., Brown, M. A., Mao, G., Rameezdeen, R., and Chen, H. (2015). Expanding and shifting trends in carbon market research: a quantitative bibliometric study. *Journal of Cleaner Production*, 103:104–111.

Esmaeili-Najafabadi, E., Azad, N., and Nezhad, M. S. F. (2021). Risk-averse supplier selection and order allocation in the centralized supply chains under disruption risks. *Expert Systems with Applications*, 175:114691.

Fattahi, M., Govindan, K., and Keyvanshokooh, E. (2017). Responsive and resilient supply chain network design under operational and disruption risks with delivery lead-time sensitive customers. *Transportation research part E: Logistics and transportation review*, 101:176–200.

Feng, S., Zhang, R., and Li, G. (2022). Environmental decentralization, digital finance and green technology innovation. *Structural Change and Economic Dynamics*, 61:70–83.

Firouzmakan, P., Hooshmand, R.-A., Bornapour, M., and Khodabakhshian, A. (2019). A comprehensive stochastic energy management system of micro-chp units, renewable energy sources and storage systems in microgrids considering demand response programs. *Renewable and sustainable energy reviews*, 108:355–368.

Foroozesh, N., Karimi, B., and Mousavi, S. (2022). Green-resilient supply chain network design for perishable products considering route risk and horizontal collaboration under robust interval-valued type-2 fuzzy uncertainty: A case study in food industry. *Journal of Environmental Management*, 307:114470.

Gao, J., Kovats, S., Vardoulakis, S., Wilkinson, P., Woodward, A., Li, J., Gu, S., Liu, X., Wu, H., Wang, J., et al. (2018). Public health co-benefits of greenhouse gas emissions reduction: A systematic review. *Science of the Total Environment*, 627:388–402.

Ghodsypour, S. H. and O'brien, C. (2001). The total cost of logistics in supplier selection, under conditions of multiple sourcing, multiple criteria and capacity constraint. *International journal of production economics*, 73(1):15–27.

Gholami-Zanjani, S. M., Klibi, W., Jabalameli, M. S., and Pishvaee, M. S. (2021). The design of resilient food supply chain networks prone to epidemic disruptions. *International Journal of Production Economics*, 233:108001.

Ghomi-Avili, M., Naeini, S. G. J., Tavakkoli-Moghaddam, R., and Jabbarzadeh, A. (2018). A fuzzy pricing model for a green competitive closed-loop supply chain network design in the presence of disruptions. *Journal of Cleaner Production*, 188:425–442.

Giri, B. C., Molla, M. U., and Biswas, P. (2022). Pythagorean fuzzy dematel method for supplier selection in sustainable supply chain management. *Expert Systems with Applications*, 193:116396.

Golpîra, H., Bahramara, S., Khan, S. A. R., and Zhang, Y. (2020). Robust bi-level risk-based optimal scheduling of microgrid operation against uncertainty. *RAIRO-Operations Research*, 54(4):993–1012.

Golpîra, H. and Javanmardan, A. (2021). Decentralized decision system for closed-loop supply chain: A bi-level multi-objective risk-based robust optimization approach. *Computers & Chemical Engineering*, 154:107472.

Golpîra, H. and Javanmardan, A. (2022). Robust optimization of sustainable closed-loop supply chain considering carbon emission schemes. *Sustainable Production and Consumption*.

Golpîra, H., Najafi, E., Zandieh, M., and Sadi-Nezhad, S. (2017). Robust bi-level optimization for green opportunistic supply chain network design problem against uncertainty and environmental risk. *Computers & Industrial Engineering*, 107:301–312.

Gong, X. and Zhou, S. X. (2013). Optimal production planning with emissions trading. *Operations Research*, 61(4):908–924.

Gorissen, B. L., Yanıkoğlu, İ., and den Hertog, D. (2015). A practical guide to robust optimization. *Omega*, 53:124–137.

Govindan, K., Khodaverdi, R., and Jafarian, A. (2013). A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach. *Journal of Cleaner Production*, 47:345–354.

Govindan, K. and Sivakumar, R. (2016). Green supplier selection and order allocation in a low-carbon paper industry: integrated multi-criteria heterogeneous decision-making and multi-objective linear programming approaches. *Annals of Operations Research*, 238(1-2):243–276.

Gupta, H. and Barua, M. K. (2017). Supplier selection among smes on the basis of their green innovation ability using bwm and fuzzy topsis. *Journal of Cleaner Production*, 152:242–258.

