Robust and Optimal Design of Sustainable Closed Loop Supply Chain Considering E-commerce and Environmental Impacts

（電子商取引と環境への影響を考慮した持続可能な閉ループサプライチェーンのロバスト最適設計）

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Doctor of Philosophy (Engineering)

ESSAM KAOUD MOHAMMED MOUHRAN

イサム　カオド　ムハマド　ムーヘラン

Toyohashi University of Technology

I would like to dedicate this thesis to my loving parents, my wife, and my kids, Albaraa, and the twin Tamim and Tayem . I love you to the moon and back.

Declaration

I hereby certify that the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification at this or any other university, except when specific references to the work of others are made. Except as stated in the text and acknowledgements, this dissertation is my own work and contains nothing that is the result of collaboration with others.

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Abstract

In recent years, governments have been applying pressure and refining legislation to encourage organizations and a broad sector of customers to adopt green and sustainable practices in their production and service activities. This is to handle the population growth, which requires more products to be manufactured, resulting in the limited availability of raw materials and an increase in the rate of pollution emissions. The depletion of natural resources and the degradation of the ecosystem have led many countries to adopt closed-loop supply activities in both their industrial and service sectors. With the widespread use of Internet technology, these aspects motivate the incorporation of e-commerce with the classical closed-loop supply chain. This dissertation suggests a novel mixed-integer linear programming (MILP) model that addresses the integration of e-commerce with a multi-echelon closed-loop supply chain with a multi-period planning time horizon by considering dual channels in manufacturing, and recovery facilities. To validate the model, we obtain optimal decision variables and examine the robustness and applicability of the model, and comprehensive computational experiments are performed. Moreover, sensitivity analysis is carried out to illustrate the efficacy of e-commerce integration by considering the two channels in the closed-loop supply chain. Accordingly, the total cost of the dual-channel closed-loop supply chain decreases with an increase in customer demand via online retailers, the returned end of life products, recycling ratio, and recovery ratio. Some useful managerial implications are provided based on the conducted analysis.

Most real-life optimization problems are subjected to uncertainty, and the robust optimization approach is one of the efficient techniques to deal with uncertain optimization problems. Supply chain optimization problems are highly sensitive to data perturbations mostly due to the inappropriate estimation of the problem's parameters and the highly dynamic environment. In this dissertation, we propose an adaptable robust optimization model for the dual-channel closed-loop supply chain and present two counterpart models; the first model is an MILP model based on the adjustable box uncertainty set, while the second robust model is a mixed integer nonlinear programming (MINLP) model based on the adjustable ellipsoidal uncertainty set. We provide a novel approach for considering multiple uncertainty sets in the objective function, that provide flexibility and control risk based on the preferences of the decision-makers. This study aims at minimizing the total cost of the dual-channel closed-loop supply chain network considering uncertain purchasing, transportation, fixed, and processes costs, in addition to uncertain customer demand. Intensive computational experiments are

conducted on the two robust models using GAMS software. Robust solutions are obtained, and sensitivity analysis is conducted on both models considering 10% perturbation of the uncertain parameters around their nominal values as well as a probability guarantee for not violating the constraints.

In this study, we propose a robust bi-objective optimization model of the green closed-loop supply chain network considering presorting, heterogeneous transportation system, and carbon emissions. The proposed model is an uncertain bi-objective MILP model aims at maximizing the profit and minimizing carbon emissions considering uncertain cost, selling price, and carbon emissions. Robust optimization approach is implemented using "Interval+ polyhedral " uncertainty set to model the robust counterpart of the bi-objective model. The robust Pareto optimal solutions are obtained using lexicographic weighted Tchebycheff optimization approach of the bi-objective model. Intensive computational experiments are conducted, and robust Pareto optimal front is obtained with the probability guarantee of the constraints that contains uncertain parameters are not violated (constraints satisfaction).

Table of contents

List of figures xiii

List of tables xv

1 Introduction 1

1.1 Supply chain definition and its significance 1
1.2 Reverse logistics in supply chain 2
1.3 Closing the loop of supply chain 3
1.4 Sustainable closed-loop supply chain 4
1.5 Motivations of the study 6
1.6 Contributions of the study 7
1.7 Literature review 8
1.7.1 Relevant literature of the robust and optimal design of dual-channel CLSC network 8
1.7.2 Relevant literature of robust design of uncertain single and multiple-objective CLSC network 10
1.8 Thesis outlines 13

2 Design and optimization of the closed-loop supply chain with considering e-commerce 17

2.1 Introduction 17
2.2 Problem description 18
2.2.1 Model assumptions 19
2.3 Mathematical formulation 19
2.4 Computational experiments 27
2.4.1 Description of the data 28
2.4.2 Results 29
2.4.3 Sensitivity analysis of the dual-channel CLSC parameters 30

2.4.4 Managerial implications for the dual-channel CLSC 34
2.5 Conclusions 34

3 An adaptable robust optimization model for a dual-channel closed-loop supply chain considering cost and demand uncertainty 37
3.1 Introduction 37
3.2 Robust optimization paradigm 38
3.2.1 Robust counterpart of MILP based on the box uncertainty set 40
3.2.2 Robust counterpart of uncertain MILP model based on the ellipsoidal uncertainty set 41
3.3 Mathematical formulation of uncertain dual-channel CLSC 43
3.3.1 Robust model of the dual-channel CLSC based on the adjustable box uncertainty set 44
3.3.2 Robust model of the dual-channel CLSC based on the adjustable ellipsoidal uncertainty set 46
3.4 Computational experiments 47
3.4.1 Impact analysis of multiple-uncertainty sets to the OF 47
3.4.2 Performance of interactive multiple-uncertainty sets OF with demand uncertainty 52
3.4.3 Selecting an adequate uncertainty set shape and size 54
3.5 Conclusions 54

4 Robust optimization for a bi-objective green closed-loop supply chain with heterogeneous transportation system and presorting consideration 57
4.1 Inroduction 57
4.2 Problem statement and mathematical formulation 60
4.3 The robust model of bi-objective green closed-loop supply chain 69
4.3.1 Probability upper bound of constraint violation in the robust optimization 74
4.3.2 Solution approach 75
4.4 Computational experiments 77
4.5 Conclusions 82

5 Conclusions and directions for future work 83
5.1 Conclusions 83
5.2 Directions for future work 84

References 87

Appendix A List of publications 97

List of figures

1.1 Forward supply chain network. 2
1.2 Reverse supply chain network. 3
1.3 Closing the loop of supply chain. 4
1.4 Sustainable supply chain aspects. 5
1.5 Thesis outline. 15

2.1 The proposed dual-channel closed-loop supply chain. 20
2.2 Influence of the demand via online retailers on the number of opening times of traditional retailers. 32
2.3 Impact of the ratio of EOL products on purchasing and transportation costs. 33

3.1 Illustration of the adjustable box uncertainty set. 41
3.2 Illustration of the adjustable ellipsoidal uncertainty set. 42
3.3 Results of the robust dual-channel CLSC with transportation cost uncertainty. 49
3.4 Results of the robust dual-channel CLSC with purchasing cost uncertainty. . 50
3.5 Results of the robust dual-channel CLSC with operations cost uncertainty. . 51
3.6 Results of the robust dual-channel CLSC with fixed cost uncertainty. 52

4.1 The logical framework of the proposed robust GCLSC network. 59
4.2 The proposed GCLSC network. 64
4.3 Illustration of the "Interval+Polyhedral" uncertainty set. 71
4.4 Pareto optimal solution representation. 75
4.5 Robust Pareto front with 90% probability of constraints satisfaction (5% perturbation). 81
4.6 Robust Pareto front with 90% probability of constraints satisfaction (10% perturbation). 81

List of tables

1.1 Relevant literature of the robust and optimal design of dual- channel CLSC network . . . 9
1.2 Relevant literature pertinent to uncertain CLSC models . . . 14

2.1 Nomenclature of the mathematical formulation of the dual-channel CLSC model. . . . 21
2.2 The capacities of CLSC facilities for different periods of time. . . . 28
2.3 The model's parameter values. . . . 29
2.4 The customers demand of products. . . . 29
2.5 Strategic and tactical decisions for the dual-channel CLSC. . . . 31
2.6 The impact of the ratios of manufactured and recovered products for traditional retailers on the dual-channel CLSC's cost. . . . 32
2.7 The effect of customer demand on the dual-channel CLSC's cost. . . . 32
2.8 Effect of the proportion of the EOL products directed to reverse logistics. . . 33
2.9 The change in reverse ratios of recycling, disposal, and recovery centers. . . 35

3.1 Nominal values of model's input parameters . . . 48
3.2 Total cost incurred in the robust dual-channel CLSC. . . . 53

4.1 Nomenclature of the proposed bi-objective GCLSC model. . . . 61
4.2 Cost, carbon emissions rate, and capacity of transportation modes . . . 77
4.3 Returned products, operations cost, and selling price of refurbished products 77
4.4 Capacities and fixed opening costs of different IR center sizes . . . 77
4.5 Distances between the GCLSC facilities . . . 78
4.6 Rest of the model's parameters . . . 78
4.7 Robust Pareto front at 80% constraints satisfaction (5% perturbations). . . 78
4.8 Robust Pareto front at 80% constraints satisfaction (10% perturbations). . . 79
4.9 Robust Pareto front at 85% constraints satisfaction (5% perturbations). . . 79
4.10 Robust Pareto front at 85% constraints satisfaction (10% perturbations). . . 79

4.11 Robust Pareto front at 90% constraints satisfaction (5% perturbations). . . 80
4.12 Robust Pareto front at 90% constraints satisfaction (10% perturbations). . . 80

Chapter 1

Introduction

1.1 Supply chain definition and its significance

The terms "supply chain management" and "logistics" are so closely connected that it's difficult to distinguish between them. Furthermore, it is difficult to define supply chain management since it has developed through time as the aims and components of supply chains have changed [102]. The Council of Supply Chain Management Professionals (CSCMP) offers one of the most authorized definitions of supply chain as:

"Supply chain management encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies" [2].

The supply chain as actually represented as schematic network as shown in Figure 1.1 each vertical level (Suppliers, plants, distributers, and customers) is called echelon, the node is represent the locations of facilities, and the arrows the represent the flow of commodities or information. Regardless of the type of business or the customer's location, supply chain management affects every consumer and every firm. In the United States, supply chain management practices cost the companies about $US 1.5 trillion per year that constitutes around 8% of the USA gross domestic product. These practices include numerous tasks such as production planning, supplier selection,inventory management, procurement, and shipping.

Optimization methods have been widely performed in supply chain management which support the managers to improve the quality of their decisions, apply risk mitigation strate-

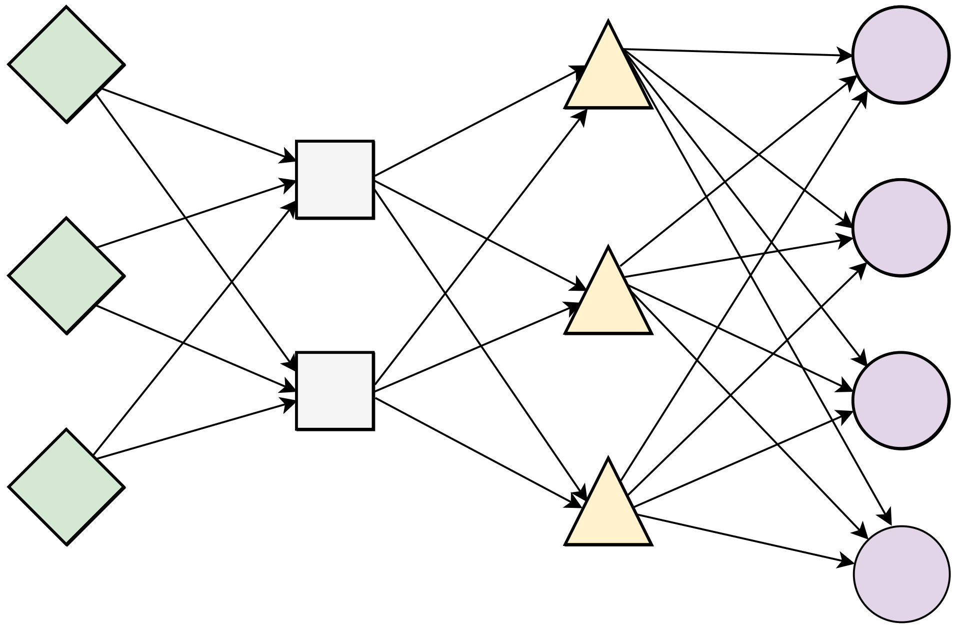


Fig. 1.1 Forward supply chain network.

gies for SC, and propose optimal responses in trade-off problems, involving, for instance, Economic, environmental , and social considerations.

1.2 Reverse logistics in supply chain

According to the American Reverse Logistics Executive Council, reverse logistics is defined as “The process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal” [95] .

Indeed, reverse logistics, in general forms, as shown in Figure 1.2 start from end users (first customers) where used products are collected from customers (return products) and then attempts to manage end of life (EOL) products through different decisions are undertaken including recycling (to have more raw materials or raw parts), remanufacturing (to resale them to second markets or if possible to first customers), repairing (to sell in the second markets through repairing), and finally, disposing of some used parts Reverse logistics has become an important source of opportunity for companies to improve visibility and profitability and lower costs across supply chain. Therefore, environmental issues are also

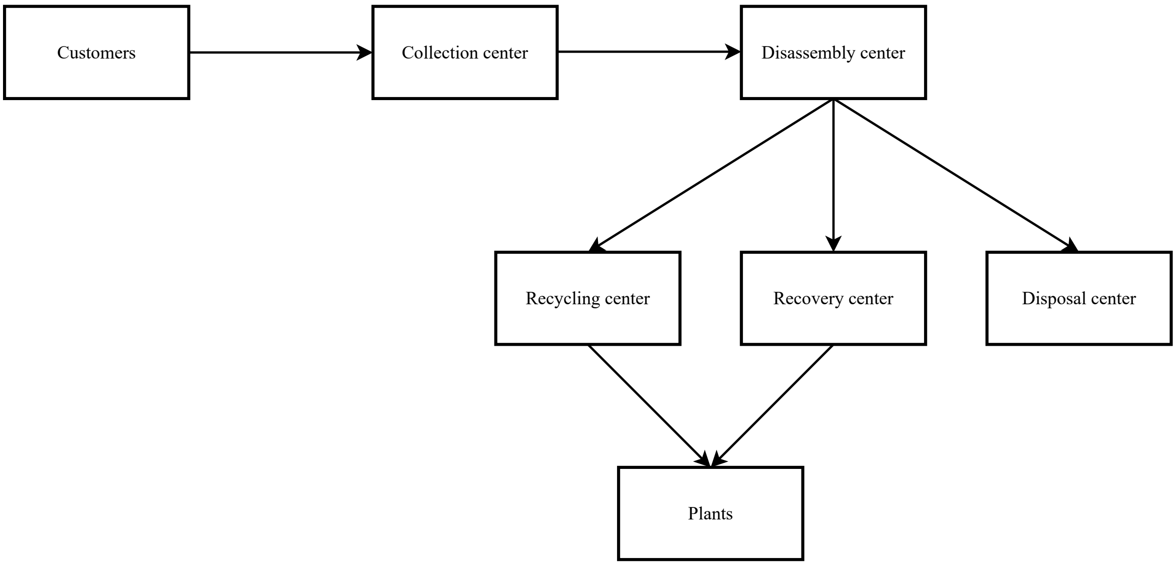


Fig. 1.2 Reverse supply chain network.

increasing awareness of the importance of reverse logistics [31] .
This enhanced supply chain is, therefore, capable of effectively using resources that were not previously considered or utilized [36].

1.3 Closing the loop of supply chain

Companies have begun to close the loop in their supply chains in order to comply with regulations and improve the sustainability of their systems in recent years. The term of "closing loops" refers to the integration of forward and reverse supply chains as shown in Figure 1.3; it is one of the alternatives for improving sustainability [15].
Forward supply chains (FSC) are responsible for satisfying demand for new items in a closed-loop supply chain (CLSC), whereas reverse supply chains (RSC) are responsible for collecting and recovering returned products.

CLSCs are being implemented by a variety of businesses. P&G, for example, is trying to make its whole production activities closed-loop by reducing or recycling nearly 650,000 metric tons of trash that would have gone to a landfill, according to Scott et al. [100].
One of California's largest wineries, Fetzer Vineyards, has likewise successfully implemented a closed-loop supply chain, Dell is attempting to introduce CLSC [7]. There are several challenges for implementing CLSCs concept, and in some industries, it is difficult but not impossible. The conventional supply chain tries to reduce costs and increase supply chain efficiency in order to maximize economic advantages. CLSC also aims to maximize

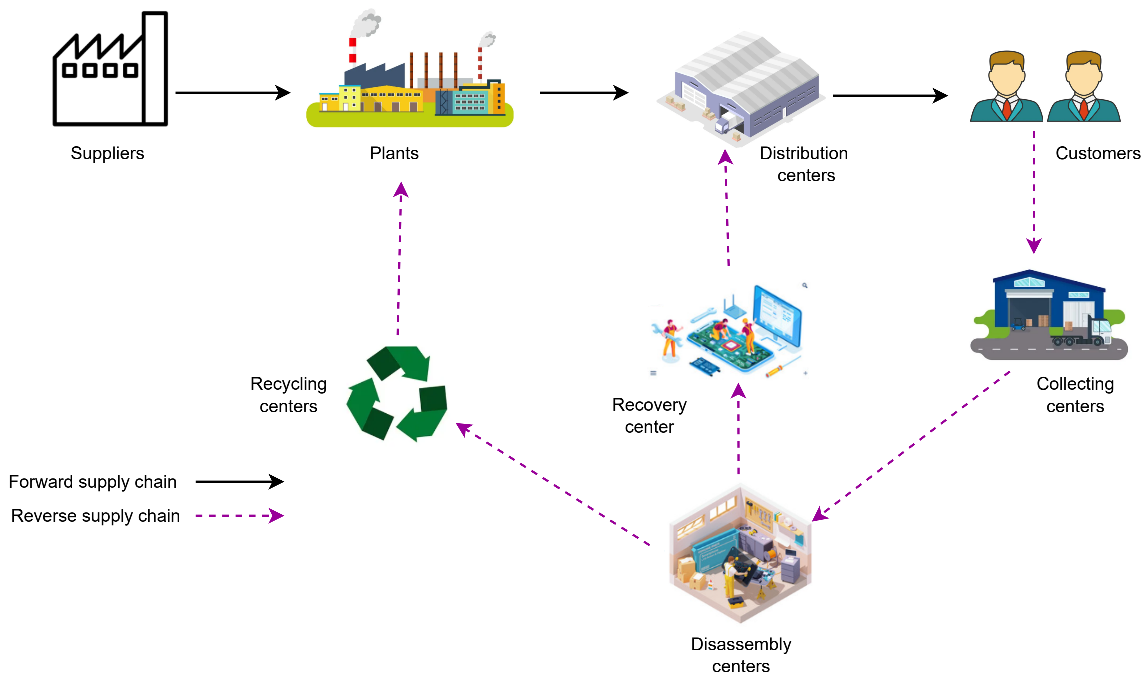


Fig. 1.3 Closing the loop of supply chain.

economic gains while lowering consumption. Everything in an effort to conserve resources and energy, as well as to limit pollutant emissions. Attempt to develop a socially responsible business and to achieve economic balance. Benefits, social consequences, and environmental impacts are all factors to consider.

1.4 Sustainable closed-loop supply chain

The European Commission recognise the importance to the economy of efficient and effective supply chains, and also recognise the potential negative impacts on society and the environment [32]. Supply chain management should be concerned with its sustainability as well.

Lean, resilient, and green approaches are referred to as sustainable supply chain management (SSCM) paradigms which allow companies to become more competitive and sustainable in a volatile and high demand market. Seuring and Müller [101] defined the SSCM as the consideration of environmental and social impacts of supply chain operations as well as its economic performance in the management of information, material and capital flow as shown in figure 1.4 [27].

Sustainable closed-loop supply chain (SCLSC) that means considering the economic, envi-

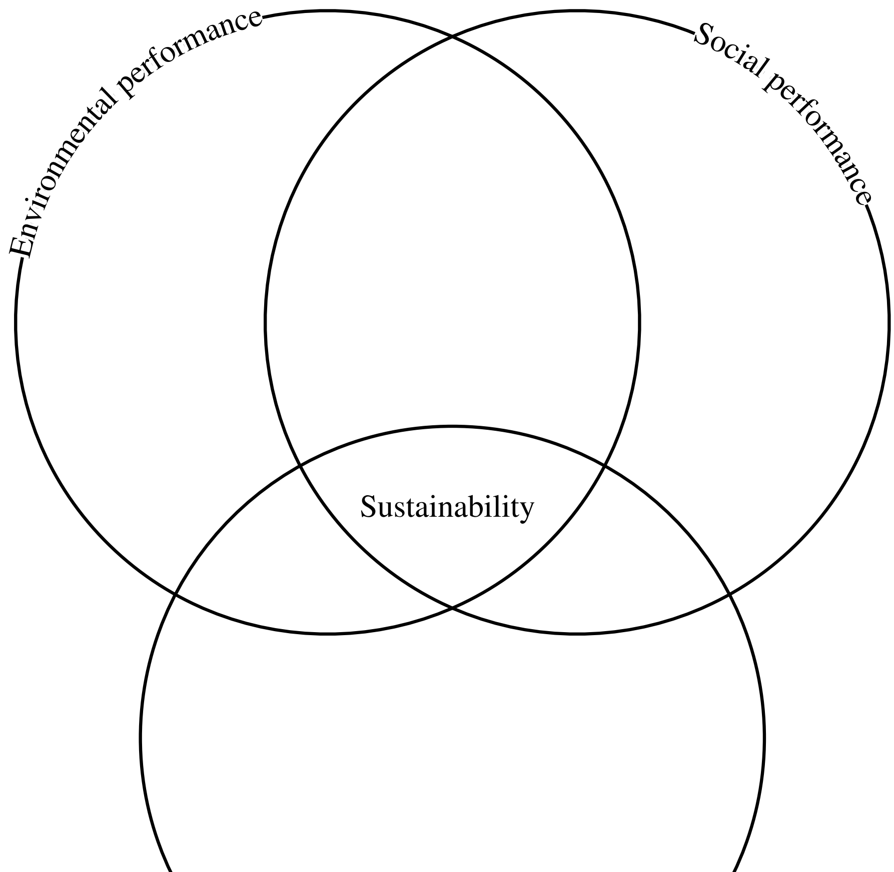


Fig. 1.4 Sustainable supply chain aspects.

ronmental, and social factors in designing and optimization of the CLSC network which are defined in subsection 1.3.

1.5 Motivations of the study

Because of the Internet and related technologies, a survey conducted by America Online in 2004 found that 43% of young Web users in the United States had made online purchases, followed by Sweden (41%), Germany (33%), Canada (25%), and the UK (22%) [51]. Hence, many companies have constructed their online platform via online retailers, in addition to traditional ones, that can accommodate the provision to customers of the products from manufacturers or via recovery centers. Online retailers as part of the CLSC side by side with traditional ones are increasing due to large accessibility, fast consumer response, low distribution costs, and fast shipping. The practice of combining online shopping with the traditional retail channel in the supply chain design has emerged recently. However, a limited number of studies have addressed the optimal design of a dual-channel supply chain network, Motivated by this, we investigate the design and optimization of the CLSC with the dual-channel supply chain considering e-commerce in mathematical modeling. Specifically, we present a novel MILP model of the CLSC with the consideration of the dual channel of the traditional and online retailers in both forward and reverse logistics, which aims at minimizing the total cost of shipment, purchasing, operations, and fixed costs.

To the best of our knowledge, there are few studies concerned with uncertain dual-channel CLSC optimization problem. Yu et al. [118] studied uncertain dual-channel FSC to minimize the operations cost and maximize the degree of logistics satisfaction using the fuzzy set theory. Rahmani, et al. [90] developed a probabilistic dual-channel CLSC using a possibilistic chance constrained programming to determine the degree of greenness of products from manufacturers. Motivated by this lack of research about uncertain dual-channel CLSC optimization problems, we present a robust optimization (RO) model for the dual-channel CLSC network with the objective of minimizing the total cost, considering the uncertainty of costs and customer demand.

When designing multiobjective CLSC models, researchers rarely consider the RO based on a predefined uncertainty set. To fill this gap, the current study proposes a bi-objective robust optimization model for designing a green closed-loop supply chain (GCLSC) network based on the "Interval + Polyhedral" uncertainty set while considering presorting and heterogeneous transportation system to maximize the total profit and minimize the carbon emissions in the network.

1.6 Contributions of the study

This thesis investigates an optimal robust design of the sustainable CLSC considering the integration of e-commerce activities with the CLSC through manufacturing and recovery facilities. Moreover, designing robust GCLSC with considering the carbon emissions, presorting and heterogeneous transportation system consideration through a bi-objective optimization model. The main contributions of this study are summarized as follow:

- The integration of e-commerce activities into both forward and reverse supply chains.
- The development of an MILP model that considers the dual channel of both traditional and online retailers through manufacturing and recovery facilities.
- A sensitivity analysis study of the key parameters associated with traditional and online retailers, and exploring their effect on the total cost and number of open traditional retailers.
- Propose an adaptable robust dual-channel CLSC model with cost and demand uncertainty using the (RO) approach.
- Consider multiple uncertainty sets in the objective function (OF) for the dual-channel CLSC optimization problem, this provides flexibility and controls risk based on the preferences of the decision-makers.
- Propose a novel mathematical formulation of two robust counterpart models of the dual-channel CLSC model based on two different uncertainty sets, the adjustable box and ellipsoidal uncertainty sets, this contributes to the areas of operations research and operations management.
- Conduct intensive sensitivity analyses of the key parameters of the robust dual-channel CLSC model to investigate their impact on the study objective.
- Presenting a bi-objective mixed integer linear programming (MILP) model for the GCLSC while considering presorting and a heterogeneous transportation system as well as uncertain cost, selling price, and carbon emissions uncertainties.
- Presenting a robust counterpart model formulation of the bi-objective MILP model of the GCLSC network under uncertainties using the well-known RO approach based on the "Interval + Polyhedral" uncertainty set.

- Performing intensive computational experiments using a lexicographic weighted Tchebycheff approach to obtain the Pareto optimal solutions of the robust bi-objective model, in which the probability bounds on constraint satisfaction are not violated.

