SUSTAINABLE CLOSED-LOOP SUPPLY CHAIN NETWORK DESIGN

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In Partial Fulfillment of the Requirements
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By
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FACULTY OF GRADUATE STUDIES AND RESEARCH

SUPERVISORY AND EXAMINING COMMITTEE

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ABSTRACT
Sustainable Closed Loop Supply Chain (CLSC) management is increasingly adopted by companies, due to increasing concerns for the environmental, legislative compliance, decreasing availability of raw materials, and customer demands for environmentally friendly products. Sustainable CLSC network design provides a platform which ensures an effective and efficient supply chain management.

In this thesis, the sustainable CLSC network design problem was formulated deterministically via Mixed Integer Linear Programming (MILP), and non-deterministically via Fuzzy Multi-objective Mixed Integer Linear Programming (FMOMILP) model, by considering sustainability and uncertainty. Fuzzy programming approaches were utilized to solve the problem. Two multi-objective evolutionary algorithms were employed to find the optimal solutions for large cases. Computational experiments were conducted, as well as studying actual industrial cases, to illustrate the applicability and significance of the proposed approaches and solution methods.

Results showed that the Fuzzy Programming approach presents a systematic framework that enables management to obtain a satisfactory solution by adjusting the search direction. The results also demonstrated that the adopted Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is a satisfactory technique to solve large scale sustainable CLSC network design problems.

Keywords: Closed Loop Supply Chain, Sustainability, Uncertainty, Fuzzy, Multi-objective Evolutionary Algorithms
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DEDICATION

Dedicated to my beloved parents and sisters for their patience, help, inspiration, and encouragement which made the completion of this work possible.
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CHAPTER ONE: INTRODUCTION

1.1. Motivation and scope

With the advent of a new era of business where change is regarded as one of its main features, ensuring the success and survival of organizations has become more difficult (Shahin et al., 2017). Supply Chain Management (SCM) is one of the tools companies use to improve performance. SCM includes a competitive strategy for integrating supplier and customers, with the aim of improving responsiveness and flexibility in production and service organizations (Shahin et al., 2017). SCM integrates key processes from end-user to original suppliers. These processes provide products, services and information that add value to customers and other stakeholders (Lambert, 2006), in order to improve the long-term performance of companies and the supply chain as a whole (Mentzer et al., 2001).

Supply Chain Network Design (SCND) involves strategic decisions, such as network configurations, structure, capacities, and coordination and tactical decisions, such as transportation, production, and material schedules (Pishvae et al. 2011). Two chains are identified in supply chain design; forward and reverse. If decisions in the forward and reverse supply chain networks are made interdependently, the SCND problem leads to suboptimal outputs (Pishvae & Torabi, 2010). Therefore, in order to design an efficient network for supply chain, both forward and reverse supply chain decisions must be taken into account simultaneously (Lee & Dong, 2008). A Closed-Loop Supply Chain (CLSC) network is established by integration of forward and reverse supply chains (Guide and Wassenhove, 2009).
In recent years, a sharp decline in natural resources and the ever-increasing assets of huge organizations expanded sustainable supply chain management into the realm of environmental and social responsibility (Govindan et al., 2013). Employing sustainable SCM enables enterprises to decrease their negative environmental effects and boost social and economic profits (Zailani et al., 2012), which are important competitive advantages. Hence, the three pillars of sustainably (economic, environmental and social) should be considered for CLSC network design. In most studies, a CLSC network is designed based on a single objective function (minimizing the total cost or maximizing the profit), which can by itself be a challenging problem (Klibi et al., 2010). The problem becomes even more complicated when other sustainability criteria (environmental and social impacts) are added, due to the involvement of conflicting, inexpressible, sophisticated, and interpenetrating and multiple incommensurable objectives (Tang and Zhou, 2012).

This problem is challenged by inherent uncertainty of reverse chains, caused for instance by the ambiguous nature of the quantity and quality of the returned products (Pishvae et al., 2011). There is the environmental uncertainty caused by the performance of suppliers and customers such as customer demand. There is also system uncertainties caused by supply chain processes, such as uncertainty of utilities’ capacity (Vahdani et al., 2013). Mistakes and delays in the supplier’s deliveries and the unpredictability of customer demands are other sources of uncertainties or vagueness (Zhang and Ma, 2009). Therefore uncertainties should be taken into account and addressed in order to reach an optimum sustainable supply chain network.
The next Sections provide a brief overview of the concepts of supply chain management, networks, logistics and design. The scope and objectives of this thesis are outlined in the last section of the Chapter.

1.2. Supply Chain Management and Networks
Supply Chain Management (SCM) is the set of operations and procedures which are employed to integrate suppliers, producers, warehouses distributors, and stores efficiently. This integration aims at producing goods in the appropriate quantities and distributing them to the designated locations at the right time, to maximize profits and meet customer requirements (Simchi-Levi et al. 2003). SCM is also recognized as a structure to manage information, financial, and physical flows in all stages of the supply chain, in order to improve customer service and increase the earned profit for all chain members (Sahin and Robinson, 2002). In effect, SCM is a network of operations that facilitates the efficient flow of information, materials and merchandises to satisfy customer. New information technologies provide opportunities in supply chain communication by enabling visibility throughout the chain.

The components (called “echelon”) of an SCM typically include suppliers, producers, distributors, warehouses, customer centers, collection, recycling, remanufacturing, recovering, and disposal centers. A problem of supply chain network design can be formulated for one time period, in which period represents the time it takes from the start of a cycle to its end. Also, this problem can be presented for multi time periods. Designing supply chain network by considering multiple periods helps managers to better plan a network for a long time.
1.2.1. Forward logistics

A forward supply chain is the set of activities in the process of converting raw materials into finished products. Demand management, procurement, and customer demands are the main contexts which are taken into account by managers in forward supply (Cooper et al., 1997). In a forward supply chain, manufacturers receive raw material from suppliers and deliver the products to the distributors, who in turn deliver them to customers. Customer centers define the end of the process.

1.2.2. Reverse logistics

Products are eventually discarded or disposed by customers. Sustainability demands that the supply chain’s responsibilities continue to the end of products’ life cycle. In a reverse supply chain, end-of-life products are collected from customers by disassembly centers. Some of these products may be still in reusable conditions and can be sold to other customers via redistributors. Some of these products are repaired in disassembly centers and then redistributed to new customers. Some end-of-life products can be recycled and used partially as raw material. Products that are not repeatable, reusable or recyclable are sent to disposal centers.

1.2.3. Closed-Loop logistics

A Closed loop supply chain (CLSC) is defined as “the design, control, and operation of a system to maximize value creation over the entire life cycle of a product with dynamic recovery of value from different types and volumes of returns over time” (Guide and Wassenhove, 2009). A CLSC is achieved when forward and reverse supply chains are considered simultaneously (Soleimani and Kannan, 2015). Integrated operations and
management of forward and reverse supply chains result in improving performance in the supply chain as a whole (Fleischmann et al. 2001; Uster et al. 2007; Pishvaee et al. 2010). The resource scarcity and environmental concerns have given importance to the integration of forward and reverse material flows in supply chains (Seuring, 2013). However, this integration is a challenging problem due to the often contradictory demands of forward and reverse supply chains (Visich et al., 2005).

1.2.4. Supply Chain Network Design

The design of a supply chain encompasses a set of decisions that include: production and distribution schedules, inventory control, number of echelons in a network, facilities locations, transportation between facilities, supplier selection, third-party logistics, transportation methods, and the type of technology to use (Pishvaee et al. 2011). In addition, fixed costs of investment, such as plant building cost or acquiring a certain technology, should be taken into consideration. The effect of these decisions will persist for many years, while the business environment may change.

1.2.5. Sustainable supply chain network design

Sustainable Supply Chain Management (SSCM) can be defined “an important new archetype for enterprises to achieve profit and market share objectives by lowering their environmental risks and impacts, while raising their ecological efficiency” (Zhu et al. 2005). Minimum waste generation, maximization of environmental performance and cost savings resulting in increased profit and market-share objectives are the benefits of the implementing SSCM (Zhu et al. 2005).
1.3. Thesis Objectives and Outlines

The main goal of this thesis is to design and optimize a Sustainable Closed-Loop Supply Chain Network under uncertainty. The major features that differentiate this thesis from the existing and reported methods are:

I. Both forward and reverse supply chains are optimized simultaneously considering the multi-echelon and multi-period conditions of a network; most previous studies considered forward and reverse chain networks, separately.

II. Three pillars of sustainability are considered in CLSC network design, while most reported studies tended to consider one dimension (minimization cost).

III. Uncertainties at the different levels of supply chain networks are considered to provide a realistic solution. Uncertainty has not been considered in studies that added environmental impacts to CLSC network design and used meta-heuristics algorithms to solve this problem.

IV. Analytical methods and commercial software are not suitable to solve the SCND optimization problem for large industrial cases. Single-objective meta-heuristic algorithms (SOMAs) can be to overcome this obstacle. But, SOMAs do not allow multiple objective functions. Multi-objective evolutionary algorithms (MOEAs), Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and non-dominated ranking genetic algorithm (NRGA) are adopted to solve this multi-objectives optimization problem for large cases.

The problem of “Sustainable Closed-Loop Supply Chain Network Design under Uncertainty” is investigated and improved by several approaches and solutions. Chapter 2
provides a literature review of the state-of-the art to show the need for the further development outlined in this work.

In Chapter 3, a general closed loop supply chain network is developed. The forward chain in this network includes raw material suppliers, producers, distributors, warehouses, and customer entities. The collection & inspection, disposal, recycling, recovering, remanufacturing, redistributors, and second customer centers are considered in the reverse chain. In addition, a mixed integer linear programming model (MILP) is proposed to optimize the CLSC network design. The model determines the location of facilities, which is recognized as a strategic decision. Also, tactical decisions, such as the amount of supplied raw material, the level of production, and shipments among the network entities are made. Uncertainty is not considered in this Chapter and the proposed mathematical model is formulated as deterministic. The objective of the model is to minimize transportation, production, collection, reverse costs, and the fixed costs of establishment of new entities. The proposed model is implemented for an actual industrial case to demonstrate the significance and applicability of the optimization process.

In Chapter 4, uncertainty and sustainability are added to problem of CLSC network design. In order to accommodate uncertainties, a Fuzzy Multi-Objective Mixed Integer Linear Programming (FMOMILP) model is presented for designing a sustainable CLSC network. The model takes into consideration the three objective of sustainability: cost minimization, environmental impact minimization, and social benefits maximization. A three-phase fuzzy mathematical programming approach is developed to solve this model. Also, all aspects of sustainability (cost, environmental, and social) are taken into account
for designing CLSC network. This study is among the first investigations that employ Fuzzy multi-objective mathematical models in sustainable CLSC network design. There are several fuzzy programming approaches to solve fuzzy mathematical models. In Chapter 5, three commonly used interactive fuzzy programming approaches are employed and their efficiency is analyzed.

The expansive nature of CLSC networks design as an NP-hard (Non-deterministic polynomial time) problem (Schrijver, 2003; Soleimani and Kannan, 2015) makes an efficient solution a requirement. Achieving reliable solutions within a practical time becomes more important when dealing with real industrial problems. This type of problems cannot be solved easily by analytical methods and commercial software for large. In Chapter 6, two multi-objective meta-heuristic approaches are adopted to solve problem of sustainable CLSC network design. The Non-dominated Sorting Genetic Algorithm (NSGA-II) and the Non-dominated Ranking Genetic Algorithm (NRGA) are methods employed in this Chapter.

Partial or overall reverse logistic operations are outsourced to third-party reverse logistics providers (3PRLPs). For this reason 3PRLPs play an important role in improving the performance of CLSC networks. In Chapter 7, an integrated Fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) (Dalalah et al. 2011) and Fuzzy Inference System (FIS) (Mamadani and Asilian 1975) are used to evaluate and select the best 3PRLPs based on sustainability criteria.
CHAPTER TWO: LITERATURE REVIEW

2.1. Introduction
In this Chapter, a review of the Supply Chain Network Design (SCND) problem is provided. Methods are reported according to the following features:

- Type of network (forward, reverse, closed) and considered components and flows
- Sustainability dimensions (considered objective functions)
- Uncertainty
- Modelling
- Solution methods

Table 2.1 summarizes current studies and shows their main features.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Network type</th>
<th>Sustainability objective</th>
<th>Modeling</th>
<th>Solution method</th>
<th>Uncertainty</th>
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<td>GAMS</td>
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<tr>
<td>Ferretti et al. (2007)</td>
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<td>Cost and Environmental</td>
<td>Mathematical model</td>
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<tr>
<td>Pati et al. (2008)</td>
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<td>MIGP</td>
<td>LINDO</td>
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<td>Linear programming</td>
<td>LINDO</td>
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<td>Cost and Environmental</td>
<td>Linear programming</td>
<td>LINDO</td>
<td>–</td>
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<tr>
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<td>Cost and Environmental</td>
<td>MILP</td>
<td>LINGO</td>
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<tr>
<td>Diabat and Theodorou (2015)</td>
<td>CLSC</td>
<td>Cost and Environmental</td>
<td>MINLP</td>
<td>CPLEX</td>
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<tr>
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<td>Integer programming</td>
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<td>MILP</td>
<td>CPLEX</td>
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<td>Cost</td>
<td>MILP</td>
<td>CPLEX</td>
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<td>Type</td>
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<td>Model Type</td>
<td>Solver</td>
<td>Heuristic (Algorithm)</td>
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<tr>
<td>Lu et al. (2015)</td>
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<td>Cost</td>
<td>Robust Optimization</td>
<td>CPLEX</td>
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<td>Subulan et al. (2012)</td>
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<td>CPLEX</td>
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<tr>
<td>Dai and Li (2017)</td>
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<td>Cost, Environmental</td>
<td>Fuzzy MILP</td>
<td>CPLEX</td>
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<tr>
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<td>Linear programming</td>
<td>CPLEX</td>
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<td>MINLP</td>
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<td>Linear programming</td>
<td>–</td>
<td>GA and PSO</td>
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<td>MILP</td>
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<td>Cost</td>
<td>MILP</td>
<td>CPLEX</td>
<td>PSO-GA</td>
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<td>Khalilpourazari and Mohammadi (2016)</td>
<td>CLSC</td>
<td>Cost</td>
<td>MINLP</td>
<td>GAMS</td>
<td>Water Cycle Algorithm</td>
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In Section 2.2, a review based on the type of Networks (forward, reverse, closed) and characteristics of models (decision variables, components of supply chain network) is provided. Section 2.3 considers the sustainability dimensions: cost, environmental, and social. In Section 2.4, presents methods dealing with uncertainties, classified as: Stochastic, Robust, and Fuzzy. In Section 2.5, current studies are compared based on the solution methodologies (meta-heuristic algorithms); not including the methods based on commercial software packages. Finally, in Section 2.6 the limitations of existing methods are summarized.
2.2. Supply Chain Network Design

Supply chain network design problems can be classified into three categories according to the underlying network structure: forward, reverse, and closed loop supply chain (CLSC). As Table 2.1 most reported studies formulated the network design problem as a Mixed Integer Linear Programming (MILP) problem. Two main variables are considered for this type of problems; integer variables for transferred products between facilities, and binary variables for used/unused (open/closed) facilities in a network. A few studies formulated SCND problems as Mixed Integer Non-linear Programming (MINLP). These are deterministic methods, i.e. they do not consider stochastic effects. Commercial software: LINGO (LINDO Systems Inc.), LINDO (LINDO Systems Inc.), GAMS (GAMS Development Corp.), and CPLEX (IBM) are available for solving these problems.

For forward supply chains networks, Tsiakis and Papageorgiou (2008) formulated a mixed integer linear programming model. They determined the optimal configuration of a production and distribution network considering financial and operational constraints. The objective function of this model was minimization of the costs of fixed infrastructure, transportation, production, and material handling costs. Thanh et al. (2008) employed a mixed integer linear programming model for the design of a production-distribution system for forward chains. They designed a multi-echelon network with deterministic demands. Sadjady and Davoudpour (2012) formulated a mixed integer programming model which aims to minimize total costs of network and opening and operating for facilities. The proposed model determined locations of plants and
warehouses, best transportation method, and best strategy for distributing the products. Balaman and Selim (2014) presented a mixed integer linear programming model to design a supply chain network for the production of biogas through anaerobic digestion of biomass. The model determined numbers, capacities and locations of biogas plants and biomass storages and the biomass supply and product distribution.

For reverse chain networks, Shih (2001) suggested a mixed integer programming model in order to optimize the infrastructure design for recycling electrical appliances and computers in Taiwan. This model aimed to minimize transportation cost, operating cost, fixed cost for new facilities, final disposal cost and landfill cost in reverse logistics. Kim et al. (2006) also developed a mathematical model to optimize the supply planning function for a reverse chain. Their model determines the number of purchased parts from the subcontractors and the number of parts to be processed at each remanufacturing facility. They used a set of experimental data to validate their model. Srivastava (2008) presented a conceptual framework based on literature and informal interviews with 84 stakeholders to design location–allocation of facilities in a reverse logistics network. Xanthopoulos and Iakovou (2009) proposed a model to design of the recovery processes of the end-of-life (EOL) electric and electronic products. Their model includes two phases; identifying components that need to be disassembled for recovery by a decision making model and presenting a multi-period, multi-product mixed-integer linear programming model to design recovery processes. Achillas et al. (2010) presented a decision support tool for policy-makers and regulators in order to optimize reverse logistics network of electronic products. They formulated a Mixed Integer Linear Programming mathematical model in which the cost elements are considered for
objective function of model. Sasikumar et al. (2010) formulated a mixed integer nonlinear programming model to design a multi-echelon reverse logistics network with the aim of maximizing the profit. Their model determines the locations and required number of facilities and product flows between facilities in reverse chain. They applied this model for network design of truck tire remanufacturing for the secondary market segment. Alumur et al. (2012) proposed a framework of profit maximization modeling to design a reverse logistics network. They presented a mixed-integer linear programming formulation to solve this problem. They applied this model for reverse network design of washing machines and tumble dryers in Germany. Alshamsi and Diabat (2015) presented a mixed-integer linear programming model for designing a complex network of reverse logistic system in which the model results provide decision elements on locations, capacities of inspection centers and remanufacturing facilities.

In a closed loop supply chain (SCND) problem both forward and reverse supply chain decisions must be taken into account simultaneously (Lee & Dong, 2008). Generally, a single objective function (minimizing cost or maximizing profit) is considered in most reported studies (Pishvae et al, 2011).

Fleischmann et al. (2001) presented a mixed integer linear programming model for designing a recovery network considering the forward flow. The proposed network includes un-capacitated disassembly and re-manufacturing facilities in the reverse channel. Suppliers and the relations between forward and reverse flows were not considered in designing network. Shen and Daskin (2005) presented a model to improve customer service and minimize cost of supply chain network design simultaneously. They
formulated the problem as a nonlinear model. The proposed model determined distribution center locations and the assignment of demand nodes to distribution centers.

Uster et al. (2007) employed an MILP model for a closed-loop supply chain network design problem. The manufacturing and remanufacturing were considered separately. Also, they considered a single source for meeting customer demands. Jayaraman (2006) introduced an analytical Re-manufacturing Aggregate Production Planning (RAPP) model, for aggregating production planning and controlling for closed-loop supply chains with product recovery and reuse. The output of that model included the number of units of core type with a nominal quality level which are to be disassembled, disposed, remanufactured, or acquired within a given time period. Kumar and Yamaoka (2007) presented a system dynamics modeling method to design a closed loop supply chain for the Japanese car industries. They also explored the relationship between reducing, reusing, recycling and disposal with base scenario analysis using consumption data and forecast. Kusumastuti et al. (2008) developed a facility location–allocation model to redesign a closed-loop service network at a Singapore-based company, which provides after-sales service. They considered four repair facilities in the model: service providers (for the collection of faulty equipment), local sub hubs (for consolidation of faulty parts), regional distribution centers (for handling faulty and good parts), and part manufacturers and third-party repair vendors (as repair facilities for faulty parts). They considered the possibility of having the network span across several countries and multi-period planning horizons. Yang et al. (2009) introduced a general closed-loop supply chain network which consisted of raw material suppliers, manufacturers, retailers, consumers and recovery centers. They aimed to formulate the
equilibrium state of the network by using the theory of variational inequalities. They used examples to investigate the effects of models’ parameters on the equilibrium shipments. Ozceylan and Paksoy (2013) presented a mixed integer mathematical model for a CLSC network that contained both forward and reverse flows with multi-periods and multi-parts. The transportation amounts of manufactured and disassembled products and the location of plants and retailers were determined.

Ramezani et al. (2014) modeled a CLSC design considering a financial approach. Economic aspects were considered as exogenous variables in this study. They incorporated the financial aspects and a set of budgetary constraints representing balances of payment delays, discounts, securities, and cash in the supply chain planning. Özceylan et al. (2014) described a mixed integer non-linear programming model to optimize strategic decisions (amounts of goods flowing on the forward and reverse chains) and tactical decisions in the reverse chain. The objective function in this model minimizes costs of transportation, purchasing, refurbishing, and operating the disassembly workstations. Gaur et al. (2017) presented a CLSC model for new product and its reconditioned version. The model specified production plan and configuration of CLSC for new products. They applied the model for a battery manufacturer in India.

The reviewed studies in this Section consider one objective function for optimizing supply chain network design. Considering other objective functions can provide more realistic solutions for problems of supply chain network design. Moreover, these studies used deterministic mathematical models for optimizing the design of supply chain networks. While, in the real world parameters may not be definite, as for example the return rates and customer demands which are uncertain.
2.3. Sustainable SCND

In most studies, one or two pillars of sustainability (cost and environmental) were taken into account to design supply chain network (Seuring, 2013). The social dimension is neglected, at least those reported in Table 2.1.