Haeri, S. A. S. and Rezaei, J. (2019). A grey-based green supplier selection model for uncertain environments. *Journal of cleaner production*, 221:768–784.

Handfield, R., Walton, S. V., Sroufe, R., and Melnyk, S. A. (2002). Applying environmental criteria to supplier assessment: A study in the application of the analytical hierarchy process. *European Journal of Operational Research*, 141(1):70–87.

Hasani, A., Mokhtari, H., and Fattahi, M. (2021). A multi-objective optimization approach for green and resilient supply chain network design: a real-life case study. *Journal of Cleaner Production*, 278:123199.

Hashemi, S. H., Karimi, A., and Tavana, M. (2015). An integrated green supplier selection approach with analytic network process and improved grey relational analysis. *International Journal of Production Economics*, 159:178–191.

Hendricks, K. B. and Singhal, V. R. (2005). An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production and Operations management*, 14(1):35–52.

Hosseini, S. and Ivanov, D. (2019). A new resilience measure for supply networks with the ripple effect considerations: A bayesian network approach. *Annals of Operations Research*, pages 1–27.

Hosseini, S. and Ivanov, D. (2022). A new resilience measure for supply networks with the ripple effect considerations: A bayesian network approach. *Annals of Operations Research*, 319(1):581–607.

Hosseini, S., Ivanov, D., and Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, 125:285–307.

Hosseini, S., Ivanov, D., and Dolgui, A. (2020). Ripple effect modelling of supplier disruption: integrated markov chain and dynamic bayesian network approach. *International Journal of Production Research*, 58(11):3284–3303.

Hosseini-Motlagh, S.-M., Nouri-Harzvili, M., Choi, T.-M., and Ebrahimi, S. (2019). Reverse supply chain systems optimization with dual channel and demand disruptions: Sustainability, csr investment and pricing coordination. *Information Sciences*, 503:606–634.

Hsu, C.-W. and Hu, A. H. (2009). Applying hazardous substance management to supplier selection using analytic network process. *Journal of Cleaner Production*, 17(2):255–264.

Hu, Z., Rao, C., Zheng, Y., and Huang, D. (2015). Optimization decision of supplier selection in green procurement under the mode of low carbon economy. *International Journal of Computational Intelligence Systems*, 8(3):407–421.

Huang, Y., Wang, K., Zhang, T., and Pang, C. (2016). Green supply chain coordination with greenhouse gases emissions management: a game-theoretic approach. *Journal of Cleaner Production*, 112:2004–2014.

Ivanov, D. and Dolgui, A. (2022). Stress testing supply chains and creating viable ecosystems. *Operations Management Research*, 15(1):475–486.

Ivanov, D., Dolgui, A., and Sokolov, B. (2015). Supply chain design with disruption considerations: Review of research streams on the ripple effect in the supply chain. *IFAC-PapersOnLine*, 48(3):1700–1707.

Ivanov, D., Dolgui, A., and Sokolov, B. (2019). The impact of digital technology and industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3):829–846.

Ivanov, D., Pavlov, A., Dolgui, A., Pavlov, D., and Sokolov, B. (2016). Disruption-driven supply chain (re)-planning and performance impact assessment with consideration of pro-active and recovery policies. *Transportation Research Part E: Logistics and Transportation Review*, 90:7–24.

Jabbarzadeh, A., Fahimnia, B., and Sabouhi, F. (2018). Resilient and sustainable supply chain design: sustainability analysis under disruption risks. *International Journal of Production Research*, 56(17):5945–5968.

Jabbarzadeh, A., Haughton, M., and Pourmehdi, F. (2019). A robust optimization model for efficient and green supply chain planning with postponement strategy. *International Journal of Production Economics*, 214:266–283.

Jeyakumar, V., Li, G., and Suthaharan, S. (2014). Support vector machine classifiers with uncertain knowledge sets via robust optimization. *Optimization*, 63(7):1099–1116.

Jiang, X., Wang, L., Cao, B., and Fan, X. (2021). Benefit distribution and stability analysis of enterprises' technological innovation cooperation alliance. *Computers & Industrial Engineering*, 161:107637.

John, S. T., Sridharan, R., Kumar, P. R., and Krishnamoorthy, M. (2018). Multi-period reverse logistics network design for used refrigerators. *Applied Mathematical Modelling*, 54:311–331.