In addition, the thesis presents a comprehensive review on the robust optimization of the uncertain dual-channel CLSC models and the uncertain single and multi-objective CLSC network models.

1.7 Literature review

The relevant literature of this thesis is comprehensive and intensive reviewed and presented in the following subsections:

1.7.1 Relevant literature of the robust and optimal design of dual-channel CLSC network

In this subsection, two review lines of the relevant literature are provided. The first line focuses on the uncertain CLSC models based on the RO approach, whereas the second focuses on the dual-channel CLSC optimization problem.

CLSC optimization problems more often than not are uncertain. Data uncertainty are due to measurement/estimation errors that are the results of the difficulties of exactly measuring/estimating the data entries. Some studies consider the design of CLSC networks on the basis of uncertain parameters, following RO approach.

To the best of our knowledge, Pishvaee et al. [84] is the first study to implement RO approach in the optimization of CLSC problem, they proposed an MILP model for designing the CLSC, then the model was extended to deal with uncertain parameters, such as transportation costs, returned products from first-hand customers to collection centers, and demand of second customers for recovered products. The tractable robust counterpart model was achieved using the box uncertainty set. Hasani et al. [53] suggested a robust CLSC network for perishable goods in agile manufacturing considering uncertain customer demands and purchasing costs based on interval uncertainty set to minimize the cost of the network.

Hasani et al. [54] proposed a mixed integer nonlinear programming (MINLP) model for designing a global CLSC network for a medical device manufacturer, considering uncertain purchasing costs and consumer demand, managed with an RO technique based on budget uncertainty, "Bertsimas and Sim," set. A robust MILP model considering uncertain production cost and demand for designing a three-echelon CLSC network based on the budget

Table 1.1 Relevant literature of the robust and optimal design of dual- channel CLSC network

Study	Supply chain type			Retailing channel		Optimization problem		OF uncertainty set		Mathematical formulation	
	FSC	RSC	CLSC	single	multiple	deterministic	uncertain	single	multiple	MINLP	MILP
Pishvaee et al. [84]			✓	✓		✓	✓	✓			✓
Hasani et al. [53]			✓		✓		✓	✓		✓	✓
Rahmani et al. [91]	✓			✓			✓	✓			✓
Mohammed et al. [75]			✓	✓			✓	✓			✓
Prakash et al. [87]			✓	✓		✓	✓	✓			✓
Yadav and Singh [112]	✓				✓	✓					✓
Yu et al. [118]	✓				✓		✓				✓
Niranjan et al. [79]			✓		✓	✓					✓
Chen et al. [29]			✓		✓	✓				✓	
Almaraj and Trafalis [8]			✓	✓			✓	✓			✓
Kaoud et al. [63]			✓		✓	✓					✓
The proposed study			✓		✓		✓	✓	✓	✓	✓

uncertainty set was studied by Rahmani and Mahoodian [91] to minimize total costs. Mohammed et al. [75] suggested an MILP model considering uncertain carbon emissions due to transportation and facilities in CLSC optimization problem based on variety of carbon emission policies that are considered using stochastic scenarios and RO approach based on the bound box uncertainty set. Prakash et al. [87] proposed an MILP model for the CLSC optimization problem under demand and risk uncertainty using the RO approach based on the box uncertainty set .

Almaraj and Trafalis [8] presented a multi-echelon, multi-period, and multi-product CLSC optimization problem with imperfect quality production under uncertain parameters based on box, polyhedral, and combined interval and polyhedral uncertainty sets.

In recent years, customer shopping behaviour has changed due to the spread of the Internet and related technology, which in turn have prompted companies and organizations to establish online retailers in addition to traditional ones. Xu et al. [111] reported that approximately 68% of manufacturers use direct sales through the Internet. Henceforth, the integration of traditional and online retailers becomes inevitable. Niranjan et al. [79] presented a deterministic MILP model for the dual-channel CLSC for an Indian kitchenware company to minimize the total cost of the entire network and balance between economic benefits and environmental costs. Chen et al. [29] conducted a study of the dual-channel CLSC network and proposed a deterministic MINLP model of the remanufacturing network with the objective of maximizing the manufacturer's profit. An MILP model for the dual-channel CLSC network was provided by Kaoud et al. [63], where the objective of the model is to minimize the total cost by focusing on the strategic and tactical decisions of the dual-channel CLSC. Based on the analysis of the relevant literature , which is summarized in Table 1.1, there is a notable research gap for the dual-channel CLSC about considering uncertainty of the parameters using RO approach. Motivated by the relevant literature, in this study, we consider the transportation, purchasing, processing, fixed costs, as well as customer demand uncertainties in the proposed model of a dual-channel CLSC using the RO approach as well as taking into account multiple uncertainty sets in the OF that, in turn, provide greater flexibility for decision-maker's preferences.

1.7.2 Relevant literature of robust design of uncertain single and multiple-objective CLSC network

Recently, several studies have focused on uncertain and multiobjective nature of CLSC optimization models. Uncertainty is inherent in the CLSC models due to the dynamic nature of parameter data and errors that occur when measuring or estimating the input data. While

some of these studies have focused on the uncertain CLSC optimization problem with a single objective, which is their primary target of minimizing the total cost incurred in the CLSC network, the rest are concerned with the inherent nature of the uncertainties and conflicting objectives of CLSC optimization networks.
Two streams of literature are reviewed: the first deals with the design of uncertain CLSC with a single objective, whereas the second involves the design of uncertain CLSC with multiple objectives.

The uncertain optimization problem of single objective CLSC models based on the RO technique has recently been developed and expanded; its efficiency and robustness have also been demonstrated. For designing the CLSC, Pishvaee et al. [84] presented an MILP model, which was further extended to tackle uncertain parameters, such as transportation costs, returned products from first-hand customers to collection centers, and the demand of second customers for recovered products using the RO approach; their study objective is a minimization of the total cost.
The RO model for the CLSC network based on the regret value to determine facilities' locations and quantity of flows between facilities in the network were studied by Wang et al. [107].
Almaraj and Trafalis [9] proposed an adjustable RO approach for designing an uncertain CLSC network based on the budget uncertainty set to model the dynamic behavior of the customer demand over the planning horizon to minimize the total cost of the CLSC network. Ramezani et al. [93] proposed a scenario-based optimization model using the min–max regret criterion with uncertain demand and the return rate for designing the CLSC to maximize the total profit using a scenario relaxation algorithm.
Some studies are concerned with real case studies of the uncertain CLSC. For instance, Gholizadeh et al. [45] suggested a robust CLSC optimization model for disposable appliances considering demand, transportation, and operational costs uncertainties using a robust scenario-based stochastic optimization to maximize the total revenue of the network. Hasani et al. [54] proposed an MINLP model for designing a global CLSC network for a medical device manufacturer, considering uncertain purchasing costs and consumer demand, managed with an RO technique based on the budget uncertainty, "Bertsimas and Sim," set. Jabbarzadeh et al. [58] proposed an SO approach for designing a CLSC network of glass company by considering disruption risks across different disruption scenarios using the Lagrangian relaxation algorithm.
Gao and Ryan [41] proposed a hybrid model for designing a GCLSC network that combines SO and RO approaches aimed at minimizing the total cost incurred in the network. Samuel et

al. [99] presented scenario-based robust model for designing a GCLSC network of electronic products with considering uncertain quality of returned product to minimize the total cost .

Due to the realistic multiobjective and uncertain nature of the CLSC design and optimization problems, researchers have paid attention to designing robust models that hedge against uncertain realization and provide optimal solutions for the conflicting nature of objectives. The uncertainty in a multi-objective CLSC network using the SO approach is usually characterized by a probability distribution on the parameters. Zhalechian et al. [120] proposed an MINLP model to minimize the total cost and environmental impacts and maximize the positive social impacts of designing a supply chain network using a hybrid meta-heuristic algorithm; they applied SO and modified the game theory to handle uncertainty.
Ghasemzadeh et al. [43] suggested an MILP model to develop a stochastic CLSC network aimed to minimize Eco-indicator 99 and maximize profit. The model implemented in a real-world case study of the tire manufacturing industry, two-stage stochastic optimization approach was implemented to cope with uncertainties in their study.
Moheb-Alizadeh et al. [76] developed a stochastic integrated multiobjective MINLP model, in which the design of a sustainable CLSC network considers sustainability outcomes and the efficiency of facility resource utilization, using a Lagrangian relaxation algorithm. A chance-constrained programming model has been proposed for handling uncertainties in a GCLSC network design aimed to minimize the expected value and variance of the total of cost Co_2 emissions using the general algebraic modeling system (GAMS) software; four multiobjective decision-making methods were applied by Abad and Pasandideh [3].
The fuzzy robust optimization (FRO) approach was implemented for dealing with uncertain parameters when the available information is vague. Soleimani et al. [103] developed a multiobjective model for designing CLSC network using an FRO approach, and their objective was to maximize the total profit and the responsiveness of customer demand while minimizing lost working days due to occupational accidents. In addition, a genetic algorithm was implemented for solving their model. Nayeri et al. [78] proposed an MILP model for designing a sustainable CLSC network for a water tank industry using an FRO approach to handle uncertainties in order to minimize the cost and environmental impact and maximize the social impacts using the goal programming approach.
Hybridization between SO and FRO approaches was implemented by Yu and Solvang [116] for handling uncertainties in designing the CLSC network to minimize the total cost and carbon footprint induced by the network. Scenario-based robust optimization (SRO) was also implemented to handle uncertain parameters of the design of CLSC networks.
Ruimin et al. [96] proposed a robust MINLP model to deal with GCLSC by considering two conflicting objectives simultaneously, the economic cost and environmental impact, using

scenario-based optimization.
An uncertain multi-objective MILP model of the CLSC network design was studied to minimize the total costs, maximize the on-time delivery of the products purchased from suppliers, and maximize the quality of the produced products on the forward chain that can be recovered in the reverse supply chain using an SRO method [5]. Gholizadeh et al. [44] proposed a bi-objective model to minimize the environmental impact and maximize profit for a dairy CLSC using a heuristic approach and robust optimization scenario-based. Some studies have implemented an interval-based robust optimization (IRO) approach where the uncertainty is predefined within an uncertainty. Darestani and Hemmati [33] used the IRO approach for designing a CLSC network for perishable products to minimize the environmental and cost objectives. Yavari and Geraeli [113] proposed an MILP model for a multi-period and multi-product GCLSC network of dairy products with limited life shelf under uncertainties of demands, rate of return, and the quality of returned products based on the IRO approach using a heuristic method to minimize the total cost and the environmental pollutants.
Jiao et al. [62] proposed a data-driven model in CLSC to mitigate recovery uncertainty and greenhouse emissions (GHE) based on uncertain customers' demand to minimize the total cost using the chance constraint method to control the GHE and define the perturbation of uncertain demand using the IRO approach based on" Bertsimas and Sim" uncertainty set.
According to the above-mentioned literature which is summarized in Table 1.2 , researchers seldom consider the RO based on a predefined uncertainty set while designing multiobjective CLSC models. To fill this gap, the current study proposes a multiobjective robust optimization model for designing a GCLSC network based on the "Interval + Polyhedral" uncertainty set while considering presorting and heterogeneous transportation system to maximize the total profit and minimize the carbon emissions in the network.

1.8 Thesis outlines

The hierarchy of this thesis is shown in Figure 1.5. Chapters 2-5 form the main body of thesis.

Chapter 1: This chapter includes background about the CLSC network models, motivation of the study, relevant literature review pertinent to our study, research gaps in the literature that are fulfilled in thesis, and the objectives of the thesis.

Chapter 2: This chapter suggests a novel MILP model that addresses the integration of e-commerce with a multi-echelon CLSC with a multi-period planning time horizon by considering dual channels in manufacturing, and recovery facilities. To validate the model,

Table 1.2 Relevant literature pertinent to uncertain CLSC models

Authors	Presorting presence		Model's objective(s)		Uncertainty modelling				Transportation system		Formulation
	Yes	No	single	multiple	SO	IRO	SRO	FRO	HOM	HET	
Mohammed et al. [74]		✓	✓			✓				✓	MILP
Samuel et al. [99]	✓		✓				✓		✓		MILP
zhalechian et al. [120]		✓		✓	✓				✓		SMIP
Soleimani et al. [103]		✓		✓				✓	✓		FMIP
Fathollahi-Fard et al. [40]		✓		✓	✓				✓		SMIP
Wang et al. [107]		✓	✓				✓		✓		MILP
Jabbarzadeh et al. [58]		✓	✓				✓		✓		SMIP
Gao and Ryan [41]		✓	✓			✓	✓		✓		SMIP
Ramezani et al. [93]		✓	✓				✓		✓		MILP
Hasani et al. [54]		✓	✓			✓			✓		MINLP
Ghasemzadeh et al. [43]		✓		✓	✓				✓		MILP
Moheb-Alizadeh et al. [76]		✓		✓	✓				✓		MINLP
Yavari and Geraeli [113]		✓		✓		✓			✓		MILP
Abad and Pasan [3]		✓		✓	✓				✓		MINLP
Abdolazimi et al. [5]		✓		✓			✓		✓		MILP
Almaraj and Trafalis [9]		✓	✓			✓			✓		MILP
Gholizadeh et al. [44]		✓		✓			✓		✓		MILP
Jiao at al. [62]		✓		✓	✓	✓			✓		SMIP
Yu and Solvang [116]		✓		✓	✓			✓	✓		FMIP
Ruimin et al. [96]		✓		✓			✓		✓		MINLP
Nayeri et al. [78]		✓		✓				✓		✓	FMIP
Darestani and Hemmati [33]		✓		✓		✓			✓		MINLP
The proposed study	✓			✓		✓				✓	MILP

SMIP: stochastic integer programming; FMIP: Fuzzy mixed integer programming; HOM: Homogeneous; HET: Heterogeneous.

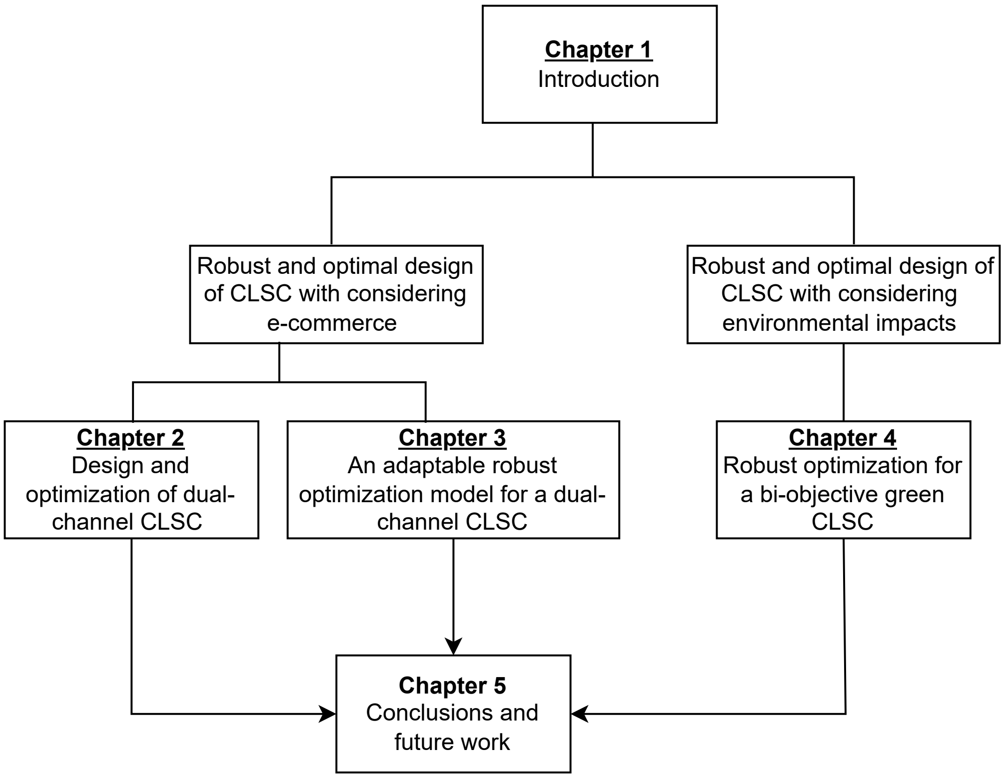


Fig. 1.5 Thesis outline.

we obtain optimal decision variables and examine the robustness and applicability of the model, and comprehensive computational experiments are performed. Moreover, sensitivity analysis is carried out to illustrate the efficacy of e-commerce integration by considering the two channels in the CLSC network.

Chapter 3: In this chapter, we propose an adaptable RO model for the dual-channel CLSC network and present two counterpart models; the first model is an MILP model based on the adjustable box uncertainty set, while the second robust model is an MINLP model based on the adjustable ellipsoidal uncertainty set. We provide a novel approach for considering multiple uncertainty sets in the objective function, that provide flexibility and control risk based on the preferences of the decision-makers. This study aims at minimizing the total chapter of the dual-channel CLSC network considering uncertain purchasing, transportation, fixed, and processes costs, in addition to uncertain customer demand.

Chapter 4: In this chapter, we propose a robust bi-objective optimization model of the GCLSC network considering presorting, heterogeneous transportation system, and carbon emissions. The proposed model is an uncertain bi-objective MILP model that aims at maximizing the profit and minimizing carbon emissions considering uncertain cost, selling price, and carbon emissions. The RO approach is implemented using the "Interval+ polyhedral " uncertainty set to model the robust counterpart of the bi-objective model. Robust Pareto optimal solutions are obtained using lexicographic weighted Tchebycheff optimization approach to obtain the Pareto optimal solutions of the bi-objective model. Intensive computational experiments are conducted, and a robust Pareto optimal front is obtained with a probability guarantee of the constraints that contain uncertain parameters are not violated.

Chapter 5: This chapter contains conclusions and recommendations for future research work.

Chapter 2

Design and optimization of the closed-loop supply chain with considering e-commerce

2.1 Introduction

In recent years, governments have been applying pressure and refining legislation to encourage organizations and a broad sector of customers to adopt green and sustainable practices in their production and service activities. This is to handle the population growth, which requires more products to be manufactured, resulting in the limited availability of raw materials and an increase in the rate of pollution emissions [72, 52]. These factors are motivating companies and governments to adopt and implement rational closed-loop supply chain (CLSC) activities in both the production and service sectors [49, 86]. A CLSC incorporates both forward and reverse supply chain activities [115, 85, 11]. The forward supply chain is defined as a network involving raw material procurement, manufacturing of parts, assembly of parts, and delivery through distribution networks [38]. Meanwhile, the reverse supply chain is defined as a network of facilities and includes all activities from collecting end of life (EOL) products to their inspection, disassembly, and the determination of which components should be disposed of, recovered, recycled, and remanufactured to form final products that can be reused by customers [28, 50, 82]. The European Union and European Parliament came up with several changes to the Directive 2002/96/EC on Waste Electrical and Electronic Equipment (WEEE) with the objective of improved human health [35]. Many companies adhere to this legislation, and the recycling of WEEE has led to a myriad of environmental and economic benefits due to the recovery of valuable metals and plastics in these pieces of equipment [16]. Implementing CLSC planning strategies helps in reducing companies' production costs, eliminating environmental pollution, creating social gains, and promoting the rapid development of economic benefits by applying reverse logistics to the company's activities including recycling, recovering, and remanufacturing of disused products [116]. For instance, Fuji Xerox saves around 40–65% of production costs from the manufacturing of recycled materials [114] . The rise of the Internet and related technologies has led many companies to sell their products through online retailers in addition to traditional retailers. For example, Dell sells its electronic products through online retailers such as Amazon, Flipkart, and Snapdeal [1]. Both types of retailer sell the same basic product and determine their respective optimal retail prices. In acting as the market leader, the producer has to split the market share between online and traditional retailers and decide on the wholesale price [94]. A myriad of benefits have boosted the spread of online retailers, including high accessibility, fast responses to consumer demand, low distribution costs, and fast shipping [12] as well as the positive impact from an environmental perspective [61, 77]. The practice of combining online shopping with the traditional retail channel in the supply chain design has emerged recently. However, a limited number of studies have addressed the optimal design of a dual-channel supply chain network, Yadav and Singh [112] proposed multiple channel distribution for a forward supply chain network using MILP, their proposed model is a single-period single-product multi-channel forward supply chain with the aim to maximize the service level and minimize the total cost. Chen et al. [29] proposed a mixed integer nonlinear programming (MINLP) for modeling the remanufacturing network for the dual-channel CLSC. The authors investigated the proposed mathematical model while computational experiments and sensitivity analysis for model validity were not preformed. Motivated by this, we investigate the design and optimization of the CLSC with the dual-channel supply chain considering e-commerce in mathematical modeling. Specifically, we present a novel MILP model of the CLSC with the consideration of the dual channel of the traditional and online retailers in both forward and reverse logistics, which aims at minimizing the total cost of shipment, purchasing, operations, and fixed costs.

2.2 Problem description

The dual-channel CLSC is a multi-echelon multi-period supply chain that consists of two parts, as shown in Figure 2.1, the forward supply chain, which is connected by black solid arrows, and the reverse supply chain, which is connected by red dashed arrows. The suppliers and recycling centers provide the manufacturers with the raw materials, and the manufacturer then produces the final products that are transported to either traditional retailers or online retailers. Both online and traditional retailers provide the final products to the end customers of new products to satisfy their demands. Dismantlers collect the EOL products for reverse logistics in the dual channel and then decide whether to dispose of, recycle, or recover those collected EOL products. The model proposed in this study determines the optimal amounts to be manufactured from the raw materials provided by the suppliers and the recycled materials supplied by recycling centers, the optimal amounts transported to both traditional and online retailers via the manufacturers or recovery centers, the optimal amounts transported to customers to satisfy their demand, the optimal number of EOL products to be collected and inspected, the disposed amounts, the optimal amounts to be recycled, and the amounts to be recovered. Additionally, the model determines the optimal number of facilities for operating the dual-channel CLSC over the planning horizon. Various parameter uncertainties were determined by applying sensitivity analysis to examine the effects of the parameters on the performance of the dual-channel CLSC to provide managerial insights for the decision-makers.

2.2.1 Model assumptions

- The potential locations of the facilities and distances between these locations are predefined and known.
- The capacities of facilities and demands of customers are predetermined and deterministic.
- The shipment cost, purchasing cost, operating costs, such as manufacturing, collecting, disposing, recycling, and recovering, and fixed costs are predetermined and fixed.
- The rates of online demands in the forward and reverse chain are predefined and deterministic.
- The ratio of EOL products to be collected and inspected is predefined and deterministic.
- The ratios of the disposed, recycled, and recovered products are predetermined and deterministic.

2.3 Mathematical formulation

In this section, an MILP model for the dual-channel CLSC with e-commerce is proposed. Our proposed model is an extension of the traditional models of CLSC [75, 80] in that it incorporates e-commerce activities. The objective function shown in Equation (2.1),

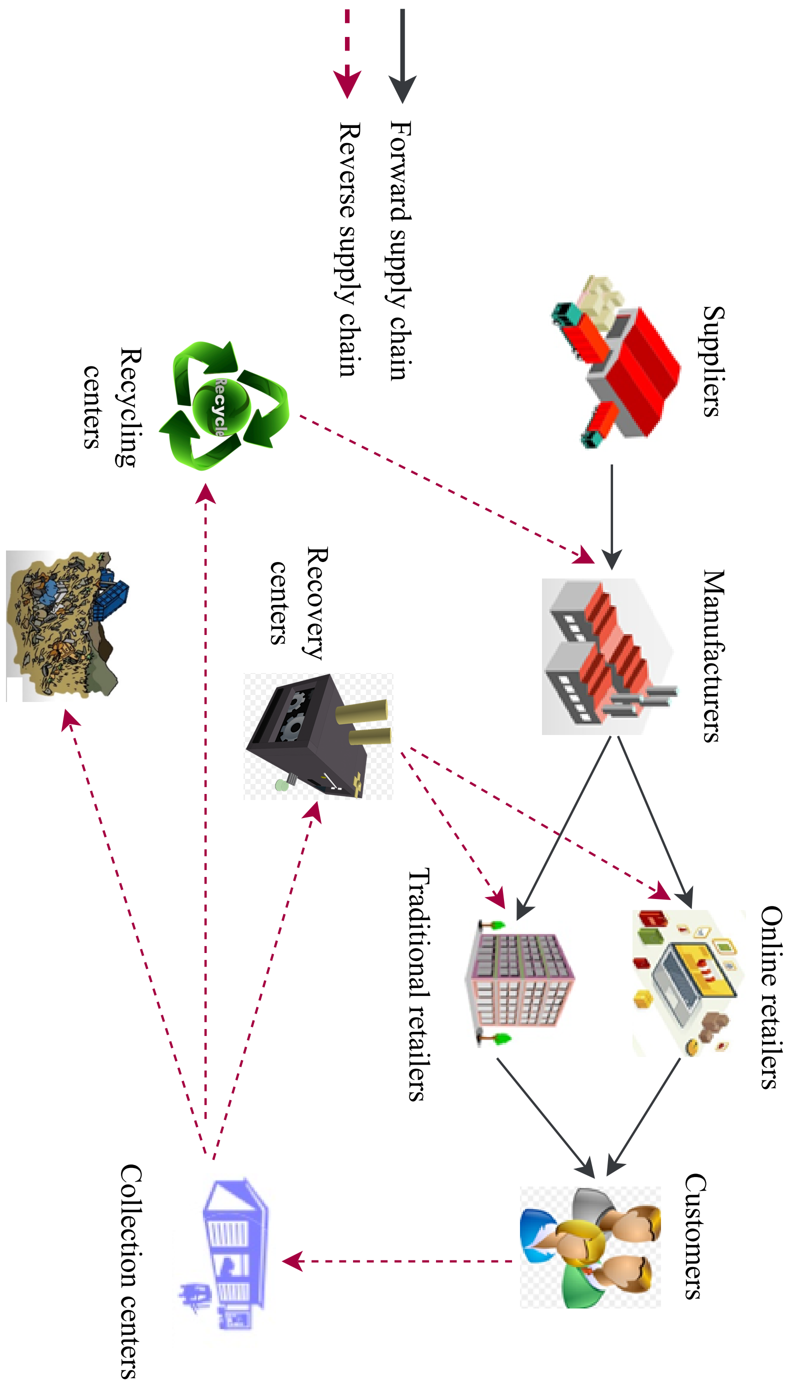


Fig. 2.1 The proposed dual-channel closed-loop supply chain.

composed of four parts, represents the total cost that is to be minimized. The first part of the objective function, z_1, is the transportation cost between each successive set of facilities in the CLSC during the total periods of time, represented by Equation (2.2). The second part, z_2, is the cost of the set of manufacturers purchasing raw materials from suppliers and is represented by Equation (2.3). The third part, z_3, is the cost of the operations, which includes manufacturing, collecting, inspection, disposal, recycling, and recovery, and is represented by Equation (2.4). The last part, z_4, represents the fixed costs of opening facilities in the CLSC and is represented by Equation (2.5). The nomenclature that is used in the mathematical formulation of the dual-channel CLSC is presented in Table 2.1, including the indices, parameters, and the continuous and integer decision variables.