Ferretti et al. (2007) reported a model for a single buyer, single vendor green supply chain, that minimizes the cost and pollution of production and distribution for an aluminum supply chain. Pati et al. (2008) used a mixed integer goal programming (MIGP) model to assist in the appropriate management of a paper recycling logistics system. They took three objectives into account; reduction in reverse logistics cost, product quality improvement through increased segregation at the source, and environmental benefits through increased wastepaper recovery. Their model determined a facility location, route, and flow of different varieties of recyclable waste paper. Paksoy et al. (2010) developed a multi-objective linear programming model to minimize cost and environmental impacts (CO2 emissions). Paksoy et al. (2011) introduced a linear programming model to optimize a CLSC problem which captured the trade-offs between various costs, including those of emissions and of transporting commodities within the chain. They also investigated several operational and environmental performance criteria, in particular, those related to transportation operations. Millet (2011) analyzed 18 reverse logistics structures based on environmental and social dimensions. Kannan et al. (2012) presented a mixed integer linear programming model to design a reverse logistic network based on carbon footprint. Their model aims to minimize cost and climate change. Diabat and Theodorou (2015) developed a mixed integer non-linear programming model for a location-inventory problem in a supply chain. They also analyzed the amount of
emissions. A simulation-based optimization methodology was introduced by Keramydas et al. (2017) to design supply chains with objective functions of minimization cost and CO2 emissions.

To the author’s knowledge, no studies appeared in the open literature on the design of a CLSC network considered simultaneously economic, environmental, and social objectives.

2.4. SCND under uncertainty
There are several approaches to handling the uncertainty of CLSC network design problem. Stochastic programming (Kerachian & Karamouz, 2007) is one of the methods used. Francas and Minner (2009) studied optimal capacity acquisition and expected network performance in a supply-chain setting with remanufacturing options under uncertain demand and returns. A two-stage stochastic programming approach was utilized to present design models for two different generic network structures and two different market structures. They considered uncertainty for demands and returns.

Shu et al. (2005) formulated a stochastic transportation-inventory network design model. They considered one supplier and multiple retailers. One objective function (minimize cost) was considered for the model. El-Sayed et al. (2010) developed a multi-period, multi-echelon and multi-stage forward-reverse logistics network design under risk. Their model was formulated in a stochastic mixed integer linear programming (SMILP) decision-making form. Demands of customer zones were considered to be stochastic. Zeballos et al. (2012) developed a two-stage scenario-based modeling approach to deal with the design and planning decisions in multi-period, multi-product CLSCs. They considered demand and returns as uncertain parameters. A mixed-integer
linear stochastic programming model for a single-period multi-product CLSC location problem including multiple plants, collection centers, and demand markets was introduced by Amin and Zhang (2013). Ramezani et al. (2013) employed a stochastic multi-objective model to design a forward/reverse supply chain network under an uncertain environment. They adopted a stochastic optimization approach to coping with the uncertainty of demand and the return rate. The performance of proposed supply chain was assessed through three criteria: profit, customer responsiveness, and quality of suppliers. Calmon and Graves (2016) formulated a new inventory management problem in the reverse logistics operations of an electronics retailer as a stochastic optimization problem. They proposed an algorithm which is possible to use a Monte-Carlo simulation to find the solutions.

The stochastic approach has three major disadvantages. First, the lack of historical data for parameters with uncertainty jeopardizes the validity of the obtained probability distribution functions. The disadvantage is more severe in approaches such as chance constrained programming (Hannon, 2002). In this approach the convexity properties are shattered, which leads to more complexity of the original problem. In studies that apply scenario-based stochastic programming, the large number of required scenarios to represent uncertainty results in large-sized problems that are computationally demanding. If the number of scenarios is restricted for computational reasons, the range of future states under which decisions are made and evaluated becomes limited (Pishvaee et al, 2011).

Robust programming is also recognized as a method to design supply chain network under uncertainty. Pishvaee et al. (2011) proposed a bi-objective possibilistic mixed
integer programming model to cope with uncertain and imprecise parameters in closed-loop supply chain network design problems. They compared the obtained results from robust optimization model with a deterministic model under different test problems. Hasani et al. (2012) used an interval robust optimization technique to model a strategic closed-loop supply chain network design. They considered assumptions such as multiple periods, multiple products, and multiple supply chain echelons as well as uncertain demand and purchasing cost in their model.

There are two major advantages for robust optimization compared to stochastic programming (Alumur et al. 2012). First, there are no computational challenges for robust optimization, even when there are many uncertain parameters. Second, in robust optimization, there is no need to use precise approximations of probability distributions to define uncertainty sets; they can be determined using rough historical data and decision makers’ experiences. Lu et al. (2015) proposed a robust optimization model to design a reliable facility location network. They considered only one objective function (minimize cost) for model.

Fuzzy programming was applied to accommodate uncertainty in supply chain network design problem. Subulan et al. (2012) employed a fuzzy mixed integer programming model with non-linear constraints for medium term planning in a supply chain network with remanufacturing option. They took into account storage capacities, retailers’ and wholesalers’ demands, return rates, acceptance ratios, weekly available production/remanufacturing times, transportation upper bounds and objective function value as fuzzy. Phuc et al. (2013) used fuzzy parameters to model an multi electrical and electronic equipment supply chain network. They converted the proposed fuzzy model
into the equivalent auxiliary crisp model in order to find preferred compromise solutions. The uncertainties of capacity, demand, and price were taken into consideration in the model of Dai and Li (2017). They presented a fuzzy mixed integer model for CLSC network design which maximizes the total profit and minimizes the wastes of facilities.

Fuzzy programming has the advantages of being more practical and non-deterministic and it measures the degree of satisfaction of each objective functions (Gholamian et al. 2015). The latter feature helps decision makers to select a preferred efficient solution (Torabi and Hassini, 2008). Although the uncertainty is addressed in the aforementioned studies, they did not consider the environmental and social impacts in designing the supply chain networks. In addition, the proposed models and solution methods in these studies were applied for small cases.

2.5. Solution methods (Meta-heuristics)
As seen from Table 2.1, most studies employed commercial software such as LINGO (Sasikumar et al. 2010; Kusumastuti et al. 2008; Kannan et al. 2012; Hasani et al. 2012), LINDO (Pati et al. 2008; Paksoy et al. 2010; Paksoy et al. 2011), GAMS (Jayaraman, 2006; Gaur et al. 2017), and CPLEX (Tsiakis and Papageorgiou, 2008; Xanthopoulos and Iakovou, 2009; Achillas et al. 2010; Alumur et al. 2012; Alshamsi and Diabat, 2015; Ozcelylan and Paksoy, 2013; Ramezani et al. 2014; Zeballos et al. 2012; Amin and Zhang, 2013). CLSC network design problem is identified as a NP-hard (Non-deterministic polynomial-time) problem, for which and analytical methods and commercial software are not able to provide optimal solutions for large problem situations. Therefore meta-heuristics methods are used to solve such problems.
Lee and Dong (2008) employed a deterministic programming model to optimize forward and reverse logistics flows for end-of-lease computer products recovery. They developed a Tabu Search (TS) algorithm to determine transportation amounts for returned products. TS algorithm is a meta-heuristic algorithm that use local search method for optimizing mathematical models. A mixed-integer nonlinear facility location-allocation model was proposed by Aras et al. (2008) to explore the best locations for collection centers and the optimal incentive values for different return types. They employed a Tabu search solution procedure to solve this model. Kannan et al. (2009) utilized genetic algorithm and particle swarm optimization methods to design and a forward logistics multi-echelon distribution inventory supply chain model. Kannan et al. (2010) developed a multi echelon, multi period, multi-product closed-loop supply chain network model for returned batteries in India. They proposed heuristics based genetic algorithm as a solution methodology to solve mixed integer linear programming model. Wang and Hsu (2010) modeled a generalized closed-loop supply chain design by an integer linear programming model, which integrated forward and reverse logistics. They also developed a revised spanning-tree-based genetic algorithm using determinant encoding representation. Pishvaee et al. (2010) used a mixed integer linear programming model to design a multistage reverse logistics network in which both opening and transportation costs are taken in their model into consideration. They introduced simulated annealing algorithm with special neighborhood search mechanisms. Soleimani et al. (2013) developed a multi-echelon, multi-product, and multi-period in a mixed integer linear programming framework for CLSC network, and employed genetic algorithm to solve this problem. They validated the solution method by solving a number
of large-size cases. Soleimani and Kannan (2015) developed a hybrid meta-heuristic algorithm based on algorithm (GA) and particle swarm optimization (PSO) to solve large-size instances of CLSC network design problem. They used CPLEX solver software to validate the results of this eta-heuristic algorithm for small-size instances. Khalilpourazari and Mohammadi (2016) introduced a Meta-heuristic algorithm, called the Water Cycle Algorithm to solve the mathematical model of CLSC network design.

The above studies applied meta-heuristic algorithms to solve deterministic mathematical models with one objective function. Single-objective Evolutionary Algorithms (SOEAs) were used in these studies. However, these algorithms are inadequate in solving multi-objective mathematical models. Moreover, the studies reported in this Section did not consider uncertainties.

2.6. Conclusions

Current methods that consider problems of Supply Chain Network Design optimization are quite diverse, since they formulate an optimization problem considering a variety: objective functions (cost minimization, etc.), decision variables (facility locations, number of echelons, transportation between facilities, etc.), and constraints (capacity, balance, etc.). With respect to the modeling feature, current methods could be classified mainly as Mixed Integer Linear Programming (MILP) or Mixed Integer Non-linear programming (MINLP). Although MILP and MINLP modelling methods are common; they can have different model characteristics, such as: number of periods (single-period or multiple-period), product (single-product or multi-product), decisions variables, constraints, connections between facilities, and objective functions. However, methods based on MINLP may include some general characteristics ignored in MILP formulations
but, in the other hand, MINLP formulations may be complex, and cumbersome and difficult to solve.

Reported studies use a deterministic Linear or Non-linear programming (MILP, MINLP) models. Also, they use commercial software to solve these models. They consider only one objective function for modelling a problem. The main limitations of these studies are, neglecting sustainability and uncertainty in designing supply chain network and also that they cannot be used for large cases. All the studies reported in Section 2.3 also are formulated as deterministic MILP, MINLP. Also, all these studies use commercial software for a solution. Also, all the studies on uncertainty, reported in Section 2.4, use commercial software and do not consider other dimensions of sustainability (environmental and social) for modelling the problem. It should be noted that published studies that used meta-heuristic algorithms to solve problem are formulated as a deterministic MILP or MINLP, and consider only one objective function (Cost) for modelling of problem.

The review given in this Chapter and summarized in Table 2.1, indicate that few studies considered and optimized both forward and reverse chains networks. While some works designed a CLSC network, all entities of forward and reverse logistics were not considered. Few studies analyzed the applicability of their CLSC network for actual industrial case studies. Most studies presented only computational experiments for their models.

In spite of the importance of sustainability issues for supply chain management, most studies considered one objective function, minimization costs (e.g., transportation, manufacturing, and establishing facilities costs) for the problem of CLSC network
design. While some scholars (Paksoy et al. 2001; Chaabane et al. 2012; Amin and Zhang 2013) identified the environmental concerns, a gap exists in considering the social benefits, as an important sustainability dimension, in designing CLSC networks. Although some studies included the environmental concerns to design a CLSC network; the uncertainty issue was neglected in these studies. The main parameters of the problem, such as customer demand and return rates, were considered as deterministic.

SCND is identified as a NP-hard problem. Hence, analytical methods and commercial software are not able to provide optimal solutions for large problems. Using meta-heuristics was suggested by some scholars to solve this type of problems. The conducted literature review shows that the studies that used meta-heuristics for solving problem of SCND considered only one objective function. The use of multi-objective evolutionary algorithms for solving the sustainable CLSC network design problem with three objective functions (cost and environmental impacts minimization and social benefits maximization) has not been fully explored, at least in the open literature, at least to the author`s knowledge.
CHAPTER THREE: AN OPTIMIZATION MODEL FOR NETWORK DESIGN OF A CLOSED-LOOP SUPPLY CHAIN: A CASE STUDY

3.1. Introduction

A Closed-loop Supply Chain (CLSC) is achieved when forward and reverse supply chains are simultaneously taken into account (Soleimani and Kannan, 2015). Design and planning are identified as the most important decisions that should be made in coping with a CLSC. Strategic decisions such as network configuration, structure, capacity, and coordination are the main characteristics of all facilities in the design stage. However at the planning level, one of the most important parameters adopted in supply chain network is to determine the amount of shipped products between all supply chain network entities (Chopra and Meindl, 2007).

This Chapter presents a closed-loop supply chain (CLSC) network design model (in the forward and reverse chains) in an actual case study for glass manufacturing industry located in the center part of IRAN. However, a generalized formulation is first provided for the CLSC network design problem. The forward model included raw material suppliers, producers, distributors, warehouses, and customer entities. The reverse chain considered collection & inspection, disposal, recycling, recovering, remanufacturing, redistributors, and second customer centers. A mixed integer linear programming model (MILP) is used to optimize the CLSC network design. The model determines the location of facilities, which is recognized as a strategic decision. In addition, tactical decisions, such as the amount of supplied raw material, the level of production, and shipments among the network entities are made. The objective of the model is to minimize
transportation, production, collection, reverse costs, and the fixed costs of establishment of new entities. Also, a comprehensive sensitivity analysis is carried out to investigate the effect of parameters, such as demand and return rates, have on the strategic and tactical decisions of supply chain network. In addition, the optimum solution for CLSC network design of this industrial case is compared with one non-optimized case to show advantage of optimization.

3.2. Problem description
The CLSC model proposed here is a multi-echelon and multi-period. This model integrates activities of purchase, production, distribution, collection, and return in a CLSC network, which is more complicated and needs more efforts to investigate than both forward and reverse networks. The general structure of the proposed closed-loop logistic network is shown in Figure 3.1. Not only does the proposed model consist of five layers in the forward logistics, which are suppliers, producers, distributors, warehouses, and customer centers, but it also has seven layers in the reverse logistics, which are collection & inspection, disposal, recycling, recovering, re-manufacturing centers, redistributors, and second-customer centers.

In the forward logistics, the suppliers provide raw materials to producers. The manufactured goods are forwarded from producers to customers via warehouses and distribution centers to satisfy customer demands. In the reverse logistics, the returned products are gathered from customers by collection & inspection centers to be examined. In the proposed model four treatment processes are taken into account for the returned goods in the reverse chain: (i) Recovering: the returned products are recovered and sent
to redistributors for reuse; (ii) Remanufacturing: the returned products are remanufactured and provided for reuse; (iii) Recycling: the returned products are recycled and sent to suppliers; and (iv) Disposal: the returned products which have low quality for manufacturing are completely disposed. This approach helps supply chains to inhibit excessive transportations of returned products and transfer these products to the relevant facilities directly. The following assumptions and limitations are made in the network configuration:

- The locations of suppliers, customer, and second-customer centers are known and fixed. This is typically the case in a stable operation.
- The potential locations of plants, warehouses, distributors, collection & inspection, disposal, recycling, remanufacturing, recovering centers, and redistributors are known. This requires the designer to acquire such information before the design process.
- The flows are only allowed to be sent between two consecutive stages in forward and reverse logistics. Furthermore, there are no defined flows between facilities at the same layer. This is typically the case, as for example, a supplier in a network cannot receive or deliver products to another supplier.
- The quantities of all parameters are deterministic, i.e. there is no uncertainty for parameters. Uncertainty is addressed in ensuring Chapters.
- The transportation cost of products between all layers remains fixed for all the periods. This simplifies problem and shows there is no fluctuation for transportation costs for all time periods.
• The inspection cost of the returned products is included in the transportation cost from customer zones to collection & inspection centers. This reduces the number of optimization parameters, but requires repetition of the optimization process if these costs significantly change.

• All customer demands should be satisfied. This is a reasonable expectation in any supply chain, and not meeting it can have an adverse effect on the entire operation.

• The model is multi-period (four time period) and single-product. This reflects the current state of the operations of network, any change will require re-optimization of the design.

Figure 3.1. Conceptual framework for the CLSC network
3.3. Model Formulation

A network can be formulated as a mixed-integer linear programming model. Sets, parameters, and decision variables are defined in the following sub-sections:

3.3.1. Notations

Indices and Sets

S: Set of Suppliers, indexed by ‘s’.

P: Set of Producers, indexed by ‘p’.

W: Set of Warehouses, indexed by ‘w’.

D: Set of Distributors, indexed by ‘d’.

C: Set of Customer Centers, indexed by ‘c’.

I: Set of Collection & Inspection Centers, indexed by ‘i’.

J: Set of Re-Manufacturing Centers, indexed by ‘j’.

K: Set of Recovering Centers, indexed by ‘k’.

L: Set of Recycling Centers, indexed by ‘l’.

M: Set of Disposal Centers, indexed by ‘m’.

N: Set of Redistribution Centers, indexed by ‘n’.

F: Set of Second Customer Centers, indexed by ‘f’.

T: Periods, indexed by ‘t’.

Parameters

\(ca_{st}\) : Capacity of Supplier ‘s’ at time period ‘t’

\(ca_{pt}\) : Capacity of Producer ‘p’ at time period ‘t’

\(ca_{wt}\) : Capacity of Warehouse ‘w’ at time period ‘t’
$ca_{dt}$ : Capacity of Distributor ‘$d$’ at time period ‘$t$’

$ca_{it}$ : Capacity of Collection & Inspection Center ‘$i$’ at time period ‘$t$’

$ca_{mt}$ : Capacity of Disposal Center ‘$m$’ at time period ‘$t$’

$ca_{lt}$ : Capacity of Recycling Center ‘$l$’ at time period ‘$t$’

$ca_{jt}$ : Capacity of Remanufacturing Center ‘$j$’ at time period ‘$t$’

$ca_{kt}$ : Capacity of Recovering Center ‘$k$’ at time period ‘$t$’

$ca_{nt}$ : Capacity of Re-distributor ‘$n$’ at time period ‘$t$’

$tc_{pw}$ : Transportation cost a product from producer ‘$p$’ to warehouse ‘$w$’

$tc_{pd}$ : Transportation cost a product from producer ‘$p$’ to distributor ‘$d$’

$tc_{wc}$ : Transportation cost a product from warehouse ‘$w$’ to customer center ‘$c$’

$tc_{dc}$ : Transportation cost a product from distributor ‘$d$’ to customer center ‘$c$’

$tc_{ci}$ : Transportation cost a product from customer center ‘$c$’ to collection & inspection center ‘$i$’

$tc_{im}$ : Transportation cost a product from collection & inspection center ‘$i$’ to disposal center ‘$m$’

$tc_{il}$ : Transportation cost a product from collection & inspection center ‘$i$’ to recycling center ‘$l$’

$tc_{lj}$ : Transportation cost a product from collection & inspection center ‘$i$’ to remanufacturing center ‘$j$’

$tc_{lk}$ : Transportation cost a product from collection & inspection center ‘$i$’ to recovering center ‘$k$’

$tc_{ls}$ : Transportation cost a product from recycling center ‘$l$’ to supplier ‘$s$’

$tc_{jp}$ : Transportation cost a product from remanufacturing center ‘$j$’ to producer ‘$p$’
\( tc_{ln} \): Transportation cost a product from recycling center ‘l’ to re-distributor ‘n’

\( tc_{jn} \): Transportation cost a product from remanufacturing center ‘j’ to re-distributor ‘n’

\( tc_{kn} \): Transportation cost a product from recovering center ‘k’ to re-distributor ‘n’

\( tc_{nf} \): Transportation cost a product from re-distributor ‘n’ to second customer center ‘f’

\( fc_p \): Fixed cost of opening producer ‘p’

\( fc_w \): Fixed cost of opening warehouse ‘w’

\( fc_i \): Fixed cost of establishing collection & inspection center ‘i’

\( fc_m \): Fixed cost of establishing disposal center ‘m’

\( fc_l \): Fixed cost of establishing recycling center ‘l’

\( fc_j \): Fixed cost of establishing remanufacturing center ‘j’

\( fc_k \): Fixed cost of establishing recovering center ‘k’

\( fc_n \): Fixed cost of establishing re-distributor center ‘n’

\( mc_{pt} \): Manufacturing cost at producer ‘p’ at time period ‘t’

\( dc_{mt} \): Disposal cost at disposal center ‘m’ at time period ‘t’

\( rc_{lt} \): Recycling cost at recycling center ‘l’ at time period ‘t’

\( ec_{jt} \): Remanufacturing cost at remanufacturing center ‘j’ at time period ‘t’

\( bc_{kt} \): Recovering cost at recovering center ‘k’ at time period ‘t’

\( pc_{st} \): Material cost of product supplied by supplier ‘s’ at time period ‘t’

\( de_{ct} \): Demand of customer center ‘c’ at time period ‘t’

\( de_{ft} \): Demand of second customer center ‘f’ at time period ‘t’

\( sc \): Shortage cost of product
\( r_{yt} \) : Recycling ratio at time period ‘t’

\( rm_t \) : Remanufacturing ratio at time period ‘t’

\( rv_t \) : Recovering ratio at time period ‘t’

\( rd_t \) : Disposal ratio at time period ‘t’

Decision Variables

\( O_{st} \) : 1 if a supplier is open in location ‘s’ at time period ‘t’; 0 otherwise

\( O_{pt} \) : 1 if a producer is open in location ‘p’ at time period ‘t’; 0 otherwise

\( O_{wt} \) : 1 if a warehouse is open in location ‘w’ at time period ‘t’; 0 otherwise

\( O_{dt} \) : 1 if a distributor is open in location ‘d’ at time period ‘t’; 0 otherwise