Kamalahmadi, M. and Mellat-Parast, M. (2016). Developing a resilient supply chain through supplier flexibility and reliability assessment. *International Journal of Production Research*, 54(1):302–321.

Kannan, D., Govindan, K., and Rajendran, S. (2015). Fuzzy axiomatic design approach based green supplier selection: a case study from singapore. *Journal of Cleaner Production*, 96:194–208.

Khalil, F. and Lawarree, J. (1995). Collusive auditors. *The American Economic Review*, 85(2):442–446.

Khaloie, H., Abdollahi, A., Shafie-Khah, M., Anvari-Moghaddam, A., Nojavan, S., Siano, P., and Catalão, J. P. (2020). Coordinated wind-thermal-energy storage offering strategy in energy and spinning reserve markets using a multi-stage model. *Applied Energy*, 259:114168.

Kim, Y., Chen, Y.-S., and Linderman, K. (2015). Supply network disruption and resilience: A network structural perspective. *Journal of operations Management*, 33:43–59.

Knoope, M., Ramírez, A., and Faaij, A. (2015). The influence of uncertainty in the development of a co2 infrastructure network. *Applied Energy*, 158:332–347.

Krass, D., Nedorezov, T., and Ovchinnikov, A. (2013). Environmental taxes and the choice of green technology. *Production and operations management*, 22(5):1035–1055.

Kumar, P., Singh, R. K., and Vaish, A. (2017). Suppliers' green performance evaluation using fuzzy extended electre approach. *Clean Technologies and Environmental Policy*, 19(3):809–821.

Kundu, A., Guchhait, P., Maiti, M., and Castillo, O. (2021). Inventory of a deteriorating green product with preservation technology cost using a hybrid algorithm. *Soft Computing*, 25(17):11621–11636.

Kuo, R. J., Wang, Y. C., and Tien, F. C. (2010). Integration of artificial neural network and mada methods for green supplier selection. *Journal of Cleaner Production*, 18(12):1161–1170.

Lamba, K. and Singh, S. P. (2019). Dynamic supplier selection and lot-sizing problem considering carbon emissions in a big data environment. *Technological Forecasting and Social Change*, 144:573–584.

Lee, A. H., Kang, H.-Y., Hsu, C.-F., and Hung, H.-C. (2009). A green supplier selection model for high-tech industry. *Expert Systems with Applications*, 36(4):7917–7927.

Lehmann, D. R. and O'shaughnessy, J. (1974). Difference in attribute importance for different industrial products: A bi-national study analyzes how industrial buyers evaluate different product categories. *Journal of Marketing*, 38(2):36–42.

Letmathe, P. and Balakrishnan, N. (2005). Environmental considerations on the optimal product mix. *European Journal of Operational Research*, 167(2):398–412.

Li, Liao, G., Wang, Z., and Huang, Z. (2018a). Green loan and subsidy for promoting clean production innovation. *Journal of Cleaner Production*, 187:421–431.

Li, Zheng, H., Ji, X., and Li, H. (2018b). Game theoretical analysis of firms' operational low-carbon strategy under various cap-and-trade mechanisms. *Journal of Cleaner Production*, 197:124–133.

Liao, T.-Y. (2018). Reverse logistics network design for product recovery and remanufacturing. *Applied Mathematical Modelling*, 60:145–163.

Liu, M., Liu, Z., Chu, F., Dolgui, A., Chu, C., and Zheng, F. (2022a). An optimization approach for multi-echelon supply chain viability with disruption risk minimization. *Omega*, page 102683.

Liu, S., He, X., Chan, F. T., and Wang, Z. (2022b). An extended multi-criteria group decision-making method with psychological factors and bidirectional influence relation for emergency medical supplier selection. *Expert Systems with Applications*, 202:117414.

Lu, X., Liu, Z., Ma, L., Wang, L., Zhou, K., and Feng, N. (2020). A robust optimization approach for optimal load dispatch of community energy hub. *Applied Energy*, 259:114195.

Ludkovski, M. (2011). Stochastic switching games and duopolistic competition in emissions markets. *SIAM Journal on Financial Mathematics*, 2(1):488–511.

Luthra, S., Govindan, K., Kannan, D., Mangla, S. K., and Garg, C. P. (2017). An integrated framework for sustainable supplier selection and evaluation in supply chains. *Journal of Cleaner Production*, 140:1686–1698.