Table 2.1 Nomenclature of the mathematical formulation of the dual-channel CLSC model.

	Indices & Sets
i	Set of suppliers.
j	Set of manufacturers.
k^{tr}	Set of traditional retailers.
k^{on}	Set of online retailers.
l	Set of customers.
m	Set of collection and inspection centers.
n	Set of recycling centers.
v	Set of recovery centers.
s	Set of disposal centers.
t	Set of time periods.
	Parameters
sc_{ij}	Shipment cost of the quantity transported between supplier i and manufacturer j.
sc_{jk}^{tr}	Shipment cost of the quantity transported between manufacturer j and traditional retailer k^{tr}.
sc_{jk}^{on}	Shipment cost of the quantity transported between manufacturer j and online retailer k^{on}.
$sc_{k^{tr}l}$	Shipment cost of the quantity transported between traditional retailers k^{tr} and customer l.
$dc_{k^{on}l}$	Delivery cost of the quantity transported between online retailers k^{on} and customer l.
sc_{lm}	Shipment cost of the quantity transported between customer l and collection center m.

sc_{ms}	Shipment cost of the quantity transported between collection center m and disposal center s.
sc_{mv}	Shipment cost of the quantity transported between collection center m and recovery center v.
sc_{nj}	Shipment cost of the quantity transported between recycling center n and manufacturer j.
$sc_{vk^{on}}$	Shipment cost of the quantity transported between recovery center v and online retailer k^{on}.
$ca_{\zeta t}$	The capacity of the CLSC facilities belongs to ζ in period t where ζ:$\{i,\ j,\ k^{tr},\ k^{on},\ l,\ m,\ s,\ n,\ v.\ \}$
de_{lt}	Demand of customer l in period of time t.
pc	Purchasing cost of the unit of product transported between supplier i and manufacturer j.
jc	Manufacturing cost of a product.
mc	Collection and inspection cost of an EOL product.
sic	Disposing cost of an EOL product.
yc	Recycling cost of an EOL product.
vc	Recovery cost of an EOL product.
fc_{it}	Fixed cost associated with selected supplier i in period t.
fc_{jt}	Fixed cost of opening manufacturer j in period t.
$fc_{k^{tr}t}$	Fixed cost of opening traditional retailer k^{tr} in period t.
fc_{mt}	Fixed cost of opening collection center m in period t.
fc_{vt}	Fixed cost of opening covering center v in period t.
fc_{nt}	Fixed cost of opening recycling center n in period t.
fc_{st}	Fixed cost of opening disposal center s in period t.
	Decision Variables
A_{ijt}	The quantity provided by supplier i to manufacturer j in period t.
$B_{jk^{tr}t}$	The quantity provided by manufacturer j to traditional retailer k^{tr} in period t.
$B_{jk^{on}t}$	The quantity provided by manufacturer j to online retailer k^{on} in period t.
$C_{k^{tr}lt}$	The quantity provided by traditional retailer k^{tr} to customer l in period t.
$C_{k^{on}lt}$	The quantity provided by online retailer k^{on} to customer l in period t.
D_{lmt}	The quantity provided by customer l to collection centers m

	in period t.
H_{mst}	The quantity provided by collection center m to disposal center s in period t.
F_{mnt}	The quantity provided by collection center m to recycling center n in period t.
E_{mvt}	The quantity provided by collection center m to recovery center v in period t.
I_{njt}	The quantity provided by recycling center n to manufacturer j in period t.
$J_{vk^{tr}t}$	The quantity provided by recovery center v to traditional retailer k^{tr} in period t.
$J^{on}_{vk^{tr}t}$	The quantity provided by the recovery center v to online retailer k^{on} in period t.
O_{it}	A binary variable; its value is 1 if the supplier i is selected in period t; it takes a value of 0 otherwise.
O_{jt}	A binary variable; its value is 1 if the manufacturer j is opened in period t; it takes a value of 0 otherwise.
$O_{k^{tr}t}$	A binary variable; its value is 1 if the traditional retailers k^{tr} is opened i n period t; it takes a value of 0 otherwise.
$O_{k^{on}t}$	A binary variable; its value is 1 if the online retailers k^{on} is selected in period t; it takes a value of 0 otherwise.
O_{mt}	A binary variable; its value is 1 if the collection center m is opened in period t; it takes a value of 0 otherwise.
O_{st}	A binary variable; its value is 1 if the disposal center s is opened in period t; it takes a value of 0 otherwise.
O_{nt}	A binary variable; its value is 1 if the recycling center n is opened in period t; it takes a value of 0 otherwise.
O_{vt}	A binary variable; its value is 1 if the recovery center v is opened in period t; it takes a value of 0 otherwise.

$$\text{Min } Z = z_1 + z_2 + z_3 + z_4 \tag{2.1}$$

$$\begin{aligned} z_1 = &\sum_i \sum_j \sum_t sc_{ij} A_{ijt} + \sum_j \sum_{k^{tr}} \sum_t sc_{jk^{tr}} B_{jk^{tr}t} + \sum_j \sum_{k^{on}} \sum_t sc_{jk^{on}} B_{jk^{on}t} + \sum_{k^{on}} \sum_l \sum_t dc_{k^{on}l} C_{k^{on}lt} \\ &+ \sum_{k^{tr}} \sum_l \sum_t sc_{k^{tr}l} C_{k^{tr}lt} + \sum_l \sum_m \sum_t sc_{lm} D_{lmt} + \sum_m \sum_s \sum_t sc_{ms} H_{mst} + \sum_m \sum_n \sum_t sc_{mn} F_{mnt} \\ &+ \sum_m \sum_v \sum_t sc_{mv} E_{mvt} + \sum_n \sum_j \sum_t sc_{nj} I_{njt} + \sum_v \sum_{k^{tr}} \sum_t sc_{vk^{tr}} J_{vk^{tr}t} + \sum_v \sum_{k^{on}} \sum_t sc_{vk^{on}} J_{vk^{on}t} \end{aligned} \tag{2.2}$$

$$z_2 = \sum_i \sum_j \sum_t pc A_{ijt} \tag{2.3}$$

$$\begin{aligned} z_3 = jc\,(&\sum_j \sum_{k^{tr}} \sum_t B_{jk^{tr}t} + \sum_j \sum_{k^{on}} \sum_t B_{jk^{on}t}) + mc \sum_l \sum_m \sum_t D_{lmt} \\ &+ sic \sum_m \sum_s \sum_t H_{mst} + nc \sum_m \sum_n \sum_t F_{mnt} + vc \sum_m \sum_v \sum_t E_{mvt} \end{aligned} \tag{2.4}$$

$$\begin{aligned} z_4 = &\sum_i \sum_t fc_{it} O_{it} + \sum_j \sum_t fc_{jt} O_{jt} + \sum_{k^{tr}} \sum_t fc_{k^{tr}t} O_{k^{tr}t} + \sum_m \sum_t fc_{mt} O_{mt} + \\ &\sum_s \sum_t fc_{st} O_{st} + \sum_n \sum_t fc_n O_{nt} + \sum_v \sum_t fc_{vt} O_{vt} \end{aligned} \tag{2.5}$$

The model is subject to a set of constraints expressed in the following relations: the capacity constraint of the suppliers described by Equation (2.6): the quantity transported from each supplier to all the manufacturers during each period must not surpass the capacity of that supplier.

$$\sum_j A_{ijt} \leq ca_{it} O_{it} \quad \forall i, t \tag{2.6}$$

Constraints described by Equation (2.7) present the capacity of the manufacturer such that the quantity transported from any manufacturer to the set of forward traditional and online retailers must not exceed the capacity of that manufacturer during any period of the planning horizon.

$$\sum_{k^{tr}} B_{jk^{tr}t} + \sum_{k^{on}} B_{jk^{on}t} \leq ca_{jt} O_{jt} \quad \forall j, t \tag{2.7}$$

Constraints described by Equations (2.8) and (2.9) address the capacities of traditional and online retailers and ensure that the quantity transported to the customers should not exceed the capacity of each retailer during any period of the planning horizon.

$$\sum_l C_{k^{tr}lt} \leq ca_{k^{tr}t} O_{k^{tr}t} \quad \forall k^{tr}, t \tag{2.8}$$

$$\sum_l C_{k^{on}lt} \leq ca_{k^{on}t} O_{k^{on}t} \quad \forall k^{on}, t \tag{2.9}$$

Constraints described by Equation (2.10) guarantee the satisfaction of the customer's demand over the planning horizon.

$$\sum_{k^{tr}} C_{k^{tr}lt} + \sum_{k^{on}} C_{k^{on}lt} \geq de_{lt} \;\; \forall l,t \tag{2.10}$$

Constraints represented by Equation (2.11) identify the capacity of the collection and inspection centers and make sure that the amounts transferred to the disposal, recycling, and recovery centers will not exceed those centers' capacities at any time of the planning horizon.

$$\sum_{s} H_{mst} + \sum_{n} F_{mnt} + \sum_{v} E_{mvt} \leq ca_{mt}\, O_{mt} \;\; \forall m,t \tag{2.11}$$

Constraints on the capacity of disposal centers described by Equation (2.12) ensure that the quantity transported to the disposal centers from the collection and inspection centers do not exceed their capacities at any period of the planning horizon.

$$\sum_{m} H_{mst} \leq ca_{st}\, O_{st} \;\; \forall s,t \tag{2.12}$$

The Constraints described by Equation (2.13) identify the capacity of the recycling centers and guarantee that the quantities transported to the manufacturers from the recycling centers do not exceed their capacities at any period of the planning horizon.

$$\sum_{j} I_{njt} \leq ca_{nt}\, O_{nt} \;\; \forall n,t \tag{2.13}$$

The constraints described by Equation (2.14) present the limitations on the capacity of the recovery centers and ensure that the quantities transported to both the traditional and online retailers do not exceed the capacity of those centers at any period of the planning horizon.

$$\sum_{k^{tr}} J_{vk^{tr}t} + \sum_{k^{on}} J_{vk^{on}t} \leq ca_{vt}\, O_{vt} \;\; \forall v,t \tag{2.14}$$

Moreover, the equilibrium constraints of the facilities of the dual-channel CLSC show that the amounts produced by the manufacturers, which are supplied by the suppliers and recycling centers, are divided between the traditional retailers and the online retailers as described by Equations (2.15) and (2.16).

$$\lambda \left(\sum_{i} A_{ijt} + \sum_{n} I_{njt}\right) - \sum_{k^{tr}} B_{jk^{tr}t} = 0 \;\; \forall j,t \tag{2.15}$$

$$(1-\lambda)(\sum_{i} A_{ijt} + \sum_{n} I_{njt}) - \sum_{k^{on}} B_{jk^{on}t} = 0 \ \forall j,t \tag{2.16}$$

Another set of equilibrium constraints on the traditional retailers assures that the quantity transported from the manufacturers and recovery centers to a traditional retailer is equal to the quantity transported from these retailers to the customers as described by Equation (2.17).

$$\sum_{j} B_{jk^{tr}t} + \sum_{v} J_{vk^{tr}t} - \sum_{l} C_{k^{tr}lt} = 0 \ \forall k^{tr},t \tag{2.17}$$

Another set of equilibrium constraints on the online retailers is considered to make sure that the quantity transported from the manufacturers and recovery centers to this retailer is equal to the quantity transported from this retailer to the customers as described by Equation (2.18).

$$\sum_{j} B_{jk^{on}t} + \sum_{v} J_{vk^{on}t} - \sum_{l} C_{k^{on}lt} = 0 \ \forall k^{on},t \tag{2.18}$$

Equilibrium constraints on the demands of the customers show that the quantity provided by the customer is equal to a certain amount that is a proportion of End of Life products (EOL), μ, that is transported to the collection and inspection centers as described by Equation (2.19).

$$\mu\,(\sum_{k^{tr}} C_{k^{tr}lt} + \sum_{k^{on}} C_{k^{on}lt}) - \sum_{m} D_{lmt} = 0 \ \forall l,t \tag{2.19}$$

The equilibrium constraints on the collection and inspection centers show that the quantity of the EOL product transported to these centers are distributed in proportions of the π, ρ, and τ of these products that are disposed, recycled, and recovered, respectively, as described by Equations (2.20)–(2.23).

$$\sum_{s} H_{mst} - \pi \sum_{l} D_{lmt} = 0 \ \forall m,t \tag{2.20}$$

$$\sum_{n} F_{mnt} - \rho \sum_{l} D_{lmt} = 0 \ \forall m,t \tag{2.21}$$

$$\sum_{v} E_{mvt} - \tau \sum_{l} D_{lmt} = 0 \ \forall m,t \tag{2.22}$$

where

$$\pi + \rho + \tau = 1 \tag{2.23}$$

Equilibrium constraints on the amount transported to the manufacturers from the recycling centers such that it equals the amount transported from the collection and inspection centers to these centers as described by Equation (2.24).

$$\sum_{m} F_{mnt} - \sum_{j} I_{njt} = 0 \ \forall n,t \tag{2.24}$$

Equilibrium constraints of the recovery centers, such that a proportion ϕ of the recovered products is transported to the traditional retailers, and the remainder of the recovered products is transported to the online retailers, described by Equations (2.25) and (2.26).

$$\phi \sum_{m} E_{mvt} - \sum_{k^{tr}} J_{vk^{tr}t} = 0 \ \forall v,t \tag{2.25}$$

$$(1-\phi) \sum_{m} E_{mvt} - \sum_{k^{on}} J_{vk^{on}t} = 0 \ \forall v,t \tag{2.26}$$

Finally, non-negativity and integrity constraints for the decision variable as described by Equations (2.27) and (2.28).

$$A_{ijt}, B_{jk^{tr}t}, B_{jk^{on}t}, C_{k^{tr}lt}, C_{k^{on}lt}, D_{lmt}, H_{mst}, F_{mnt}, E_{mvt}, I_{njt}, J_{vk^{tr}t}, J_{vk^{on}t} \geq 0 \tag{2.27}$$

$$O_{\Omega t} = \begin{cases} 1 & \text{if the facility } \Omega \text{ opens in period } t \\ 0 & \text{otherwise} \end{cases} \quad forall\, \Omega\colon \ \{i, j, k^{tr}, k^{on}, m, s, n, v\} \tag{2.28}$$

2.4 Computational experiments

In this section, numerical experiments were performed using the GAMS-CPLEX 12.9 solver to validate the dual-channel CLSC using a personal computer (Intel Core i7, 3 GHz CPU, RAM 16 GB, Windows 10 OS). The proposed mathematical model is composed of 389 decision variables (317 continuous and 72 binary variables) and 200 constraints. It is well known that the complexity of the dual-channel CLSC problem is NP-hard because of number of binary variables. The computational requirements are proportional with the number of binary variables [26, 37] of the dual-channel CLSC, which are O_{it}, O_{jt}, $O_{k^{tr}t}$, $O_{k^{on}t}$, O_{mt}, O_{st}, O_{nt}, and O_{vt} and equal to $|i+j+k^{tr}+k^{on}+m+s+n+v| * |t|$ in the studied problem. Small size instances are used in this study for model validation. NP-hard problems are validated by implementing the small size instances using the exact solution obtained by GAMS software [97, 89].

2.4.1 Description of the data

The dual-channel CLSC proposed in this study, which is depicted in Figure 2.1, is a single product. Multiple echelons and four time periods are composed of four suppliers, two manufacturers, two traditional retailers, two online retailers, and three customer sets. Moreover, the facilities in the reverse chain are composed of two collection and inspection centers, two disposal centers, two recycling centers and two recovery centers. Some of the data implemented in this study are taken from a study presented by Mohammed et al. [75], shown in Table 2.3.

Table 2.2 The capacities of CLSC facilities for different periods of time.

	t_1	t_2	t_3	t_4
Supplier 1	1400	1440	1470	1480
Supplier 2	1500	1520	1530	1540
Supplier 3	1400	1410	1420	1440
Supplier 4	1450	1520	1500	1530
Manufacturer 1	1250	1170	1120	1150
Manufacturer 2	1240	1210	1200	1250
Manufacturer 3	1400	1400	1410	1410
Manufacturer 4	1200	1280	1280	1320
Traditional retailer 1	1900	1710	1120	1100
Traditional retailer 2	1650	1300	900	1050
Online retailer 1	720	740	750	730
Online retailer 2	900	920	810	840
Collection-center1	2700	2700	2700	2750
Collection-center2	2680	2600	2660	2680
Disposal-center 1	1660	1660	1670	1680
Disposal-center 2	1670	1670	1670	1690
Recycling-center1	1620	1680	1610	1790
Recycling-center2	1600	1760	1890	1880
Recovery-center1	1620	1810	1700	1900
Recovery-center2	1700	1780	1690	1800

The distances among the different facilities which varied from 80 to 200 kilometers. The shipment cost of a product is estimated as 0.08 USD per km, and the delivery cost of a product requested from the online retailers is 1.0 USD per product. The capacities of the dual-channel CLSC facilities are presented in Table 2.2, and the customer demand is

Table 2.3 The model's parameter values.

Parameters	Values
fc_{it}	uniform(5,000, 10,000)
fc_{jt}	uniform(30,000, 60,000)
fc_{mt}	uniform(2500, 5000)
fc_{nt}	uniform(20,000, 30,000)
fc_{st}	uniform(4000, 5000)
$fc_{k^{tr}t}$	uniform(10,000, 12,000)
fc_{vt}	uniform(10,000, 30,000)
PC	uniform(11,13)
jc	uniform(21,24)
mc	uniform(6,9)
sic	uniform(7,9)
yc	uniform(2,4)
vc	uniform(10,15)

presented in Table 2.4.

Table 2.4 The customers demand of products.

	t_1	t_2	t_3	t_4
Customer 1	550	550	540	540
Customer 2	620	600	610	650
Customer 3	740	750	620	710

A fraction of the customers demand ($\lambda = 0.70$) of products is supplied by traditional retailers, while the remainder of the demand is supplied by online retailers. The fraction of the EOL products ($\mu = 0.70$) is transported to the collection centers, a fraction of the collected and inspected products ($\rho = 0.30$) is recycled, and another fraction of these products ($\tau = 0.30$) is recovered, and the remainder ($\pi = 0.40$) of these products is disposed. The fraction of the recovered products ($\phi = 0.70$) is transported to the traditional retailers, while the remainder of these products is transported to the online retailers. Strategic and tactical decisions are obtained, and sensitivity analysis of dual-channel CLSC parameter changes that are beneficial from managerial perspectives is considered.

2.4.2 Results

Strategic and tactical decision variables for the dual-channel CLSC were obtained, and the optimal flow between facilities and the optimal opening and closure times of facilities are determined as presented in Table 2.5. Manufacturers are provided by the raw material through suppliers and recycling centers, and these manufacturers cooperate with recovery centers to provide the products for traditional and online retailers. The total cost of the dual-channel CLSC is 1,165,352 USD, of which 19% is transportation costs, 5% is purchasing costs, 18% is operation costs, and the remainder is the fixed costs.

2.4.3 Sensitivity analysis of the dual-channel CLSC parameters

This section provides a comprehensive sensitivity analysis of the dual-channel CLSC parameters and their effect on the overall cost. The experimental computation manipulates four scenarios of parameter sensitivity analysis and their impact on the total supply chain cost. The baseline scenario is the current situation as presented in the previous section for all such analyses in this section using the same approach implemented in the literature [25, 24, 10] . A crucial question that the baseline can address relates to knowing that the model is valid [110]. The first scenario considers customer demand variations. The second scenario investigates the variations in the quantity produced by the manufacturer directed at both traditional and online retailers. For example, e-commerce retail grows six-fold in the US from 2000 to 2009 [67]. The third scenario handles the change in the proportions of EOL products returned for recycling, disposal, and recovery, and their effect on the dual-channel CLSC. The last scenario considers an adjustment in the inspection ratios of items for recycling, disposal, and recovery.

Customer demand ratio change from traditional retailers

Due to the advantages of e-commerce and the availability of the Internet, customer demand through online retailers has increased dramatically, and competition from traditional retailers has decreased. This study proposes changing the fraction of the products supplied to traditional retailers due to the change in the fraction of products supplied to online retailers. Therefore, the number of opening times of traditional retailers has been decreased over the planning horizon due to the increase in the online retailer demand ratio, as shown in Figure 2.2. Additionally, the effect of the ratios of manufactured and recovered products directed to traditional retailers on the dual-channel CLSC cost is presented in Table 2.6.

Influence of customers demand change on dual-channel CLSC costs

Sensitivity analysis of the incremental change of demand of customers β with incremental demand between 10% and 40% was performed, and the effect on the related types of costs

Table 2.5 Strategic and tactical decisions for the dual-channel CLSC.

Decision Variables	From/to	t_1	t_2	t_3	t_4
A_{ijt}	supplier 2 - manufacturer 4	1108	1102	0	0
	supplier 4 - manufacturer 3	0	0	1026	0
$B_{jk^{tr}t}$	manufacturer 1 - traditional retailer 1	281	279	0	279
	manufacturer 3 - traditional retailer 1	0	0	760	0
	manufacturer 3 - traditional retailer 2	0	0	219	0
	manufacturer 4 - traditional retailer 1	775	771	0	441
	manufacturer 4 - traditional retailer 2	0	0	0	330
$B_{jk^{on}t}$	manufacturer 1 - online retailer 1	120	120	0	120
	manufacturer 3 - online retailer 2	0	0	420	0
	manufacturer 4 - online retailer 1	332	331	0	331
$C_{k^{tr}lt}$	traditional retailer 1 - customer 1	550	550	540	540
	traditional retailer 1 - customer 2	620	600	391	320
	traditional retailer 1 - customer 3	167	180	89	140
	traditional retailer 2 - customer 2	0	0	219	330
$C_{k^{on}lt}$	online retailer 1 - customer 3	538	570	111	570
	online retailer 2 - customer 3	35	0	419	0
D_{lmt}	customer 1 - collection center 1	0	385	378	378
	customer 1 - collection center 2	385	0	0	0
	customer 2 - collection center 1	434	420	427	455
	customer 3 - collection center 1	518	525	434	497
H_{mst}	collection center 1 - disposal center 2	381	532	496	532
	collection center 2 - disposal center 1	154	0	0	0
E_{mvt}	collection center 1 - recovery center 1	285	399	372	399
	collection center 2 - recovery center 2	116	0	0	0
I_{njt}	recycling center 1 - manufacturer 1	401	399	0	399
	recycling center 2 - manufacturer 3	0	0	372	0
F_{mnt}	collection center 1 - recycling center1	286	399	0	399
	collection center 1 - recycling center 2	0	0	372	0
	collection center 2 - recycling center 1	116	0	0	0
$J_{vk^{tr}t}$	recovery center 1 - traditional retailer 1	200	279	260	279
	recovery center 2 - traditional retailer 1	81	0	0	0
$J_{vk^{on}t}$	recovery center 1 - online retailer 1	86	120	111	120
	recovery center 2 - online retailer 2	35	0	0	0

and the total cost of the dual-channel CLSC is presented in Table 2.7. The total cost increased by 24% as a result of an increase in demand of 40%.

Table 2.6 The impact of the ratios of manufactured and recovered products for traditional retailers on the dual-channel CLSC's cost.

λ, ϕ	Transportation Cost	Purchasing Cost	Operations Cost	Fixed Cost	Total Cost (USD)	Total Cost Change
1.0	241,303.4	55,152.1	208,792.9	698,971.4	1,204,219.8	3.3%
0.9	235,389.3	55,152.1	208,792.9	698,971.4	1,198,305.6	2.9%
0.8	229,532.8	55,152.1	208,792.9	688,271.7	1,181,749.5	1.4%
0.7	223,835.5	55,152.1	208,792.9	677,572.1	1,165,352.6	0
0.6	218,269.8	55,152.1	208,792.9	683,430.8	1,165,645.6	0.02%
0.5	214,189.8	55,152.1	208,792.9	662,031.5	1,140,166.3	−2.2%
0.4	207,650.7	55,152.1	208,792.9	662,031.5	1,133,627.2	−2.8%

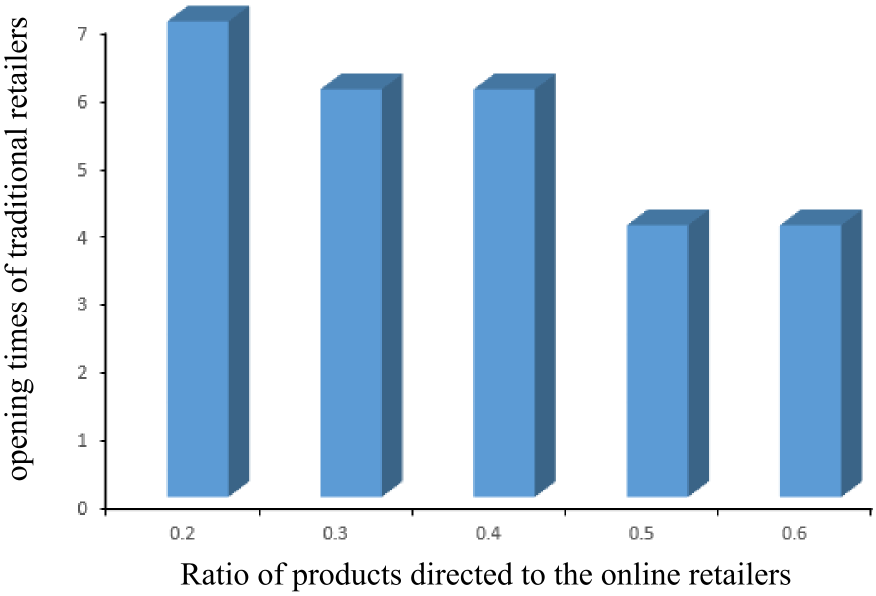


Fig. 2.2 Influence of the demand via online retailers on the number of opening times of traditional retailers.