\( O_{it} \) : 1 if a collection & inspection center is open in location ‘i’ at time period ‘t’; 0 otherwise

\( O_{mt} \) : 1 if a disposal center is open in location ‘m’ at time period ‘t’; 0 otherwise

\( O_{lt} \) : 1 if a recycling center is open in location ‘l’ at time period ‘t’; 0 otherwise

\( O_{jt} \) : 1 if a remanufacturing center is open in location ‘j’ at time period ‘t’; 0 otherwise

\( O_{kt} \) : 1 if a recovering center is open in location ‘k’ at time period ‘t’; 0 otherwise

\( O_{nt} \) : 1 if a re-distributor is open in location ‘n’ at time period ‘t’; 0 otherwise

\( X_{spt} \) : Quantity shipped from supplier ‘s’ to producer ‘p’ at time period ‘t’

\( X_{pwt} \) : Quantity shipped from producer ‘p’ to warehouse ‘w’ at time period ‘t’

\( X_{pdt} \) : Quantity shipped from producer ‘p’ to distributor ‘d’ at time period ‘t’

\( X_{wct} \) : Quantity shipped from warehouse ‘w’ to customer center ‘c’ at time period ‘t’

\( X_{dct} \) : Quantity shipped from distributor ‘d’ to customer center ‘c’ at time period ‘t’
$X_{cit}$ : Quantity shipped from customer center ‘c’ to Collection & Inspection center ‘i’ at time period ‘t’

$X_{int}$ : Quantity shipped from collection & inspection center ‘i’ to disposal center ‘m’ at time period ‘t’

$X_{ilt}$ : Quantity shipped from collection & inspection center ‘i’ to recycling center ‘l’ at time period ‘t’

$X_{ijt}$ : Quantity shipped from collection & inspection center ‘i’ to remanufacturing center ‘j’ at time period ‘t’

$X_{ikt}$ : Quantity shipped from collection & inspection center ‘i’ to recovering center ‘k’ at time period ‘t’

$X_{int}$ : Quantity shipped from recycling center ‘l’ to re-distributor ‘n’ at time period ‘t’

$X_{lst}$ : Quantity shipped from recycling center ‘l’ to supplier ‘s’ at time period ‘t’

$X_{jpt}$ : Quantity shipped from remanufacturing center ‘j’ to producer ‘p’ at time period ‘t’

$X_{jnt}$ : Quantity shipped from remanufacturing center ‘j’ to re-distributor ‘n’ at time period ‘t’

$X_{knt}$ : Quantity shipped from recovering center ‘k’ to re-distributor ‘n’ at time period ‘t’

$X_{nft}$ : Quantity shipped from re-distributor ‘n’ to second customer ‘f’ at time period ‘t’
3.3.2. Objective Function

The objective function of the proposed CLSC model aims at minimizing the total cost:

\[
\text{Minimize Total Cost} = \text{fixed costs} + \text{producing cost} + \text{recycling cost} + \text{remanufacturing cost} + \text{recovering cost} + \text{disposal cost} + \text{transportation cost} + \text{material cost} + \text{shortage cost} + \text{collection cost}
\]

Fixed Cost =

\[
\sum_{p \in P} \sum_{t \in T} f_{ct} O_{pt} + \sum_{w \in W} \sum_{t \in T} f_{ct} O_{wt} + \sum_{d \in D} \sum_{t \in T} f_{ct} O_{dt} + \sum_{i \in I} \sum_{t \in T} f_{ct} O_{it} + \sum_{m \in M} \sum_{t \in T} f_{ct} O_{mt}
\]

\[
+ \sum_{i \in I} \sum_{t \in T} f_{ct} O_{it} + \sum_{j \in J} \sum_{t \in T} f_{ct} O_{jt} + \sum_{k \in K} \sum_{t \in T} f_{ct} O_{kt} + \sum_{n \in N} \sum_{t \in T} f_{ct} O_{nt} \quad (3.1)
\]

Manufacturing Cost =

\[
\sum_{p \in P} \sum_{w \in W} \sum_{t \in T} m_{ct} X_{pwt} + \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} m_{ct} X_{pdt} \quad (3.2)
\]

Recycling Cost =

\[
\sum_{i \in I} \sum_{t \in T} r_{ct} X_{ilt} \quad (3.3)
\]

Remanufacturing Cost =

\[
\sum_{j \in J} \sum_{i \in I} \sum_{t \in T} e_{ct} X_{ijt} \quad (3.4)
\]

Recovering Cost =

\[
\sum_{k \in K} \sum_{i \in I} \sum_{t \in T} b_{ct} X_{ikt} \quad (3.5)
\]

Disposal Cost =

\[
\sum_{m \in M} \sum_{i \in I} \sum_{t \in T} d_{ct} X_{imt} \quad (3.6)
\]

Transportation Cost =
\[
\sum_{w \in \mathcal{W}} \sum_{p \in \mathcal{P}} \sum_{t \in \mathcal{T}} t_{cw} X_{pwt} + \sum_{d \in \mathcal{D}} \sum_{p \in \mathcal{P}} \sum_{t \in \mathcal{T}} t_{cd} X_{pdt} + \sum_{w \in \mathcal{W}} \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} t_{cw} X_{wct} + \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} t_{cd} X_{dct} \\
+ \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} t_{ci} X_{cit} + \sum_{i \in \mathcal{I}} \sum_{l \in \mathcal{L}} \sum_{t \in \mathcal{T}} t_{cm} X_{mint} + \sum_{l \in \mathcal{L}} \sum_{t \in \mathcal{T}} t_{cm} X_{lmt} \\
+ \sum_{j \in \mathcal{J}} \sum_{l \in \mathcal{L}} \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} t_{cj} X_{jnt} + \sum_{k \in \mathcal{K}} \sum_{l \in \mathcal{L}} \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} t_{ck} X_{knt} \\
+ \sum_{f \in \mathcal{F}} \sum_{n \in \mathcal{N}} \sum_{t \in \mathcal{T}} t_{nf} X_{nft} \tag{3.7}
\]

Material Cost =
\[
\sum_{s \in \mathcal{S}} \sum_{p \in \mathcal{P}} \sum_{t \in \mathcal{T}} p_{cs} X_{spt} - \sum_{s \in \mathcal{S}} \sum_{l \in \mathcal{L}} \sum_{t \in \mathcal{T}} (p_{cs} - r_{cl}) X_{lst} \tag{3.8}
\]

Shortage Cost =
\[
\left( \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} d_{ct} - \sum_{w \in \mathcal{W}} \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} X_{wct} - \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} X_{dct} \right) s_c \tag{3.9}
\]

Collection cost =
\[
\sum_{c \in \mathcal{C}} \sum_{l \in \mathcal{L}} \sum_{t \in \mathcal{T}} t_{cl} X_{cit} \tag{3.10}
\]

3.3.3. Constraints

The constraints of the model are represented as follows:

Capacity Constraints
\[
\sum_{p \in \mathcal{P}} X_{spt} \leq O_{st} c_{as} \quad \forall s \in \mathcal{S}, t \in \mathcal{T} \tag{3.11}
\]
\[
\sum_{w \in \mathcal{W}} X_{pwt} + \sum_{d \in \mathcal{D}} X_{pdt} \leq O_{pt} c_{ap} \quad \forall p \in \mathcal{P}, t \in \mathcal{T} \tag{3.12}
\]
\[
\sum_{p \in \mathcal{P}} X_{pwt} \leq O_{wt} c_{aw} \quad \forall w \in \mathcal{W}, t \in \mathcal{T} \tag{3.13}
\]
\[
\sum_{p \in \mathcal{P}} X_{pd} \leq O_{dt} c_{ad} \quad \forall d \in \mathcal{D}, t \in \mathcal{T} \tag{3.14}
\]
\[
\sum_{c \in \mathcal{C}} X_{cit} \leq O_{it} c_{ai} \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{3.15}
\]
\[
\sum_{i \in I} X_{int} \leq O_{mt} c_{am} \quad \forall \ m \in M, t \in T
\]

(3.16)

\[
\sum_{s \in S} X_{lst} + \sum_{n \in N} X_{nt} \leq O_{lt} c_{al} \quad \forall \ l \in L, t \in T
\]

(3.17)

\[
\sum_{p \in P} X_{ipt} + \sum_{n \in N} X_{jnt} \leq O_{jt} c_{aj} \quad \forall \ j \in J, t \in T
\]

(3.18)

\[
\sum_{n \in N} X_{knt} \leq O_{kt} c_{ak} \quad \forall \ k \in K, t \in T
\]

(3.19)

\[
\sum_{i \in I} X_{int} + \sum_{j \in J} X_{jnt} + \sum_{k \in K} X_{knt} \leq O_{nt} c_{an} \quad \forall \ n \in N
\]

(3.20)

Constraint (3.11) guarantees that, the sum of the flow exiting from suppliers to all producers does not exceed the capacity of suppliers. Constraint (3.12) shows that, in each period, the sum of shipped products from producers to warehouses and distributors is lower than capacity of producers. Constraint (3.13) states that, in each period, the sum of the flow entering to warehouses from producers does not exceed the holding capacity of warehouses. Constraint (3.14) ensures that in each period the sum of the flow entering from producers to distributors is not more than capacity of relevant distributor.

Constraint (3.15) states that the all collected products from customer centers which are entered to collection and inspection centers do not exceed the relevant capacity. Constraint (3.16) ensures that the sum of the flow entering from collection and inspection centers to disposal centers does not exceed the disposing capacity of disposal centers. Constraint (3.17) guarantees that the sum of recycled products which are sent to suppliers and redistributors is not more than of capacity of relevant recycling center. Constraint (3.18) demonstrates that the sum of the flow exiting from remanufacturing centers to producers and redistributors does not exceed the remanufacturing capacity of remanufacturing centers. Constraint (3.19) guarantees that sum of recovered products
which are shipped to redistributors from recovering centers are not more than the relevant capacity. Constraint (3.20) states that the sum of the flow entering to redistributors from recycling, remanufacturing, and recovering centers does not exceed the holding capacity of redistributors.

**Balance Constraints**

\[ \sum_{s \in S} X_{spt} + \sum_{j \in J} X_{jpt} = \sum_{w \in W} X_{wpt} + \sum_{d \in D} X_{dpt} \quad \forall p \in P, t \in T \quad (3.21) \]

\[ \sum_{p \in P} X_{pwt} = \sum_{c \in C} X_{wct} \quad \forall w \in W, t \in T \quad (3.22) \]

\[ \sum_{p \in P} X_{pdt} = \sum_{c \in C} X_{dct} \quad \forall d \in D, t \in T \quad (3.23) \]

\[ \sum_{c \in C} X_{cit} = \sum_{m \in M} X_{imt} + \sum_{l \in L} X_{ilt} + \sum_{j \in J} X_{ijt} + \sum_{k \in K} X_{ikt} \quad \forall i \in I, t \in T \quad (3.24) \]

\[ \sum_{r \in R} r_{yt} X_{cit} = \sum_{j \in J} X_{ijt} \quad \forall i \in I, t \in T \quad (3.25) \]

\[ \sum_{i \in I} X_{ilt} = \sum_{n \in N} X_{int} + \sum_{s \in S} X_{lst} \quad \forall l \in L, t \in T \quad (3.26) \]

\[ \sum_{c \in C} r_{mt} X_{cit} = \sum_{j \in J} X_{ijt} \quad \forall i \in I, t \in T \quad (3.27) \]

\[ \sum_{i \in I} X_{ijt} = \sum_{m \in M} X_{jmt} + \sum_{p \in P} X_{jpt} \quad \forall j \in J, t \in T \quad (3.28) \]

\[ \sum_{r \in R} r_{vt} X_{cit} = \sum_{k \in K} X_{ikt} \quad \forall i \in I, t \in T \quad (3.29) \]

\[ \sum_{i \in I} X_{ikt} = \sum_{n \in N} X_{knt} \quad \forall k \in K, t \in T \quad (3.30) \]

\[ \sum_{c \in C} r_{dt} X_{cit} = \sum_{m \in M} X_{imt} \quad \forall i \in I, t \in T \quad (3.31) \]

\[ \sum_{l \in L} X_{lnt} + \sum_{j \in J} X_{jnt} + \sum_{k \in K} X_{knt} = \sum_{n \in N} X_{nt} \quad \forall n \in N, t \in T \quad (3.32) \]
Constraint (3.21) shows that the flow entering from suppliers and remanufacturing centers to producers is equal to sum of the existing from producers to warehouses and distributors at each period. Constraint (3.22) ensures that in each period, the sum of the flow entering from producers to warehouses is equal to sum of the existing from warehouses to customer centers. Constraint (3.23) guarantees that in each period, the sum of the flow entering from producers to distributors is equal to sum of the existing from distributors to customer centers. Constraint (3.24) states that in each period, the sum of the flow entering from customer centers to collection and inspection centers is equal to existing from collection and inspection centers to recycling, remanufacturing, recovering, and disposal centers. Constraints (3.25) and (3.26) ensures that in each period, all returned products from customer centers which are entered to recycling centers after a required inspection in collection and inspection centers are delivered to suppliers and redistributors. Constraints (3.27) and (3.28) ensures that in each period, all returned products from customer centers which are delivered to remanufacturing centers after a required inspection in collection and inspection centers are delivered to producers and redistributors. Constraints (3.29) and (3.30) states that in each period, all collected products from customer centers which are entered to recovering centers after a required inspection in collection and inspection centers are delivered to redistributors. Constraint (3.31) states that in each period, all returned products which are sent to disposal centers are disposed. Constraint (3.32) ensures that in each period, the sum of the flow entering from recycling, remanufacturing, recovering centers to redistributors is equal to existing from redistributors to second customer centers.
Maximum number of allowable locations constraints

\[ \sum_{s \in S} O_{st} \leq S \quad \forall t \in T \quad (3.33) \]

\[ \sum_{p \in P} O_{pt} \leq P \quad \forall t \in T \quad (3.34) \]

\[ \sum_{w \in W} O_{wt} \leq W \quad \forall t \in T \quad (3.35) \]

\[ \sum_{d \in D} O_{dt} \leq D \quad \forall t \in T \quad (3.36) \]

\[ \sum_{l \in L} O_{lt} \leq L \quad \forall t \in T \quad (3.39) \]

\[ \sum_{j \in J} O_{jt} \leq J \quad \forall t \in T \quad (3.40) \]

\[ \sum_{k \in K} O_{kt} \leq K \quad \forall t \in T \quad (3.41) \]

\[ \sum_{n \in N} O_{nt} \leq N \quad \forall t \in T \quad (3.42) \]

Constraints (3.33)–(3.42) limit the maximum number of allowable locations. In fact, these constraints do not allow the supply chain to have more nodes than relative possible limitations.

\[ \sum_{w \in W} X_{wct} + \sum_{d \in D} X_{dct} = d_{ct} \quad \forall c \in C, t \in T \quad (3.43) \]

\[ \sum_{n \in N} X_{nt} = d_{ft} \quad \forall f \in F, t \in T \quad (3.44) \]

\[ \sum_{l \in l} X_{cit} = d_{ct} \quad \forall c \in C, t \in T \quad (3.45) \]
Constraints (3.43) and (3.44) ensure that all customer demands should be met in customer and second-customer centers, respectively. Constraint (3.45) guarantees that all products should be collected from customer centers. Constraints (3.46) and (3.47) represent the non-negativity and integrality of variables.

### 3.4. Computational Case Study

In this section, the application of the proposed MILP model for CLSC network design is investigated through an actual case study. The selected company for this study is a glass manufacturing industry located in the center part of IRAN. The entities of considered CLSC network for the case study consisted of: (1) three given suppliers which for the flow of material between suppliers and producers should be determined; (2) one producer which is currently operative and one identified potential location to establish new producer; (3) two considered selected locations for building required warehouses; (4) one active distribution center and one candidate location to meet demands of customers (it should be noted that these distributors work for other companies as well); (5) four customer centers that use the products; (6) two candidate locations to collect and inspect returned products; (7) one active disposal center and two candidate places in order to dispose defective products; (8) two considered positional locations to establish recycling centers to convert recyclable products into reusable materials and send to suppliers; (9) two candidate locations to establish recovering centers; (10) two considered locations to establish redistributors. With respect to the functionality of the processes, three approaches have been considered for the returned products in this study. (i) a percentage
of returned products are disposed; (ii) unbroken glasses are washed at recovering centers and redistributed through redistributors for second customers; (iii) broken glasses are ground and washed at recycling centers and the raw material are delivered to suppliers.

There are several global optimization software solvers such as LINDO (LINDO Systems Inc.), LINGO (LINDO Systems Inc.), GAMS (GAMS Development Corp.), and CPLEX (IBM). The latter solver has very good performance to solve Linear Programming (LP), Mixed Integer Programming (MIP) and Quadratic Programming (QP/QCP/MIQP/MIQCP) problems. Also, it can solve very large, real-world optimization problems in less time in comparison with other optimization solvers (Gearhart et al. 2013). The optimization software package, CPLEX 12.6, was implemented to solve the CLSC mixed-integer linear programming model of this study (Appendix A). The CPLEX software uses Branch & Cut algorithm to solve the problems. The CPLEX software starts with an initial feasible solution. Then, it finds other feasible solutions. For each iteration, the feasibility of solution is investigated by feeding the solutions into the constrains. The method continues until the objective function cannot be further improved. For optimality conditions, the obtained solution is also checked with regards to the constraints and the objective function. All computational work was accomplished on a personal computer (32-bit operating system, 2.53 GHz CPU, and 4.00 GB). The presented study involved 369 variables, 180 constraints and took approximately 2.37 seconds to solve by using commercial solver.
3.4.1. Description data

The used data for the considered case study is illustrated in Table 3.1. With regards to this issue that reverse logistic is included in the business process of this company, the information related to demand for new and returned products are predicted based on historical data of sales to the customer centers. Distributors can calculate the exact demands of customers in terms of their records for selling new and recovered goods or similar products from other companies. It should be noted that distributors in the forward chain are used to distributing recovered products in the reverse chain.

The collection and inspection costs of the returnable products consist of encouragements for motivating customers to turn back products to collection centers and storage costs, required activities to collect products, as well as their margins. The road-based transportation is implemented to carry out the shipping operation in this company. The transportation costs of products include the operating costs and service provided such as salaries, wages, costs of fuel, insurance and depreciation. Transportation cost between utilities is calculated for each product. In addition to the input parameters shown in Table 3.1, the fixed costs for establishing producers, opening warehouses, contractual arrangement with collection & inspection centers for collecting returned products, contractual arrangement with disposal, recycling, and recovering centers to treat with returned products are taken into account. It is worth noting that fixed costs are same for all time periods.
Table 3.1. Capacities, Costs, Demands, Return Rates parameters for defined computational case study (glass manufacturing industry)

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</tbody>
</table>

3.4.2. Results

The optimal results for the proposed case study during any period (four periods) are illustrated in Table 3.2. The calculated total cost for CLSC network of this company is found to be CAD$265,347 for all periods.
Table 3.2. Distribution flow between utilities for defined case study in Section 3.4 (glass manufacturing industry)

<table>
<thead>
<tr>
<th>Utility</th>
<th>Time Periods</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$t_1$</td>
</tr>
<tr>
<td>Suppliers</td>
<td>900</td>
</tr>
<tr>
<td></td>
<td>300</td>
</tr>
<tr>
<td>Producers</td>
<td>1200</td>
</tr>
<tr>
<td>Warehouse</td>
<td>1200</td>
</tr>
<tr>
<td>Distributors</td>
<td>0</td>
</tr>
<tr>
<td>Collection &amp; Inspection</td>
<td>900</td>
</tr>
<tr>
<td></td>
<td>300</td>
</tr>
<tr>
<td>Disposal</td>
<td>0</td>
</tr>
<tr>
<td>Recycling</td>
<td>480</td>
</tr>
<tr>
<td>Recovering</td>
<td>240</td>
</tr>
<tr>
<td>Redistributors</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>280</td>
</tr>
<tr>
<td></td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>300</td>
</tr>
</tbody>
</table>

The purchased raw materials from suppliers are shown in the first three rows in Table 3.2. The results indicate two of three considered suppliers can be chosen to provide raw materials. As indicated in Table 3.2, plants did not purchase raw materials from supplier 3. The condition is found for suppliers 2 in periods 2 and 3. For this case study, one producer was operative and one potential location was identified to establish new producer. Based on the optimum solution (Table 3.2), producer #2 is the only one needed to manufacture products. In terms of customer demands and other conditions of this case, that one producer would suffice to meet the required customer demands.

One of the most important strategic decisions for this case study is determining the needed warehouses to distribute final products. The supply chain managers of this case study wanted to decide which potential locations are suitable for a contractual arrangement for the warehouse. The obtained results indicate that this company needs to
make a contract with one of these warehouses to distribute products. According to Table 2, 73% of customers’ demands are met via a warehouse. This company also was looking for the required distributors to distribute products. They had one active distributor and considered one extra distributor on contract basis if needed. As it can be inferred from the results, one active distributor suffices for the supply chain of the company. It should be mentioned that 27% of final products are forwarded from producers to customers via a distributor.

Two centers were identified to collect the returned products from customer zones. The obtained results show these two collections & inspection centers are needed for this company. In all periods, these centers are occupied to gather the returned products. For the defined supply chain for this case study, two potential and one active disposal centers were considered, with the results demonstrating the sufficiency of the active disposal center for study. In fact, it is not required to have a contractual arrangement with candidate disposal centers for the company. As indicated Table 3.2, disposal center 3 has been used to dispose returned products in all periods.