Mafakheri, F., Breton, M., and Ghoniem, A. (2011). Supplier selection-order allocation: A two-stage multiple criteria dynamic programming approach. *International Journal of Production Economics*, 132(1):52–57.

Mahmoudi, A., Govindan, K., Shishebori, D., and Mahmoudi, R. (2021). Product pricing problem in green and non-green multi-channel supply chains under government intervention and in the presence of third-party logistics companies. *Computers & Industrial Engineering*, 159:107490.

Memon, M. S., Lee, Y. H., and Mari, S. I. (2015a). Group multi-criteria supplier selection using combined grey systems theory and uncertainty theory. *Expert Systems with Applications*, 42(21):7951–7959.

Memon, M. S., Lee, Y. H., and Mari, S. I. (2015b). Group multi-criteria supplier selection using combined grey systems theory and uncertainty theory. *Expert Systems with Applications*, 42(21):7951–7959.

Mirzaee, H., Naderi, B., and Pasandideh, S. H. R. (2018). A preemptive fuzzy goal programming model for generalized supplier selection and order allocation with incremental discount. *Computers & Industrial Engineering*, 122:292–302.

Mirzaee, H., Samarghandi, H., and Willoughby, K. (2022). A three-player game theory model for carbon cap-and-trade mechanism with stochastic parameters. *Computers & Industrial Engineering*, page 108285.

Mohammed, A., Wang, Q., and Li, X. (2017). A cost-effective decision-making algorithm for an rfid-enabled hmsc network design: A multi-objective approach. *Industrial Management & Data Systems*.

Moheb-Alizadeh, H. and Handfield, R. (2018). An integrated chance-constrained stochastic model for efficient and sustainable supplier selection and order allocation. *International Journal of Production Research*, 56(21):6890–6916.

Mohebalizadehgashti, F., Zolfagharinia, H., and Amin, S. H. (2020). Designing a green meat supply chain network: A multi-objective approach. *International Journal of Production Economics*, 219:312–327.

Monostori, J. (2021). Mitigation of the ripple effect in supply chains: Balancing the aspects of robustness, complexity and efficiency. *CIRP Journal of Manufacturing Science and Technology*, 32:370–381.

Mulvey, J. M., Vanderbei, R. J., and Zenios, S. A. (1995). Robust optimization of large-scale systems. *Operations Research*, 43(2):264–281.

Muneeb, S. M., Adhami, A. Y., Jalil, S. A., and Asim, Z. (2018). Decentralized bi-level decision planning model for municipal solid waste recycling and management with cost reliability under uncertain environment. *Sustainable Production and Consumption*, 16:33–44.

Ni, N., Howell, B. J., and Sharkey, T. C. (2018). Modeling the impact of unmet demand in supply chain resiliency planning. *Omega*, 81:1–16.

Nouira, I., Frein, Y., and Hadj-Alouane, A. B. (2014). Optimization of manufacturing systems under environmental considerations for a greenness-dependent demand. *International Journal of Production Economics*, 150:188–198.

Oberthür, S. and Ott, H. E. (1999). *The Kyoto Protocol: international climate policy for the 21st century*. Springer Science & Business Media.

Oksuz, M. K. and Satoglu, S. I. (2020). A two-stage stochastic model for location planning of temporary medical centers for disaster response. *International Journal of Disaster Risk Reduction*, 44:101426.

Özçelik, G., Faruk Yılmaz, Ö., and Betül Yeni, F. (2021). Robust optimisation for ripple effect on reverse supply chain: an industrial case study. *International Journal of Production Research*, 59(1):245–264.

O'Brien, C. (2013). Fifty years of shifting paradigms. *International Journal of Production Research*, 51(23-24):6740–6745.

Pan, Y., Yang, W., Ma, N., Chen, Z., Zhou, M., and Xiong, Y. (2019). Game analysis of carbon emission verification: A case study from shenzhen's cap-and-trade system in china. *Energy Policy*, 130:418–428.

Pavlov, A., Ivanov, D., Dolgui, A., and Sokolov, B. (2017). Hybrid fuzzy-probabilistic approach to supply chain resilience assessment. *IEEE Transactions on Engineering Management*, 65(2):303–315.

Pishvaee, M. S., Rabbani, M., and Torabi, S. A. (2011). A robust optimization approach to closed-loop supply chain network design under uncertainty. *Applied Mathematical Modelling*, 35(2):637–649.