Table 2.7 The effect of customer demand on the dual-channel CLSC's cost.

β	Transportation Cost	Purchasing Cost	Operations Cost	Fixed Cost	Total Cost (USD)	Total Cost Change
0%	223,835.5	55,152.1	208,792.9	677,572.1	1,165,352.6	0
10%	239,992.9	60,387.1	228,611.5	749,428.5	1,278,420.0	9.7%
20%	263,073.0	66,108.8	250,272.4	760,128.1	1,339,582.3	14.9%
30%	286,139.5	71,697.7	271,430.8	760,128.1	1,389,396.2	19.2%
40%	308,340.3	77,212.9	292,310.1	771,845.6	1,449,708.9	24.4%

Table 2.8 Effect of the proportion of the EOL products directed to reverse logistics.

μ	Transportation Cost	Purchasing Cost	Operations Cost	Fixed Cost	Total Cost (USD)	Total Cost Change
0.6	208,339.1	60,857.4	201,620.5	738,728.8	1,209,545.9	3.8%
0.7	223,835.5	55,152.1	208,792.9	677,572.1	1,165,352.6	0
0.8	245,353.0	46,023.4	220,268.7	622,274.1	1,133,919.3	−2.7%
0.9	253,911.9	43,741.3	223,137.7	566,976	1,087,767.1	−6.6%

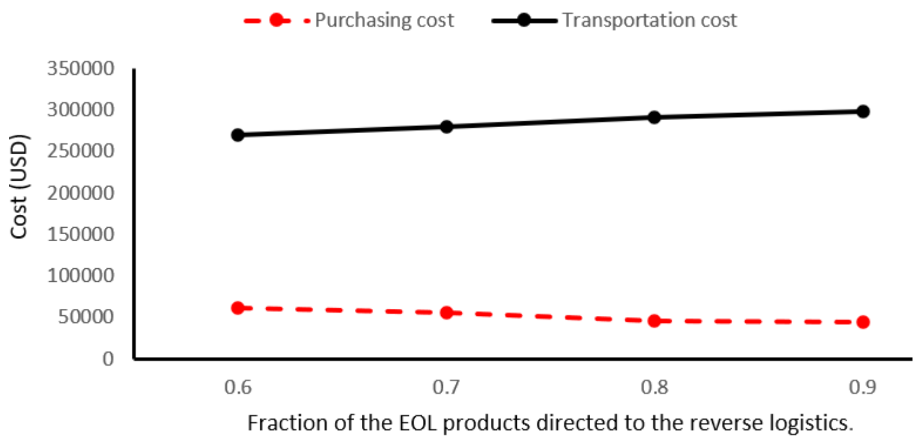


Fig. 2.3 Impact of the ratio of EOL products on purchasing and transportation costs.

Effect of the proportion of EOL products on the dual-channel CLSC cost

Recently, some companies and governments have begun to encourage the customer to return EOL products. To do so, they offer incentives or discounts on new products by changing the EOL products [106] as well as subsidies that play a crucial role in promoting the overall operational performance of the CLSC and social surplus [108].

Increasing the ratio of EOL products to the CLSC's reverse activities, such as recycling, recovery, and disposal, leads to a reduction in the CLSC's overall cost, as shown in Table 2.8, due to an increase in the amount of recycling and recovered products, and a decrease in the purchase of new (not recycled) raw materials as shown in Figure 2.3.

Impact of reverse ratios of recycling, disposal, and recovery on the dual-channel CLSC's cost

The ratios of the the quantities directed after collection and inspection for recycling, recovery, and disposal affect the total performance of the dual-channel CLSC. Sensitivity analysis was performed on the change in the ratios directed to disposal, recycling, and recovery centers, as shown in Table 2.9.

Increasing the ratio of the amount directed to disposal centers contributes to an increase in the CLSC's overall cost due to an increase in demand for the purchase of new raw material, as seen in the first portion of Table 2.9. Conversely, an increment in the recovery and recycling ratios of returned EOL products reduces the total cost by reducing the amount of new material purchased and increasing the number of recovered products, and this is depicted in the second and third portions of Table 2.9.

2.4.4 Managerial implications for the dual-channel CLSC

Inspired by the numerical results and sensitivity analysis from Section 2.4.3, this section presents some managerial implications for the dual-channel CLSC from the prospective of manufacturers, recovery centers, and governments. Manufacturers and recovery centers are recommended to increase the ratio of products directed to online retailers by considering advertisements and promotions for online shopping. This will result in a decrease in the total cost of the dual-channel CLSC, thereby increasing the total profit due to the drastic spread of the increased volume of e-commerce. The ratio of the returned products has a major impact on the total cost of dual-channel CLSC. To increase this ratio, governments are advised to support the companies and encourage the costumers to return the EOL products. This move has large economic, social, and environmental benefits.

2.5 Conclusions

This chapter proposes an MILP model of the dual-channel CLSC to address the increasingly widespread adoption of e-commerce, facilitated by the Internet and related technologies. The adoption of e-commerce and the customer trends of online shopping for new, remanufactured, and recovered products are driven by a variety of brands and products, the comfort afforded by e-commerce, and savings of customer time and effort. From the industry and service sector perspectives, e-commerce represents increased revenue due to cost savings and reduced air pollution, resulting in a significant environmental impact benefiting health. A computational experimental using GAMS–CPLEX 12.9 is performed to obtain optimum values of strategic and decision variables and to minimize the total cost of the dual-channel CLSC. Sensitivity analysis is conducted to investigate the impact and dependency the of strategic and tactical decisions on the major key parameters of the developed model, and the robustness, validity, and applicability of the proposed model are demonstrated.

Table 2.9 The change in reverse ratios of recycling, disposal, and recovery centers.

Reverse Ratios			Dual Channel CLSC Costs					
π	ρ	τ	Transportation Cost	Purchasing Cost	Operations Cost	Fixed Cost	Total Cost (USD)	Total Cost Change
0.2	0.4	0.4	228,202.4	41,839.5	206,926.6	534,600.2	1,011,568.7	−13%
0.3	0.4	0.4	219,926.6	48,495.8	207,859.8	677,572.1	1,153,854.3	−1.0%
0.4	0.3	0.3	223,835.5	55,152.1	208,792.9	677,572.1	1,165,352.6	0.0
0.4	0.4	0.3	223,546.9	51,823.9	210,321.5	677,572.1	1,163,264.4	−0.18%
0.3	0.3	0.4	228,308.8	48,495.8	203,869.4	534,600.2	1,015,274.2	−12.9%
0.3	0.3	0.5	215,228.6	45,167.7	197,417.4	534,600.2	992,413.8	−14.8%
0.4	0.3	0.3	223,835.5	55,152.1	208,792.9	677,572.1	1,165,352.6	0.0
0.3	0.4	0.3	223,258.2	48,495.8	211,850.1	677,572.1	1,161,176.2	−0.36%
0.2	0.5	0.3	222,681.0	41,839.5	214,907.3	677,572.1	1,156,999.9	−0.72%

Among the key findings of the conducted computational experiments and comprehensive sensitivity analysis compared with baseline , the number of opened traditional retailers decreases with the increase in the online retailer demand ratio, accordingly, the total dual-channel CLSC decreases. Moreover, the total dual-channel CLSC decreases with the increase of the returned EOL products, recycling ratio, and recovery ratio.

Chapter 3

An adaptable robust optimization model for a dual-channel closed-loop supply chain considering cost and demand uncertainty

3.1 Introduction

Recently, the proliferation of the Internet and related technologies has expanded to online activities that include shopping activities.

Hence, many companies have constructed their online platform via online retailers, in addition to traditional ones, which can accommodate the delivery of products to customers directly from manufacturers or through recovery centers. The implementation of online retailers, as part of the CLSC along with traditional ones, is increasing due to large accessibility, fast consumer response, low distribution costs, and fast shipping [12].

Most studies dealing with the optimization of the dual-channel CLSC network assumes that the CLSC design parameters are certain, which contradicts the reality due to improper estimation of their values due to measurement errors. CLSCs optimization problems are sensitive to data perturbations and as proved by Ben-Tal et al. [17], neglecting these perturbations results in infeasible or sub-optimal solutions.

There are two common approaches to handle uncertain optimization problems. The first one is the stochastic optimization (SO) approach, where the probability distributions of the uncertain parameters should be well defined. On the one hand, it is really difficult to accurately define these probability distributions whereas, on the other hand, the main drawbacks of the SO approach, e.g., the chance constrained programming, are destroying the convexity and mitigating the complexity of the original problem [84]. The second approach to handle uncertain optimization problems is the robust optimization (RO) approach, where the uncertain parameters are defined within a predefined uncertainty set which can overcome some difficulties and drawbacks of the SO approach.

To the best of our knowledge, there are few studies concerned with uncertain dual-channel CLSC optimization problem. Yu et al. [118] studied uncertain dual-channel FSC to minimize the operations cost and maximize the degree of logistics satisfaction using the fuzzy set theory. Rahmani, et al. [90] developed a probabilistic dual-channel CLSC using a possibilistic chance constrained programming to determine the degree of greenness of products from manufacturers. Motivated by this lack of research about uncertain dual-channel CLSC optimization problems, we present a robust optimization model for the dual-channel CLSC network with the objective of minimizing the total cost, considering the uncertainty of costs and customer demand. This study proposes an adaptable robust optimization model for the dual-channel closed-loop supply chain, two robust counterpart models are presented, the first model is an MILP model based on the adjustable box uncertainty set, while the second robust model is an MINLP model based on the adjustable ellipsoidal uncertainty set. We provide a novel approach for considering multiple uncertainty sets in the objective function, that provide flexibility and control risk based on the preferences of the decision-makers. This study aims at minimizing the total cost of the dual-channel closed-loop supply chain network considering uncertain purchasing, transportation, fixed, and processes costs, in addition to uncertain customer demand. Intensive computational experiments are conducted on the two robust models using GAMS software. Robust solutions are obtained and sensitivity analysis is conducted on both models considering 10% perturbation of the uncertain parameters around their nominal values as well as probability guarantee for not violating the constraints (constraints satisfaction).

3.2 Robust optimization paradigm

RO approach was proposed for the first time in the early 1970s by Soyster [104] for solving uncertain linear optimization problem, an extensive development to the RO theory presented by , (Ben-Tal and Nemirovski [18]) and (Ben-Tal and Nemirovski [19]), (El Ghaoui et al. [39]) , (Bertsimas and Sim [23]). Li et al. [69] presented an intensive study that focuses on theoretical and computational linear and mixed integer counterpart optimization problems and suggests new uncertainty sets such as adjustable box and pure ellipsoidal uncertainty sets.

A general uncertain MILP model is given below:

$$
\begin{aligned}
\mathscr{P}:\quad & \min_{x,y} \quad \sum_j \tilde{c}_j x_j + \sum_k \tilde{e}_k y_k \\
& \text{s.t.} \\
& \sum_j \tilde{a}_{ij} x_j + \sum_k \tilde{b}_{ik} y_k \leq \tilde{d}_i \qquad \forall i \in I \\
& x_j \in \mathbb{R} \qquad\qquad\qquad\qquad \forall j \in J \\
& y_k \in \mathbb{Z} \qquad\qquad\qquad\qquad \forall k \in K
\end{aligned}
\tag{3.1}
$$

where x_j and y_k represent continuous and integer decision variables respectively, $\tilde{c}_j$ and $\tilde{e}_k$ are the uncertain coefficients of the OF, and $\tilde{a}_{ij}$, $\tilde{b}_{ik}$, and $\tilde{d}_i$ are the true value of i^{th} constraint coefficients that are subject to uncertainty, the $\mathscr{P}$ model can be rewritten as:

$$
\begin{aligned}
\mathscr{P}:\quad & \min_{x,y,\beta} \quad \beta \\
& \text{s.t.} \\
& \sum_j \tilde{c}_j x_j + \sum_k \tilde{e}_k y_k \leq \beta \\
& \sum_j \tilde{a}_{ij} x_j + \sum_k \tilde{b}_{ik} y_k \leq \tilde{d}_i \qquad \forall i \in I \\
& x_j \in \mathbb{R} \qquad\qquad\qquad\qquad \forall j \in J \\
& y_k \in \mathbb{Z} \qquad\qquad\qquad\qquad \forall k \in K
\end{aligned}
\tag{3.2}
$$

Without loss of generality, we consider the general i^{th} constraint where the true value of uncertain constraint parameters $\tilde{a}_{ij}$, $\tilde{b}_{ik}$, and $\tilde{d}_i$ are $a_{ij} + \hat{a}_{ij}\xi_{ij}$, $b_{ik} + \hat{b}_{ik}\xi_{ik}$, and $d_i + \hat{d}_i\xi_{i0}$ respectively, a_{ij}, b_{ik}, and d_i are the nominal value of the parameters, $\hat{a}_{ij}, \hat{b}_{ik}$, and $\hat{d}_i$ are the perturbations of the parameters around their nominal values, and ξ_{ij}, ξ_{ik}, and ξ_{i0} are random independent variables that take values of $[-1,1]$. Hence, the i^{th} constraint can be reformulated as:

$$
\sum_{j \notin J_i} a_{ij} x_j + \sum_{j \in J_i} \tilde{a}_{ij} x_j + \sum_{k \notin K_i} b_{ik} y_k + \sum_{k \in K_i} \tilde{b}_{ik} y_k - \hat{d}_i \xi_{i0} \leq d_i \tag{3.3}
$$

J_i, K_i are the sets that contain the uncertain parameters in the i^{th} constraint. For simplicity, we consider $\xi = \{\xi_{ij}, \xi_{ik}, \xi_{i0}\}$ and U as the predefined set of random variables. To become immune against infeasibility that would result from any realization of uncertainty, the i^{th}

constraint can be rewritten as:

$$\sum_j a_{ij}x_j + \sum_k b_{ik}y_k + \max_{\xi\in U}\left\{\sum_{j\in J_i}\xi_{ij}\hat{a}_{ij}x_j + \sum_{k\in K_i}\xi_{ik}\hat{b}_{ik}y_k - \hat{d}_i\xi_{i0}\right\} \leq d_i \tag{3.4}$$

3.2.1 Robust counterpart of MILP based on the box uncertainty set

Uncertainty sets are characterized by their shape and size, which reflect the conservative and risk preferences of decision-makers [4]. In this section, the robust counterpart reformulation of MILP based on the box uncertainty set which is characterized using the supremum norm of the perturbation variables as depicted in Eq.(3.5) where Ψ is the adjustable size of the uncertainty set size as shown in Fig. 3.1 which reflect the degree of conservativeness. The box uncertainty set contains the full range of realizations of each component of ξ and ensures that the constraint is never violated [47].

$$U_{box} = \{\xi \mid \|\xi\|_\infty \leqslant \Psi\} = \{\xi \mid |\xi| \leqslant \Psi\} \tag{3.5}$$

The robust counterpart model of $\mathscr{P}$ based on the box uncertainty set is reformulated as :

$$\begin{aligned}
\mathscr{RC}-\mathscr{P}_{box}: \quad & \min \quad \beta \\
& \text{s.t.} \\
& \sum_j c_j x_j + \sum_k e_k y_k + \Psi\left[\sum_{j\in J_i}\hat{c}_j|x_j| + \sum_{k\in K_i}\hat{e}_{ik}|y_k|\right] \leq \beta \\
& \sum_j a_{ij}x_j + \sum_k b_{ik}y_k + \Psi\left[\sum_{j\in J_i}\hat{a}_{ij}|x_j| + \sum_{k\in K_i}\hat{b}_{ik}|y_k| + \hat{d}_i\right] \leqslant d_i \quad \forall i\in I \\
& -w_j \leqslant x_j \leqslant w_j \quad \forall j\in J_i \\
& -u_k \leqslant y_k \leqslant u_k \quad \forall k\in K_i \\
& x_j \in \mathbb{R} \quad \forall j\in J \\
& y_k \in \mathbb{Z} \quad \forall k\in K
\end{aligned} \tag{3.6}$$

Proof of $\mathscr{RC}-\mathscr{P}_{box}$ model : see Li et al. [69].

where w_j and u_k are non negative auxiliary variables. If x_j and y_k are non negative continuous and integer variables respectively, third and forth set of constraints, $-w_j \leqslant x_j \leqslant w_j$ and $-u_k \leqslant y_k \leqslant u_k$, can be eliminated from $\mathscr{RC}-\mathscr{P}_{box}$ model. When the robust counterpart of the constraint is satisfied, the upper bound of the probability of constraint violation,

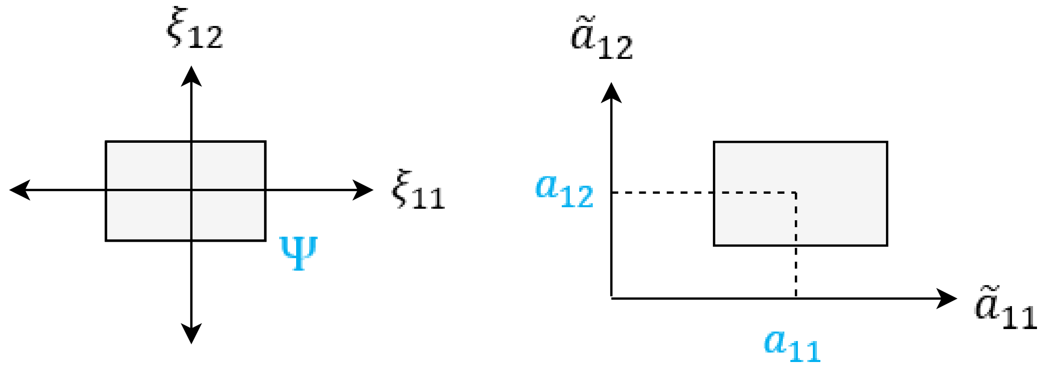


Fig. 3.1 Illustration of the adjustable box uncertainty set.

assuming the probability distribution of uncertainty is symmetric, independent, and bounded, is given by the following relation that proved by Li et al. [71]:

$$\text{Prob}\left\{\sum_j a_{ij}x_j + \sum_k b_{ik}y_k + \sum_{j\in J_i} \xi_{ij}\hat{a}_{ij}x_j + \sum_{k\in K_i} \xi_{ik}\hat{b}_{ik}y_k - \hat{d}_i\xi_{i0} > d_i\right\} \leq \exp\left(-\frac{\Psi^2}{2(|J_i|+|K_i|)}\right) \tag{3.7}$$

where $|J_i|$ is the cardinality of the uncertain parameters which are the coefficients of real variables, while $|K_i|$ is the cardinality of the uncertain parameters which are the coefficients of integer variables of the i^{th} constraint.

3.2.2 Robust counterpart of uncertain MILP model based on the ellipsoidal uncertainty set

For the ellipsoidal uncertainty set, the uncertain space is characterized using the the Euclidean norm of perturbation variables, as depicted in Eq.(3.8).

$$U_{ellipse} = \{\xi \mid \|\xi\|_2 \leqslant \Omega\} = \left\{\xi \,|\, \sqrt{\sum \xi^2} \leqslant \Omega\right\} \tag{3.8}$$

where Ω is the controllable size of the uncertainty set as shown in Fig. 3.2 which reflects the degree of conservativeness and preference of the decision-makers. The robust counterpart

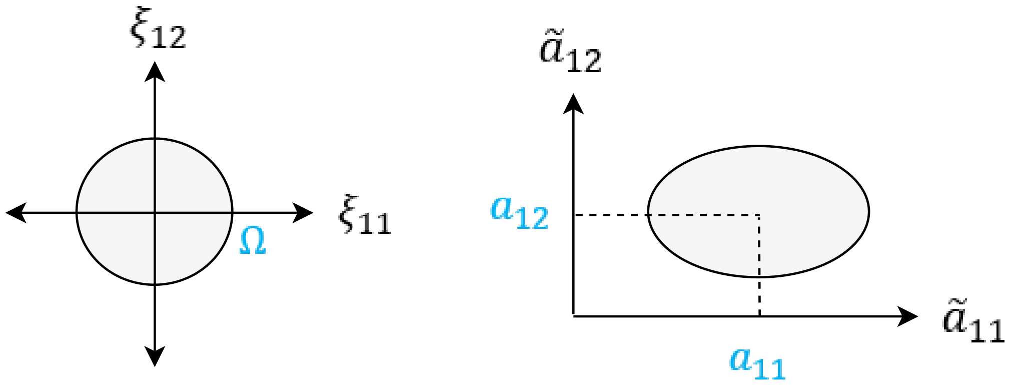


Fig. 3.2 Illustration of the adjustable ellipsoidal uncertainty set.

model of $\mathscr{P}$ based on the ellipsoidal uncertainty set is reformulated as :

$$
\begin{aligned}
\mathscr{RC}-\mathscr{P}_{ellipse}: \quad & \min \quad \beta \\
& \text{s.t.} \\
& \sum_j c_j x_j + \sum_k e_k y_k + \Omega \sqrt{\sum_{j\in J_i} \hat{c}_j^2 x_j^2 + \sum_{k\in K_i} \hat{e}_k^2 y_k^2} \leq \beta \\
& \sum_j a_{ij} x_j + \sum_k b_{ik} y_k + \Omega \sqrt{\sum_{j\in J_i} \hat{a}_{ij}^2 x_j^2 + \sum_{k\in K_i} \hat{b}_{ik}^2 y_k^2 + \hat{d}_i^2} \leqslant d_i && \forall i \in I \\
& x_j \in \mathbb{R} && \forall j \in J \\
& y_k \in \mathbb{Z} && \forall k \in K
\end{aligned}
\tag{3.9}
$$

Proof of $\mathscr{RC}-\mathscr{P}_{ellipse}$ model: see Li et al. [69].
The upper bound on the probability of constraint violation is given by the following relation that proved by Li et al. [71]:

$$
\text{Prob}\left\{\sum_j a_{ij}x_j + \sum_k b_{ik}y_k + \sum_{j\in J_i} \xi_{ij}\hat{a}_{ij}x_j + \sum_{k\in K_i} \xi_{ik}\hat{b}_{ik}y_k - \hat{d}_i\xi_{i0} > d_i\right\} \leq \exp\left(-\frac{\Omega^2}{2(|J_i|+|K_i|)}\right) \tag{3.10}
$$

Assuming that the probability distribution of uncertainty is symmetric, independent, and bounded.

3.3 Mathematical formulation of uncertain dual-channel CLSC

The uncertain dual-channel CLSC network has the same structure, description, assumptions, and model characteristics and notations explained in section 2.2, the uncertain MILP model of the dual-channel CLSC network, $\mathscr{P}$ model, , the notation " $\sim$ " for uncertain parameters, is given below:

$$\mathscr{P}: \ \min \tilde{g}_1 + \tilde{g}_2 + \tilde{g}_3 + \tilde{g}_4 \tag{3.11}$$

$$\begin{aligned}\tilde{g}_1 = &\sum_i \sum_j \sum_t \widetilde{sc}_{ij} A_{ijt} + \sum_j \sum_{k^{tr}} \sum_t \widetilde{sc}_{jk^{tr}} B_{jk^{tr}t} + \sum_j \sum_{k^{on}} \sum_t \widetilde{sc}_{jk^{on}} B_{jk^{on}t} + \sum_{k^{on}} \sum_l \sum_t \widetilde{dc}_{k^{on}l} C_{k^{on}lt} \\ &+ \sum_{k^{tr}} \sum_l \sum_t \widetilde{sc}_{k^{tr}l} C_{k^{tr}lt} + \sum_l \sum_m \sum_t \widetilde{sc}_{lm} D_{lmt} + \sum_m \sum_s \sum_t \widetilde{sc}_{ms} H_{mst} + \sum_m \sum_n \sum_t \widetilde{sc}_{mn} F_{mnt} \\ &+ \sum_m \sum_v \sum_t \widetilde{sc}_{mv} E_{mvt} + \sum_n \sum_j \sum_t \widetilde{sc}_{nj} I_{njt} + \sum_v \sum_{k^{tr}} \sum_t \widetilde{sc}_{vk^{tr}} J_{vk^{tr}t} + \sum_v \sum_{k^{on}} \sum_t \widetilde{sc}_{vk^{on}} J_{vk^{on}t}\end{aligned} \tag{3.12}$$

$$\tilde{g}_2 = \sum_i \sum_j \sum_t \widetilde{pc} A_{ijt} \tag{3.13}$$

$$\begin{aligned}\tilde{g}_3 = &\widetilde{jc} \left(\sum_j \sum_{k^{tr}} \sum_t B_{jk^{tr}t} + \sum_j \sum_{k^{on}} \sum_t B_{jk^{on}t}\right) + \widetilde{mc} \sum_l \sum_m \sum_t D_{lmt} + \widetilde{sic} \sum_m \sum_s \sum_t H_{mst} \\ &+ \widetilde{nc} \sum_m \sum_n \sum_t F_{mnt} + \widetilde{vc} \sum_m \sum_v \sum_t E_{mvt}\end{aligned} \tag{3.14}$$

$$\begin{aligned}\tilde{g}_4 = &\sum_i \sum_t \widetilde{fc}_{it} O_{it} + \sum_j \sum_t \widetilde{fc}_{jt} O_{jt} + \sum_{k^{tr}} \sum_t \widetilde{fc}_{k^{tr}t} O_{k^{tr}t} + \sum_m \sum_t \widetilde{fc}_{mt} O_{mt} + \sum_s \sum_t \widetilde{fc}_{st} O_{st} \\ &+ \sum_n \sum_t \widetilde{fc}_{nt} O_{nt} + \sum_v \sum_t \widetilde{fc}_{vt} O_{vt}\end{aligned} \tag{3.15}$$

s.t.

$$\sum_{k^{tr}} C_{k^{tr}lt} + \sum_{k^{on}} C_{k^{on}lt} \geq \widetilde{de}_{lt} \quad \forall l, t \tag{3.16}$$

and constraints (2.6–2.9) and (2.11–2.28).

The proposed model's OF is to minimize the total cost incurred in the dual-channel CLSC network as shown in Eq. (3.11), which consists of four parts $\tilde{g}_1$, $\tilde{g}_2$, $\tilde{g}_3$, and $\tilde{g}_4$ that define transportation, purchasing, operations, and fixed costs, respectively. A set of constraints that ensure the satisfaction of the uncertain customer's demand is shown in Eq. (3.16). For detailed explanation of the rest of model constraints please refer to subsection 2.3.