Another strategic decision to be made by the supply chain managers of the company is to determine the required recycling centers for the returned products. They identified two potential locations for recycling centers. With reference to Table 3.2, both of these centers are needed for the company. Recycling center 1 is implemented in period 2 and center 2 is used in periods 1, 3, and 4. It should be mentioned that 930 of the returned products were recycled by the two predetermined recycling centers. However, the results indicate that the two recycling centers are used through this supply chain. However, this company can make a contractual arrangement with only recycling center 2 since
recycling center 1 is applied to 180 items in one period. By using recycling center 2 for all returned products, this company does not need to pay the extra fixed cost. These results also help supply chain managers determine how many recovering centers is needed to repair returned products. As it can be seen from Table 3.2, these two potential recovering centers are required. Recovering center 1 is used to repair 1370 items in all periods and recovering center 2 is applied to recover 280 of returned products in period 1.

3.5. Sensitivity analysis

A sensitivity analysis is carried out to measure the performance of presented CLSC network of this company under different operational conditions. The performed sensitivity analysis included the effect of changing demands, reverse rates, changing the capacity of suppliers, and reverse utilities on total costs.

3.5.1. Effect of changing demands

The effect of increasing customer demands on the total costs of supply chain was analyzed. Products demands were increased eight times with a 5%. Table 3.3 demonstrates the increase in total costs of supply chain by changing demands.

<table>
<thead>
<tr>
<th>Demand</th>
<th>Total cost</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>273,145</td>
<td>2.9</td>
</tr>
<tr>
<td>10</td>
<td>284,875</td>
<td>7.4</td>
</tr>
<tr>
<td>15</td>
<td>292,485</td>
<td>10.2</td>
</tr>
<tr>
<td>20</td>
<td>301,214</td>
<td>13.5</td>
</tr>
<tr>
<td>25</td>
<td>311,441</td>
<td>17.4</td>
</tr>
<tr>
<td>30</td>
<td>319,450</td>
<td>20.4</td>
</tr>
<tr>
<td>35</td>
<td>427,453</td>
<td>61.1</td>
</tr>
<tr>
<td>40</td>
<td>439,544</td>
<td>65.7</td>
</tr>
</tbody>
</table>
As expected, increase in demand results in an increase in the total costs of supply chain. For instance, when customer demands increased by 5%, the total costs of supply chain increased by 2.9% and reached $273,145. It can be easily implied from Table 3.3 that the total costs of supply chain increased by about roughly 2.9% for a 5% increase of demands at each time. However, when customers’ demands increase by 35%, the total cost of supply chain increased by 61% and reached $427,453. The total costs increased by 39% when demands of customers grew from 6370 to 6615 while it was expected to have 3.5% increases for the total costs of supply chain (Figure 3.2).

The main reason for this drastic increase is using two producers to meet the customers’ demands. Initial results indicated that one producer is enough to meet 4900 products. This number of opened entities supports the demands of customers, if they increase to 30%. That is, if customer demands increase from 4900 to 6370, one producer will be needed. On the other hand, if customer demands increase by 35%, the another producer should be established by this company to meet demands. Fixed costs of opening

![Total Cost](image.png)

Figure 3.2. Effect of changing demands on total costs for network design of case study (glass manufacturing industry)
new entities increase the costs dramatically. The obtained results of sensitivity analysis of changing demands help managers to find maximum demands that they can meet at minimum cost.

3.5.2. Effect of changing reverse rates

The effect of changing disposal rate, recycling rate, recovering rate on total costs were investigated. Hence, different \( r_d \), \( r_y \), \( r_v \), where the sum of them equals to 1 are generated to the analyze total costs of supply chain. The associated results of these investigations are shown in Table 3.4 and Figure 3.3.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disposal</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( r_d )</td>
<td>0.3</td>
<td>0.4</td>
<td>0.5</td>
<td>0.6</td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>( r_y )</td>
<td>0.35</td>
<td>0.3</td>
<td>0.25</td>
<td>0.2</td>
<td>0.15</td>
<td>0.1</td>
</tr>
<tr>
<td>( r_v )</td>
<td>0.35</td>
<td>0.3</td>
<td>0.25</td>
<td>0.2</td>
<td>0.15</td>
<td>0.1</td>
</tr>
<tr>
<td>Total Cost</td>
<td>245,412</td>
<td>258,475</td>
<td>264,839</td>
<td>364,587</td>
<td>371,105</td>
<td>379,845</td>
</tr>
<tr>
<td>Recycling</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( r_d )</td>
<td>0.35</td>
<td>0.3</td>
<td>0.25</td>
<td>0.2</td>
<td>0.15</td>
<td>0.1</td>
</tr>
<tr>
<td>( r_y )</td>
<td>0.3</td>
<td>0.4</td>
<td>0.5</td>
<td>0.6</td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>( r_v )</td>
<td>0.35</td>
<td>0.3</td>
<td>0.25</td>
<td>0.2</td>
<td>0.15</td>
<td>0.1</td>
</tr>
<tr>
<td>Total Cost</td>
<td>247,462</td>
<td>247,436</td>
<td>249,875</td>
<td>230,112</td>
<td>222,874</td>
<td>218,756</td>
</tr>
<tr>
<td>Recovering</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( r_d )</td>
<td>0.35</td>
<td>0.3</td>
<td>0.25</td>
<td>0.2</td>
<td>0.15</td>
<td>0.1</td>
</tr>
<tr>
<td>( r_y )</td>
<td>0.35</td>
<td>0.3</td>
<td>0.25</td>
<td>0.2</td>
<td>0.15</td>
<td>0.1</td>
</tr>
<tr>
<td>( r_v )</td>
<td>0.3</td>
<td>0.4</td>
<td>0.5</td>
<td>0.6</td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>Total Cost</td>
<td>246,875</td>
<td>250,115</td>
<td>328,452</td>
<td>321,423</td>
<td>317,463</td>
<td>311,010</td>
</tr>
</tbody>
</table>
Table 3.4 includes changing disposal rate, recycling rate, and recovering rate. The effect of changing disposal rate on total cost is analyzed first. For instance, 0.3 was taken into consideration for the disposal rate and 0.35 for recycling and recovering rates for all periods in the first scenario. The obtained results indicate increasing disposal rate and decreasing recycling and recovering rates simultaneously increase the total costs of supply chain. The increasing of total costs is normally followed until third scenario. The total costs increase drastically while disposal rate changes from 0.5 to 0.6. The second section of Table 3.4 shows the effect of recycling rate variations on the total cost. For this analysis, the rate value of recycling increases and disposal and recovering rates decrease simultaneously. The calculated results demonstrate the increasing recycling rate continuously reduces the total costs. The last part of Table 3.4 shows the effect of changing recovering rate on total costs. The calculated results display two different trends for total costs by increasing the recovering rates. At first, when the recovering rate soars from 0.3 to 0.4, the total cost decreased. On the other hand, for the next scenario where
the recovering rate increased from 0.4 to 0.5, an intense increase in the total cost is incurred. Consequently, these costs started to decline by increasing the recovering rate.

3.5.3. Effect of changing capacity of suppliers and reverse utilities (disposal, recycling, recovering centers)

The effect of changing suppliers’ capacities on links in the supply network and the total costs of supply chain was examined. The changing of reverse utilities’ capacity was also analyzed in this section. Five scenarios were generated: (1) increasing the capacity of disposal centers; (2) increasing the capacity of recycling centers; (3) increasing the capacity of recovering; (4) increasing the capacity of reverse utilities simultaneously and increasing the capacity of suppliers. The capacities of suppliers and reverse utilities were gradually increased in increments of 5% to 40%. The achieved results from changing suppliers’ capacities are demonstrated in Table 3.5 and Figure 3.4.

Table 3.5. The impact of changing supplier capacity on total cost of network design for case study (glass manufacturing industry)

<table>
<thead>
<tr>
<th>Total Cost</th>
<th>0%</th>
<th>5%</th>
<th>10%</th>
<th>15%</th>
<th>20%</th>
<th>25%</th>
<th>30%</th>
<th>35%</th>
<th>40%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>263,547</td>
<td>265,047</td>
<td>264,747</td>
<td>264,447</td>
<td>264,147</td>
<td>264,147</td>
<td>264,147</td>
<td>264,147</td>
<td>264,147</td>
</tr>
</tbody>
</table>

As indicated in Table 3.5, increasing the supplier capacity leads to decrease of the total costs of supply chain whose decline continues until the supplier capacity increases by 20%. Based on the results, when supplier capacity increased from 20% to 25%, the total cost does not change. Also, the obtained results from other scenarios show the increasing the capacity of reverse utilities does not effect on the total costs. The existing capacity of reverse utilities covers all returned products.
3.6. Discussion

In Section 3.4, a mixed integer linear programming model was applied for an actual case study. The optimal distribution flow of between utilities is summarized in Table 3.2, giving the best supply chain network for this industry. The optimum distribution determined the best supplier for raw material procurement, the best plant to produce the products, the best distributor to distribute the products to customer centers, the best collection centers to collect returned products, the best disposal centers to dispose the useless products, the best recovering center to recover returned products, and the best recycling centers in the reverse chain.

The optimum solution also determines how many products are to be transferred from suppliers to producers, from plants to distributors, from distributors to customer centers, from customer centers to collection centers, from collection centers to disposal, recycling, and recovering centers. The optimum solution minimizes the objective function (cost)
while respecting all the constraints (capacity, balance, etc.). The optimum solution meets the customer demands, which is one of the main aims of supply chain network design.

The optimum solution (Table 3.2) for this network is compared to the non-optimized current (at the time of writing) operating conditions (from the company). This comparison is summarized in Table 3.6.

Table 3.6. Comparison optimized case and current operating system for studied case study (glass manufacturing industry)

<table>
<thead>
<tr>
<th></th>
<th>Optimized case</th>
<th>Current operating system</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective function value</td>
<td>CAD 265,347</td>
<td>CAD 330,810</td>
</tr>
<tr>
<td>Capacity constraints</td>
<td>Satisfied</td>
<td>Not satisfied</td>
</tr>
<tr>
<td>Balance constraints</td>
<td>Satisfied</td>
<td>Not satisfied</td>
</tr>
<tr>
<td>Customer demands</td>
<td>On-time</td>
<td>Backlogged</td>
</tr>
</tbody>
</table>

In the current operating system, 1,100 products are requested from supplier #1 to be delivered to producer #1, while the optimum value, as shown in Table 3.2, is 900. Based on defined utility capacities in Table 3.1, the maximum capacity of supplier #1 is 1,000. That means, supplier #1 cannot meet the current order on time, which leads to producer #1 receiving the products with delay. Consequently, the current network faces challenges in responding to customers demand in a timely fashion.

The optimum solution guarantees finding the best network with the minimum total costs. The obtained value of objective function based on optimum solution was CAD $265,347, while meeting the same customers demand with the current conditions will be around CAD $330,810.

In the current operating system, one collection and inspection center is utilized to collect the returned products, while the optimum results showed (Table 3.2) that two
centers are needed. The current operating conditions lead to failure in collecting all the returned products.

The optimum solution (Table 3.2) shows that supplier #3 was not selected to supply the raw material in this network, while the company currently procures the raw material from this supplier. Supplying the raw material by supplier #3, results in extra costs.

3.7. Conclusions
A Mixed Integer Linear Programming model was formulated to design a CLSC network, where the location of facilities and the material flows in the entire network were determined. The model incorporated both strategic and tactical decisions. The presented CLSC network included five echelons (i.e. suppliers, producers, warehouses, distributors, and customer zones) in the forward direction and seven echelons (i.e. collection & inspection centers, disposal centers, recycling centers, remanufacturing centers, recovering centers, redistributors, and second customers) in the reverse direction. The model was applied to an actual industrial case (glass manufacturing). However, the proposed mathematical model is generalized enough to be implemented to other industries. Also, a detailed sensitivity analysis was done to investigate the effects of change in demands, capacity, and reverse rates on network total cost. Moreover, the created optimum network for this industrial case was compared with current operating conditions, showing the benefits of an optimized network.

As shown in Table 3.2 the obtained results of this study determine how many facilities (supplier, producers, etc.) should be utilized, which facilities should be opened, how many products should be transferred between facilities for each period. In this study, the changing capacity of disposal, recycling, and recovering centers had no effect on total
costs. While increasing the capacity of suppliers decreased the total costs. These conclusions show that the recycling ratio has more effect on total cost in comparison with disposal and recovering ratios.

The introduced approach has some limitations. A single-objective approach, minimizing costs, was applied for designing CLSC network, while other important objectives such as minimizing the environmental effects maximizing the social impacts can be considered. Accordingly, it is suggested that the deterministic approach of the study be improved by taking non-deterministic parameters into account. In order to solve the MILP model and reach the optimal solutions in a reasonable time, using meta-heuristics, such as genetic algorithms or particle swarm optimization algorithms are recommended.

In this Chapter, uncertainty was not considered and the MILP model was formulated as deterministic. Also, only one objective function (cost minimization) was considered to optimize CLSC network design. In next Chapter uncertainty and all dimensions of sustainability (cost, environmental, social) are considered for modelling of this problem. In addition, fuzzy programming is employed to solve the mathematical model.
CHAPTER FOUR: A FUZZY PROGRAMMING APPROACH FOR A MULTI-OBJECTIVE CLOSED LOOP SUPPLY CHAIN NETWORK CONSIDERING SUSTAINABLE DEVELOPMENT

4.1. Introduction

In Chapter 3, a closed loop supply chain network was optimized using a deterministic single-objective (cost minimization) mathematical programming. The uncertainty of variables, such as demand, return rates in CLSC network design, was not considered. In this Chapter, a multi-objective mathematical model is introduced to minimize cost and environmental impacts and maximize social impacts of supply chain network. In addition, the uncertainty of model parameters is taken into account.

In recent years, the importance of reverse supply chain network has been highlighted by people and companies due to environmental and social responsibilities and the economic benefits of used products (Meade et al. 2007). Environmental and social, in addition to economic, impacts objectives should be considered in designing an SCN such as for optimum sustainability. Then sustainable SCND problems become complicated due to the involvement of conflicting, inexpressible, sophisticated, and interpenetrating and multiple incommensurable objectives (Chen and Lee, 2004; Zhou et al., 2000).

Also, this problem can also be threatened by uncertain decision elements, because of the inherent uncertainty of reverse chain, caused for instance by the ambiguous nature of the quantity and quality of returned products (Pishvaee et al., 2011). Several inexact optimization methods are implemented to address uncertainties in SCND problems such as interval (Zhang et al., 2011), stochastic (Kerachian & Karamouz, 2007), and fuzzy
programming. Fuzzy programming has the advantages of being more practical and non-deterministic and it measures the degree of satisfaction of each objective functions (Gholamian et al. 2015). The latter feature helps decision makers to select a preferred efficient solution (Torabi and Hassini, 2008).

Hence, in this Chapter, a CLSC network design model considering sustainably measures is presented. A three-phase fuzzy mathematical programming approach is presented to optimize this model. In the first two phases, a fuzzy multi-objective mixed-integer linear programming (FMOMILP) model is converted into a Multi-Objective Mixed-Integer Linear Programming (MOMILP) model. In the third phase, the approach of Torabi and Hassini (2008) is used to solve MOMILP model. The presented model in this Chapter attempts to specify the location of the facilities and a number of products to be supplied in the network facilities. Three conflicting objectives are taken into account in the proposed model simultaneously, which is (i) to minimize the total cost of the supply chain (fixed cost, manufacturing costs, transportation cost, shortage cost, and purchasing costs), (ii) to minimize the environmental impacts, and (iii) to maximize societal benefits. To examine the significance of the proposed model and the solution approach, a computational experiment is conducted. In addition, the problem is solved by considering crisp numbers to investigate the effect of uncertainty on sustainable CLSC network design.

4.2. Problem formulation
Figure 4.1 depicts the structure of CLSC network in this Chapter. This model integrates activities of purchasing, manufacturing, distribution, collection, and return in a CLSC network, which requires analysis of both forward and reverse networks simultaneously.
The proposed model consists of four layers in the forward logistics (suppliers, plants, distributors, and customer centers) and four layers in the reverse logistics (collection & inspection, disposal, recycling, and repairing centers).

In the forward logistics, the suppliers provide raw materials to plants. The manufactured products are forwarded from plants to customers via distributors to meet customer demands. In the reverse logistics, the returned products are gathered from customers by collection & inspection centers for testing. In the model, three treatment processes are considered for returned products in the reverse chain; repairing, recycling, and disposal centers. This approach helps supply chains to inhibit excessive transportations of returned products and transfers these products to the relevant facilities directly. The assumptions of Chapter 3 are also considered for network of this Chapter. Customer demand and return rates are represented by fuzzy numbers due to the innate uncertainty in customer behavior that directly affects them. Similarly, due to the uncertainty in forecasting process the capacities are represented as fuzzy numbers.

![Figure 4.1. Structure of the proposed CLSC network](image)
4.2.1. Notations

*Indices and Sets*

S: Set of Suppliers, indexed by ‘s’.

P: Set of Plants, indexed by ‘p’.

D: Set of Distributors, indexed by ‘d’.

C: Set of Customer Centers, indexed by ‘c’.

I: Set of Collection & Inspection Centers, indexed by ‘i’.

K: Set of Repairing Centers, indexed by ‘k’.

L: Set of Recycling Centers, indexed by ‘l’.

M: Set of Disposal Centers, indexed by ‘m’.

T: Periods, indexed by ‘t’.

*Parameters*

\( \bar{c}a_{st} \): Capacity of Supplier ‘s’ at time period ‘t’

\( \bar{c}a_{pt} \): Capacity of Plants ‘p’ at time period ‘t’

\( \bar{c}a_{dt} \): Capacity of Distributor ‘d’ at time period ‘t’

\( \bar{c}a_{it} \): Capacity of Collection & Inspection Center ‘i’ at time period ‘t’

\( \bar{c}a_{mt} \): Capacity of Disposal Center ‘m’ at time period ‘t’

\( \bar{c}a_{lt} \): Capacity of Recycling Center ‘l’ at time period ‘t’
\( \tilde{c}_{kt} \): Capacity of Repairing Center ‘k’ at time period ‘t’

\( tc_{pd} \): Transportation cost a product from plant ‘p’ to distributor ‘d’

\( tc_{dc} \): Transportation cost a product from distributor ‘d’ to customer center ‘c’

\( tc_{ci} \): Transportation cost a product from customer center ‘c’ to collection & inspection center ‘i’

\( tc_{im} \): Transportation cost a product from collection & inspection center ‘i’ to disposal center ‘m’

\( tc_{il} \): Transportation cost a product from collection & inspection center ‘i’ to recycling center ‘l’

\( tc_{ik} \): Transportation cost a product from collection & inspection center ‘i’ to repairing center ‘k’

\( tc_{ls} \): Transportation cost a product from recycling center ‘l’ to supplier ‘s’

\( fc_p \): Fixed cost of opening plant ‘p’

\( fc_d \): Fixed cost of opening distributor ‘d’

\( fc_i \): Fixed cost of opening collection & inspection center ‘i’

\( fc_m \): Fixed cost of opening disposal center ‘m’

\( fc_l \): Fixed cost of opening recycling center ‘l’

\( fc_k \): Fixed cost of opening repairing center ‘k’

\( es_{sp} \): Environmental impacts of shipping a product from supplier ‘s’ to plant ‘p’

\( es_{pd} \): Environmental impacts of shipping a product from plant ‘p’ to distributor ‘d’
\( es_{dc} \): Environmental impacts of shipping a product from distributor ‘d’ to customer center ‘c’

\( es_{ci} \): Environmental impacts of shipping a product from customer center ‘c’ to collection & inspection center ‘i’

\( es_{im} \): Environmental impacts of shipping a product from collection & inspection center ‘i’ to disposal center ‘m’

\( es_{il} \): Environmental impacts of shipping a product from collection & inspection center ‘i’ to recycling center ‘l’

\( es_{ik} \): Environmental impacts of shipping a product from collection & inspection center ‘i’ to repairing center ‘k’

\( es_{ls} \): Environmental impacts of shipping a product from recycling center ‘l’ to supplier ‘s’

\( ep \): Environmental impacts of producing at plant ‘p’

\( ed \): Environmental impacts of disposing at disposal center ‘m’

\( fj_p \): The number of fixed job opportunities created by establishing plants

\( fj_d \): The number of fixed job opportunities created by establishing distributors

\( fj_i \): The number of fixed job opportunities created by establishing collection & inspection centers

\( fj_m \): The number of fixed job opportunities created by establishing disposal centers

\( fj_l \): The number of fixed job opportunities created by establishing recycling centers
\( f_{jk} \): The number of fixed job opportunities created by establishing repairing centers

\( v_{jp} \): The number of variable job opportunities created by establishing plants

\( v_{jd} \): The number of variable job opportunities created by establishing distributors

\( v_{j1} \): The number of variable job opportunities created by establishing collection & inspection centers

\( v_{jm} \): The number of variable job opportunities created by establishing disposal centers

\( v_{jl} \): The number of variable job opportunities created by establishing recycling centers

\( v_{jk} \): The number of variable job opportunities created by establishing repairing centers

\( mc_{pt} \): Manufacturing cost at plant ‘p’ at time period ‘t’

\( dc_{mt} \): Disposal cost at disposal center ‘m’ at time period ‘t’

\( rc_{lt} \): Recycling cost at recycling center ‘l’ at time period ‘t’

\( bc_{kt} \): Repairing cost at repairing center ‘k’ at time period ‘t’

\( pc_{st} \): Material cost of product supplied by supplier ‘s’ at time period ‘t’

\( de_{ct} \): Demand of customer center ‘c’ at time period ‘t’

\( sc \): Shortage cost of product

\( ry_{lt} \): Recycling ratio at time period ‘t’

\( rv_{lt} \): Repairing ratio at time period ‘t’
\( r_{dt} \) : Disposal ratio at time period ‘t’