Qin, J., Liu, X., and Pedrycz, W. (2017). An extended todim multi-criteria group decision making method for green supplier selection in interval type-2 fuzzy environment. *European Journal of Operational Research*, 258(2):626–638.

Rao, P. and Holt, D. (2005). Do green supply chains lead to competitiveness and economic performance? *International Journal of Operations & Production Management*, 25(9):898–916.

Rao, S. S. (2019). *Engineering optimization: theory and practice*. John Wiley & Sons.

Rashidi, K. and Cullinane, K. (2019). A comparison of fuzzy dea and fuzzy topsis in sustainable supplier selection: Implications for sourcing strategy. *Expert Systems with Applications*, 121:266–281.

Reuters (2020).

Rezaei, J., Nispeling, T., Sarkis, J., and Tavasszy, L. (2016). A supplier selection life cycle approach integrating traditional and environmental criteria using the best worst method. *Journal of Cleaner Production*, 135:577–588.

Rezapour, S., Farahani, R. Z., and Pourakbar, M. (2017). Resilient supply chain network design under competition: A case study. *European Journal of Operational Research*, 259(3):1017–1035.

Rout, C., Paul, A., Kumar, R. S., Chakraborty, D., and Goswami, A. (2021). Integrated optimization of inventory, replenishment and vehicle routing for a sustainable supply chain under carbon emission regulations. *Journal of Cleaner Production*, 316:128256.

Sang, X. and Liu, X. (2016). An interval type-2 fuzzy sets-based todim method and its application to green supplier selection. *Journal of the Operational Research Society*, 67(5):722–734.

Saputro, T. E., Figueira, G., and Almada-Lobo, B. (2023). Hybrid mcdm and simulation-optimization for strategic supplier selection. *Expert Systems with Applications*, page 119624.

Sawik, T. (2019). Disruption mitigation and recovery in supply chains using portfolio approach. *Omega*, 84:232–248.

Sharma, M., Joshi, S., Luthra, S., and Kumar, A. (2022). Managing disruptions and risks amidst covid-19 outbreaks: role of blockchain technology in developing resilient food supply chains. *Operations Management Research*, 15(1):268–281.

Shen, B., Dai, F., Price, L., and Lu, H. (2014). California's cap-and-trade programme and insights for china's pilot schemes. *Energy & Environment*, 25(3-4):551–575.

Sheu, J.-B. and Chen, Y. J. (2012). Impact of government financial intervention on competition among green supply chains. *International Journal of Production Economics*, 138(1):201–213.

Sinayi, M. and Rasti-Barzoki, M. (2018). A game theoretic approach for pricing, greening, and social welfare policies in a supply chain with government intervention. *Journal of Cleaner Production*, 196:1443–1458.

Snyder, L. V., Atan, Z., Peng, P., Rong, Y., Schmitt, A. J., and Sinsoysal, B. (2016). Or/ms models for supply chain disruptions: A review. *Iie Transactions*, 48(2):89–109.

Song, Y., Liu, T., Liang, D., Li, Y., and Song, X. (2019). A fuzzy stochastic model for carbon price prediction under the effect of demand-related policy in china's carbon market. *Ecological Economics*, 157:253–265.

Srivastava, S. K. (2007). Green supply-chain management: a state-of-the-art literature review. *International Journal of Management Reviews*, 9(1):53–80.

Sun, Y., Guan, W., Razzaq, A., Shahzad, M., and An, N. B. (2022). Transition towards ecological sustainability through fiscal decentralization, renewable energy and green investment in oecd countries. *Renewable Energy*, 190:385–395.

Thevenin, S., Ben-Ammar, O., and Brahimi, N. (2022). Robust optimization approaches for purchase planning with supplier selection under lead time uncertainty. *European Journal of Operational Research*, 303(3):1199–1215.

Tomlin, B. (2006). On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management science*, 52(5):639–657.

Tordecilla, R. D., Juan, A. A., Montoya-Torres, J. R., Quintero-Araujo, C. L., and Panadero, J. (2021). Simulation-optimization methods for designing and assessing resilient supply chain networks under uncertainty scenarios: A review. *Simulation modelling practice and theory*, 106:102166.

Tseng, M.-L. and Chiu, A. S. (2013). Evaluating firm's green supply chain management in linguistic preferences. *Journal of Cleaner Production*, 40:22–31.

Tucker, E. L., Daskin, M. S., Sweet, B. V., and Hopp, W. J. (2020). Incentivizing resilient supply chain design to prevent drug shortages: policy analysis using two-and multi-stage stochastic programs. *IISE Transactions*, 52(4):394–412.