3.3.1 Robust model of the dual-channel CLSC based on the adjustable box uncertainty set

This section presents a robust counterpart model, $(\mathscr{RC}-\mathscr{P}_{box})$, of the proposed dual-channel CLSC model $(\mathscr{P})$ based on the box uncertainty set. This robust counter reformulation induced an MILP formulation. We split the OF into four parts, and substitute a constraint for each part as presented in Eqs. (3.18-3.21), each constraint contains independent box uncertainty set associated with each cost type which improves the objective by providing the flexibility to independently adjust the size of each uncertainty set based on the available data, history of each type of cost, and the preferences of the decision makers.

$$\mathscr{RC}-\mathscr{P}_{box}: \min \delta_{tc}+\delta_{pc}+\delta_{oc}+\delta_{fc} \tag{3.17}$$

s.t.

$$g_1+\Psi_{tc}\,\hat{g}_1 \leqslant \delta_{tc} \tag{3.18}$$

$$g_2+\Psi_{pc}\,\hat{g}_2 \leqslant \delta_{pc} \tag{3.19}$$

$$g_3+\Psi_{oc}\,\hat{g}_3 \leqslant \delta_{oc} \tag{3.20}$$

$$g_4+\Psi_{fc}\,\hat{g}_4 \leqslant \delta_{fc} \tag{3.21}$$

$$\sum_{k^{tr}} C_{k^{tr}lt}+\sum_{k^{on}} C_{k^{on}lt}-\Psi_{de}\,\widehat{de}_{lt} \geq de_{lt} \forall l,t \tag{3.22}$$

$$\begin{aligned} g_1 =& \sum_i\sum_j\sum_t sc_{ij}\,A_{ijt}+\sum_j\sum_{k^{tr}}\sum_t sc_{jk^{tr}}\,B_{jk^{tr}t}+\sum_j\sum_{k^{on}}\sum_t sc_{jk^{on}}\,B_{jk^{on}t}+\sum_{k^{on}}\sum_l\sum_t dc_{k^{on}l}\,C_{k^{on}lt}\\ &+\sum_{k^{tr}}\sum_l\sum_t sc_{k^{tr}l}\,C_{k^{tr}lt}+\sum_l\sum_m\sum_t sc_{lm}\,D_{lmt}+\sum_m\sum_s\sum_t sc_{ms}\,H_{mst}+\sum_m\sum_n\sum_t sc_{mn}\,F_{mnt}\\ &+\sum_m\sum_v\sum_t sc_{mv}\,E_{mvt}+\sum_n\sum_j\sum_t sc_{nj}\,I_{njt}+\sum_v\sum_{k^{tr}}\sum_t sc_{vk^{tr}}\,J_{vk^{tr}t}+\sum_v\sum_{k^{on}}\sum_t sc_{vk^{on}}\,J_{vk^{on}t} \end{aligned} \tag{3.23}$$

$$\begin{aligned} \hat{g}_1 =& \sum_i\sum_j\sum_t \widehat{sc}_{ij}\,A_{ijt}+\sum_j\sum_{k^{tr}}\sum_t \widehat{sc}_{jk^{tr}}\,B_{jk^{tr}t}+\sum_j\sum_{k^{on}}\sum_t \widehat{sc}_{jk^{on}}\,B_{jk^{on}t}+\sum_{k^{on}}\sum_l\sum_t \widehat{dc}_{k^{on}l}\,C_{k^{on}lt}\\ &\sum_{k^{tr}}\sum_l\sum_t \widehat{sc}_{k^{tr}l}\,C_{k^{tr}lt}+\sum_l\sum_m\sum_t \widehat{sc}_{lm}\,D_{lmt}+\sum_m\sum_s\sum_t \widehat{sc}_{ms}\,H_{mst}+\sum_m\sum_n\sum_t \widehat{sc}_{mn}\,F_{mnt}\\ &\sum_m\sum_v\sum_t \widehat{sc}_{mv}\,E_{mvt}+\sum_n\sum_j\sum_t \widehat{sc}_{nj}\,I_{njt}+\sum_v\sum_{k^{tr}}\sum_t \widehat{sc}_{vk^{tr}}\,J_{vk^{tr}t}+\sum_v\sum_{k^{on}}\sum_t \widehat{sc}_{vk^{on}}\,J_{vk^{on}t} \end{aligned} \tag{3.24}$$

$$g_2 = \sum_i \sum_j \sum_t pc A_{ijt} \tag{3.25}$$

$$\hat{g}_2 = \sum_i \sum_j \sum_t \widehat{pc} A_{ijt} \tag{3.26}$$

$$\begin{aligned} g_3 =\, & jc \Big(\sum_j \sum_{k^{tr}} \sum_t B_{jk^{tr}t} + \sum_j \sum_{k^{on}} \sum_t B_{jk^{on}t}\Big) + mc \sum_l \sum_m \sum_t D_{lmt} + sic \sum_m \sum_s \sum_t H_{mst} \\ & + nc \sum_m \sum_n \sum_t F_{mnt} + vc \sum_m \sum_v \sum_t E_{mvt} \end{aligned} \tag{3.27}$$

$$\begin{aligned} \hat{g}_3 =\, & \widehat{jc} \Big(\sum_j \sum_{k^{tr}} \sum_t B_{jk^{tr}t} + \sum_j \sum_{k^{on}} \sum_t B_{jk^{on}t}\Big) + \widehat{mc} \sum_l \sum_m \sum_t D_{lmt} + \widehat{sic} \sum_m \sum_s \sum_t H_{mst} \\ & + \widehat{nc} \sum_m \sum_n \sum_t F_{mnt} + \widehat{vc} \sum_m \sum_v \sum_t E_{mvt} \end{aligned} \tag{3.28}$$

$$\begin{aligned} g_4 =\, & \sum_i \sum_t fc_{it} O_{it} + \sum_j \sum_t fc_{jt} O_{jt} + \sum_{k^{tr}} \sum_t fc_{k^{tr}t} O_{k^{tr}t} + \sum_m \sum_t fc_{mt} O_{mt} + \sum_s \sum_t fc_{st} O_{st} \\ & + \sum_n \sum_t fc_n O_{nt} + \sum_v \sum_t fc_{vt} O_{vt} \end{aligned} \tag{3.29}$$

$$\begin{aligned} \hat{g}_4 =\, & \sum_i \sum_t \widehat{fc}_{it} O_{it} + \sum_j \sum_t \widehat{fc}_{jt} O_{jt} + \sum_{k^{tr}} \sum_t \widehat{fc}_{k^{tr}t} O_{k^{tr}t} + \sum_m \sum_t \widehat{fc}_{mt} O_{mt} + \sum_s \sum_t \widehat{fc}_{st} O_{st} \\ & + \sum_n \sum_t \widehat{fc}_{nt} O_{nt} + \sum_v \sum_t \widehat{fc}_{vt} O_{vt} \end{aligned} \tag{3.30}$$

and constraints (2.6–2.9) and (2.11–2.28).

The $\mathscr{RC} - \mathscr{P}_{box}$ model's OF is reformulated as depicted in Eq. (3.11) composed of uncertain transportation, purchasing, operations, and fixed costs. The nominal deterministic values of these cost elements are as follows: g_1, g_2, g_3, and g_4, respectively. $\widehat{g}_1$, $\widehat{g}_2$, $\widehat{g}_3$, and $\widehat{g}_4$ represent their perturbations around the deterministic nominal values, and $\Psi_{tc}, \Psi_{pc}, \Psi_{oc}$, and Ψ_{fc} represent the adjustable parameters that control their uncertain sets, respectively, as is shown in Eqs. (3.18-3.21). Henceforward, we use the hat notation, " $\widehat{}$ ", to indicate the perturbation of parameters around their nominal values.
The robust counterpart of the uncertain customer demand is presented as shown in Eq. (3.22), where $de_{lt}, \widehat{de}$, and Ψ_{de} represent the nominal value of demand, perturbation of demand around its nominal value, and adjustable size of the demand uncertainty set, respectively.

3.3.2 Robust model of the dual-channel CLSC based on the adjustable ellipsoidal uncertainty set

This section presents a robust counterpart model, ($\mathscr{RC} - \mathscr{P}_{ellipse}$), of the proposed dual-channel CLSC model ($\mathscr{P}$) based on the ellipsoidal uncertainty set. This robust counterpart induced an MINLP reformulation.

$$\mathscr{RC} - \mathscr{P}_{ellip} : \min \gamma_{tc} + \gamma_{pc} + \gamma_{oc} + \gamma_{fc} \tag{3.31}$$

s.t.

$$g_1 + \Omega_{tc} \sqrt{\sum_{element} (\hat{g}_1)^2_{element}} \leqslant \gamma_{tc} \tag{3.32}$$

$$g_2 + \Omega_{pc} \sqrt{\sum_{element} (\hat{g}_2)^2_{element}} \leqslant \gamma_{pc} \tag{3.33}$$

$$g_3 + \Omega_{oc} \sqrt{\sum_{element} (\hat{g}_3)^2_{element}} \leqslant \gamma_{oc} \tag{3.34}$$

$$g_4 + \Omega_{fc} \sqrt{\sum_{element} (\hat{g}_4)^2_{element}} \leqslant \gamma_{fc} \tag{3.35}$$

$$\sum_{k^{tr}} C_{k^{tr}lt} + \sum_{k^{on}} C_{k^{on}lt} - \Omega_{de} \widehat{de}_{lt} \quad \geq de_{lt} \;\; \forall l,t \tag{3.36}$$

$$\begin{aligned}\sum_{element} (\hat{g}_1)^2_{element} =& \sum_i \sum_j \sum_t \widehat{sc}^2_{ij} A_{ijt} + \sum_j \sum_{k^{tr}} \sum_t \widehat{sc}^2_{jk^{tr}} B_{jk^{tr}t} + \sum_j \sum_{k^{on}} \sum_t \widehat{sc}^2_{jk^{on}} B_{jk^{on}t} + \\ & \sum_{k^{on}} \sum_l \sum_t \widehat{dc}^2_{k^{on}l} C_{k^{on}lt} + \sum_{k^{tr}} \sum_l \sum_t \widehat{sc}^2_{k^{tr}l} C_{k^{tr}lt} + \sum_l \sum_m \sum_t \widehat{sc}^2_{lm} D_{lmt} + \\ & \sum_m \sum_s \sum_t \widehat{sc}^2_{ms} H_{mst} + \sum_m \sum_n \sum_t \widehat{sc}^2_{mn} F_{mnt} + \sum_m \sum_v \sum_t \widehat{sc}^2_{mv} E_{mvt} + \\ & \sum_n \sum_j \sum_t \widehat{sc}^2_{nj} I_{njt} + \sum_v \sum_{k^{tr}} \sum_t \widehat{sc}^2_{vk^{tr}} J_{vk^{tr}t} + \sum_v \sum_{k^{on}} \sum_t \widehat{sc}^2_{vk^{on}} J_{vk^{on}t}\end{aligned} \tag{3.37}$$

$$\sum_{element} (\hat{g}_2)^2_{element} = \sum_i \sum_j \sum_t \widehat{pc}^2 A_{ijt} \tag{3.38}$$

$$\begin{aligned}\sum_{element} (\hat{g}_3)^2_{element} =& \widehat{jc}^2 \left(\sum_j \sum_{k^{tr}} \sum_t B_{jk^{tr}t} + \sum_j \sum_{k^{on}} \sum_t B_{jk^{on}t}\right) + \widehat{mc}^2 \sum_l \sum_m \sum_t D_{lmt} + \\ & \widehat{sic}^2 \sum_m \sum_s \sum_t H_{mst} + \widehat{nc}^2 \sum_m \sum_n \sum_t F_{mnt} + \widehat{vc}^2 \sum_m \sum_v \sum_t E_{mvt}\end{aligned} \tag{3.39}$$

$$\sum_{element} (\hat{g}_4)^2_{element} = \sum_i \sum_t \widehat{fc}^2_{it} O_{it} + \sum_j \sum_t \widehat{fc}^2_{jt} O_{jt} + \sum_{k^{tr}} \sum_t \widehat{fc}^2_{k^{tr}t} O_{k^{tr}t} + \sum_m \sum_t \widehat{fc}^2_{mt} O_{mt} + \sum_s \sum_t \widehat{fc}^2_{st} O_{st} + \sum_n \sum_t \widehat{fc}^2_{nt} O_{nt} + \sum_v \sum_t \widehat{fc}^2_{vt} O_{vt} \tag{3.40}$$

and constraints (2.6–2.9) and (2.11–2.28).

3.4 Computational experiments

To evaluate the performance of the proposed robust dual-channel CLSC, we conduct a set of numerical examples and perform intensive sensitivity analysis using GAMS/CPLEX software for solving $\mathscr{RC} - \mathscr{P}_{box}$ model and GAMS/BARON for solving $\mathscr{RC} - \mathscr{P}_{ellipse}$ model. The studied network of the dual-channel CLSC network multi-echelon, has four periods planning horizon, as well as a single product, and is composed of four suppliers, two manufacturers, two traditional retailers, two online retailers, three customer zones, two collection and inspection centers, two disposal centers, two recycling centers, and two recovery centers.

The shipping costs depend on the distances between the facilities which varied from 80 to 200 kilometers, with a shipment cost of 0.08 USD per kilometer and a delivery cost of 1.0 USD per product. In the conducted computational experiments, we assumed that the perturbations of the uncertain parameters 10% around their nominal values, the nominal values of the input parameters implemented in this study are adopted from the literature i.e., Mohammed et al. [75] and Kaoud et al. [63]. The nominal values of the input parameters are presented in Table 3.1. In this section, we focus on two main aspects. The first is to conduct a sensitivity analysis, taking into account the influence of each of the uncertainty set in the OF on the overall cost and the related upper bound of the probability of constraints violation, the second is conducting a sensitivity analysis of interactive OF uncertainty set with the uncertain demand.

3.4.1 Impact analysis of multiple-uncertainty sets to the OF

In this subsection, we present the analysis of impact of each cost uncertainty in the OF, namely, transportation, purchasing, operations, and fixed costs on their true values and the total cost of the dual-channel CLSC network based on the adjustable box and ellipsoidal uncertainty sets and also the upper bound of constraint violation probability. The conducted experiments are considered from the worst case scenario perspective, in other words, the uncertainty set must cover the entire uncertain space to guarantee that solutions are robust for any realization of uncertainty as well as there is no constraint violation.

Table 3.1 Nominal values of model's input parameters

Input parameter	Value
ca_{it}	uniform (1400, 1600)
ca_{jt}	uniform (1200, 1400)
$ca_{k^{tr}t}$	uniform (900, 1900)
$ca_{k^{on}t}$	uniform (700, 900)
ca_{mt}	uniform (2600, 2700)
ca_{st}	uniform (1600, 1800)
ca_{nt}	uniform (1600, 1900)
ca_{vt}	uniform (1500, 1900)
de_{lt}	uniform (500, 800)
fc_{jt}	uniform (30,000, 60,000)
fc_{mt}	uniform (2500, 5000)
fc_{nt}	uniform (20,000, 30,000)
fc_{st}	uniform (4000, 5000)
$fc_{k^{tr}t}$	uniform (10,000, 12,000)
fc_{vt}	uniform (10,000, 30,000)
pc	uniform (11, 13)
jc	uniform (21, 24)
mc	uniform (6, 9)
sic	uniform (7, 9)
yc	uniform (2, 4)
vc	uniform (10, 15)
λ	0.7
μ	0.7
ρ	0.3
τ	0.3
ϕ	0.7

The minimum size necessary for covering the entire uncertain space for the adjustable box and ellipsoidal uncertainty sets is $\Psi = 1$, and $\Omega = \sqrt{|J_i| + |K_i|}$ for the box and ellipsoidal uncertainty sets, respectively, based on their geometrical shape; the upper bound of constraints violation probability is given by $\exp\left(-\frac{\Psi^2}{2(|J_i|+|K_i|)}\right)$, and $\exp\left(-\frac{\Omega^2}{2(|J_i|+|K_i|)}\right)$ for the adjustable box and ellipsoidal uncertainty sets, respectively, (Li et al., 2012). For the uncertain transportation cost, the value of $\Omega_{tc} = \Psi_{tc}\sqrt{|J_i^{tc}| + |K_i^{tc}|}$ where Ψ_{tc}, Ω_{tc}, and $|J_i^{tc}| + |K_i^{tc}|$ are the adjustable size of box , ellipsoidal, and cardinality of the uncertain transportation cost parameters.

Figure. 3.3 illustrates the results obtained from both robust counterpart models $\mathscr{RC} - \mathscr{P}_{box}$ and $\mathscr{RC} - \mathscr{P}_{ellipse}$ based on the adjustable box and ellipsoidal uncertainty sets, respectively,

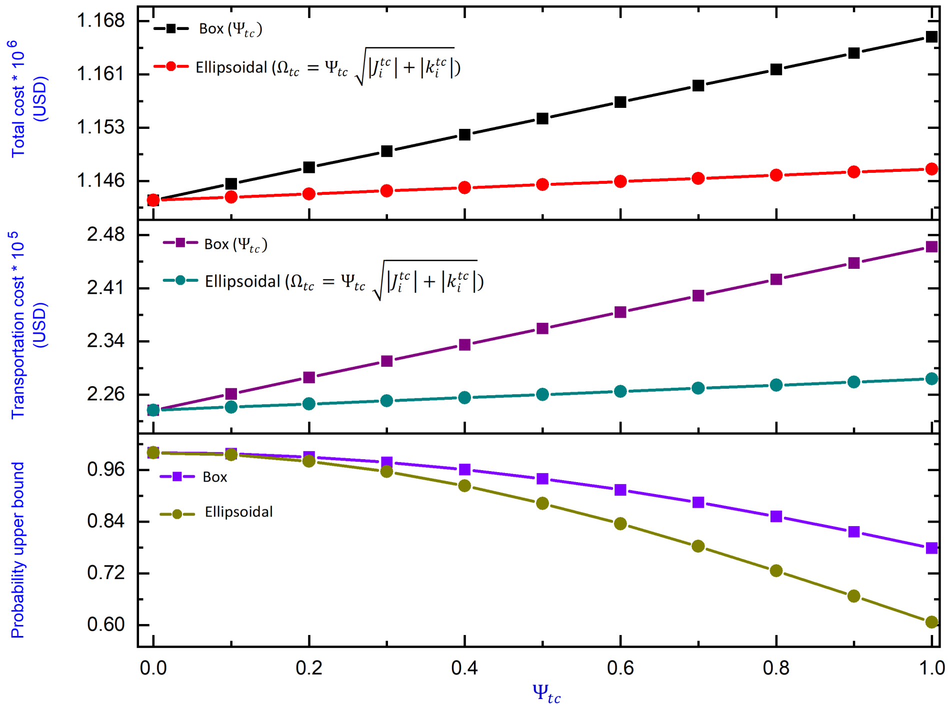


Fig. 3.3 Results of the robust dual-channel CLSC with transportation cost uncertainty.

as well as the upper bound of the constraint violation probability. As long as, the size of both uncertainty sets increases, the real value of robust transportation cost increases, this results in an increase in the total cost incurred in the entire network. As depicted in the middle portion in Fig. 3.3 , real values of robust transportation cost are equal for both models when Ψ_{tc}, and Ω_{tc} equal zero that lead to the value of nominal (deterministic) transportation cost and increase gradually for both models while the size of uncertainty sets increase to reach the worst-case scenario when $\Psi_{tc} = 1$ with deviation 10% and 2% from the deterministic value of transportation cost. Meanwhile, an associated change of the robust total cost deviates 2%, and 0.4% from the deterministic value of the total cost incurred in the entire network for the robust counterpart reformulation of the box and ellipsoidal uncertainty sets, respectively, as shown in the upper portion in Fig. 3.3
The impact of purchasing cost uncertainty on both the real robust value of purchasing cost and total cost incurred in the entire dual-channel CLSC network as well as the upper bound of the probability of the purchasing cost constraint violation based on robust counterpart reformulation models, the adjustable box and ellipsoidal, is shown in Fig. 3.4.

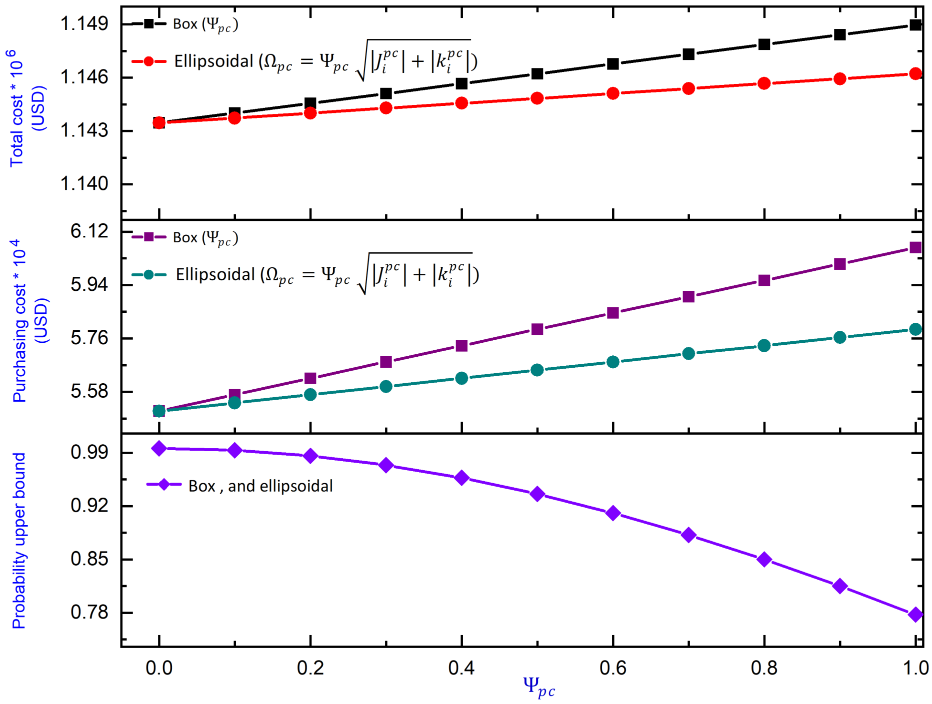


Fig. 3.4 Results of the robust dual-channel CLSC with purchasing cost uncertainty.

The value of Ω_{pc} becomes equal to $\Psi_{pc}\sqrt{|J_i{}^{pc}| + |K_i{}^{pc}|}$ because the cardinality of uncertain parameters in the purchasing cost uncertainty set is equal to 1; in addition, for this reason, the upper bound for constraint violation probability has the same value for both models. As shown in Fig. 3.4, when $\Psi_{pc} = \Omega_{pc} = 0$, the value of purchasing cost and the total cost incurred in the entire network is equal to their deterministic values. The real robust values of purchasing cost and total cost for both models increase with the size of uncertainty sets; when $\Psi_{pc} = \Omega_{pc} = 1$, the change of the real value of purchasing cost from its deterministic value is 10% and 5% and the change in the real value of the total cost is 0.5% and 0.25% from their their deterministic values for the robust counterpart models based on the box and ellipsoidal uncertainty sets, respectively. The impact of uncertain operation costs on the real robust operation cost and the total cost incurred in the entire network as well as the upper bound for the constraint violation probability associated with uncertain operations cost stemming from the robust counterpart models based on the box and ellipsoidal uncertainty sets are shown in Fig. 3.5.
We set the value of Ω_{oc} to be equal to $\Psi_{oc}\sqrt{|J_i{}^{oc}| + |K_i{}^{oc}|}$ where $|J_i{}^{oc}| + |K_i{}^{oc}|$ is the cardinality of the uncertain operations cost parameters, the value of real robust operations cost and

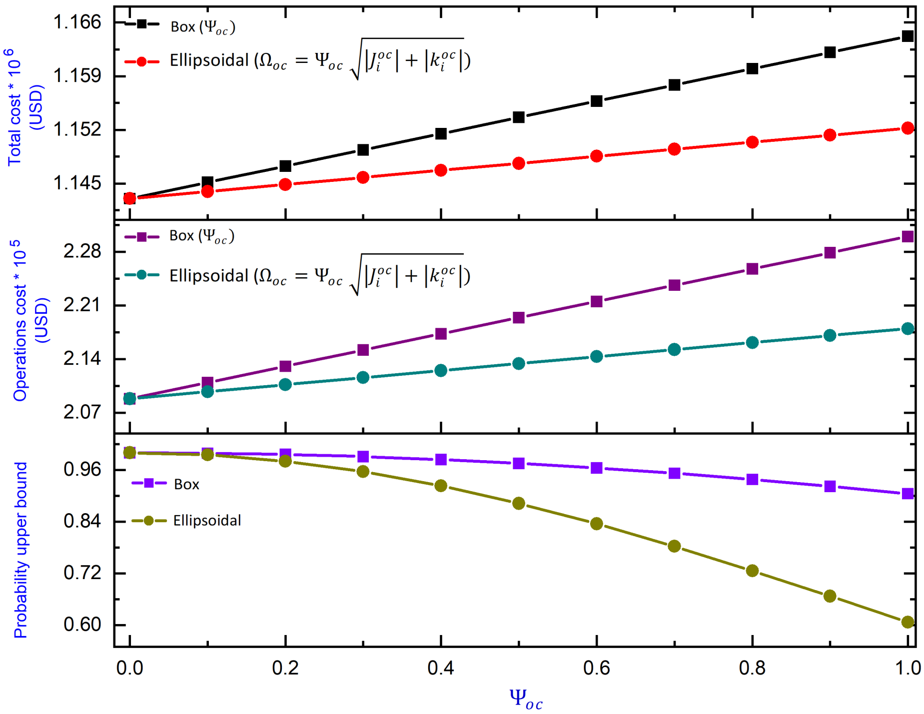


Fig. 3.5 Results of the robust dual-channel CLSC with operations cost uncertainty.

total cost are equal to their deterministic values for both models based on box and ellipsoidal uncertainty sets when $\Psi_{oc} = \Omega_{oc} = 0$. Increasing the adjustable size of uncertainty sets for both models, the real value of the operations and total cost gradually increase, when $\Psi_{oc} = 1$ the real value of operations and total cost increases by 10%, 4.3% and 1.82%, and 0.8% for both robust counterpart model based on the box and ellipsoidal uncertainty sets, respectively. The impact of uncertainty of the fixed cost on its real robust value and corresponding total cost and the upper bound of the constraint violation probability are shown in Fig. 3.6. The value of Ω_{fc} is set to be equal to $\Psi_{fc}\sqrt{|J_i{}^{fc}| + |K_i{}^{fc}|}$, where $|J_i{}^{fc}| + |K_i{}^{fc}|$ is the cardinality of fixed cost uncertain parameters. Increasing the size of the adjustable parameters of the box and ellipsoidal uncertainty sets results in an increase in the real value of fixed cost and thus increased the total cost as shown in Fig. 3.6. When $\Psi_{fc} = 1$ the change of the real robust fixed and total cost from their deterministic values, $\Psi_{fc} = 0$, by 10%, 6.4% and 5.7%, 3.7% for both robust counterpart models based on box and ellipsoidal uncertainty sets, respectively.