\( \bar{y}_{ct} \) : Reverse ratio at time period ‘t’

**Decision Variables**

\( O_{st} \) : 1 if a supplier is open in location ‘s’ at time period ‘t’; 0 otherwise

\( O_{pt} \) : 1 if a plant is open in location ‘p’ at time period ‘t’; 0 otherwise

\( O_{dt} \) : 1 if a distributor is open in location ‘d’ at time period ‘t’; 0 otherwise

\( O_{it} \) : 1 if a collection & inspection center is open in location ‘i’ at time period ‘t’; 0 otherwise

\( O_{mt} \) : 1 if a disposal center is open in location ‘m’ at time period ‘t’; 0 otherwise

\( O_{lt} \) : 1 if a recycling center is open in location ‘l’ at time period ‘t’; 0 otherwise

\( O_{kt} \) : 1 if a repairing center is open in location ‘k’ at time period ‘t’; 0 otherwise

\( X_{spt} \) : Quantity shipped from supplier ‘s’ to plant ‘p’ at time period ‘t’

\( X_{pdt} \) : Quantity shipped from plant ‘p’ to distributor ‘d’ at time period ‘t’

\( X_{dct} \) : Quantity shipped from distributor ‘d’ to customer center ‘c’ at time period ‘t’

\( X_{cit} \) : Quantity shipped from customer center ‘c’ to Collection & Inspection center ‘i’ at time period ‘t’

\( X_{int} \) : Quantity shipped from collection & inspection center ‘i’ to disposal center ‘m’ at time period ‘t’

\( X_{itt} \) : Quantity shipped from collection & inspection center ‘i’ to recycling center ‘l’ at time period ‘t’
$X_{i_{kt}}$ : Quantity shipped from collection & inspection center ‘i’ to repairing center ‘k’ at time period ‘t’

$X_{l_{st}}$ : Quantity shipped from recycling center ‘l’ to supplier ‘s’ at time period ‘t’

$X_{k_{dt}}$ : Quantity shipped from repairing center ‘k’ to distributor ‘d’ at time period ‘t’

4.2.2. Objective functions

Three objective functions of sustainability are defined for the multi-echelon and multi-period closed loop supply chain model by the following equations:

$$\text{Min } Z_1 = \text{Total cost}$$

$$= \sum_{p \in P} \sum_{t \in T} fc_p \sum_{O_{pt}} + \sum_{d \in D} \sum_{t \in T} fc_d O_{dt} + \sum_{i \in I} \sum_{t \in T} fc_i O_{it} + \sum_{m \in M} \sum_{t \in T} fc_m O_{mt} + \sum_{d \in D} \sum_{t \in T} fc_d O_{dt}$$

$$+ \sum_{k \in K} \sum_{t \in T} fc_k O_{kt} + \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} mc_{pt} X_{pdt} + \sum_{i \in I} \sum_{t \in T} \sum_{l \in L} r_{it} X_{ilt} + \sum_{k \in K} \sum_{i \in I} \sum_{t \in T} b_{kt} X_{ikt}$$

$$+ \sum_{m \in M} \sum_{i \in I} \sum_{t \in T} dc_{mt} X_{imit} + \sum_{i \in I} \sum_{t \in T} \sum_{d \in D} tc_{pd} X_{pdt} + \sum_{i \in I} \sum_{t \in T} \sum_{e \in E} tc_{dc} X_{dct}$$

$$+ \sum_{i \in I} \sum_{t \in T} \sum_{k \in K} tc_{ik} X_{ikt} + \sum_{i \in I} \sum_{t \in T} \sum_{k \in K} tc_{ik} X_{ikt} + \sum_{s \in S} \sum_{p \in P} \sum_{t \in T} pc_{st} X_{spt}$$

$$- \sum_{s \in S} \sum_{t \in T} (pc_{st} - r_{ct}) X_{lst}$$

$$+ \sum_{c \in C} \sum_{l \in L} \sum_{t \in T} tc_{cl} X_{clt} \quad (4.1)$$

In this objective, the first six terms are related to the fixed costs of establishing facilities. The seventh to tenth terms are related to manufacturing, recycling, repairing, and disposal costs. The eleventh to seventeenth summations are related to transportation costs between facilities. The last three terms are associated with material and collection costs.
Mini $Z_2 =$ Environmental impacts

$$
\sum_{p \in P} \sum_{d \in D} \sum_{t \in T} e_p X_{pdt} + \sum_{i \in I} \sum_{d \in D} \sum_{t \in T} e_d X_{idt} + \sum_{s \in S} \sum_{p \in P} \sum_{t \in T} e_{sp} X_{sp} + \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} e_{pdt} + \sum_{d \in D} \sum_{c \in C} \sum_{t \in T} e_{dc} X_{dct} + \sum_{c \in C} \sum_{i \in I} \sum_{t \in T} e_{ci} X_{cit} + \sum_{i \in I} \sum_{m \in M} \sum_{t \in T} e_{im} X_{int} + \sum_{i \in I} \sum_{l \in L} \sum_{t \in T} e_{it} X_{ilt} + \sum_{i \in I} \sum_{k \in K} \sum_{t \in T} e_{ik} X_{ikt} + \sum_{i \in I} \sum_{s \in S} \sum_{t \in T} e_{is} X_{ist} + \sum_{k \in K} \sum_{d \in D} \sum_{t \in T} e_{kd} X_{kdt}
$$

(4.2)

The first and second terms are the environmental impacts manufacturing products in plants and disposing returned products in disposal center. The rest terms in this objective function stand for the environmental impacts of shipping products between facilities.

Max $Z_3 =$ Social impacts

$$
\sum_{p \in P} \sum_{t \in T} f_p O_{pt} + \sum_{d \in D} \sum_{t \in T} f_{dt} O_{dt} + \sum_{i \in I} \sum_{t \in T} f_{it} O_{it} + \sum_{m \in M} \sum_{t \in T} f_{mt} O_{mt} + \sum_{l \in L} \sum_{t \in T} f_{lt} O_{lt} + \sum_{k \in K} \sum_{t \in T} f_{kt} O_{kt} + \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} v_{pd} X_{pdt} / \bar{c} \bar{a}_{pt} + \sum_{d \in D} \sum_{c \in C} \sum_{t \in T} v_{dc} X_{dct} / \bar{c} \bar{a}_{dt} + \sum_{c \in C} \sum_{i \in I} \sum_{t \in T} v_{ci} X_{cit} / \bar{c} \bar{a}_{it} + \sum_{i \in I} \sum_{m \in M} \sum_{t \in T} v_{im} X_{int} / \bar{c} \bar{a}_{mt} + \sum_{i \in I} \sum_{l \in L} \sum_{t \in T} v_{il} X_{ilt} / \bar{c} \bar{a}_{lt} + \sum_{i \in I} \sum_{k \in K} \sum_{t \in T} v_{ik} X_{ikt} / \bar{c} \bar{a}_{kt}
$$

(4.3)

The first six terms are the created fixed job opportunities opening new facilities. In fact, fixed jobs are taken the job positions like managers that are needed independent of the utilized capacity of the facilities into account. The seventh to tenth terms stand for the created variable jobs. It should be noted that variable jobs depend on the applied capacity of facilities.
4.2.3. Constraints

This section is a representation of the constraints of the model:

**Capacity constraints**

\[
\sum_{p \in P} X_{spt} \leq O_{st} \bar{a}_{st} \quad \forall \, s, t \tag{4.4}
\]

\[
\sum_{d \in D} X_{ptd} \leq O_{pt} \bar{a}_{pt} \quad \forall \, p, t \tag{4.5}
\]

\[
\sum_{p \in P} X_{pdt} \leq O_{dt} \bar{a}_{dt} \quad \forall \, d, t \tag{4.6}
\]

\[
\sum_{c \in C} X_{cit} \leq O_{it} \bar{a}_{it} \quad \forall \, i, t \tag{4.7}
\]

\[
\sum_{m \in M} X_{imt} \leq O_{mt} \bar{a}_{mt} \quad \forall \, m \in M \tag{4.8}
\]

\[
\sum_{s \in S} X_{lst} \leq O_{lt} \bar{a}_{lt} \quad \forall \, l \in L \tag{4.9}
\]

\[
\sum_{n \in N} X_{knt} \leq O_{kt} \bar{a}_{kt} \quad \forall \, k \in K \tag{4.10}
\]

Constraint (4.4) guarantees that, in each period, the sum of the products which is sent to producers from suppliers are lower than the capacity of suppliers. Constraint (4.5) shows that, in each period, the sum of the flow exiting from plants to distributors does not exceed the production capacity of plants. Constraint (4.6) ensures that in each period the sum of the flow entering from plants to distributors does not exceed the relevant capacity. Constraint (4.7) states that the all returned products from customer centers which are entered to collection and inspection centers do not exceed the relevant capacity. Constraint (4.8) ensures that the sum of the flow entering from collection and inspection centers to disposal centers does not exceed the disposing capacity of disposal centers. Constraint (4.9) guarantees that the sum of the products that are existed from recycling
centers to suppliers are lower than capacity of recycling centers. Constraint (4.10) shows that the sum of the flow exiting from repairing centers to distributors does not exceed the remanufacturing capacity of remanufacturing centers.

**Balance constraints**

\[
\sum_{s \in S} X_{spt} = \sum_{d \in D} X_{pd} \quad \forall p, t \tag{4.11}
\]

\[
\sum_{k \in K} X_{kdt} + \sum_{p \in P} X_{pdt} = \sum_{c \in C} X_{dct} \quad \forall d, t \tag{4.12}
\]

\[
\sum_{c \in C} X_{cit} = \sum_{m \in M} X_{mit} + \sum_{l \in L} X_{ilt} + \sum_{k \in K} X_{ikt} \quad \forall i, t \tag{4.13}
\]

\[
\sum_{c \in C} r_{yt} X_{cit} = \sum_{l \in L} X_{ilt} \quad \forall i, t \tag{4.14}
\]

\[
\sum_{l \in L} X_{ilt} = \sum_{s \in S} X_{ist} \quad \forall l, t \tag{4.15}
\]

\[
\sum_{c \in C} r_{yt} X_{cit} = \sum_{k \in K} X_{ikt} \quad \forall i, t \tag{4.16}
\]

\[
\sum_{l \in L} X_{ikt} = \sum_{d \in D} X_{kdt} \quad \forall k, t \tag{4.17}
\]

\[
\sum_{c \in C} r_{dt} X_{kdt} = \sum_{m \in M} X_{imi} \quad \forall i, t \tag{4.18}
\]

Constraint (4.11) shows that the flow entering from suppliers to plants is equal to sum of the existing from plants to distributors at each period. Constraint (4.12) guarantees that in each period, the sum of the flow entering from plants and repairing centers to distributors is equal to sum of the existing from distributors to customer centers. Constraint (4.13) states that in each period, the sum of the flow entering from customer centers to collection and inspection centers is equal to existing from collection and inspection centers to recycling, repairing, and disposal centers. Constraints (4.14) and (4.15) guarantees that in each period, all collected products from customer centers which
are entered into recycling centers after required activities are delivered to suppliers. Constraints (4.16) and (4.17) ensures that in each period, all collected products from customer centers which are entered into repairing centers after required repair activities are sent to distributors. Constraint (4.18) states that in each period, all returned products which are sent to disposal centers are disposed.

**Maximum number of allowable locations constraints**

\[
\sum_{s \in S} O_{st} \leq S \quad \forall t \quad (4.19)
\]

\[
\sum_{p \in P} O_{pt} \leq P \quad \forall t \quad (4.20)
\]

\[
\sum_{d \in D} O_{dt} \leq D \quad \forall t \quad (4.21)
\]

\[
\sum_{t \in T} O_{it} \leq I \quad \forall t \quad (4.22)
\]

\[
\sum_{m \in M} O_{mt} \leq M \quad \forall t \quad (4.23)
\]

\[
\sum_{t \in T} O_{lt} \leq L \quad \forall t \quad (4.24)
\]

\[
\sum_{k \in K} O_{kt} \leq K \quad \forall t \quad (4.25)
\]

Constraints (4.19)–(4.25) limit the maximum number of allowable locations. In fact, these constraints do not allow the supply chain to have more nodes than relative possible limitations.

\[
\sum_{d \in D} X_{dct} = \overline{d}_{ct} \quad \forall c, t \quad (4.26)
\]

\[
\sum_{t \in T} X_{cit} = \overline{d}_{ct} \ast \overline{y}_{ct} \quad \forall c, t \quad (4.27)
\]

\[
X_{spt}, X_{pdt}, X_{dct}, X_{cit}, X_{imt}, X_{ilt}, X_{ikt}, X_{lst}, X_{kdt} \geq 0 \quad \forall i, j, k, l, m, p, t, c, d \quad (4.28)
\]
Constraints (4.26) ensure that all customer demands should be met in customer centers. Constraint (4.27) shows the amount of returned products which are collected from customer centers. Constraints (4.28) and (4.29) represent the non-negativity and integrality of variables.

4.3. Solution methodology

The proposed FMOMILP model to design a sustainable supply chain network has fuzzy parameters in its objective functions (third objective, Eq. 4.3) and constraints (capacity constraints (4.4)-(4.10) and constraints that related to demand (4.24)-(4.27)). A three-phase approach is presented to solve this problem. In the first two phases, the proposed FMOMILP model is converted into an equivalent auxiliary crisp multiple objective mixed integer linear programming MOMILP model. The weighted average method and the proposed model by Lai and Hwang (1992) are applied for this aim. The main advantage of this approach is the number of fuzzy constraints remains the same after converting FMOMILP model into MOMILP model (deterministic). It means this approach does not complicate the model. In addition, gives us this opportunity to determine weights for most pessimistic, possible, and optimistic values.

In the final phase, TH approach (Torabi and Hassini, 2008) is implemented to solve the MOMILP model. The advantages of the TH approach are (i) it provides solutions consistent with the decision maker’s preferences; (ii) it has low sensitivity to values in comparison to other fuzzy approaches in finding high number of different efficient solutions. (iii) it produces efficient, robust and reliable solutions; and (iv) it provides
balanced and unbalanced solutions according to decision maker’s preferences (Torabi and Hassini, 2008). These steps are explained in detail in the following sections.

4.3.1. Strategy for solving the fuzzy/imprecise constraints

Several patterns, such as trapezoid, bell-shaped, triangular, and exponential are defined to demonstrate fuzzy numbers. The pattern of triangular distribution is employed to present all of the fuzzy numbers in the constraints in this study. The simplicity and flexibility of fuzzy arithmetic operations is recognized as the main advantage of the triangular fuzzy numbers (Lai & Hwang, 1992; Rommelferger, 1996; Tanaka et al., 1984; Zimmermann, 1996; Tanaka et al. 2000; Wang and Liang 2005; Liang 2006). Triangular patterns provide decision makers to define fuzzy numbers in three prominent data points: the most pessimistic value and the optimistic value with possibility degree of 0, and the most likely value with possibility degree of 1 (Liang 2006). The triangular fuzzy numbers membership functions as linear, which makes it computationally efficient by having simple formulation in comparing to nonlinear distributions constructions. The triangular fuzzy numbers membership functions are defined with these parameters (p, m, o) (Jamalnia and Soukhakian, 2009). Membership functions for triangular numbers have a unique maximum value; enable them to fit linguistic terms (Jamalnia and Soukhakian, 2009).

A triangular distribution of $\bar{a}_{st}$ consists of:

1. the most pessimistic value ($ca^p_{st}$) : it has a very low probability (possibility degree 0) of belonging to the set of accessible values;
(2) the most possible value \((ca^m_{st})\); it has a very high probability (possibility degree 1) of belongings to the set of accessible values;

(3) the most optimistic value \((ca^o_{st})\): it has a very low probability (possibility degree 0) of belonging to the set of available values (Liang and Cheng, 2009).

Figure 4.2 illustrates the distribution of the triangular fuzzy number \(\bar{ca}_{st} = (ca^p_{st}, ca^m_{st}, ca^o_{st})\) in constraint (4.3).

![Figure 4.2. Triangular fuzzy number \(\bar{ca}_{st}\)](image)

In this study, the weighted average is used to convert fuzzy numbers (such as \(\bar{ca}_{st}\)) into a crisp number. Taking considerations “\(\beta\)” as the minimum suitable membership level, the corresponding inequality of constraint (4.4) can be reformulated as:

\[
\sum_{p \in P} X_{sp} \leq O_{st} (W_1 ca^p_{st,\beta} + W_2 ca^m_{st,\beta} + W_3 ca^o_{st,\beta}) \quad \forall s, t
\] (4.30)

Similarly, considering “\(\beta\)” as the minimum acceptable membership level, the corresponding auxiliary crisp inequalities of constraints (4.5-4.10) and (4.26-4.27) can be expresses as follows:

\[
\sum_{p \in D} X_{pt} \leq O_{pt}(W_1 ca^p_{pt,\beta} + W_2 ca^m_{pt,\beta} + W_3 ca^o_{pt,\beta}) \quad \forall p, t
\] (4.31)
where \( W_1 + W_2 + W_3 = 1 \), \( W_1 \), \( W_2 \) and \( W_3 \) express the corresponding weight of the most pessimistic, most likely and most optimistic values, respectively. It should be noted that, the suitable values of weights and \( \beta \) are determined by the decision maker and experience. However, in this work, these parameters are set as \( W_2 = 4/6, W_1 = W_3 = 1/6 \) and \( \beta = 0.5 \) for all constraints, according to the concept of the most likely values proposed by Lai and Hwang (1992) and considering relevant studies (Liang, 2006; Wang and Liang, 2005).

### 4.3.2. Strategy for solving the imprecise objective function

Owing to the use of fuzzy/imprecise coefficients in the third objective function, \( \tilde{SI} \), the proposed FMOMILP model does not ensure finding an ideal solution. Several approaches have been presented to obtain compromise solutions see in for example in the literature, such as Lai and Hwang (1992), Luhandjula (1989), Sakawa and Yano (1989), Tanaka and
Asai (1984), and Tanaka et al. (1984). Lai and Hwang (1992)' approach has less restrictive assumptions in comparison with other methods and practically is easy to use. Hence, the approach of Lai and Hwang (1992) was employed to deal with fuzzy objective functions in this study. This approach is defuzzification process and transfer fuzzy objective functions (including fuzzy parameters) into crisp ones.

Therefore, an auxiliary MOMILP model was provided with three objective functions to convert the fuzzy objective function of $SI$ to precise one. As it can be seen from equation (4.3), some parameters of this objective function have triangular possibility distributions. Hence, the $\tilde{SI}$ objective function would have a triangular possibility distribution. This fuzzy objective is fully geometrically defined by three corner points $(SI^p, 0), (SI^m, 1)$ and $(SI^o, 0)$. So, maximizing this fuzzy objective function can be obtained by guiding these three critical points in to the direction of the right-hand side of the triangular possibility distribution (Lai and Hwang, 1992). It should be noted that the vertical coordinates of the critical points are fixed at either 0 or 1, hence the horizontal coordinates is the only item that should be taken into account. Consequently, maximizing the imprecise objective function $\tilde{SI}$ needs maximizing $SI^p, SI^m$, and $SI^o$, simultaneously. However, there may exist a conflict in the simultaneous maximization of these crisp objectives. Hence, according to the proposed approach by Lai and Hwang (1992), we maximize $SI^m$, minimize $(SI^m - SI^p)$, maximize $(SI^o - SI^m)$ instead of maximizing $SI^p$, $SI^m$, and $SI^o$, simultaneously.