Vahdani, B., Tavakkoli-Moghaddam, R., Modarres, M., and Baboli, A. (2012a). Reliable design of a forward/reverse logistics network under uncertainty: a robust-m/m/c queuing model. *Transportation Research Part E: Logistics and Transportation Review*, 48(6):1152–1168.

Vahdani, B., Tavakkoli-Moghaddam, R., Modarres, M., and Baboli, A. (2012b). Reliable design of a forward/reverse logistics network under uncertainty: a robust-m/m/c queuing model. *Transportation Research Part E: Logistics and Transportation Review*, 48(6):1152–1168.

Wang, F., Lai, X., and Shi, N. (2011). A multi-objective optimization for green supply chain network design. *Decision support systems*, 51(2):262–269.

Wang, W., Zhang, Y., Zhang, W., Gao, G., and Zhang, H. (2021). Incentive mechanisms in a green supply chain under demand uncertainty. *Journal of Cleaner Production*, 279:123636.

Weber, C. A., Current, J. R., and Benton, W. (1991). Vendor selection criteria and methods. *European Journal of Operational Research*, 50(1):2–18.

Wu, C., Lin, Y., and Barnes, D. (2021). An integrated decision-making approach for sustainable supplier selection in the chemical industry. *Expert Systems with Applications*, 184:115553.

Xia, L., Guo, T., Qin, J., Yue, X., and Zhu, N. (2018). Carbon emission reduction and pricing policies of a supply chain considering reciprocal preferences in cap-and-trade system. *Annals of Operations Research*, 268:149–175.

Xing, J., Meng, H., and Meng, X. (2020). An urban pipeline accident model based on system engineering and game theory. *Journal of Loss Prevention in the Process Industries*, 64:104062.

Xu, X., Chen, Y., He, P., Yu, Y., and Bi, G. (2021a). The selection of marketplace mode and reselling mode with demand disruptions under cap-and-trade regulation. *International Journal of Production Research*, pages 1–20.

Xu, X., He, P., Xu, H., and Zhang, Q. (2017). Supply chain coordination with green technology under cap-and-trade regulation. *International Journal of Production Economics*, 183:433–442.

Xu, X., He, P., and Zhang, S. (2021b). Channel addition from marketplace or reselling under regional carbon cap-and-trade regulation. *International Journal of Production Economics*, 236:108130.

Yang, Y., Goodarzi, S., Bozorgi, A., and Fahimnia, B. (2021). Carbon cap-and-trade schemes in closed-loop supply chains: Why firms do not comply? *Transportation Research Part E: Logistics and Transportation Review*, 156:102486.

Yeh, W.-C. and Chuang, M.-C. (2011). Using multi-objective genetic algorithm for partner selection in green supply chain problems. *Expert Systems with Applications*, 38(4):4244–4253.

Yılmaz, Ö. F., Özçelik, G., and Yeni, F. B. (2021). Ensuring sustainability in the reverse supply chain in case of the ripple effect: A two-stage stochastic optimization model. *Journal of cleaner production*, 282:124548.

Yu and Li, H.-L. (2000). A robust optimization model for stochastic logistic problems. *International Journal of Production Economics*, 64(1-3):385–397.

Yu, Li, X., and Xu, X. (2021). Reselling or marketplace mode for an online platform: the choice between cap-and-trade and carbon tax regulation. *Annals of Operations Research*, pages 1–37.

Yu, Yang, Y., and Chang, D. (2018). Carbon footprint based green supplier selection under dynamic environment. *Journal of Cleaner Production*, 170:880–889.

Zahiri, B., Jula, P., and Tavakkoli-Moghaddam, R. (2018). Design of a pharmaceutical supply chain network under uncertainty considering perishability and substitutability of products. *Information Sciences*, 423:257–283.

Zhang, Wang, C., and Yu, C. (2019a). The evolutionary game analysis and simulation with system dynamics of manufacturer's emissions abatement behavior under cap-and-trade regulation. *Applied Mathematics and Computation*, 355:343–355.

Zhang and Xu, L. (2013). Multi-item production planning with carbon cap and trade mechanism. *International Journal of Production Economics*, 144(1):118–127.

Zhang, S., Zhang, P., and Zhang, M. (2019b). Fuzzy emergency model and robust emergency strategy of supply chain system under random supply disruptions. *Complexity*, 2019.