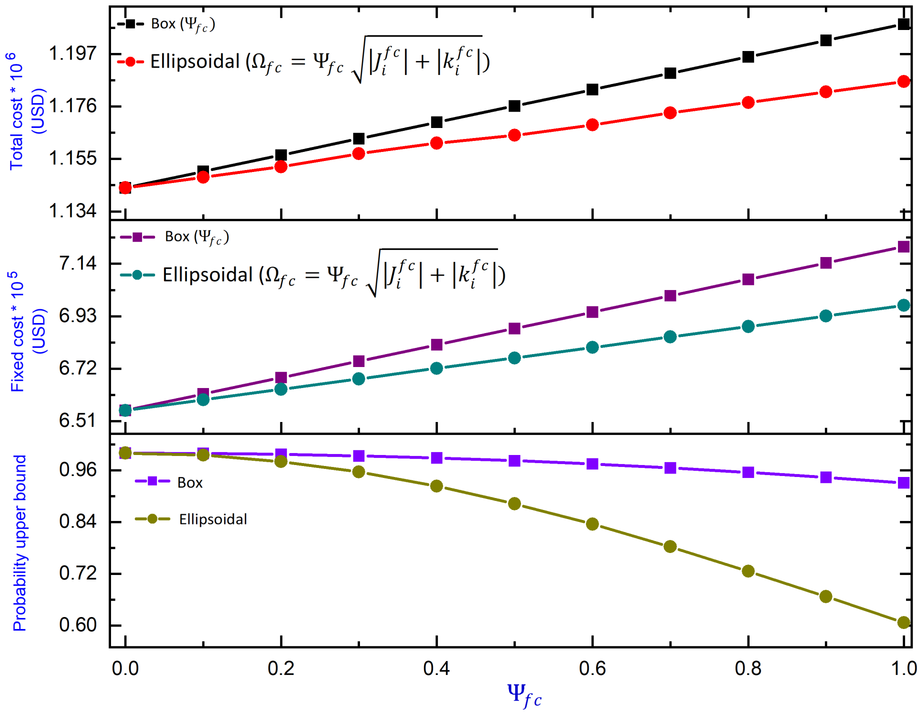


Fig. 3.6 Results of the robust dual-channel CLSC with fixed cost uncertainty.

3.4.2 Performance of interactive multiple-uncertainty sets OF with demand uncertainty

In this subsection, we consider interactive transportation, purchasing, operations, fixed costs, and demand uncertainty. As presented in Table 3.2, Ex00-Ex10 are 11 computational experiments on robust counterpart models assuming the perturbation of uncertain parameters is 10% of their nominal values based on adjustable box and ellipsoidal uncertainty sets, for a total of 22 experiments.

We design each experiment based on the worst case scenario perspective. The adjustable size of the box uncertainty sets takes a value from 0 to 1.0 with an increment of 0.1 as shown in Table 3.2. The values of the total cost of robust model based on the box uncertainty set has bigger value than that obtained from the robust model based on the ellipsoidal uncertainty set.

Table 3.2 Total cost incurred in the robust dual-channel CLSC.

Instance	Box Ψ					Ellipsoidal $\Omega = \Psi * \sqrt{\lvert J_i\rvert + \lvert K_i\rvert}$					Total cost (USD)	
	Ψ_{tc}	Ψ_{pc}	Ψ_{oc}	Ψ_{fc}	Ψ_{de}	Ω_{tc}	Ω_{pc}	Ω_{oc}	Ω_{fc}	Ω_{de}	$\mathscr{RC} - \mathscr{P}_{box}$	$\mathscr{RC} - \mathscr{P}_{ellipse}$
Ex00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1,143,458	1,143,458
Ex01	0.1	0.1	0.1	0.1	0.1	0.14	0.1	0.22	0.24	0.1	1,210,741	1,204,427
Ex02	0.2	0.2	0.2	0.2	0.2	0.28	0.2	0.45	0.49	0.2	1,227,674	1,216,747
Ex03	0.3	0.3	0.3	0.3	0.3	0.42	0.3	0.67	0.73	0.3	1,244,704	1,226,651
Ex04	0.4	0.4	0.4	0.4	0.4	0.57	0.4	0.89	0.98	0.4	1,261,831	1,236,168
Ex05	0.5	0.5	0.5	0.5	0.5	0.71	0.5	1.12	1.22	0.5	1,279,056	1,246,807
Ex06	0.6	0.6	0.6	0.6	0.6	0.85	0.6	1.34	1.47	0.6	1,296,377	1,257,477
Ex07	0.7	0.7	0.7	0.7	0.7	0.99	0.7	1.57	1.71	0.7	1,325,255	1,278,842
Ex08	0.8	0.8	0.8	0.8	0.8	1.13	0.8	1.79	1.96	0.8	1,342,889	1,289,539
Ex09	0.9	0.9	0.9	0.9	0.9	1.27	0.9	2.01	2.20	0.9	1,360,634	1,295,561
Ex10	1.0	1.0	1.0	1.0	1.0	1.41	1.0	2.24	2.45	1.0	1,378,484	1,310,988

3.4.3 Selecting an adequate uncertainty set shape and size

Choosing an adequate shape of the uncertainty set depends on the preferences of the decision-makers. At the same time, it depends on the available information about the uncertain data, i.e., historical observation, coherent risk, and bounds on uncertain parameters. In our study, we used two types of uncertainty sets, the adjustable box and ellipsoidal uncertainty sets, as we noticed from the results discussed in the previous subsection 3.4, the total costs of the robust dual-channel CLSC based on the box are worse than those obtained based on the adjustable ellipsoidal uncertainty set. On the other hand, those solutions obtained based on the adjustable box uncertainty set are the most robust choices and ensure fully constraints satisfaction. The shape of the uncertainty set determines the tractability of the robust counterpart reformulation that is a trade-off between the computational complexity and robustness of the obtained solutions. For constructing uncertainty sets based on historical data and risk coherence of uncertain parameters, refer to Bertsimas et al. [22], and Bertsimas and Brown [20].
Selecting the size of the uncertainty set reflects the degree of conservativeness or robustness of the obtained solutions. In other words, control the maximum probability of constraints violation. In our proposed study, the larger the size of the uncertainty sets, the more conservatively, higher values of the total cost are incurred in the dual-channel CLSC network, resulting in a decrease in the upper bound of constraint violation probability.

3.5 Conclusions

This chapter proposes an adaptable robust optimization model for the dual-channel CLSC network, offering multiple uncertainty sets for uncertain costs and uncertain customer demand. The goal of the study is to design the dual-channel CLSC at the minimum total cost and achieving robust solutions. Two robust models based on the adjustable box and ellipsoidal uncertainty sets of the dual-channel CLSC are considered. Intensive computational experiments are conducted using GAMS programming language. We focus on the impact of each uncertain cost type on the total cost and the maximum probability of the constraint violation based on the two robust counterpart models. Moreover, we consider simultaneous effect of uncertain cost and demand on the dual-channel CLSC model performance. The obtained results from both models conclude that solutions based on the box uncertainty set are more conservative than that obtained based on the ellipsoidal uncertainty set. The box uncertainty set immunizes the solution against any possible realization of uncertain parameters, whereas the ellipsoid uncertainty set does not immunize the solution against all uncertain realizations of the parameters; however it cannot immunize against the uncertain parameter realizations in the corners of the box uncertainty set. Decision-makers must choose the characteristics of the uncertainty set, such as shape and size. We present an adaptable robust dual-channel CLSC model that provides decision-makers with the flexibility of choosing the uncertainty set characteristics and alleviate their risk preferences. This in turn, contributes to the operations management and operations research areas.

Chapter 4

Robust optimization for a bi-objective green closed-loop supply chain with heterogeneous transportation system and presorting consideration

4.1 Introduction

In April of 2018, the concentration of carbon dioxide, CO_2, in the atmosphere reached 410 parts per million (ppm), which was the highest level in the previous 800,000 years; compared to the previous highest level in 1780 which was just 280 ppm [6]. Many crises have resulted from carbon emissions, including rising sea levels and accelerating species extinction [123, 6].

The transportation sector was the second-largest source of CO_2 emissions in 2018, around 25% of the total carbon emissions, according to a report by the International Energy Agency [119]. As a result, limiting transportation's excessive CO_2 emission growth has become a critical component of global CO_2 emission reduction [14].

Many governments pay attention to conducting measures and refining legislation to motivate organizations and a broad sector of customers to adopt green and sustainable practices in their production and service activities [56, 63].

Approximately 197 countries at the UN climate summit in November 2021 agreed on new measures for carbon emission reduction, including standards for reporting national emissions and the ground rules for trading credits [81].

A green closed-loop supply chain (GCLSC) involves the integration of environmental aspects into all activities of the traditional closed-loop supply chain (CLSC) network [77, 122]. Recently, customers' behavior has remarkably changed. They are concerned about the environmental aspects of the products and their price and quality [92, 121].

Numerous companies are pursuing greenness and sustainability by employing inspection, recycling, and refurbishing activities to recover the used products collected from end customers to increase their return rates [59]. For instance, Xerox, Canon, Kodak, Dell, and Acer have been pushing green operations. For example, by the year 2012, Xerox had effectively cut their emissions by 42% and their energy consumption by 31% [30]. Transportation fleets that move goods between supply chain hubs are a significant contributor to rising environmental consequences. According to Golicic et al. [46], fleet management has a favorable influence on energy efficiency and reduces fleet-related environmental consequences.

Using a heterogeneous fleet comprised of vehicles of varied sizes, the amount of fuel required to serve a given request portfolio can be drastically reduced [68]. Moreover, it provides a better balance of economic and environmental sustainability simultaneously [73, 34].

Government policymakers should incentivize businesses to collect used products from customer zones for reverse logistics activities that in turn consolidate greenness and sustainability [60]. Considering efficient presorting centers at the customer zones substantially separates the low-quality returned products at the early stage from the refurbishment stream, thereby causing a reduction in the induced cost and carbon emissions [99].

Most real-life optimization problems are multi-objective and, usually, are uncertain due to the inherent errors of parameter values [13]. These errors result from inappropriate measurement or estimation due to a lack of knowledge of parameter values [4], a highly dynamic environment, and the physical impossibility to implement a computing solution in real-life problems [47]. Ignoring these uncertainties in optimization problems leads to infeasible and sub-optimal solutions [17].

Stochastic optimization (SO) and robust optimization (RO) are well-known approaches for solving uncertain optimization problems. In the SO approach, the probability of uncertain parameters must be defined accurately, but precisely defining this probability is difficult [47, 88]. In addition, this approach devastates the convexity property and alleviates the complexity of the original problem in the chance constraints. However, in the RO approach, the uncertainty of the parameter is predefined in an uncertainty set characterized by its shape and size, and this approach overcomes some drawbacks of the SO approach [84].

As far as we are aware, few studies [42, 33, 55] have focused on the RO-based multi-objective optimization of CLSC networks. In these investigations, the implemented uncertainty set is the box uncertainty set with a homogeneous transportation system and no presorting centers in client zones. Motivated by the above facts, we developed a bi-objective

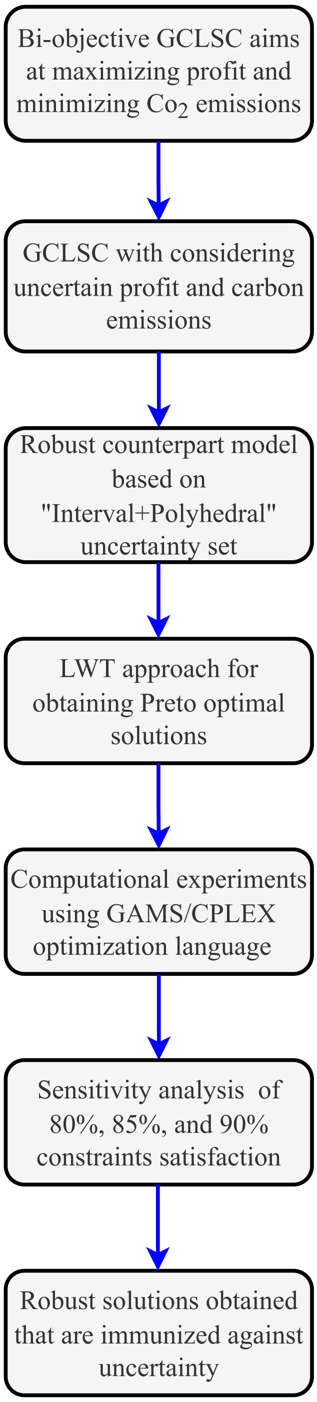


Fig. 4.1 The logical framework of the proposed robust GCLSC network.

robust optimization model for the GCLSC by considering presorting and heterogeneous transportation systems. The logical interpretation of the proposed study's framework is depicted in Figure 4.1. The main contributions of this study are as follows:

- Presenting a bi-objective mixed-integer linear programming (MILP) model for the GCLSC while considering presorting and a heterogeneous transportation system as well as uncertain cost, selling price, and carbon emissions uncertainties.
- Presenting a robust counterpart model formulation of the bi-objective MILP model of the GCLSC network under uncertainties using the well-known RO approach based on the "Interval + Polyhedral" uncertainty set.
- Performing intensive computational experiments using a lexicographic weighted Tchebycheff (LWT) approach to obtain the Pareto optimal solutions of the robust bi-objective model, in which the probability bounds on constraint satisfaction are not violated.

4.2 Problem statement and mathematical formulation

The GCLSC proposed in this study compromises a set of customer zones where the returned products are collected, a set of presorting centers located at these zones, a recycling center, and an inspection and refurbishment (IR) center with different capacity sizes: small, medium, and big. The structure of the proposed GCLSC network (Figure 4.2) is the same structure presented by Samuel et al. [99]. Transportation between the facilities is a heterogeneous transportation system comprising different vehicle fleets that are varied in capacity, cost, and carbon emissions. The returned products at customer zones are either subject to presorting or nonpresorting, depending on the quality of the returned products. For high or very low-quality products, it is obvious that they can be transferred directly to the IR and recycling centers, respectively. Otherwise, the returned products are presorted in the presorting center depending on the quality of these products and the efficiency of the presorting center. A fraction of these products are sent to the recycling center, and the rest are sent to the IR center.

To maximize the profit that results from the difference between the selling of refurbished products and the total cost incurred in the network and minimize the total carbon emissions due to processes and transportation activities in the network, we consider further assumptions as follows:

- The refurbished products are in a condition as good as new ones.
- Selling price, costs, and carbon emissions are subject to uncertainty with an unknown probability distribution.

- The capacities, costs, and carbon emissions due to transportation modes are predefined. Costs and emissions are based on the round trip distances between network facilities.
- The locations of customers zones, the recycling center, and the IR center are predefined.
- The capacities of the facilities are predefined and deterministic.
- Only one transportation mode can be used between any two consecutive facilities in the GCLSC network.

Based on the above assumptions and description, an MILP model of the proposed bi-objective GCLSC network and its nomenclature are as follow:

Table 4.1 Nomenclature of the proposed bi-objective GCLSC model.

	Indices & Sets
p	Set of products $\{1,2,3\ldots\ldots P\}$.
v	Set of transportation modes $\{1,2,3\ldots\ldots V\}$.
k	Set of customer zones$\{1,2,3\ldots\ldots K\}$.
s	Set of IR center sizes {small, medium, big}.
	Binary variables
$\dot{O}_{pkv}$	A binary variable, if the mode of transportation v is used to transfer product p from customer zone k to the IR center without presorting , take a value 1, otherwise 0.
$\dot{O}^{pre}_{pkv}$	A binary variable, if the mode of transportation v is used to transfer product p from customer zone k to the IR center after presorting, take a value 1, otherwise 0.
O^{ref}_{pv}	A binary variable, if the mode of transportation v is used to transfer refurbished product p from IR center to customer zone k , take a value 1, otherwise 0.
$\ddot{O}_{kv}$	A binary variable, if the mode of transportation v is used to transfer scrapped product p without presorting from customer zone k to the recycling center , take a value 1, otherwise 0.
$\ddot{O}^{pre}_{kv}$	A binary variable, if the mode of transportation v is used to transfer scrapped product p after presorting from customer zone k to the recycling center , take a value 1, otherwise 0.
$\dddot{O}_{kv}$	A binary variable, if the mode of transportation v is used to transfer scrapped product p shipped from IR center to the recycling center, take a value 1, otherwise 0.

U_s	A binary variable, if the IR center of size s opens , take a value 1, otherwise 0.
U_k	A binary variable, if the presorting center opens at customer zone k , take a value 1, otherwise 0.
U_r	A binary variable, if the recycling center opens, take a value 1, otherwise 0.
	Continuous variables
X_{pkv}^{ins}	Quantity of returned product p sent from customer zone k to the IR center without presorting using transportation mode v.
X_{pk}^{pre}	Quantity of product p presorted at the presorting center at customer zone k.
X_{pkv}^{rec}	Quantity of product p transported from customer zone k to the recycling center without presorting using transportation mode v.
Y_{pkvt}^{ins}	Quantity of presorted product p sent from the presorting center at customer zone k to the IR center using transportation mode v.
Y_{pkv}^{rec}	Quantity of presorted product p transported from the presorting center at customer zone k to the recycling center using transportation mode v.
Z_{pkv}^{ref}	Quantity of product p sent from customer zone k to the IR center without presorting using transportation mode v .
Z_{pv}^{rec}	Quantity of recycled product p sent from the IR center to the recycling center using transportation mode v.
	Integer variables
$\dot{N}_{kv}$	Number of selected vehicle v for transporting products from customer zone k to the IR center without presorting.
$\dot{N}_{kv}^{pre}$	Number of selected vehicle v for transporting products from customer zone k to the IR center after presorting.
N_{kv}^{ref}	Number of selected vehicle v for transporting refurbished products from the IR center to customer zone k.
$\ddot{N}_{kv}$	Number of selected vehicle v for transporting scrapped products without presorting from customer zone k to the recycling center.
$\ddot{N}_{kv}^{pre}$	Number of selected vehicle v for transporting scrapped products after presorting from customer zone k to the recycling center.
$\dddot{N}_{v}$	Number of selected vehicle v for transporting scrapped product p shipped from the IR center to the recycling center.
	Parameters
r_{pk}	Collected product p at customer zone k.
s_{pk}	Selling price of refurbished product p at customer zone k using transportation mode v.

f_s	Fixed cost of opening an IR center of size s.
f_k^p	Fixed cost of opening a presorting center at customer zone k.
q_{pk}	Quality of returned product p at customer zone k.
c_v^{tr}	Cost of transportation of a unit weight of product using transportation mode v .
ev_v	Carbon emissions due to using transportation mode v.
$\hat{c}_{cap}$	Carbon cap (kg of co_2).
em_p^{col}	Carbon emissions due to collecting product p.
em_p^{pre}	Carbon emissions due to presorting product p.
em_p^{ins}	Carbon emissions due to inspecting a product p at the IR center.
em_p^{ref}	Carbon emissions due to refurbishing a product p at the IR center.
em_{pt}^{rec}	Carbon emissions due to scrapping a product p at the recycling center.
p_p^{ins}	Operation cost of inspecting a product p.
p_{pt}^{rec}	Operation cost of recycling a product p.
p_p^{ref}	Operation cost of refurbishing a product p.
p_p^{pre}	Operation cost of presorting a product p.
d_{ki}	Distance between customer zone k and the IR center.
d_{kr}	Distance between customer zone k and the recycling center.
d_{ir}	Distance between the IR center and the recycling center.
ca_s	Capacity of the IR center of size s.
ca^{big}	Capacity of the IR center of size "big".
ca_v	Capacity of vehicle mode v (kg).

On the one hand, the first objective function, $\tilde{g}_{\text{pro}}$, of the proposed model is the maximization of the profit; it comprises four parts: the first part, $\tilde{g}_1$, represents the selling price of the refurbished products at the IR center; the second part, $\tilde{g}_2$, represents the fixed costs of opening facilities in the entire network; the third part, $\tilde{g}_3$, represents the transportation costs due to transportation activities in the GCLSC network using heterogeneous modes of transportation of vehicles v; the last part, $\tilde{g}_4$, represents the cost of processing activities in the network, including presorting, inspection, refurbishment, and recycling.

On the other hand, the second objective function, $\tilde{g}_{\text{emi}}$, of the proposed model is the minimization of the carbon emissions due to the various activities in the GCLSC network; it comprises two parts: the first part, $\widetilde{em}_{tr}$, represents the emissions due to transportation activities using different modes of transportation vehicles in the network part of the objective function. The second part, $\widetilde{em}_{pr}$, is the emissions due to different processing activities in the network, such as presorting, inspection, refurbishing, and recycling.

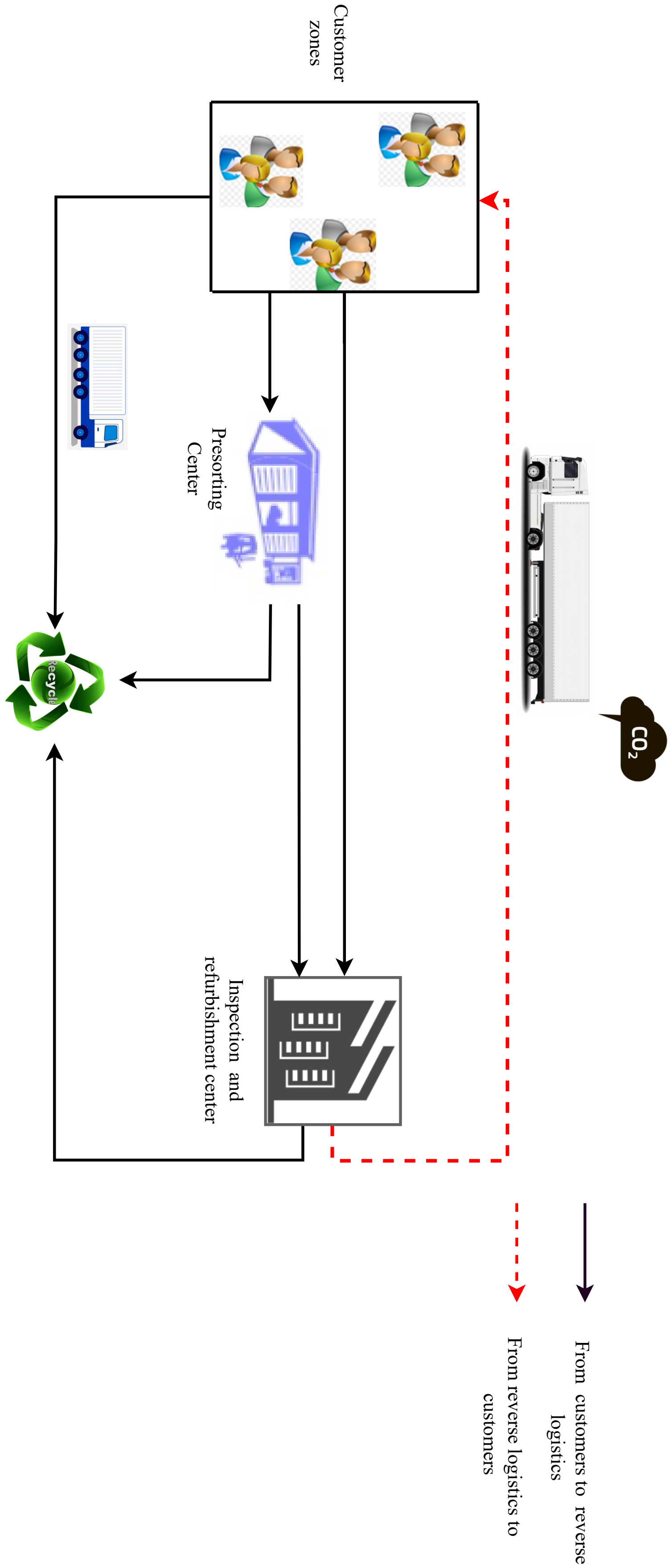


Fig. 4.2 The proposed GCLSC network.