The fuzzy objective function $\tilde{SI}$ is, therefore, changed to the three crisp objectives to obtain a compromise solution:
\begin{align*}
\text{Min } Z_3 &= (S^m - S^p) \\
&= \sum_{p \in P} \sum_{t \in T} f_{lp} \ O_{pt} + \sum_{d \in D} \sum_{t \in T} f_{ld} \ O_{dt} + \sum_{i \in I} \sum_{t \in T} f_{li} \ O_{it} + \sum_{m \in M} \sum_{t \in T} f_{lm} \ O_{mt} + \sum_{l \in L} \sum_{t \in T} f_{lt} \ O_{lt} \\
&\quad + \sum_{k \in K} \sum_{t \in T} f_{tk} \ O_{kt} + \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} v_{jp} \ X_{pat} / (ca_{pt}^m - ca_{pt}^p) + \sum_{d \in D} \sum_{c \in C} \sum_{t \in T} v_{jd} \ X_{dct} / (ca_{dt}^m) \\
&\quad - ca_{dt}^p + \sum_{c \in C} \sum_{i \in I} \sum_{l \in L} v_{jl} \ X_{cit} / (ca_{it}^m - ca_{it}^p) + \sum_{i \in I} \sum_{m \in M} \sum_{t \in T} v_{jm} \ X_{imt} / (ca_{mt}^m - ca_{mt}^p) \\
&\quad + \sum_{i \in I} \sum_{l \in L} \sum_{t \in T} v_{jl} \ X_{ilt} / (ca_{it}^m - ca_{it}^p) + \sum_{i \in I} \sum_{k \in K} \sum_{t \in T} v_{jk} \ X_{ikt} / (ca_{kt}^m) - ca_{kt}^p \\
&= (4.39)
\end{align*}

\begin{align*}
\text{Max } Z_4 &= S^m \\
&= \sum_{p \in P} \sum_{t \in T} f_{lp} \ O_{pt} + \sum_{d \in D} \sum_{t \in T} f_{ld} \ O_{dt} + \sum_{i \in I} \sum_{t \in T} f_{li} \ O_{it} + \sum_{m \in M} \sum_{t \in T} f_{lm} \ O_{mt} + \sum_{l \in L} \sum_{t \in T} f_{lt} \ O_{lt} \\
&\quad + \sum_{k \in K} \sum_{t \in T} f_{tk} \ O_{kt} + \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} v_{jp} \ X_{pat} / ca_{pt}^m + \sum_{d \in D} \sum_{c \in C} \sum_{t \in T} v_{jd} \ X_{dct} / ca_{dt}^m \\
&\quad + \sum_{c \in C} \sum_{i \in I} \sum_{l \in L} v_{jl} \ X_{cit} / ca_{it}^m + \sum_{i \in I} \sum_{m \in M} \sum_{t \in T} v_{jm} \ X_{imt} / ca_{mt}^m + \sum_{i \in I} \sum_{l \in L} \sum_{t \in T} v_{jl} \ X_{ilt} / ca_{it}^m \\
&\quad + \sum_{i \in I} \sum_{k \in K} \sum_{t \in T} v_{jk} \ X_{ikt} / ca_{kt}^m \\
&= (4.40)
\end{align*}

\begin{align*}
\text{Max } Z_5 &= (S^o - S^m) \\
&= \sum_{p \in P} \sum_{t \in T} f_{lp} \ O_{pt} + \sum_{d \in D} \sum_{t \in T} f_{ld} \ O_{dt} + \sum_{i \in I} \sum_{t \in T} f_{li} \ O_{it} + \sum_{m \in M} \sum_{t \in T} f_{lm} \ O_{mt} + \sum_{l \in L} \sum_{t \in T} f_{lt} \ O_{lt} \\
&\quad + \sum_{k \in K} \sum_{t \in T} f_{tk} \ O_{kt} + \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} v_{jp} \ X_{pat} / (ca_{pt}^o - ca_{pt}^m) + \sum_{d \in D} \sum_{c \in C} \sum_{t \in T} v_{jd} \ X_{dct} / (ca_{dt}^o) \\
&\quad - ca_{dt}^m + \sum_{c \in C} \sum_{i \in I} \sum_{l \in L} v_{jl} \ X_{cit} / (ca_{it}^o - ca_{it}^m) + \sum_{i \in I} \sum_{m \in M} \sum_{t \in T} v_{jm} \ X_{imt} / (ca_{mt}^o - ca_{mt}^m) \\
&\quad + \sum_{i \in I} \sum_{l \in L} \sum_{t \in T} v_{jl} \ X_{ilt} / (ca_{it}^o - ca_{it}^m) + \sum_{i \in I} \sum_{k \in K} \sum_{t \in T} v_{jk} \ X_{ikt} / ca_{kt}^o - ca_{kt}^m \\
&= (4.41)
\end{align*}
4.3.3. Solving the auxiliary MOMILP problem

There are several methods to solve the obtained auxiliary MOMILP model: utility theory, goal programming, and fuzzy programming (Zimmerman, 1987). Fuzzy programming approaches are able to evaluate the satisfaction degree of each objective function explicitly, which is the main benefit of fuzzy approaches (Torabi and Hassini, 2008). Positive Ideal Solutions (PIS) and Negative Ideal Solutions (NIS) of all the crisp objective functions were calculated as follows, (Hwang and Yoon, 1981; Lai and Hwang, 1992), to define corresponding linear membership function, respectively.

\[
\begin{align*}
Z_1^{PIS} &= \text{Min } TC & Z_1^{NIS} &= \text{Max } TC \\
Z_2^{PIS} &= \text{Min } EI & Z_2^{NIS} &= \text{Max } EI \\
Z_3^{PIS} &= \text{Min } (SI^m - SI^p) & Z_3^{NIS} &= \text{Max } (SI^m - SI^p) \\
Z_4^{PIS} &= \text{Max } SI^m & Z_4^{NIS} &= \text{Min } SI^m \\
Z_5^{PIS} &= \text{Max } (SI^o - SI^m) & Z_5^{NIS} &= \text{Min } (SI^o - SI^m)
\end{align*}
\]

(4.42) \hspace{1cm} (4.43) \hspace{1cm} (4.44) \hspace{1cm} (4.45) \hspace{1cm} (4.46)

The related linear membership functions of these objective functions are calculated by:

\[
\begin{align*}
\mu_{z1} &= \begin{cases} 
1 & \text{if } Z_1 < Z_1^{PIS} \\
\frac{Z_1^{NIS} - Z_1}{Z_1^{NIS} - Z_1^{PIS}} & \text{if } Z_1^{PIS} \leq Z_1 \leq Z_1^{NIS} \\
0 & \text{if } Z_1 > Z_1^{NIS}
\end{cases} \\
\mu_{z2} &= \begin{cases} 
1 & \text{if } Z_2 < Z_2^{PIS} \\
\frac{Z_2^{NIS} - Z_2}{Z_2^{NIS} - Z_2^{PIS}} & \text{if } Z_2^{PIS} \leq Z_2 \leq Z_2^{NIS} \\
0 & \text{if } Z_2 > Z_2^{NIS}
\end{cases} \\
\mu_{z3} &= \begin{cases} 
1 & \text{if } Z_3 < Z_3^{PIS} \\
\frac{Z_3^{NIS} - Z_3}{Z_3^{NIS} - Z_3^{PIS}} & \text{if } Z_3^{PIS} \leq Z_3 \leq Z_3^{NIS} \\
0 & \text{if } Z_3 > Z_3^{NIS}
\end{cases} \\
\mu_{z4} &= \begin{cases} 
1 & \text{if } Z_4 < Z_4^{NIS} \\
\frac{Z_4^{PIS} - Z_4}{Z_4^{PIS} - Z_4^{NIS}} & \text{if } Z_4^{PIS} \leq Z_4 \leq Z_4^{NIS} \\
0 & \text{if } Z_4 > Z_4^{NIS}
\end{cases}
\end{align*}
\]

(4.47) \hspace{1cm} (4.48) \hspace{1cm} (4.49) \hspace{1cm} (4.50)
\[
\mu_{z_5} = \begin{cases} 
1 & \text{if } Z_5 > Z_5^{PIS} \\
\frac{Z_5 - Z_5^{NIS}}{Z_5^{PIS} - Z_5^{NIS}} & \text{if } Z_5^{NIS} \leq Z_5 \leq Z_5^{PIS} \\
0 & \text{if } Z_5 < Z_5^{NIS} 
\end{cases}
\]

Figure 4.3. Membership functions of Min objective functions

Figure 4.4. Membership functions of Max objective functions

Figure 4.3 and Figure 4.4 display a graph of the linear membership function defined for objective functions. One of the well-known approaches to solving the obtained auxiliary MOMILP model is Zimmermann max–min approach (Zimmermann, 1978):

\[
\begin{align*}
\max \lambda \\
\text{s.t.} \\
\lambda \leq \mu_z(x) \quad Z = 1, \ldots, N, \\
\lambda \in [0,1] \quad x \in X
\end{align*}
\]

(4.52)

But, the calculated optimal solution by max-min operator may not be efficient (Torabi and Hassini, 2008; Lai and Hwang, 1992; Mula et al., 2010; Lai and Hwang
Several methods were suggested to overcome the existing inefficiencies, the Li, Zhang, and Li (LZL) approach from Li et al. (2006), the Selim and Ozkarahan (SO) approach (2008), and Torabi and Hassini (TH) approach (2008). Among these methods, the TH approach is more robust and reliable as it always provides efficient solutions, and is able to reach both unbalanced and balanced solutions based on the decision maker’s preferences (Torabi and Hassini 2008). Hence, the TH approach was utilized to solve auxiliary MOMILP model.

\[
\begin{align*}
\max & \; \gamma \lambda_0 + (1 - \gamma) \sum_z \theta_z \mu_z(x) \\
\text{s.t.} & \; \lambda_0 \leq \mu_z(x), \quad z = 1, \ldots, N \\
& \; x \in F(x), \lambda_0 \quad \text{and} \quad \gamma \in [0,1],
\end{align*}
\]  

(4.53)

where \( \mu_z(x) \), \( \lambda_0 = \min_z \{ \mu_z(x) \} \), \( \theta_z \) and \( \gamma \) indicate the satisfaction degree of \( z \)th objective function and the minimum satisfaction degree of objectives, the relative importance of the \( z \)th objective function and the coefficient of compensation, respectively. In this model, a convex combination of the lower bound for satisfaction degree of objectives \( \lambda_0 \), and the weighted sum of these achievement degrees \( \mu_z(x) \) are implemented in order to ensure yielding an adjustably balanced compromise solution. The \( \theta_z \) parameters are specified by the decision makers according to their preferences such that \( \sum_z \theta_z = 1, \theta_z > 0 \). It should be noted that, \( \gamma \) adjusts the minimum satisfaction level of objectives and the compromise degree among the objectives implicitly. Torabi and Hassini (2008)’ model has yields both unbalanced and balanced compromised solutions for a problem according to a decision maker’s preferences by modifying the value of parameter \( \gamma \).
The optimal solution is calculated by solving this auxiliary model. The final values of objective functions are provided by placement variable values into the deterministic objective functions of the proposed model. Then, the final objective values are obtained by placement variable values into the objective functions of the main model.

4.4. Algorithm

The interactive solution procedure for solving FMOMILP problem includes the following steps:

**Step 1.** Formulate the original FMOMILP model for solving the sustainable closed loop supply chain network design problem with multiple fuzzy objectives according to Eqs. (4.1)–(4.29).

**Step 2.** Considering the minimum acceptable possibility level for imprecise parameters, \( \beta \), and then converting the fuzzy inequality constraints into deterministic ones employing the weighted average method, as Eqs. (4.30)-(4.38).

**Step 3.** Convert the original fuzzy social impact \( \hat{SI} \) into the three equivalent crisp objectives Eqs. (4.39)–(4.41).

**Step 4.** Specify the positive ideal solution (PIS) and negative ideal solution (NIS) for each of the fuzzy objectives, Eqs (4.42)-(4.46).

**Step 5.** Determine a linear membership function for each objective function, Eqs (4.47)-(4.51).

**Step 6.** Convert the auxiliary MOMILP model into an equivalent single-objective MILP using the proposed fuzzy programming of Torabi and Hassini (2008).

**Step 7.** Solve and modify the model interactively.
4.5. A computational experiment
To indicate the validity of the FMOMILP model for designing sustainable supply chain network and the efficiency of the proposed solution methodology, a numerical experiment was conducted. Consider a multi-echelon closed-loop supply chain network similar to the one displayed in Figure 4.1. The computational experiment considered: (1) four locations are considered for the first raw material suppliers; (2) three potential locations for establishing the plants; (3) two candidate locations for required distributors; (4) five customer centers for use of products; (5) two candidate locations to collect and inspect returned products; (6) three location for disposal centers; (7) two positional locations to establish recycling centers to convert recyclable products into reusable materials and send to suppliers; (8) two maximum number of repairing centers that can be opened. Four time periods were considered in this experiment. It should be noted that three approaches were taken for returned products: a percentage of returned products disposed, a percentage of returned products that have repair capability were repaired and delivered to distributors, and some of the returned products were recycled and sent to suppliers to use as raw materials.

The transportation cost was determined according to the distance between nodes on layers of the supply chain network. Only road-based transportation was taken into account to carry out the shipping operation in this experiment. It should be mentioned that transportation costs of products include operating costs and service provided such as; salaries, wages, costs of fuel, insurance and depreciation. Some of the used data for this example are illustrated in Table 4.1. Other parameters (fixed job, variable jobs, transportation cost between facilities, environmental impacts of shipping, production, and
disposal of products) for this Chapter are presented in Appendix B. In addition to the input parameters shown in Table 4.1, the fixed costs for setting up plants, opening distributors, collection & inspection centers for collecting returned products, opening disposal, recycling, and recovering centers to treat with returned products taken into account. Fixed costs were same for all periods. Also, the parameters of customer demands, facilities’ capacity, and return rates are fuzzy parameters which were represented by triangular fuzzy numbers. In Table 4.1, uncertain parameters were defined with fuzzy numbers (p, m, o). For example, the capacity of supplier # 1 is (1000, 1500, 2000) for time period #1. The most possible value (m) for this fuzzy number is 1500. Generation of data for this experiment example was done in such a way that they actual data available in some companies. The same optimization software package (CPLEX 12.6) in Chapter 3 was implemented to solve the proposed FMOMILP model for this experiment (Appendix C). It should be noted, the solver execution time to solve this problem, based on each objective function individually, is around 3-4 seconds.
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Table 4.1. Model’ parameters values for computational experiment for 4 time periods
4.5.1. Solution procedure

FMOMILP was formulated for solving the sustainable CLSC network design problem according to Eqs. (4.1)-(4.29). Then, the weighted average method was implemented to convert the fuzzy inequality constraints to crisp forms at $\beta = 0.5$. Subsequently, the modified objective functions of the auxiliary MOMILP problem for the imprecise objective function of $\hat{S}$ were developed using Eqs. (4.39)-(4.41).

Table 4.2. The PIS and NIS values of objective functions for described experiment in Section 4.5

<table>
<thead>
<tr>
<th>Objective Function</th>
<th>PIS</th>
<th>NIS</th>
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<tbody>
<tr>
<td>$Z_1$</td>
<td>20,410,366</td>
<td>26,666,993</td>
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<tr>
<td>$Z_2$</td>
<td>500,248</td>
<td>841,610</td>
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<td>$Z_3$</td>
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<td>$Z_4$</td>
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<td>229</td>
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<tr>
<td>$Z_5$</td>
<td>399</td>
<td>206</td>
</tr>
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</table>

The PIS and NIS for all objective functions in the auxiliary MOMILP problem were calculated (Table 4.2). The corresponding linear membership functions for all objective functions were obtained by applying Eqs. (4.47) and (4.51):
The auxiliary MOMILP problem was converted into an equivalent ordinary single-goal LP, according to the methods of Zimmerman (1978) and Torabi and Hassini (2008). The CPLEX software was implemented to execute these ordinary LP models and calculate the related results. After placement of the variables obtained from ordinary LP models into membership functions, the degree of satisfaction degree of each objective value was provided, in

Table 4.3. The overall decision maker satisfaction was 0.876 and 0.915 for Zimmerman and TH models, respectively. The higher satisfaction values indicate a higher level of satisfaction for objective functions.
As it can be seen from Table 4.3, the obtained degree of satisfaction TH approach is better than that of Zimmerman. If the initial solutions were not satisfactory, the decision maker would try to modify the PIS and NIS values for each of the fuzzy objective functions to yield a satisfactory solution. The provided results from solving this example with the TH approach and comparing its results with those of the most commonly used method of Zimmerman demonstrates that the TH approach is the most suitable method FMOMILP model of sustainable CLSC network design problem.

4.6. Effect of uncertainty on sustainable CLSC network design

In this Section, the same experiment as in Section 4.5 is solved by considering crisp numbers to investigate the effect of uncertainty on sustainable CLSC network design. The crisp values of Table 4.1 were used to solve the problem. The most possible value of fuzzy numbers (m) were considered as crisp values to solve the problem. For example,

Uncertain Fuzzy parameters $\tilde{c_{s_1}}$ (1000,1500,2000)
Deterministic Crisp parameters $ca_{s_1}$ (1500)
The problem was formulated as a deterministic model with crisp parameters. The PIS and NIS of objective functions were calculated considering the crisp parameters and listed in Table 4.4.

Table 4.4. Objective function values with crisp parameters for described experiment in Section 4.5

<table>
<thead>
<tr>
<th>Objective functions</th>
<th>PIS</th>
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Type</td>
<td>Value</td>
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<tr>
<td>Cost</td>
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<tr>
<td>Environmental</td>
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<tr>
<td>Social</td>
<td>Max</td>
<td>420</td>
</tr>
</tbody>
</table>

Comparing the results of Table 4.4 to those of Table 4.2 where the values of objective functions with fuzzy numbers are listed, one can see that the values for cost objective function with fuzzy numbers is higher than that for the crisp one (20,410,366 and 18,158,381, respectively). On the other hand, the obtained value for environmental objective function with fuzzy numbers is lower than when the problem is solved with crisp numbers. The obtained value for social impact objective function with crisp numbers is 420 (Table 4.4) which is close to the calculated value for $SI^m$ (422) when the problem is solved with fuzzy numbers. According to the experiment, four suppliers, three plants, and two distributors are considered for this network. Figure 4.5 shows the suppliers, plants, distributors, and the flows in between these facilities for when the problem is solved with fuzzy versus crisp numbers. It should be noted that this Figure demonstrates a limited section of CLSC network for time period # 1.
As seen Figure 4.5, solving the problem with fuzzy numbers, suppliers #1, 2, and 4 are selected to supply the raw material, while solving with crisp values suppliers #2 and 4 are chosen as the best units for the network. Considering the uncertainty in parameters and solving the problem with fuzzy numbers, plants #1 and 3 were selected to produce the products, while considering crisp numbers only plant #1 is utilized in the network. These networks also show that solving the problem with both fuzzy and crisp numbers leads to considering the two distributors in the network.

In the created network from solving the problem with fuzzy numbers, suppliers #2 and 4 supply the raw materials for plant #1 and this plant delivers the goods to distributor #1, and plant #3 meets the raw material from supplier #1 and delivers the goods to distributor #2. When solving the problem with crisp numbers plant #1 purchases the raw materials from suppliers #2 and 4 and delivers the products to distributors #1 and 2.

Solving the problem with fuzzy and crisp numbers leads to different values for objective functions and decision variables that is considering uncertainty results in different strategical and technical decisions. Though, both solutions are optimal, the difference between of these solutions comes from the different conditions of the problem.
One of the main parameters to design a CLSC network is customer demand. The network is designed to meet customer demands with the lowest cost and environmental impacts and highest social benefits. In reality, demands are affected by uncertainties such as changes in customer interest and needs, the behaviors of other competitors, technology development. Hence, it is required to consider these uncertainties to find the best solutions to design a sustainable CLSC network. Therefore, because uncertainty has an impact on the solution, care should be taken in identifying the fuzzy parameters and their degree of uncertainty.

4.7. Conclusions

In this Chapter, an FMOMILP model was proposed to design a sustainable CLSC network under a fuzzy environment. The model included three objective functions: minimization of total cost, minimization of environmental impacts, and maximization of social benefits. Data uncertainties were accommodated via model fuzziness in a two-phase interactive fuzzy programming approach. Fuzzy programming model was converted into an auxiliary crisp MOMILP. Then, the approach of Torabi and Hassini (2008) was applied to solve this auxiliary model and obtain optimum solutions. To examine the significance of the proposed model and the solution approach, a computational experiment was conducted. The results demonstrate the applicability of the approach and the feasibility of the solution methodology. Results showed that the proposed model presents a systematic framework that enables management to obtain a solution by adjusting the search direction. When the experiment was solved with crisp numbers, to evaluate the effect of uncertainty, the results showed considering uncertainty can alter significantly the make different strategical and technical decisions for network.
Various sources of uncertainties were taken into account, such demand, return rates, and capacity. Three conflicting objective functions (cost, environmental, and societal) were considered simultaneously. In this study, a software package (CPLEX) was implemented to solve a small experiment, which is not applicable for large-scaled problems. Hence, the development of an efficient meta-heuristic algorithm to solve this model should be useful for achieving effective solutions.

An FMOMILP model was presented in this Chapter to optimize sustainable CLSC network and a fuzzy programming approach (TH approach) was employed. In next Chapter, other fuzzy programming approaches are employed and their performance of is analyzed.
CHAPTER FIVE: FUZZY PROGRAMMING APPROACHES TO SOLVE PROBLEM OF SUSTAINABLE CLOSED-LOOP SUPPLY CHAINS NETWORK DESIGN

5.1. Introduction
In Chapter 4, sustainability and uncertainty were added to the problem of closed loop supply chain network design. An FMOMILP was used to optimize network and a fuzzy programming approach was utilized to solve problem. In this Chapter, three fuzzy programming approaches are analyzed to solve problem.

There are several fuzzy programming approaches to solve multi objective problems, such as Zimmermann’s max–min approach (Zimmermann, 1978), the WAM (weighted average method) approach of Lai and Hwang (1992), the Li, Zhang, and Li (LZL) approach (Li et al. 2006), the Selim and Ozkarahan (SO) approach (Selim and Ozkarahan, 2008), and Torabi and Hassini (TH) approach (Torabi and Hassini, 2008).

Fuzzy programming offers the following benefits (Pishvaee and Torabi 2010): (i) it measures the satisfaction degree of each objective function (Gholamian et al. 2015), which allows the selection of a preferred solution by (Torabi and Hassini, 2008); (ii) it can be converted into equivalent crisp formats for which commercial optimization solvers could be implemented to calculate optimal solutions; (iii) the subjective and objective data could be used; (iv) the required computations are much less demanding than stochastic programming approach.

In this Chapter, three fuzzy programming approaches; LZL approach of Li et al. (2006), the SO approach of Selim and Ozkarahan (2008), and TH approach of Torabi and
Hassini (2008) are employed to solve a FMOMILP model for sustainable CLSC network design. The performance of these fuzzy programming approaches is analyzed. The FMOMILP model aims at specifying the location of the facilities and the amount of products to be supplied in network facilities.

In Section 5.2, an FMOMILP model is presented and the solution methodology along with three fuzzy programming approaches is described in Section 5.3. Section 5.4 presents a numerical experiment for the proposed model. A sensitivity analysis is conducted in Section 5.5 to investigate the performance of the used fuzzy programming approaches. Conclusions and suggestions for future work are given in Section 5.6.