$$\mathscr{P}_{MOMILP}: \begin{cases} \text{Max}\, \tilde{g}_{\text{pro}} = \tilde{g}_1 - \tilde{g}_2 - \tilde{g}_3 - \tilde{g}_4 \\ \text{Min}\, \tilde{g}_{\text{emi}} = \widetilde{em}_{tr} + \widetilde{em}_{pr} \end{cases} \tag{4.1}$$

where

$$\tilde{g}_1 = \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \tilde{s}_{pk} Z_{pkv}^{ref} \tag{4.2}$$

$$\tilde{g}_2 = \sum_{s\in S} \tilde{f}_s U_s + \sum_{k\in K} \tilde{f}_k^p U_k + \tilde{f}_r U_r \tag{4.3}$$

$$\begin{aligned} \tilde{g}_3 = &\sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \tilde{c}_v^{tr} w_p d_{ki} X_{pkv}^{ins} + \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \tilde{c}_v^{tr} w_p d_{ki} Y_{pkv}^{ins} \\ &+ \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \tilde{c}_v^{tr} w_p d_{ki} Z_{pkv}^{ref} + \sum_{p\in P}\sum_{v\in V} \tilde{c}_v^{tr} w_p d_{ir} Z_{pv}^{rec} \\ &+ \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \tilde{c}_v^{tr} w_p d_{kr} Y_{pkv}^{rec} + \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \tilde{c}_v^{tr} w_p d_{kr} X_{pkv}^{rec} \end{aligned} \tag{4.4}$$

$$\begin{aligned} \tilde{g}_4 = &\sum_{p\in P}\sum_{k\in K} \tilde{p}_{pk}^{pre} X_{pk}^{pre} + \sum_{p\in P} \tilde{p}_p^{ins} G_p^{ins} + \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \tilde{p}_p^{ref} Z_{pkv}^{ref} \\ &+ \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \tilde{p}_p^{rec} Y_{pkv}^{rec} + \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \tilde{p}_p^{rec} X_{pkv}^{rec} + \sum_{p\in P}\sum_{v\in V} \tilde{p}_p^{rec} Z_{pv}^{rec} \end{aligned} \tag{4.5}$$

$$\begin{aligned} \widetilde{em}_{tr} = &\sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \widetilde{ev}_v w_p d_{ki} Y_{pkv}^{ins} + \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \widetilde{ev}_v w_p d_{ki} X_{pkv}^{ins} \\ &+ \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \widetilde{ev}_v w_p d_{ki} Z_{pkv}^{ref} + \sum_{p\in P}\sum_{v\in V} \widetilde{ev}_v w_p d_{ir} Z_{pv}^{rec} \\ &+ \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \widetilde{ev}_v w_p d_{kr} Y_{pkv}^{rec} + \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \widetilde{ev}_v w_p d_{kr} X_{pkv}^{rec} \end{aligned} \tag{4.6}$$

$$\begin{aligned} \widetilde{em}_{pr} = &\sum_{p\in P}\sum_{k\in K} \widetilde{em}_p^{col} r_{pk} + \sum_{p\in P}\sum_{k\in K} \widetilde{em}_p^{pre} X_{pk}^{pre} + \sum_{p\in P} \widetilde{em}_p^{ins} G_p^{ins} + \\ &+ \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \widetilde{em}_p^{ref} Z_{pkv}^{ref} + \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \widetilde{em}_p^{rec} Y_{pkv}^{rec} \\ &+ \sum_{p\in P}\sum_{v\in V} \widetilde{em}_p^{rec} Z_{pv}^{rec} + \sum_{p\in P}\sum_{k\in K}\sum_{v\in V} \widetilde{em}_p^{rec} X_{pkv}^{rec} \end{aligned} \tag{4.7}$$

Constraint (4.8) ensure the equilibrium at customer zone k; that is, the amount of returned product p equals the quantities sent to the recycling center for scrapping and IR center without presorting in addition to the amount sent for presorting centers.

$$\sum_{v\in V} X_{pkv}^{ins} + X_{pk}^{pre} + \sum_{v\in V} X_{pkv}^{rec} = r_{pk} \qquad \forall p,k \tag{4.8}$$

Constraint (4.9) guarantees that the amount sent for presorting cannot exceed the amount of returned products.

$$\sum_{p\in P} X_{pk}^{pre} \leq U_k \sum_{p\in P} r_{pk} \qquad \forall k \tag{4.9}$$

Constraint (4.10) governs the quantity sent from the presorting center to the IR center, which comprises good-quality products and a fraction of bad-quality products due to the inefficiency of the presorting process.

$$\sum_{v\in V} Y_{pkv}^{ins} = X_{pk}^{pre}\left(q_{pk} + \left(1 - q_{pk}\right)\beta\right) \qquad \forall p,k \tag{4.10}$$

Constraint (4.11) guarantees that the amount sent from the customer zone k to the IR center of size s without presorting cannot exceed the maximum capacity of the biggest size of the IR center.

$$\sum_{p\in P}\sum_{v\in V} X_{pkv}^{ins} \leq ca^{big}\left(1 - U_k\right) \qquad \forall k \tag{4.11}$$

Constraint (4.12) governs the quantity sent from the presorting center to the recycling center for scrapping.

$$\sum_{v\in V} Y_{pkv}^{rec} = \left(1 - \beta\right)\left(1 - q_{pk}\right) X_{pk}^{pre} \qquad \forall p,k \tag{4.12}$$

Constraint (4.13) ensures that the presorted quantity is presorted is directed to the IR center or the recycling center for each product p and customer zone k.

$$X_{pk}^{pre} = \sum_{v\in V} Y_{pkv}^{rec} + \sum_{v\in V} Y_{pkv}^{ins} \qquad \forall p,k \tag{4.13}$$

Constraint (4.14) governs the quantity of product p sent to the IR center from customer zone k, considering both presorted and non-presorted products. Constraint (4.15) guarantees the equilibrium at the IR center that the quantity of inspected product p is directed either for refurbishing or scrapping.

$$G_p^{ins} = \sum_{k\in K}\sum_{v\in V} Y_{pkv}^{ins} + \sum_{k\in K}\sum_{v\in V} X_{pkv}^{ins} \qquad \forall p \tag{4.14}$$

$$G_p^{ins} = \sum_{k\in K}\sum_{v\in V} Z_{pkv}^{ref} + \sum_{v\in V} Z_{pv}^{rec} \qquad \forall p \tag{4.15}$$

Constraint (4.16) determines the quantity of a product p directed from the IR center to the recycling center; this quantity comprises a fraction due to the presorting center inefficiency, and the rest due to the bad quality of non-presorted products.

$$\sum_{v\in V} Z_{pv}^{rec} = \sum_{k\in K}\sum_{v\in V} \left(1-q_{pk}\right) X_{pkv}^{ins} + \sum_{k\in K} \left(1-q_{pk}\right) \beta X_{pk}^{pre} \qquad \forall p \tag{4.16}$$

Constraint (4.17) stipulates that the quantity sent from the customer zones in the presence and absence of presorting in addition to the IR center to the recycling center cannot exceed its capacity.

$$\sum_{v\in V} X_{pkv}^{rec} + \sum_{v\in V} Y_{pkv}^{rec} + \sum_{v\in V} Z_{pv}^{rec} \leq ca_r U_r \tag{4.17}$$

Constraint (4.18) ensures that the total quantity of inspected products cannot exceed the capacity of the IR center of size s.

$$\sum_{p\in P} G_p^{ins} \leq ca_s U_s \qquad \forall s \tag{4.18}$$

Constraint (4.19) forces one size s of the IR center.

$$\sum_{s\in S} U_s \leq 1 \tag{4.19}$$

Set of constraints with respect to multimode transportation vehicles v, constraints (4.20)–(4.25) ensure that only one type of vehicle is used to transport the products between every two facilities in the proposed GCLSC network.

$$\sum_{v} \dot{O}_{kv} \leq 1 \qquad \forall k \tag{4.20}$$

$$\sum_{v} O_{kv}^{ref} \leq 1 \qquad \forall k \tag{4.21}$$

$$\sum_{v} \dot{O}_{kv}^{pre} \leq 1 \qquad \forall k \tag{4.22}$$

$$\sum_{v} \ddot{O}_{kv} \leq 1 \qquad \forall k \tag{4.23}$$

$$\sum_{v} \ddot{O}_{kv}^{pre} \leq 1 \qquad \forall k \tag{4.24}$$

$$\sum_{v} \dddot{O}_{v} \leq 1 \tag{4.25}$$

The set of constraints (4.26)–(4.31) guarantee that the quantity of transported products between two facilities cannot exceed the capacity of the total number of the vehicles of selected transportation mode v.

$$\sum_{p\in P} w_p X_{pkv}^{ins} \leq ca_v \dot{N}_{kv} \qquad \forall k,v \tag{4.26}$$

$$\sum_{p\in P} w_p X_{pkv}^{rec} \leq ca_v \ddot{N}_{kv} \qquad \forall k,v \tag{4.27}$$

$$\sum_{p\in P} w_p Y_{pkv}^{ins} \leq ca_v \dot{N}_{kv}^{pre} \qquad \forall k,v \tag{4.28}$$

$$\sum_{p\in P} w_p Y_{pkv}^{rec} \leq ca_v \ddot{N}_{kv}^{pre} \qquad \forall k,v \tag{4.29}$$

$$\sum_{p\in P} w_p Z_{pkv}^{ref} \leq ca_v N_{kv}^{ref} \qquad \forall k,v \tag{4.30}$$

$$\sum_{p\in P} w_p Z_{pv}^{rec} \leq ca_v \dddot{N}_v \qquad \forall v \tag{4.31}$$

The set of constraints (4.32)–(4.37) that ensure the total number of vehicles of transportation mode v if this mode already has been selected.

$$\dot{N}_{kv} \leq \text{big}\, M\, \dot{O}_{kv} \qquad \forall k,v \tag{4.32}$$

$$\ddot{N}_{kv} \leq \text{big}\, M\, \ddot{O}_{kv} \qquad \forall k,v \tag{4.33}$$

$$\dot{N}_{kv}^{pre} \leq \text{big}\, M\, \dot{O}_{kv}^{pre} \qquad \forall k,v \tag{4.34}$$

$$\ddot{N}_{kv}^{pre} \leq \text{big}\, M\, \ddot{O}_{kv}^{pre} \qquad \forall k,v \tag{4.35}$$

$$N_{kv}^{ref} \leq \text{big}\, M\, O_{kv}^{ref} \qquad \forall k,v \tag{4.36}$$

$$\dddot{N}_v \leq \text{big}\, M\, \dddot{O}_v \qquad \forall v \tag{4.37}$$

The set of constraint (4.38) ensures that the total number of transported quantities between the facilities using the selected vehicle modes v equals the total number of returned products p.

$$\begin{aligned}&\sum_{k\in K}\sum_{v\in V} ca_v \dot{N}_{kv} + \sum_{k\in K}\sum_{v\in V} ca_v \ddot{N}_{kv} + \sum_{k\in K}\sum_{v\in V} ca_v \dot{N}_{kv}^{pre} + \sum_{k\in K}\sum_{v\in V} ca_v \ddot{N}_{kv}^{pre} \\ &+ \sum_{k\in K}\sum_{v\in V} ca_v N_{kv}^{ref} + \sum_{v\in V} ca_v \dddot{N}_v = \sum_{p\in P}\sum_{k\in K} r_{pk}\end{aligned} \tag{4.38}$$

Constraint (4.39) ensures that the carbon emissions due to transportation and processes activities cannot exceed the maximum allowable carbon emissions, that is, the carbon cap limit.

$$\widetilde{em}_{tr} + \widetilde{em}_{pr} \leq \hat{c}_{cap} \tag{4.39}$$

Constraints (4.40)–(4.42) represent the non-negativity, binary, and integrity constraints, respectively.

$$Z_{pkv}^{ref} G_p^{ins}, X_{pkv}^{rec}, Y_{pkv}^{rec}, Z_{pv}^{rec}, X_{pk}^{pre}, Y_{pkv}^{ins}, X_{pkv}^{ins} \in \mathbb{R}_{\geq 0} \tag{4.40}$$

$$U_k, U_s, U_r, \dot{O}_{kv}, \dot{O}_{kv}^{pre}, \ddot{O}_{kv}, \ddot{O}_{kv}^{pre}, \dot{O}_{kv}^{ref}, \dddot{O}_v \in \{0,1\} \tag{4.41}$$

$$\dot{N}_{kv}, \ddot{N}_{kv}, \dot{N}_{kv}^{pre}, \ddot{N}_{kv}^{pre}, N_{kv}^{ref}, \dddot{N}_v \in \mathbb{Z}^* \tag{4.42}$$

4.3 The robust model of bi-objective green closed-loop supply chain

RO is designed to deal with a lack of information. The uncertain parameters in robust optimization are taken at their worst case values; therefore, the robust optimization approach results in a solution that is immunized against uncertainty [17].
A general uncertain MILP model is given by

$$\begin{aligned}
\mathscr{P}: \quad & \min_{x_j, y_k} \quad \sum_j \tilde{c}_j x_j + \sum_k \tilde{e}_k y_k \\
& \text{s.t.} \\
& \sum_j \tilde{a}_{ij} x_j + \sum_k \tilde{b}_{ik} y_k \leq \tilde{d}_i && \forall i \in I \\
& x_j \in \mathbb{R} && \forall j \in J \\
& y_k \in \mathbb{Z} && \forall k \in K,
\end{aligned} \tag{4.43}$$

where x_j and y_k represent continuous and integer decision variables, respectively, $\tilde{c}_j$ and $\tilde{e}_k$ are the uncertain coefficients of the objective function, and $\tilde{a}_{ij}$, $\tilde{b}_{ik}$, and $\tilde{d}_i$ are the true values of the ith constraint coefficients that are subjected to uncertainty; the $\mathscr{P}$ model can be reformulated as follows:

$$\begin{aligned}
\mathscr{P}: \quad & \min_{x_j, y_k, \beta} \quad \beta \\
& \text{s.t.} \\
& \sum_j \tilde{c}_j x_j + \sum_k \tilde{e}_k y_k \leq \beta \\
& \sum_j \tilde{a}_{ij} x_j + \sum_k \tilde{b}_{ik} y_k \leq \tilde{d}_i && \forall i \in I \\
& x_j \in \mathbb{R} && \forall j \in J \\
& y_k \in \mathbb{Z} && \forall k \in K
\end{aligned} \tag{4.44}$$

Without loss of generality, we consider the general ith constraint, where the true value of uncertain constraint parameters $\tilde{a}_{ij}$, $\tilde{b}_{ik}$, and $\tilde{d}_i$ are $a_{ij}+\hat{a}_{ij}\xi_{ij}$, $b_{ik}+\hat{b}_{ik}\xi_{ik}$, and $d_i+\hat{d}_i\xi_{i0}$, respectively; a_{ij}, b_{ik}, and d_i are the nominal value of the parameters, $\hat{a}_{ij}, \hat{b}_{ik}$, and $\hat{d}_i$ are the perturbations of the parameters around their nominal values respectively, and ξ_{ij}, ξ_{ik}, and ξ_{i0} are random independent variables that take values of $[-1,1]$. Hence, the ith constraint can be reformulated as follows:

$$\sum_{j\notin J_i} a_{ij}x_j + \sum_{j\in J_i} \tilde{a}_{ij}x_j + \sum_{k\notin K_i} b_{ik}y_k + \sum_{k\in K_i} \tilde{b}_{ik}y_k - \hat{d}_i\xi_{i0} \leq d_i \tag{4.45}$$

J_i and K_i are the sets that contain the uncertain parameters in the ith constraint. For simplicity, we consider $\xi = \{\xi_{ij}, \xi_{ik}, \xi_{i0}\}$ and U as the predefined set of random variables. To become immune against infeasibility that would result from any realization of uncertainty, the ith constraint can be rewritten as follows:

$$\sum_j a_{ij}x_j + \sum_k b_{ik}y_k + \max_{\xi\in U}\left\{\sum_{j\in J_i} \xi_{ij}\hat{a}_{ij}x_j + \sum_{k\in K_i} \xi_{ik}\hat{b}_{ik}y_k - \hat{d}_i\xi_{i0}\right\} \leq d_i \tag{4.46}$$

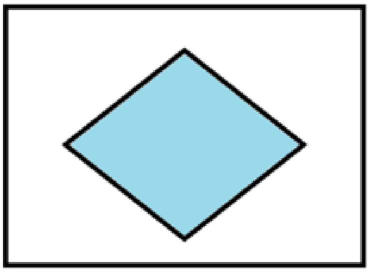
The robust counterpart optimization formulation of the ith constraint based on the combined interval and polyhedral, “Interval + polyhedral” uncertainty set is as follows:

$$\begin{cases} \sum_j a_{ij}x_j + \sum_k b_{ik}y_k + \left[\omega_i\Gamma + \sum_{j\in J_i}\theta_{ij} + \sum_{k\in K_i}\eta_{ik} + \varphi_{i0}\right] \leq d_i \\ \omega_i + \theta_{ij} \geq \hat{a}_{ij}|x_j| \quad \forall j \in J_i \\ \omega_i + \eta_{ik} \geq \hat{b}_{ik}|y_k| \quad \forall k \in K_i \\ \omega_i + \varphi_{i0} \geq \hat{d}_i \\ \omega_i, \theta_{ij}, \eta_{ik}, \varphi_{i0} \geq 0 \quad \forall j \in J_i, \quad \forall k \in K_i, \quad \forall i \in I, \end{cases} \tag{4.47}$$

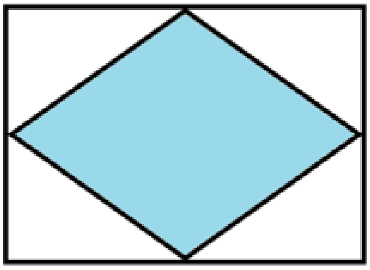
where $\theta_{ij}, \eta_{ik}, \varphi_{i0}$, and ω_i are positive dual variables, and Γ represents the adjustable size parameter of the “Interval + Polyhedral” uncertainty set which reflects the degree of conservativeness. Fig.4.3 illustrates different geometrical representations of the combined “Interval + Polyhedral” uncertainty set based on the value of the adjustable parameter Γ. The proof of robust counterpart formulation of the ith constraint, which is shown in Equation (4.47) is available in Li et al. [69] and Bertsimas and Sim [23].

Following the practical guide of the robust optimization approach proposed by Gorissen et al. [47] when the coefficients of the objective functions have uncertainty, constraints have been introduced to model the coefficients in the objective functions and approximate their values using auxiliary variables.

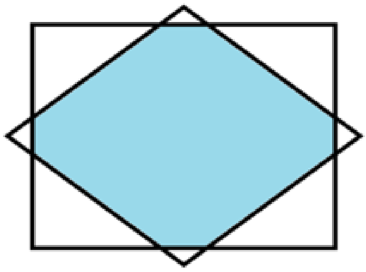
The robust counter reformulation of the $\mathscr{P}_{MOMILP}$ based on the “Interval + Polyhedral” uncertainty set induced an MILP model, $\mathscr{RC}_{I-P} - \mathscr{P}_{MOMILP}$, as follow:



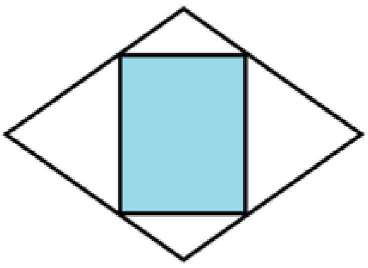
((a)) $0 < \Gamma < 1$.



((b)) $\Gamma = 1$.



((c)) $1 < \Gamma < |J_i| + |K_i|$.



((d)) $\Gamma = |J_i| + |K_i|$.

Fig. 4.3 Illustration of the "Interval+Polyhedral" uncertainty set.

$$\mathscr{RC}_{I-P} - \mathscr{P}_{MOMILP} : \begin{cases} \text{Max}\, \delta_{pro} \\ \text{Min}\, \delta_{emi} \end{cases} \tag{4.48}$$

$$\left\{ \begin{array}{ll} g_1 - & \left[\sum_{p\in P_o} \sum_{k\in K_o} \theta_{pk}\right] - g_2 - \left[\sum_{s\in S_o} \theta_s + \sum_{k\in K_o} \theta_k + \theta_r\right] - \\ g_3 - & \left[\sum_{v\in V_o} \left(\theta 1_v{}^{ins} + \theta 2_v{}^{ins} + \theta 3_v{}^{ref} + \theta 4_v{}^{rec} + \theta 5_v{}^{rec} + \theta 6_v{}^{rec}\right)\right] - \\ g_4 - & \left[\sum_{p\in P_o} \sum_{k\in K_o} \theta_{pk}{}^{pre} + \sum_{p\in P_o} \theta_p{}^{ins} + \sum_{p\in P_o} \theta_p{}^{ref} + \right. \\ & \left. \sum_{p\in P_o} \theta 1_p{}^{rec} + \sum_{p\in P_o} \theta 2_p{}^{rec} + \sum_{p\in P_o} \theta 3_p{}^{rec}\right] - \Gamma_1 \omega_1 \geq \delta_{pro} \end{array} \right. \tag{4.49}$$

$$\omega_1 + \theta_{pk} \geq \quad \hat{s}_{pk} Z^{ref}_{pkv} \qquad \forall p \in P, k \in K, v \in V \tag{4.50}$$

$$\omega_1 + \theta_s \geq \quad \hat{f}_s U_s \qquad \forall s \in S \tag{4.51}$$

$$\omega_1 + \theta_k \geq \quad \hat{f}^p_k U_k \qquad \forall k \in K \tag{4.52}$$

$$\omega_1 + \theta_r \geq \quad \hat{f}_r U_r \tag{4.53}$$

$$\omega_1 + \theta 1^{ins}_v \geq \quad \hat{c}_v X^{ins}_{pkv} \qquad \forall p \in P, k \in K, v \in V \tag{4.54}$$

$$\omega_1 + \theta 2^{ins}_v \geq \quad \hat{c}_v Y^{ins}_{pkv} \qquad \forall p \in P, k \in K, v \in V \tag{4.55}$$

$$\omega_1 + \theta 3^{ref}_v \geq \quad \hat{c}_v Z^{ref}_{pkv} \qquad \forall p \in P, k \in K, v \in V \tag{4.56}$$

$$\omega_1 + \theta 4^{rec}_v \geq \quad \hat{c}_v X^{rec}_{pkv} \qquad \forall p \in P, k \in K, v \in V \tag{4.57}$$

$$\omega_1 + \theta 5^{rec}_v \geq \quad \hat{c}_v Y^{rec}_{pkv} \qquad \forall p \in P, k \in K, v \in V \tag{4.58}$$

$$\omega_1 + \theta 6^{rec}_v \geq \quad \hat{c}_v\, Z^{rec}_{pv} \qquad \forall p \in P, v \in V \tag{4.59}$$

$$\omega_1 + \theta_{pk}{}^{pre} \geq \hat{p}^{pre}_{pk} X^{pre}_{pk} \qquad \forall p \in P, k \in K \tag{4.60}$$

$$\omega_1 + \theta_p{}^{ins} \geq \hat{p}^{ins}_p G^{ins}_p \qquad \forall p \in P \tag{4.61}$$

$$\omega_1 + \theta_p{}^{ref} \geq \hat{p}^{ref}_p Z^{ref}_{pkv} \qquad \forall p \in P, k \in K \tag{4.62}$$

$$\omega_1 + \theta 1_p{}^{rec} \geq \hat{p}^{rec}_p X^{rec}_{pkv} \qquad \forall p \in P, k \in K \tag{4.63}$$

$$\omega_1 + \theta 2_p{}^{rec} \geq \hat{p}_p^{rec} Y_{pkv}^{rec} \qquad \forall p \in P, k \in K \tag{4.64}$$

$$\omega_1 + \theta 3_p{}^{rec} \geq \hat{p}_p^{rec} Z_{pv}^{rec} \qquad \forall p \in P, v \in V \tag{4.65}$$

$$\left\{ \begin{array}{l} em_{tr} + \left[\sum_{v \in V_o} \left(\eta 1_v^{ins} + \eta 2_v^{ins} + \eta 3_v^{ref} + \eta 4_v^{rec} + \eta 5_v^{rec} + \eta 6_v^{rec}\right)\right] \\ em_{pr} + \left[\sum_{p \in P_o} \left(\eta 1_p^{col} + \eta 2_p^{pre} + \eta 3_p^{ins} + \eta 4_p^{ref} + \eta 5_p^{rec} + \eta 6_p^{rec} + \eta 7_p^{rec}\right)\right] + \\ \Gamma_2 \omega_2 \leq \delta_{emi} \end{array} \right. \tag{4.66}$$

$$\omega_2 + \eta 1_v^{ins} \geq \quad \hat{ev}_v X_{pkv}^{ins} \qquad \forall p \in P, k \in K, v \in V \tag{4.67}$$

$$\omega_2 + \eta 2_v^{ins} \geq \quad \hat{ev}_v Y_{pkv}^{ins} \qquad \forall p \in P, k \in K, v \in V \tag{4.68}$$

$$\omega_2 + \eta 3_v^{ref} \geq \quad \hat{ev}_v Z_{pkv}^{ref} \qquad \forall p \in P, k \in K, v \in V \tag{4.69}$$

$$\omega_2 + \eta 4_v^{rec} \geq \quad \hat{ev}_v X_{pkv}^{rec} \qquad \forall p \in P, k \in K, v \in V \tag{4.70}$$

$$\omega_2 + \eta 5_v^{rec} \geq \quad \hat{ev}_v Y_{pkv}^{rec} \qquad \forall p \in P, k \in K, v \in V \tag{4.71}$$

$$\omega_2 + \eta 6_v^{rec} \geq \quad \hat{ev}_v Z_{pv}^{rec} \qquad \forall p \in P, v \in V \tag{4.72}$$

$$\omega_2 + \eta 1_p^{col} \geq \quad \widehat{em}_p^{col} r_{pk} \qquad \forall p \in P, k \in K \tag{4.73}$$

$$\omega_2 + \eta 2_p^{pre} \geq \quad \widehat{em}_p^{pre} X_{pk}^{pre} \qquad \forall p \in P, k \in K \tag{4.74}$$

$$\omega_2 + \eta 3_p^{ins} \geq \quad \widehat{em}_p^{ins} G_p^{ins} \qquad \forall p \in P, k \in K \tag{4.75}$$

$$\omega_2 + \eta 4_p^{ref} \geq \quad \widehat{em}_p^{ref} Z_{pkv}^{ref} \qquad \forall p \in P, k \in K, v \in V \tag{4.76}$$

$$\omega_2 + \eta 5_p^{rec} \geq \quad \widehat{em}_p^{rec} X_{pkv}^{rec} \qquad \forall p \in P, k \in K, v \in V \tag{4.77}$$

$$\omega_2 + \eta 6_p^{rec} \geq \quad \widehat{em}_p^{rec} Y_{pkv}^{rec} \qquad \forall p \in P, k \in K, v \in V \tag{4.78}$$

$$\omega_2 + \eta 7_p^{rec} \geq \quad \widehat{em}_p^{rec} Z_{pv}^{rec} \qquad \forall p \in P, v \in V \tag{4.79}$$

and set of constraints that have been depicted in Equations (4.8)–(4.42). and set of constraints that have been depicted in Equations (4.8)–(4.42).

The auxiliary variables, δ_{pro} and δ_{emi}, are introduced to approximate the profit and carbon emissions, respectively. A set of constraints are presented in Equations (4.49)–(4.65) to model the robust counterpart of the first uncertain objective function ($\text{Max}\,\tilde{g}_{\text{pro}}$).

A set of constraints are presented in Equations (4.66)–(4.79) to model the robust counterpart of the second uncertain objective function ($\text{Min}\,\tilde{g}_{\text{emi}}$).

4.3.1 Probability upper bound of constraint violation in the robust optimization

In contrast to stochastic programming, RO does not require a known probability distribution to handle uncertain parameters. Probabilistic guarantees can be used to determine the lower bound on constraint satisfaction based on the desired constraint violation.