5.2. Problem formulation

Figure 5.1 demonstrates the presented structure of a CLSC network in this Chapter. It should be noted that the network structure of this Chapter is different with Chapter 4. In this Chapter, third-party reverse logistic providers are considered for reverse operations of CLSC network, while in Chapter 4, collection & inspection, repairing, recycling centers are used for these operations. Uncertain parameters such as return rates, customer demands, and facilities’ capacities are considered in a CLSC problem, optimized with an FMOMILP model. This model integrates activities of purchasing, manufacturing, distribution, collection, and return in a CLSC network, as shown in Figure 5.1. Four layers are considered in the forward logistics, suppliers, producers, distributors, and customer centers. This model consists of two layers in the reverse logistics: third-party providers and disposal centers. In the forward logistics, the suppliers provide raw materials to the plants. The manufactured goods are sent to customers via distributors.
In the reverse logistics, the returned products are collected by third-party, and are forwarded to suppliers, producers, and disposal centers based on product quality. Third-party providers collect and inspect all returned products and decide which operations are required for these products. This model includes three objective functions, cost and environmental impacts minimization, and social benefits maximization. The last objective function is considered as fuzzy. In this objective function, the parameters of facilities’ capacities are defined with triangular fuzzy numbers, while other objective functions are defined with deterministic parameters. The assumptions of Chapter 4 are also considered for this model.

Indices

S: set of Suppliers, indexed by ‘s’.

P: set of Producers, indexed by ‘p’.

D: set of Distributors, indexed by ‘d’.
I: set of Customer Centers, indexed by ‘i’.

J: set of third-party providers, indexed by ‘j’.

K: set of disposal centers, indexed by ‘k’

T: periods, indexed by ‘t’.

Parameters

$\tilde{a}_{st}$ : fuzzy capacity of Supplier ‘s’ at time period ‘t’

$\tilde{a}_{pt}$ : fuzzy capacity of Producer ‘p’ at time period ‘t’

$\tilde{a}_{dt}$ : fuzzy capacity of Distributor ‘d’ at time period ‘t’

$\tilde{a}_{jt}$ : fuzzy capacity of third-party providers ‘j’ at time period ‘t’

$\tilde{a}_{kt}$ : fuzzy capacity of disposal center ‘k’ at time period ‘t’

$t_{c_{sp}}$ : freight cost a product from supplier ‘s’ to producer ‘p’

$t_{c_{pd}}$ : freight cost a product from producer ‘p’ to distributor ‘d’

$t_{c_{dl}}$ : freight cost a product from distributor ‘d’ to customer center ‘i’

$t_{c_{ij}}$ : freight cost a product from customer center ‘i’ to third-party provider ‘j’

$t_{c_{js}}$: freight cost a product from third-party provider ‘j’ to supplier ‘s’

$t_{c_{jp}}$ : freight cost a product from third-party provider ‘j’ to producer ‘p’

$t_{c_{jk}}$ : freight cost a product from third-party provider ‘j’ to disposal center ‘k’

$f_{c_p}$ : opening cost of the producer ‘p’

$f_{c_d}$ : opening cost of the distributor ‘d’
$fc_j$ : opening cost of the third-party provider ‘j’

$fc_k$ : opening cost of the disposal center ‘k’

$es_{sp}$ : Environmental impacts of freight a product from supplier ‘s’ to producer ‘p’

$es_{pd}$ : Environmental impacts of freight a product from producer ‘p’ to distributor ‘d’

$es_{dl}$ : Environmental impacts of freight a product from distributor ‘d’ to customer center ‘i’

$es_{ij}$ : Environmental impacts of freight a product from customer center ‘i’ to third-party provider ‘j’

$es_{js}$ : Environmental impacts of freight a product from third-party provider ‘j’ to supplier ‘s’

$es_{jp}$ : Environmental impacts of freight a product from third-party provider ‘j’ to producer ‘p’

$es_{jk}$ : Environmental impacts of freight a product from third-party provider ‘j’ to disposal center ‘k’

$ep$ : Environmental impacts of producing at producer ‘p’

$ed$ : Environmental impacts of disposing at disposal center ‘k’

$fj_p$ : The number of fixed job opportunities created by establishing producers

$fj_d$ : The number of fixed job opportunities created by establishing distributors
\[ f_{jj} : \] The number of fixed job opportunities created by establishing third-party providers

\[ f_{jk} : \] The number of fixed job opportunities created by establishing disposal center

\[ v_{jp} : \] The number of variable job opportunities created by establishing producers

\[ v_{jd} : \] The number of variable job opportunities created by establishing distributors

\[ v_{jj} : \] The number of variable job opportunities created by establishing third-party providers

\[ v_{jk} : \] The number of variable job opportunities created by establishing disposal center

\[ mc_{pt} : \] manufacturing cost at producer ‘p’ at time period ‘t’

\[ dc_{kt} : \] disposal cost at disposal center ‘k’ at time period ‘t’

\[ \tilde{de}_{it} : \] fuzzy demand of customer center ‘i’ at time period ‘t’

\[ Ry_{t} : \] Recycling ratio at time period ‘t’

\[ Rm_{t} : \] Remanufacturing ratio at time period ‘t’

\[ Rd_{t} : \] Disposal ratio at time period ‘t’

\[ \tilde{Y}_{lt} : \] Reverse ratio at time period ‘t’

Decision Variables

\[ O_{st} : \] 1 if supplier ‘s’ is open at time period ‘t’; 0 otherwise

\[ O_{pt} : \] 1 if producer ‘p’ is open at time period ‘t’; 0 otherwise
$O_{dt}$ : 1 if distributor ‘d’ is open at time period ‘t’; 0 otherwise

$O_{jt}$ : 1 if third-party provider ‘j’ is open at time period ‘t’; 0 otherwise

$O_{kt}$ : 1 if disposal center ‘k’ is open at time period ‘t’; 0 otherwise

$X_{spt}$ : Quantity delivered from supplier ‘s’ to producer ‘p’ at time period ‘t’

$X_{pdt}$ : Quantity delivered from producer ‘p’ to distributor ‘d’ at time period ‘t’

$X_{dit}$ : Quantity delivered from distributor ‘d’ to customer center ‘i’ at time period ‘t’

$X_{ijt}$ : Quantity delivered from customer center ‘i’ to third-party provider ‘j’ at time period ‘t’

$X_{jst}$ : Quantity delivered from third-party provider ‘j’ to supplier ‘s’ at time period ‘t’

$X_{jpt}$ : Quantity delivered from third-party provider ‘j’ to producer ‘p’ at time period ‘t’

$X_{jkt}$ : Quantity delivered from third-party provider ‘j’ to disposal center ‘k’ at time period ‘t’

**Objective Function**

Three objective functions in a sustainable CLSC model minimize the cost, environmental impact, social impact, with some constraints, are considered and expressed as follows:
Min $Z_1 = \sum_{p \in P} \sum_{t \in T} fc_p O_{pt} + \sum_{d \in D} \sum_{t \in T} fc_d O_{dt} + \sum_{j \in J} \sum_{t \in T} fc_j O_{jt} + \sum_{k \in K} \sum_{t \in T} fc_k O_{kt}$

\[+ \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} mc_{pt} X_{pdt} + \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} dc_{kt} X_{jkt} + \sum_{s \in S} \sum_{p \in P} \sum_{t \in T} tc_{sp} X_{spt} \]

\[+ \sum_{d \in D} \sum_{p \in P} \sum_{t \in T} tc_{pd} X_{pdt} + \sum_{d \in D} \sum_{i \in I} \sum_{t \in T} tc_{di} X_{dit} + \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} tc_{ij} X_{ijt} \]

\[+ \sum_{j \in J} \sum_{s \in S} \sum_{t \in T} tc_{js} X_{jst} + \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} tc_{jp} X_{jpt} \]

\[+ \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} tc_{jk} X_{jkt} \quad (5.1) \]

Min $Z_2 = \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} ep X_{pdt} + \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} ed X_{jkt} + \sum_{s \in S} \sum_{p \in P} \sum_{t \in T} es_{sp} X_{spt}$

\[+ \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} es_{pd} X_{pdt} + \sum_{d \in D} \sum_{i \in I} \sum_{t \in T} es_{di} X_{dit} + \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} es_{ij} X_{ijt} \]

\[+ \sum_{j \in J} \sum_{s \in S} \sum_{t \in T} es_{js} X_{jst} + \sum_{j \in J} \sum_{p \in P} \sum_{t \in T} es_{jp} X_{jpt} \]

\[+ \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} es_{jk} X_{jkt} \quad (5.2) \]

Max $Z_3 = \sum_{p \in P} \sum_{t \in T} fj_p O_{pt} + \sum_{d \in D} \sum_{t \in T} fj_d O_{dt} + \sum_{j \in J} \sum_{t \in T} fj_j O_{jt} + \sum_{k \in K} \sum_{t \in T} fj_k O_{kt}$

\[+ \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} v_{ipt} X_{pdt} / \overline{c}_{apt} + \sum_{d \in D} \sum_{i \in I} \sum_{t \in T} v_{id} X_{dit} / \overline{c}_{adt} \]

\[+ \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} v_{ij} X_{ijt} / \overline{c}_{ijt} \]

\[+ \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} v_{jk} X_{jkt} / \overline{c}_{jkt} \quad (5.3) \]

Subject to:

\[\sum_{p \in P} X_{spt} \leq O_{st} \overline{c}_{st} \quad \forall s, t \quad (5.4)\]

\[\sum_{d \in D} X_{pdt} \leq O_{pt} \overline{c}_{apt} \quad \forall p, t \quad (5.5)\]
\[
\sum_{p \in P} X_{pdt} \leq O_{dt} \bar{c}_{dt} \quad \forall d, t \tag{5.6}
\]
\[
\sum_{i \in I} X_{ijt} \leq O_{jt} \bar{c}_{jt} \quad \forall j, t \tag{5.7}
\]
\[
\sum_{j \in J} X_{jkt} \leq O_{kt} \bar{c}_{kt} \quad \forall k, t \tag{5.8}
\]
\[
\sum_{s \in S} X_{spt} + \sum_{j \in J} X_{jpt} = \sum_{d \in D} X_{pdt} \quad \forall p, t \tag{5.9}
\]
\[
\sum_{p \in P} X_{pdt} = \sum_{i \in I} X_{dit} \quad \forall d, t \tag{5.10}
\]
\[
\sum_{i \in I} X_{ijt} = \sum_{s \in S} X_{jst} + \sum_{p \in P} X_{jpt} + \sum_{k \in K} X_{jkt} \quad \forall j, t \tag{5.11}
\]
\[
\sum_{k \in K} X_{jkt} = \sum_{i \in I} X_{ijt} R_d \quad \forall j, t \tag{5.12}
\]
\[
\sum_{s \in S} X_{jst} = \sum_{i \in I} X_{ijt} R_y \quad \forall j, t \tag{5.13}
\]
\[
\sum_{p \in P} X_{jpt} = \sum_{i \in I} X_{ijt} R_m \quad \forall j, t \tag{5.14}
\]
\[
\sum_{d \in D} X_{dit} = \bar{a}_{it} \quad \forall i, t \tag{5.15}
\]
\[
\sum_{j \in J} X_{ijt} = \bar{a}_{it} \bar{y}_{it} \quad \forall i, t \tag{5.16}
\]
\[
\sum_{s \in S} O_{st} \leq S \quad \forall t \tag{5.17}
\]
\[
\sum_{p \in P} O_{pt} \leq P \quad \forall t \tag{5.18}
\]
\[
\sum_{d \in D} O_{dt} \leq D \quad \forall t \tag{5.19}
\]
\[
\sum_{j \in J} O_{jt} \leq J \quad \forall t \tag{5.20}
\]
\[
\sum_{k \in K} O_{kt} \leq K \quad \forall t \tag{5.21}
\]
\[ X_{spt}, X_{pdt}, X_{dit}, X_{ijt}, X_{jst}, X_{jpt} \geq 0 \quad \forall i, j, k, s, p, t, d \] (5.22)

\[ O_{st}, O_{pt}, O_{dt}, O_{jt}, O_{kt} \in \{0,1\} \quad \forall k, j, p, s, t, d \] (5.23)

The first objective function, Eq. (5.1) aims at minimizing the total cost objective. In this objective function, the first four terms are the fixed costs of establishing facilities. The fifth to sixth terms are for manufacturing and disposal costs respectively, and the seventh to thirteenth summations are related to the transportation costs between facilities.

The second objective function, Eq. (5.2), refers to the environmental impacts objective in CLSC network. The first term of this function denotes the impact from producing goods and the second term denotes the impact from disposal of returned products. The other terms account for the environmental impact of shipping products between the facilities.

The third objective function, Eq. (5.3), is formulated for the social impact: the first four summations are fixed job opportunities created by opening the new facilities, the fifth to eighth terms account for the created variable jobs which depend on the capacity of facilities.

The constraint of relationship (5.4) guarantees that, in each period, the sum of the flows exiting from suppliers to all producers does not exceed the capacity of suppliers. Constraint (5.5) indicates that, in each period, the sum of the flows exiting from producers to distributors does not exceed the production capacity of plants. Constraint (5.6) ensures that in each period the sum of the flows entering from producers to distributors does not exceed the relevant capacity. Constraint (5.7) shows all of returned products from customer centers collected by third-party providers do not exceed the relevant capacity. Constraint (5.8) ensures that the sum of returned products sent to disposal centers by third-party providers does not exceed the disposing capacity of
disposal centers. Constraint (5.9) guarantees that the flow entering from suppliers and the third-party providers to producers is equal to the sum of the existing from producers to distributors at each period. Constraint (5.10) guarantees that in each period, the sum of the flow entering from producers to distributors is equal to the sum of the existing from distributors to customer centers. Constraint (5.11) states that in each period, the sum of collected returned products by the third-party providers from customer centers is equal to those existing from third-party providers to suppliers, producers, and disposal centers. Constraint (5.12) states that in each period, all returned products sent to disposal centers are disposed. Constraint (5.13) shows that in each period, all returned products that need to be recycled are sent to suppliers. Constraint (5.14) shows that in each period, all returned products that need to be remanufactured are sent to producers. Constraints (5.15) ensure that all customer demands should be met in customer centers. Constraint (5.16) shows the amount of returned products collected by third-party providers from customer centers. Constraints (5.17)–(5.21) limit the maximum number of allowable locations, and do not allow the supply chain to have more components than possible limitations. Constraints (5.22) and (5.23) represent the non-negativity and integrality of variables.

5.3. Solution methodology

A two-phase approach is proposed to solve FMOMILP expressed by Eqs. (5.1) to (5.23). The model has fuzzy parameters in its objective functions and constraints (return rates, customer demand, capacity of facilities). However, this problem is converted first to an MOMILP model. Three widely used interactive fuzzy programming approaches are then implemented to solve this model. These phases are explained in detail in the following sub-sections.
5.3.1. The auxiliary MOMILP problem

The weighted average method of Lai and Hwang (1992) is first used to convert the proposed FMOMILP model into an equivalent auxiliary crisp multiple objective mixed integer linear programming (MOMILP) model. It should be noted that the obtained linear programming model includes convex objective functions.

5.3.2. Converting Fuzzy objectives into auxiliary model

In this Section, the mentioned approach in Section 4.3.2 is employed to change Eq. (5.3) (Fuzzy objective function of social impacts) into the three crisp objectives to obtain a compromise solution:

\[
\begin{align*}
\text{Min } Z_3 &= \sum_{p \in P} \sum_{t \in T} f_{j_p} O_{pt} + \sum_{d \in D} \sum_{t \in T} f_{j_d} O_{dt} + \sum_{j \in J} \sum_{t \in T} f_{j_l} O_{lt} + \sum_{k \in K} \sum_{t \in T} f_{j_k} O_{kt} \\
&\quad + \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} v_{j_p} X_{dpt} / (c_{a_{pt}}^m - c_{a_{pt}}^p) + \sum_{d \in D} \sum_{i \in I} \sum_{t \in T} v_{j_d} X_{dit} / (c_{a_{dt}}^m - c_{a_{dt}}^p) \\
&\quad - c_{a_{dt}}^p + \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} v_{j_l} X_{ijt} / (c_{a_{jt}}^m - c_{a_{jt}}^p) + \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} v_{j_k} X_{jkt} / (c_{a_{kt}}^m - c_{a_{kt}}^p) \\
&\quad - c_{a_{kt}}^p
\end{align*}
\] (5.24)

\[
\begin{align*}
\text{Max } Z_4 &= \sum_{p \in P} \sum_{t \in T} f_{j_p} O_{pt} + \sum_{d \in D} \sum_{t \in T} f_{j_d} O_{dt} + \sum_{j \in J} \sum_{t \in T} f_{j_l} O_{lt} + \sum_{k \in K} \sum_{t \in T} f_{j_k} O_{kt} \\
&\quad + \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} v_{j_p} X_{pdt} / c_{a_{pt}}^m + \sum_{d \in D} \sum_{i \in I} \sum_{t \in T} v_{j_d} X_{dit} / c_{a_{dt}}^m \\
&\quad + \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} v_{j_l} X_{ijt} / c_{a_{jt}}^m + \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} v_{j_k} X_{jkt} / c_{a_{kt}}^m
\end{align*}
\] (5.25)
Max \( Z_s = \sum_{p \in P} \sum_{t \in T} f_{ip} O_{pt} + \sum_{d \in D} \sum_{t \in T} f_{id} O_{dt} + \sum_{j \in J} \sum_{t \in T} f_{ij} O_{jt} + \sum_{k \in K} \sum_{t \in T} f_{jk} O_{kt} \)

\[
+ \sum_{p \in P} \sum_{d \in D} \sum_{t \in T} v_{jp} X_{pdt} / (c_{at}^o - c_{at}^m) + \sum_{d \in D} \sum_{l \in I} \sum_{t \in T} v_{ld} X_{dit} / (c_{at}^o - c_{at}^m) - c_{at}^m \]

\[
- \sum_{l \in I} \sum_{j \in J} \sum_{t \in T} v_{lj} X_{ijt} / (c_{jt}^o - c_{jt}^m) + \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} v_{jk} X_{jkt} / (c_{kt}^o - c_{kt}^m) - c_{kt}^m \)

(5.26)

5.3.3. Strategy for solving the fuzzy/imprecise constraints

The Weighted Average Method (WAM) method (Lai and Hwang, 1992) is utilized to convert the fuzzy numbers of model constraints into crisp numbers. Details of this method were explained in Section 4.3.1. The corresponding auxiliary crisp inequalities of constraints (5.4-5.8) and (5.15-5.16) can be expressed as:

\[
\sum_{p \in P} X_{spt} \leq O_{st} (W_1 c_{st,0} + W_2 c_{st,0} + W_3 c_{st,0}) \quad \forall \ s, t \quad (5.27)
\]

\[
\sum_{d \in D} X_{pdt} \leq O_{pt} (W_1 c_{pt,0} + W_2 c_{pt,0} + W_3 c_{pt,0}) \quad \forall \ p, t \quad (5.28)
\]

\[
\sum_{p \in P} X_{pdt} \leq O_{dt} (W_1 c_{dt,0} + W_2 c_{dt,0} + W_3 c_{dt,0}) \quad \forall \ d, t \quad (5.29)
\]

\[
\sum_{j \in J} X_{ijt} \leq O_{jt} (W_1 c_{jt,0} + W_2 c_{jt,0} + W_3 c_{jt,0}) \quad \forall \ j, t \quad (5.30)
\]

\[
\sum_{j \in J} X_{jkt} \leq O_{kt} (W_1 c_{kt,0} + W_2 c_{kt,0} + W_3 c_{kt,0}) \quad \forall \ k, t \quad (5.31)
\]

\[
\sum_{d \in D} X_{dit} = (W_1 d_{it,0} + W_2 d_{it,0} + W_3 d_{it,0}) \quad \forall \ i, t \quad (5.32)
\]

\[
\sum_{j \in J} X_{ijt} = (W_1 y_{it,0} + W_2 y_{it,0} + W_3 y_{it,0}) \quad \forall \ i, t \quad (5.33)
\]
where $W_1 + W_2 + W_3 = 1$, $W_1$, $W_2$ and $W_3$ express the corresponding weights of the most pessimistic, most likely and most optimistic values respectively. The appropriate values for these weights, as well as $\beta$, are specified subjectively based on the experience and knowledge of the decision maker. However, in this work, these parameters are set as $W_2 = 4/6$, $W_1=W_3=1/6$ and $\beta = 0.5$ for all constraints, according to the concept of the most likely values of Lai and Hwang (1992) considering other relevant studies (Liang, 2006; Wang and Liang, 2005).