The probability upper bound of the constraint violation of the robust counterpart formulation based on the "Interval + Polyhedral" uncertainty set is proposed by Bertsimas and Sim [23] and Li et al. [71]. It is bounded $B(|Q_i|,\Gamma)$, where $|Q_i|$ is the cardinality of the uncertain parameters in the ith constraint. Assuming the probability distribution of uncertainty is symmetric, independent, and bounded, it is given as follows:

$$\Pr\left\{\sum_j a_{ij}x_j + \sum_k b_{ik}y_k + \sum_{j\in J_i} \xi_{ij}\hat{a}_{ij}x_j + \sum_{k\in K_i} \xi_{ik}\hat{b}_{ik}y_k - \hat{d}_i\xi_{i0} > d_i\right\} \le B(|Q_i|,\Gamma) \tag{4.80}$$

$$B(|Q_i|,\Gamma) = \frac{1}{2^{|Q_i|}}\left\{(1-\mu)\sum_{l=\lfloor v\rfloor}^{|Q_i|}\binom{|Q_i|}{l} + \mu\sum_{l=\lfloor v\rfloor+1}^{|Q_i|}\binom{|Q_i|}{l}\right\} \tag{4.81}$$

where

$$v = ((\Gamma+|Q_i|)/2),\ \mu = v - \lfloor v\rfloor.$$

The proof of upper bounds on the probability of constraint violation is provided by Bertsimas and Sim [23] and Li et al. [71].

4.3.2 Solution approach

Consider that $f(x)$ is a multi-objective model (MOM) with m objectives as $f(x) = \{f_1(x), f_2(x), \ldots, f_m(x)\}$. The general formulation of MOM is given below:

$$\begin{aligned}&\text{Min}\, f(x)\\&s.t.\\&x \in S\end{aligned} \tag{4.82}$$

Definition 1. A decision vector $x^* \in S$ is called Pareto optimal , or efficient , if there is no other decision vector $x \in S$ such that x dominates x^*. If $x^* \in S$ is a Pareto optimal solution, the vector $f(x^*)$ is said a non-dominated point in the objective space [64]. For instance, suppose that $S \subset \mathbb{R}^3$ and its feasible region $f \subset \mathbb{R}^2$ the continuous thick line contains all Pareto optimal solutions and $f(x^*)$ one of these solutions as shown in Fig. 4.4.

Definition 2. A decision vector $x^* \in S$ is a weakly Pareto optimal , or weakly efficient , if

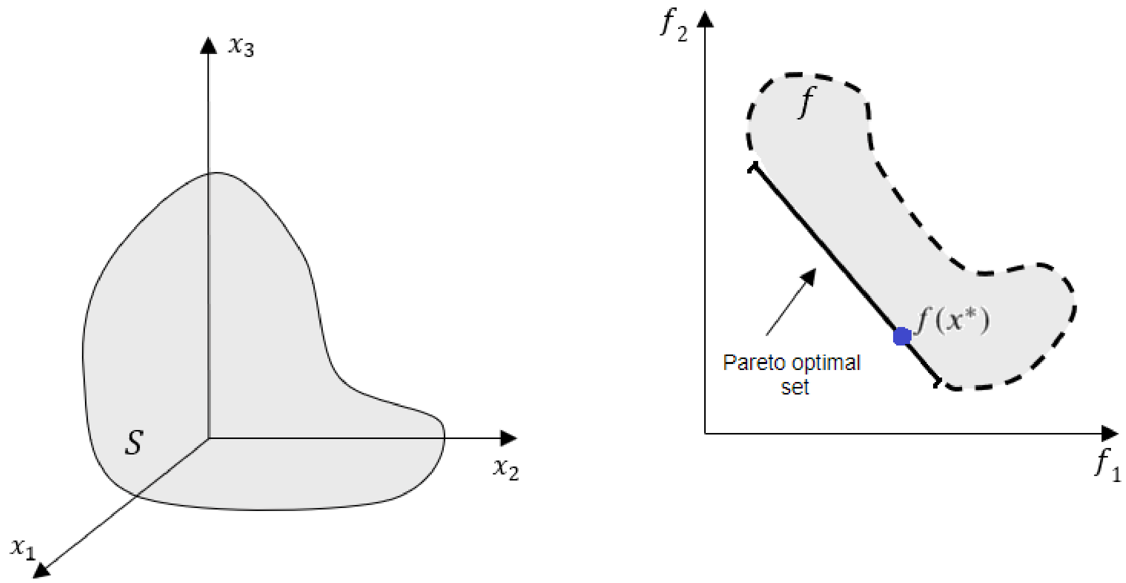


Fig. 4.4 Pareto optimal solution representation.

there is no feasible solution $x \in S$ such that $f(x) < f(x^*)$ is a weakly efficient solution, the vector $f(x^*)$ is said a weakly nondominated point in the objective space.

Definition 3. A Pareto optimum solution is said to be supported if there are positive weights $\lambda_1, \lambda_2, \ldots, \lambda_k$ that make the solution optimal in terms of the linear combination (weighted sums problem): min $\{\sum_{i=1}^{i=k} \lambda_i f_i(x)\}$ s.t. $x \in S$ with coefficients $\lambda_1, \lambda_2, \ldots, \lambda_k$. If this is not

the case, the solution is referred to be non-supported [98].
The solution approach implemented in this study is the LWT method which was developed by Steuer and Choo [105] to obtain Pareto optimal solutions by minimizing the maximum deviation of the objective functions from their values where they are optimized individually. The LWT approach outperforms existing techniques because of the following advantages [66, 65]:

- Achieves adequate optimal solutions of MOMs.
- Provides both supported and non-supported Pareto solutions, whereas the weighted sum method, which is widely utilized in the literature, can only achieve supported Pareto solutions.
- Obtains Pareto optimal solutions in both the convex and concave space hulls.

The mathematical formulation of the LWT approach for MOM is given below:

$$\begin{aligned} &\text{Min}\,\alpha \\ &s.t. \\ &\lambda_i\left(f_i(x)-f_i^*\left(x^*\right)\right)\leq\alpha \\ &\vdots \\ &\lambda_m\left(f_m(x)-f_m^*\left(x^*\right)\right)\leq\alpha \\ &\textstyle\sum_{i=1}^m\lambda_i=1 \\ &0\leq\lambda_i\leq 1 \end{aligned} \tag{4.83}$$

The mathematical formulation of LWT approach for the robust counterpart model, $RC_{I-P}-\mathscr{P}_{MOMILP}$, of the bi-objective GCLSC based on the "Interval + Polyhedral" uncertainty set is as follows:

$$\begin{aligned} LWT-(\mathscr{RC}_{I-P}-\mathscr{P}_{MOMILP}):\ &\text{Min}\,\alpha \\ &\text{s.t} \\ &\lambda_{\text{pro}}\left(\delta^*_{\text{pro}}-\delta_{\text{pro}}\right) &&\leq\alpha \\ &\lambda_{\text{emi}}\left(\delta_{\text{emi}}-\delta^*_{\text{emi}}\right) &&\leq\alpha \\ &\lambda_{\text{pro}}+\lambda_{\text{emi}} &&=1 \\ &0\leq\lambda_{\text{pro}},\lambda_{\text{emi}} &&\leq 1 \end{aligned} \tag{4.84}$$

and set of constraints that have been depicted in Equations (4.8)–(4.42) and Equations (4.49)–(4.79).

4.4 Computational experiments

In this section, to evaluate the performance of the proposed robust model of the GCLSC network by considering a presorting and heterogeneous transportation system using the LWT approach discussed in Section 4.3.2, a set of computational experiments was conducted using GAMS/CPLEX optimization solver. Most of the model input parameters were adopted from the literature [99], which are based on realistic data. Vehicle capacity and CO_2 emissions were calculated for road transport operations as in Mohammed et al. [74], and the transportation cost based on vehicle type was calculated as in Wangsa and Wee [109] as shown in Table 4.2. The number of returned products, selling price of refurbished products at customer zones, operations costs, and weight of returned products are presented in Table 4.3. Capacities and fixed opening costs of different sizes of the IR center are presented in Table 4.4. Distances between customer zones, the IR center, and the recycling center are presented in Table 4.5, and the rest of the model parameters are presented in Table 4.6.

Table 4.2 Cost, carbon emissions rate, and capacity of transportation modes

	Transportation cost ($ / kg-km)	CO_2 emissions (g/kg km)	Capacity of the vehicles (kg)
Light duty vehicles	0.00028	0.0000236	Uniform $(0-4536)$
Medium trucks	0.00014	0.0000452	Uniform $(4537-11793)$
Heavy duty trucks	0.00006	0.0000824	Uniform $(11794-14969)$

Table 4.3 Returned products, operations cost, and selling price of refurbished products

	s_{pk}			r_{pk}			p_p^{pre}	p_p^{ref}	p_p^{rec}	p_p^{ins}	w_p
	k_1	k_2	k_3	k_1	k_2	k_3					
p_1	200	200	200	40,000	40,000	40,000	10	20	10	15	0.5
p_2	300	300	300	45,000	45,000	45,000	10	25	10	18	0.8
p_3	250	250	250	40,000	40,000	40,000	10	30	10	20	1.1

Table 4.4 Capacities and fixed opening costs of different IR center sizes

	ca_s	f_s
Small	120,000	200,000
Medium	220,000	350,000
Big	300,000	500,000

Table 4.5 Distances between the GCLSC facilities

From\ to	IR center	Recycling center
k_1	100	200
k_2	150	300
k_3	200	400

Table 4.6 Rest of the model's parameters

Parameter	Value
em_p^{col}	0.03 kg CO_2 per product
em_p^{pre}	0.07 kg CO_2 per product
em_p^{ins}	0.09 kg CO_2 per product
em_p^{ref}	0.21 kg CO_2 per product
em_p^{rec}	0.07 kg CO_2 per product
$\hat{c}_{cap}$	120,000 kg CO_2
f_k^p	USD 150,000
f_r	USD 250,000
d_{ir}	150 km
ca_r	30,000 units
q_{pk}	0.7
β	0.05

For model verification and to show the robustness of the RO approach, we consider that the perturbation of uncertain parameters are 5% and 10% around their nominal values assuming that the upper bounds of constraint violation are 10%, 15%, and 20%. In other words, the lower bounds of constraint satisfaction are 90%, 85%, and 80%, respectively. Five different weight sets (λ_{pro} and λ_{emi}) were considered for both the objective functions.

Table 4.7 Robust Pareto front at 80% constraints satisfaction (5% perturbations).

λ_{pro}	λ_{emi}	Profit	Deviation	Carbon emissions	Deviation
0.1	0.9	23,169,888	−7.29%	70,394	+1.10%
0.3	0.7	26,125,054	−7.28%	74,526	+1.09%
0.5	0.5	29,488,946	−6.60%	79,191	+1.10%
0.7	0.3	33,207,854	−6.09%	84,761	+1.34%
0.9	0.1	37,607,983	−5.24%	91,607	+1.52%

Increasing the lower bound of the probability of constraint satisfaction results in an increase in the conservative of the obtained solutions; that is, increasing the size of the uncertainty set Γ increases the costs that result in a decrease in the profit from the economic aspect. However, from the environmental perspective, increasing the uncertainty set leads

Table 4.8 Robust Pareto front at 80% constraints satisfaction (10% perturbations).

λ_{pro}	λ_{emi}	Profit	Deviation	Carbon emissions	Deviation
0.1	0.9	21,346,559	−14.59%	71,162	+2.21%
0.3	0.7	24,190,076	−14.15%	75,283	+2.12%
0.5	0.5	27,335,999	−13.42%	80,122	+2.29%
0.7	0.3	31,043,425	−12.21%	85,910	+2.71%
0.9	0.1	35,530,213	−10.47%	93,000	+3.07%

Table 4.9 Robust Pareto front at 85% constraints satisfaction (5% perturbations).

λ_{pro}	λ_{emi}	Profit	Deviation	Carbon emissions	Deviation
0.1	0.9	23,071,378	−7.69%	70,433	+1.16%
0.3	0.7	25,959,839	−7.86%	74,525	+1.09%
0.5	0.5	29,233,674	−7.41%	79,195	+1.10%
0.7	0.3	32,897,246	−6.97%	84,816	+1.40%
0.9	0.1	37,291,491	−6.03%	91,693	+1.62%

Table 4.10 Robust Pareto front at 85% constraints satisfaction (10% perturbations).

λ_{pro}	λ_{emi}	Profit	Deviation	Carbon emissions	Deviation
0.1	0.9	21,137,593	−15.42%	71,241	+2.32%
0.3	0.7	23,844,940	−15.37%	75,287	+2.12%
0.5	0.5	26,866,979	−14.91%	80,088	+2.24%
0.7	0.3	30,423,876	−13.96%	86,015	+2.84%
0.9	0.1	34,897,458	−12.07%	93,171	+3.26%

to more carbon emission trade-offs between the conservatives and the values of profit and carbon emissions.

Robust objective function values were achieved at lower levels than the deterministic model. The values of the objective functions worsened as the perturbation around the nominal values increased (Tables 4.7–4.12). On the one hand, when the perturbation was increased from 5% to 10%, for example, at a lower bound of the probability of constraint satisfaction of 80% and weights of $\lambda_{pro} = \lambda_{emi} = 0.5$, the profit declined by 6.62% and 13.42%, respectively, from their deterministic values. The value of carbon emissions, on the other hand, decreased by 1.10% and 2.29% from their deterministic levels, as shown in Tables 4.7 and 4.8, respectively.

For the lower bound of constraint satisfaction at 80% with 5% data perturbations, the deviation of the robust profit decreased from its deterministic value by 5.24% to 7.29%. Meanwhile, the robust values of the carbon emission increase ranging from 1.09% to 1.52% (Table 4.7). By increasing the data perturbations to 10% the robust values for the profit and carbon emissions deviated by 10.47% to 14.59% and 2.12% to 3.07%, respectively (Table 4.8).

Increasing the lower bound of constraints satisfaction to 85% with 5% perturbations resulted in an increase in the deviation, ranging from 6.03% to 7.86% and 1.09% to 1.62% for the profit and carbon emissions, respectively, (Table 4.9). However, considering 10% perturbation, the deviation ranged from 12.07% to 15.42% and 2.12% to 3.26% for the profit and carbon emissions, respectively (Table 4.10). For the lower bound of the probability of constraints satisfaction at 90% with 5% perturbation of the uncertain parameters, the deviation ranged from 6.57% to 8.40% and 1.21% to 1.74% for the profit and carbon emissions respectively (Table 4.11). In addition, considering 10% data perturbations, the deviation ranged from 13.15% to 16.25% and 2.61% to 3.52% for the profit and carbon emissions, respectively (Table 4.12).

Table 4.11 Robust Pareto front at 90% constraints satisfaction (5% perturbations).

λ_{pro}	λ_{emi}	Profit	Deviation	Carbon emissions	Deviation
0.1	0.9	22,977,737	−8.06%	70,533	+1.30%
0.3	0.7	25,809,698	−8.40%	74,611	+1.21%
0.5	0.5	29,045,184	−8.01%	79,282	+1.21%
0.7	0.3	32,687,050	−7.56%	84,920	+1.53%
0.9	0.1	37,076,867	−6.57%	91,808	+1.74%

Table 4.12 Robust Pareto front at 90% constraints satisfaction (10% perturbations).

λ_{pro}	λ_{emi}	Profit	Deviation	Carbon emissions	Deviation
0.1	0.9	20,930,083	−16.25%	71,443	+2.61%
0.3	0.7	23,533,196	−16.48%	75,462	+2.36%
0.5	0.5	26,525,935	−15.99%	80,226	+2.42%
0.7	0.3	30,025,146	−15.09%	86,169	+3.02%
0.9	0.1	34,465,757	−13.15%	93,412	+3.52%

Moreover, the robust optimal Pareto front of the bi-objective GCLSC model with 90% probability of constraints satisfaction with 5% and 10% is presented in Figure 4.5, 4.6 respectively. By increasing the deviation from the nominal values, the optimal values of the objective functions become worse as shown in the Pareto front representation in Figure 4.5 and 4.6.

On one hand, the obtained robust Pareto front of the proposed bi-objective GCLSC model is achieved with the levels of 80%, 85%, and 90% probability of constraints satisfaction and 5% and 10% of data perturbations, revealing that our model yields more conservative solutions that are immune against the uncertainty and comply with the nature of conflicting bi-objective functions.

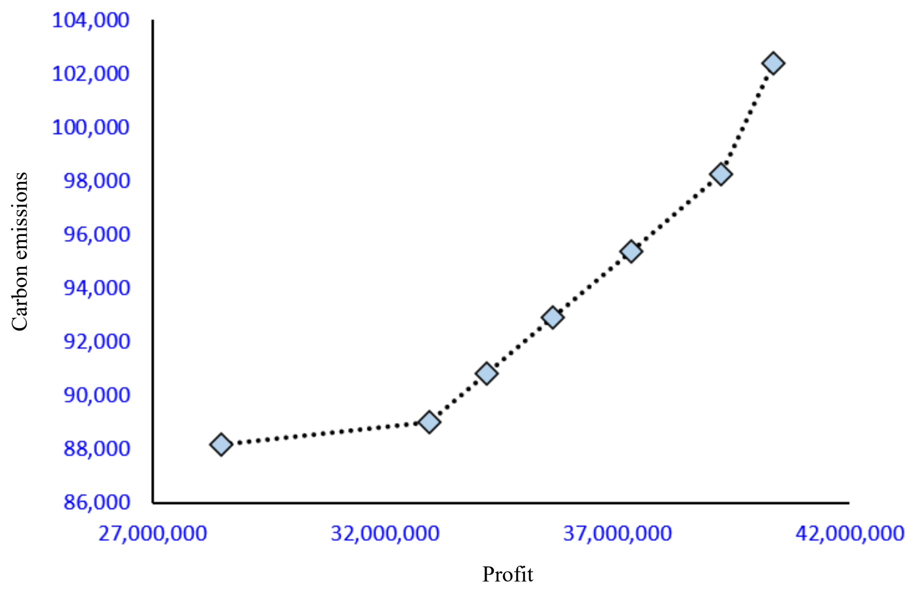


Fig. 4.5 Robust Pareto front with 90% probability of constraints satisfaction (5% perturbation).

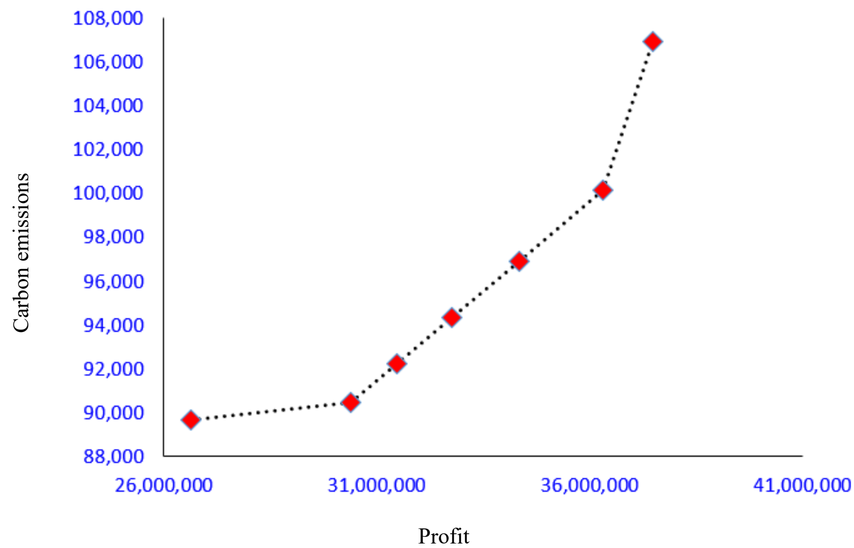


Fig. 4.6 Robust Pareto front with 90% probability of constraints satisfaction (10% perturbation).

On the other hand, increasing the probability of constraints satisfaction increases the uncertain space beside the integer variables of the model, hence increasing the model's complexity.

4.5 Conclusions

This chapter provided a robust bi-objective optimization model for the GCLSC network by considering a presorting and heterogeneous transportation system. The proposed bi-objective MILP model aims to maximize the profit and minimize the total carbon emissions incurred in the entire network by considering the selling price, costs, and carbon emissions uncertainties. A robust optimization approach based on the "Interval + Polyhedral" uncertainty set was adopted to tackle these uncertainties. An LWT approach was implemented to obtain the Pareto optimal solutions, which were hedges against perturbations of the uncertain parameters. A set of computational experiments was conducted to validate and show the performance of the proposed model.

Pareto optimal fronts of the robust bi-objective GCLSC model were examined considering the maximum probability of constraint violation. In other words, the lower bound of constraint satisfaction was considered at three levels: 80%, 85%, and 90% combined with 5% and 10% perturbations of the uncertain parameters around their nominal values. The lower the bound of constraint satisfaction, the more conservative as well as the less profit and more carbon emissions. Comparing the obtained robust solution with the deterministic solution in the experiments showed that our proposed model is more conservative and robust.

Chapter 5

Conclusions and directions for future work

This chapter presents an overview of the thesis, with a summary of research contributions in Section 5.1 and suggestions on directions for future research in Section 5.2.

5.1 Conclusions

Chapter 2: This chapter proposes an MILP model of the dual-channel CLSC to address the increasingly widespread adoption of e-commerce, facilitated by the Internet and related technologies. The adoption of e-commerce and the customer trends of online shopping for new, remanufactured, and recovered products are driven by a variety of brands and products, the comfort afforded by e-commerce, and savings of customer time and effort. From the industry and service sector perspectives, e-commerce represents increased revenue due to cost savings and reduced air pollution, resulting in a significant environmental impact benefiting health.

Chapter 3: This chapter proposes an adaptable robust optimization model for the dual-channel CLSC network, offering multiple uncertainty sets for uncertain costs and uncertain customer demand. The goal of the study is to design the dual-channel CLSC at the minimum total cost and achieving robust solutions. Two robust models based on the adjustable box and ellipsoidal uncertainty sets of the dual-channel CLSC are considered. Intensive computational experiments are conducted using GAMS programming language. We focus on the impact of each uncertain cost type on the total cost and the maximum probability of the constraint violation based on the two robust counterpart models. Moreover, we consider simultaneous effect of uncertain cost and demand on the dual-channel CLSC model performance.

Chapter 4: This chapter provided a robust bi-objective optimization model for the GCLSC network by considering a presorting and heterogeneous transportation system. The proposed bi-objective MILP model aims to maximize the total profit and minimize the total carbon emissions incurred in the entire network by considering the selling price, costs, and carbon emissions uncertainties. A robust optimization approach based on the "Interval + Polyhedral" uncertainty set was adopted to tackle these uncertainties. An LWT approach was implemented to obtain the Pareto optimal solutions, which were hedges against perturbations of the uncertain parameters. A set of computational experiments was conducted to validate and show the performance of the proposed model.

Pareto optimal fronts of the robust bi-objective GCLSC model were examined considering the maximum probability of constraint violation. In other words, the lower bound of constraint satisfaction was considered at three levels: 80%, 85%, and 90% combined with 5% and 10% perturbations of the uncertain parameters around their nominal values. The lower the bound of constraint satisfaction, the more conservative as well as the less profit and more carbon emissions. Comparing the obtained robust solution with the deterministic solution in the experiments showed that our proposed model is more conservative and robust.

5.2 Directions for future work

Regarding the limitations of this study, the study does not consider the response of customers to both traditional and online retailers, the carbon emissions due to the trade-offs between traditional and online retailers are ignored, and the uncertainty in the demand in both traditional and online retailers was not taken into consideration. Future research directions may include the following:

- The uncertainty of model parameters and the environmental and social impacts can be taken into consideration in dual-channel CLSC models using stochastic optimization approaches, such as the Mulvey robust optimization approach [99], the sample average approximation method [117], and the robust optimization approach developed by Bertsimas et al. [21] and Ben-Tal et al. [17].

- To improve the efficiency of computations and the quality of solutions for large and complex dual-channel CLSC problems is mandatory, heuristics and meta-heuristics approaches can be used [83, 48].

- The supply chain risks (operational and disruption risks) and ripple effect on the dual-channel CLSC can be considered, and alternative plans using digital supply chain twins can be provided [57].

- The linkage between dual-channel CLSC and circular economy from application and theoretical points of view can be implemented.

The proposed study was conducted on a small-size problem. For large-scale problems, the model becomes computationally hard to obtain the optimal solution using GAMS solver. Therefore, it is one of our future extension direction to propose heuristic or metaheuristic approaches to handle the large-size instances of the developed GCLSC.
However, future studies should extend the proposed robust bi-objective model to a multi-objective model by considering a social objective that contributes to the welfare and prosperity of society, such as maximizing the number of job opportunities and fair salaries for employees. Enhancement can be made using the quality of the robust solutions, the iterative solution framework proposed by Li and Floudas [70], and different uncertainty sets shapes like ellipsoidal, polyhedral, combined "ellipsoidal and polyhedral," and combined "box + ellipsoidal + polyhedral."
The findings of this study are expected to be beneficial to both academics and managerial practitioners.

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Appendix A

List of publications

Journal papers (Peer review)

1. **Kaoud, E.**, Abdel-Aal, M. A., Sakaguchi, T., & Uchiyama, N. (2020). Design and Optimization of the Dual-Channel Closed Loop Supply Chain with E-Commerce. Sustainability, 12(23), 10117.

2. **Kaoud, E.**, Abdel-Aal, M.A.M., Sakaguchi, T., Uchiyama, N. (2022). Robust Optimization for a Bi-Objective Green Closed-Loop Supply Chain with Heterogeneous Transportation System and Presorting Consideration. Sustainability, 14(16), 10281.

3. **Kaoud, E.**, Abdel-Aal, M. A., Sakaguchi, T., & Uchiyama, N. (2022). An adaptable robust optimization model for a dual-channel closed-loop supply chain considering cost and demand uncertainty. Journal of Advanced Mechanical Design, Systems, and Manufacturing. **(In press)**

Conference papers (Peer review)

1. **Kaoud, E.**, Abdel-Aal, M. A., Sakaguchi, T., & Uchiyama, N. (2021). Robust optimization for a dual-channel closed-loop supply chain with cost and demand uncertainty, International Symposium on Scheduling 2021 , virtual, pp.10-15.