5.3.4. Fuzzy programming approaches for solving MOMILP problem

There are several methods to solve the auxiliary MOMILP model. For instance, utility theory, goal programming (Charnes and Cooper, 1961), and fuzzy programming, within which the fuzzy programming approaches are being increasingly implemented (Torabi and Hassini, 2008). They are able to evaluate the satisfaction degree of each objective function explicitly which is recognized as their main benefit. To use fuzzy programming approaches, the corresponding Positive Ideal Solutions (PIS) and the Negative Ideal Solutions (NIS) of all the crisp objective functions of the auxiliary MOMILP problem are calculated (Eqs. 5.34-5.38):

\[
\begin{align*}
Z_1^{PIS} & = \text{Min } TC & Z_1^{NIS} & = \text{Max } TC \\
Z_2^{PIS} & = \text{Min } EI & Z_2^{NIS} & = \text{Max } EI \\
Z_3^{PIS} & = \text{Min } (SI^m - SI^p) & Z_3^{NIS} & = \text{Max } (SI^m - SI^p) \\
Z_4^{PIS} & = \text{Max } SI^m & Z_4^{NIS} & = \text{Min } SI^m \\
Z_5^{PIS} & = \text{Max } (SI^o - SI^m) & Z_5^{NIS} & = \text{Min } (SI^o - SI^m)
\end{align*}
\]

(5.34-5.38)

The related linear membership function is calculated for each of these objective functions:
One of the well-known approaches to solve the obtained auxiliary MOMILP model is Zimmermann max–min approach (Zimmermann, 1978).

\[
\begin{align*}
\mu_{z1} &= \begin{cases} 
1 & \text{if } Z_1 < Z_1^{PIS} \\
\frac{Z_2^{NIS} - Z_1^{NIS}}{Z_2^{NIS} - Z_1^{PIS}} & \text{if } Z_1^{PIS} \leq Z_1 \leq Z_1^{NIS} \\
0 & \text{if } Z_1 > Z_1^{NIS} \end{cases} \\
\mu_{z2} &= \begin{cases} 
1 & \text{if } Z_2^{PIS} \leq Z_2 \leq Z_2^{NIS} \\
\frac{Z_2^{NIS} - Z_2^{PIS}}{Z_2^{NIS} - Z_2^{PIS}} & \text{if } Z_2 > Z_2^{NIS} \\
0 & \text{if } Z_2 < Z_2^{PIS} \end{cases} \\
\mu_{z3} &= \begin{cases} 
1 & \text{if } Z_3^{PIS} \leq Z_3 \leq Z_3^{NIS} \\
\frac{Z_3^{NIS} - Z_3^{PIS}}{Z_3^{PIS} - Z_3^{NIS}} & \text{if } Z_3 > Z_3^{NIS} \\
0 & \text{if } Z_3 < Z_3^{PIS} \end{cases} \\
\mu_{z4} &= \begin{cases} 
1 & \text{if } Z_4^{NIS} \leq Z_4 \leq Z_4^{PIS} \\
\frac{Z_4^{PIS} - Z_4^{NIS}}{Z_4^{PIS} - Z_4^{NIS}} & \text{if } Z_4 < Z_4^{NIS} \\
0 & \text{if } Z_4 > Z_4^{PIS} \end{cases} \\
\mu_{z5} &= \begin{cases} 
1 & \text{if } Z_5^{NIS} \leq Z_5 \leq Z_5^{PIS} \\
\frac{Z_5^{PIS} - Z_5^{NIS}}{Z_5^{PIS} - Z_5^{NIS}} & \text{if } Z_5 < Z_5^{NIS} \\
0 & \text{if } Z_5 > Z_5^{NIS} \end{cases}
\end{align*}
\]

\(\mu_{x}(x)\) Z = 1,...,N, \(\lambda \in [0,1]\) x \(\in X\)

The calculated optimal solution by the max-min operator may not be efficient (Torabi and Hassini, 2008; Lai and Hwang, 1992; Mula et al., 2010; Lai and Hwang 1994). Several methods are overcome the existing inefficiencies, such as the LZL approach of Li et al. (2006), the WAM approach of Lai and Hwang (1992), the SO approach of Selim and Ozkarahan (2008), and TH approach of Torabi and Hassini (2008). The effectiveness of these approaches are investigated. These approaches are detailed below.
LZL approach

Li et al. (2006) used a two-phase approach (namely LZL (Li, Zhang, and Li)) for solving the auxiliary MOMILP. In the first phase, an optimal solution $X^0$ is found via the max-min approach (this approach focuses on maximizing the minimum membership degree) (Zimmermann, 1978). Then, all objective values’ satisfaction degrees are reached placing the initial (optimal) solution into the relative membership functions $u_h(x^0) \ (0 \leq h \leq 1)$.

In the second phase, the following model is solved to obtain the optimal solution $x^*$:

$$Max \sum_z \theta_z \mu_z(x)$$

s.t.

$$u_z(x^0) \leq \mu_z(x) \leq u_z(x) , \quad z = 1, ..., N$$

$$\sum_z \theta_z = 1$$

$$x \in F(x), \theta_z > 0$$

At the final, the optimal solution $x^*$ is placed into the objective functions of the main model.

SO approach

Selim and Özkarahan’s (2008) approach is as follows:

$$Max \gamma \lambda^0 + (1 - \gamma) \sum_z \theta_z \lambda_z$$

s.t.

$$\lambda^0 + \lambda_z \leq \mu_z(x), \quad z = 1, ..., N$$

$$\sum_z \theta_z = 1$$

$$x \in F(x), \lambda^0, \lambda_z, \gamma \in [0,1], \theta_z > 0$$
where \( z \) is the total number of fuzzy objectives, \( \mu_z(x) \) and \( \gamma \) demonstrate the membership function of fuzzy goal \( z \) and the coefficient of compensation defined within the interval \([0,1]\) respectively.

**TH approach**

The Torabi and Hassini (2008)’s approach is presented as follows:

\[
\text{Max } \gamma \lambda_0 + (1 - \gamma) \sum_z \theta_z \mu_z(x) \\
\text{s.t. } \lambda_0 \leq \mu_z(x), \quad z = 1, \ldots, N \\
\sum_z \theta_z = 1 \\
x \in F(x), \lambda_0 \text{ and } \gamma \in [0,1], \theta_z > 0
\]

where \( \mu_z(x), \lambda_0 = \min_z \{\mu_z(x)\} \), \( \theta_z \) and \( \gamma \) indicate the satisfaction degree of \( z \)th objective function and the minimum satisfaction degree of objectives, the relative importance of the \( z \)th objective function and the coefficient of compensation respectively.

In this model, a convex combination of the lower bound for satisfaction degree of objectives \( \lambda_0 \), and the weighted sum of these achievement degrees \( \mu_z(x) \) are implemented in order to ensure yielding an adjustably balanced compromise solution. It should be noted that \( \gamma \) adjusts the minimum satisfaction level of objectives to provide a compromise among the objectives implicitly. Torabi and Hassini’s approach has the ability to yield both unbalanced and balanced compromised solutions according to the decision maker’s preferences, by modification of the value of parameter \( \gamma \) (Torabi and Hassini, 2008).
5.4. Computational experiment

The validity of the proposed FMOMILP model for designing sustainable supply chain network and the effectiveness of the proposed solution methodology is demonstrated along with a numerical experiment. The considered entities for a numerical experiment consist of: (1) three potential locations for the first raw material suppliers; (2) one potential locations for establishing the plants; (3) two candidate locations to build required distributors; (4) three customer centers that use these products; (5) three potential third-party reverse providers for returned products; (6) two maximum disposal centers that can be opened. Four time periods are considered for this experiment. As indicated in Fig 1, third-party providers are taken into consideration for the required operations in reverse logistics. The returned products are collected by these providers, and suitable strategies (operations) based on the products’ quality are chosen. A portion of the returned products are forwarded to disposal centers, another portion of returned products that are reparable repair capability are delivered to producers, and the rest are recycled and sent to suppliers to use as raw materials.

The transportation cost is calculated based on the distance between nodes on layers of the supply chain network. The only road-based transportation is considered to carry out the shipping operations. It should be mentioned that transportation costs of the products include operating costs and service provided, such as; salaries, wages, costs of fuel, insurance and depreciation. Some of the used data for this example are illustrated in Table 5.1. In addition to the input parameters shown in Table 5.1, the fixed costs for setting up the producers, opening the distributors, third-party providers for collecting returned products, opening disposal centers, are all taken into account. The fixed costs
were the same for all periods. One of the most usable optimization software packages, CPLEX 12.6, (IBM) is implemented to solve the proposed FMOMILP model for this experiment. All computational work was accomplished on a personal computer (32-bit operating system, 2.53 GHz CPU, and 4.00 GB).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Corresponding random distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \bar{c}a )</td>
<td>U(18,000, 27,000)</td>
</tr>
<tr>
<td>( tc )</td>
<td>U(5, 10)</td>
</tr>
<tr>
<td>( fc )</td>
<td>U(10,000, 30,000)</td>
</tr>
<tr>
<td>( es )</td>
<td>U(3, 7)</td>
</tr>
<tr>
<td>( ep )</td>
<td>U(27,30)</td>
</tr>
<tr>
<td>( ed )</td>
<td>U(35, 40)</td>
</tr>
<tr>
<td>( fj )</td>
<td>U(3, 10)</td>
</tr>
<tr>
<td>( vj )</td>
<td>U(0.3, 0.6)</td>
</tr>
<tr>
<td>( mc )</td>
<td>U(20, 25)</td>
</tr>
<tr>
<td>( dc )</td>
<td>U(8, 10)</td>
</tr>
<tr>
<td>( \bar{d}e )</td>
<td>U(10,000, 15,000)</td>
</tr>
<tr>
<td>( Ry, Rm, Rd )</td>
<td>U(0.2, 0.5)</td>
</tr>
<tr>
<td>( \tilde{y} )</td>
<td>U(0.5, 0.8)</td>
</tr>
</tbody>
</table>

Table 5.1: The sources of random generation of data set for experiment (U: Uniform)

FMOMILP was first used to formulate and to solve the sustainable CLSC network design problem of Eqs. (5.1)-(5.23). Then the weighted average method was implemented to convert the fuzzy inequality constraints to crisp forms at \( \beta = 0.5 \). Then, the new objective functions of the auxiliary MOMILP problem for the imprecise objective function of \( \bar{Z}_3 \) were developed using Eqs. (5.24)-(5.26). Furthermore, the PIS and NIS for all objective functions in the auxiliary MOMILP problem were calculated using Eqs. (5.34)-(5.38) (Table 5.2).

<table>
<thead>
<tr>
<th>OF</th>
<th>PIS</th>
<th>NIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Z_1 )</td>
<td>14,177,604</td>
<td>16,366,513</td>
</tr>
<tr>
<td>( Z_2 )</td>
<td>7,841,653</td>
<td>8,625,114</td>
</tr>
<tr>
<td>( Z_3 )</td>
<td>201</td>
<td>288</td>
</tr>
<tr>
<td>( Z_4 )</td>
<td>209</td>
<td>132</td>
</tr>
<tr>
<td>( Z_5 )</td>
<td>275</td>
<td>192</td>
</tr>
</tbody>
</table>

| Table 5.2: The PIS and NIS values of objective functions for described experiment |
The corresponding linear membership functions for all objective functions are obtained by applying Eqs. (5.39)-(5.43) are:

\[
\mu_{z1} = \begin{cases} 
1 & \text{if } Z_1 < 14,177,604 \\
\frac{16,366,513 - Z_1}{16,366,513 - 14,177,604} & \text{if } 14,177,604 \leq Z_1 \leq 16,366,513 \\
0 & \text{if } Z_1 > 16,366,513 \\
1 & \text{if } Z_1 < 7,841,653 
\end{cases}
\]

\[
\mu_{z2} = \begin{cases} 
1 & \text{if } Z_2 < 7,841,653 \leq Z_2 \leq 8,625,114 \\
\frac{8,625,114 - Z_2}{8,625,114 - 7,841,653} & \text{if } Z_2 > 8,625,114 \\
0 & \text{if } Z_3 < 201 \\
1 & \text{if } Z_3 < 288 \\
288 - Z_3 & \text{if } 201 \leq Z_3 \leq 288 \\
288 - 201 & \text{if } Z_3 > 288 \\
0 & \text{if } Z_4 < 209 \\
1 & \text{if } Z_4 > 209 \\
209 - Z_4 & \text{if } 132 \leq Z_4 \leq 209 \\
209 - 132 & \text{if } Z_4 < 132 \\
0 & \text{if } Z_5 < 275 \\
1 & \text{if } Z_5 > 275 \\
Z_5 - 192 & \text{if } 192 \leq Z_5 \leq 275 \\
275 - 192 & \text{if } Z_5 < 192 
\end{cases}
\]

The three mentioned interactive fuzzy programming approaches in Section, LZL, SO, and TH approaches, were implemented to convert the auxiliary MOMILP problem into an equivalent ordinary single-goal LP form. It should be noted that \( \gamma \)-value was set to 0.5 for the SO and TH approaches. The reason for choosing \( \gamma = 0.5 \) is that one is looking balanced compromise solution (Torabi and Hassini, 2008) with same satisfaction degree for all objective functions. After placing the obtained optimal solution \( x^* \) from ordinary LP models into objective functions, the \( Z \) values were calculated for all objective functions. Then, these values are placed into membership functions in order to calculate satisfaction degree of objective functions (Table 5.3).
Table 5.3: Results of Fuzzy programming approaches for described experiment

<table>
<thead>
<tr>
<th></th>
<th>LZL</th>
<th>SO</th>
<th>TH</th>
<th>μ&lt;sub&gt;Z1&lt;/sub&gt;</th>
<th>LZL</th>
<th>SO</th>
<th>TH</th>
</tr>
</thead>
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<td>15,536,701</td>
<td>14,923,518</td>
<td>0.5426</td>
<td>0.3791</td>
<td>0.6592</td>
<td></td>
</tr>
<tr>
<td>Z&lt;sub&gt;2&lt;/sub&gt;</td>
<td>8,211,542</td>
<td>8,199,312</td>
<td>8,159,613</td>
<td>0.5279</td>
<td>0.5435</td>
<td>0.5942</td>
<td></td>
</tr>
<tr>
<td>Z&lt;sub&gt;3&lt;/sub&gt;</td>
<td>242</td>
<td>255</td>
<td>237</td>
<td>0.5287</td>
<td>0.3793</td>
<td>0.5862</td>
<td></td>
</tr>
<tr>
<td>Z&lt;sub&gt;4&lt;/sub&gt;</td>
<td>171</td>
<td>170</td>
<td>174</td>
<td>0.5065</td>
<td>0.4935</td>
<td>0.5455</td>
<td></td>
</tr>
<tr>
<td>Z&lt;sub&gt;5&lt;/sub&gt;</td>
<td>235</td>
<td>225</td>
<td>241</td>
<td>0.5181</td>
<td>0.3976</td>
<td>0.5904</td>
<td></td>
</tr>
</tbody>
</table>

As indicated in Table 5.3 and Figure 5.2, the TH method gave the best values for objective functions. The calculated solutions of the TH method are more effective than those of the LZL and SO methods. As Table 5.3 shows, the maximum satisfaction degrees are obtained by the TH method.

5.5. Sensitivity analysis

The sensitivity of the above interactive fuzzy programming approaches were examined by varying some important parameters, as discussed below.

Sensitivity analysis for γ

Eleven experiments are carried out in which the coefficient of compensation (γ value) was increased ten times with a 0.1 increment from 0 to 1. Table 5.4 and Table 5.5 present the obtained objective function values and satisfaction degrees of the SO and TH methods respectively.
Table 5.4. Sensitivity analysis of $\gamma$ value for the SO approach for described experiment

<table>
<thead>
<tr>
<th>$\gamma$-Value</th>
<th>$Z_1$</th>
<th>$Z_2$</th>
<th>$Z_3$</th>
<th>$Z_4$</th>
<th>$Z_5$</th>
<th>$\mu_{z1}$</th>
<th>$\mu_{z2}$</th>
<th>$\mu_{z3}$</th>
<th>$\mu_{z4}$</th>
<th>$\mu_{z5}$</th>
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<tbody>
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<td>8,022,529</td>
<td>233</td>
<td>174</td>
<td>241</td>
<td>0.5552</td>
<td>0.7691</td>
<td>0.6322</td>
<td>0.5455</td>
<td>0.5904</td>
</tr>
<tr>
<td>0.1</td>
<td>15,536,701</td>
<td>8,145,965</td>
<td>245</td>
<td>174</td>
<td>241</td>
<td>0.3791</td>
<td>0.6116</td>
<td>0.4943</td>
<td>0.5455</td>
<td>0.5904</td>
</tr>
<tr>
<td>0.2</td>
<td>15,248,621</td>
<td>8,199,312</td>
<td>251</td>
<td>164</td>
<td>228</td>
<td>0.5107</td>
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<td>0.4156</td>
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</tr>
<tr>
<td>0.3</td>
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<td>170</td>
<td>236</td>
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<td>165</td>
<td>229</td>
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<td>0.4458</td>
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<td>255</td>
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<td>225</td>
<td>0.3791</td>
<td>0.5435</td>
<td>0.3793</td>
<td>0.4935</td>
<td>0.4935</td>
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<tr>
<td>0.6</td>
<td>15,536,701</td>
<td>8,199,312</td>
<td>255</td>
<td>170</td>
<td>225</td>
<td>0.3791</td>
<td>0.5435</td>
<td>0.3793</td>
<td>0.4935</td>
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<td>255</td>
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<td>225</td>
<td>0.3791</td>
<td>0.5435</td>
<td>0.3793</td>
<td>0.4935</td>
<td>0.4935</td>
</tr>
<tr>
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<td>174</td>
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<td>0.3572</td>
<td>0.5517</td>
<td>0.5455</td>
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<tr>
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<td>8,325,471</td>
<td>255</td>
<td>175</td>
<td>235</td>
<td>0.3159</td>
<td>0.3825</td>
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<td>0.5584</td>
<td>0.5181</td>
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<td>255</td>
<td>180</td>
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<td>0.3793</td>
<td>0.6234</td>
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</table>

The results demonstrate that the TH approach has better performance than SO method, based on the degrees of satisfaction. Table 5.5 indicates the balanced solutions for $\gamma$ value which is less than 0.5, could be obtained by TH approach, which is not so sensitive to the $\gamma$ value. The TH approach achieves approximately the same objective function values for the $\gamma$ values from 0.3 to 0.9. Table 5.4 shows that the SO method is very sensitive to the $\gamma$ values, as it produces different unbalanced solutions for $\gamma$ values more than 0.8 and less than 0.4. In fact, the SO method produced about the same
objective function values for the \( y \) values between 0.5 and 0.7. It should be noted that these two methods reach unbalanced solutions for small \( y \) values.

Sensitivity analysis for \( \beta \)

Eleven experiments were conducted in which the \( \beta \) value was increased ten times with a 0.1 increment from 0 to 1 for all interactive fuzzy programming methods. Table 5.6, Table 5.7, and Table 5.8 display the achieved objective function values and satisfaction degrees for the LZL, SO, and TH methods.

<table>
<thead>
<tr>
<th>( \beta )-Value</th>
<th>( Z_1 )</th>
<th>( Z_2 )</th>
<th>( Z_3 )</th>
<th>( Z_4 )</th>
<th>( Z_5 )</th>
<th>( \mu_{x1} )</th>
<th>( \mu_{x2} )</th>
<th>( \mu_{x3} )</th>
<th>( \mu_{x4} )</th>
<th>( \mu_{x5} )</th>
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<td>239</td>
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<td>0.5663</td>
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<td>0.3033</td>
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<table>
<thead>
<tr>
<th>( \beta )-Value</th>
<th>( Z_1 )</th>
<th>( Z_2 )</th>
<th>( Z_3 )</th>
<th>( Z_4 )</th>
<th>( Z_5 )</th>
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<th>( \mu_{x4} )</th>
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<td>258</td>
<td>166</td>
<td>219</td>
<td>0.3791</td>
<td>0.5280</td>
<td>0.3448</td>
<td>0.4416</td>
<td>0.3253</td>
</tr>
<tr>
<td>1</td>
<td>15,936,812</td>
<td>8,257,262</td>
<td>268</td>
<td>161</td>
<td>208</td>
<td>0.1963</td>
<td>0.4695</td>
<td>0.2299</td>
<td>0.3766</td>
<td>0.1928</td>
</tr>
</tbody>
</table>
Table 5.8. Sensitivity analysis of $\beta$ value for the TH approach

<table>
<thead>
<tr>
<th>$\beta$-Value</th>
<th>$Z_1$</th>
<th>$Z_2$</th>
<th>$Z_3$</th>
<th>$Z_4$</th>
<th>$Z_5$</th>
<th>$\mu_{x_1}$</th>
<th>$\mu_{x_2}$</th>
<th>$\mu_{x_3}$</th>
<th>$\mu_{x_4}$</th>
<th>$\mu_{x_5}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>14,975,412</td>
<td>8,154,129</td>
<td>230</td>
<td>178</td>
<td>244</td>
<td>0.6355</td>
<td>0.6012</td>
<td>0.6667</td>
<td>0.5974</td>
<td>0.6265</td>
</tr>
<tr>
<td>0.1</td>
<td>14,861,574</td>
<td>8,155,953</td>
<td>235</td>
<td>170</td>
<td>239</td>
<td>0.6875</td>
<td>0.5988</td>
<td>0.6092</td>
<td>0.4935</td>
<td>0.5663</td>
</tr>
<tr>
<td>0.2</td>
<td>14,857,423</td>
<td>8,162,581</td>
<td>238</td>
<td>177</td>
<td>241</td>
<td>0.6894</td>
<td>0.5904</td>
<td>0.5747</td>
<td>0.5844</td>
<td>0.5904</td>
</tr>
<tr>
<td>0.3</td>
<td>14,923,518</td>
<td>8,155,613</td>
<td>236</td>
<td>174</td>
<td>238</td>
<td>0.6592</td>
<td>0.5993</td>
<td>0.5977</td>
<td>0.5455</td>
<td>0.5542</td>
</tr>
<tr>
<td>0.4</td>
<td>14,923,518</td>
<td>8,159,613</td>
<td>238</td>
<td>171</td>
<td>238</td>
<td>0.6592</td>
<td>0.5942</td>
<td>0.5747</td>
<td>0.5065</td>
<td>0.5542</td>
</tr>
<tr>
<td>0.5</td>
<td>14,923,518</td>
<td>8,159,613</td>
<td>237</td>
<td>174</td>
<td>241</td>
<td>0.6592</td>
<td>0.5942</td>
<td>0.5862</td>
<td>0.5455</td>
<td>0.5904</td>
</tr>
<tr>
<td>0.6</td>
<td>15,018,741</td>
<td>8,187,512</td>
<td>237</td>
<td>171</td>
<td>239</td>
<td>0.6157</td>
<td>0.5585</td>
<td>0.5862</td>
<td>0.5065</td>
<td>0.5663</td>
</tr>
<tr>
<td>0.7</td>
<td>15,039,451</td>
<td>8,189,562</td>
<td>237</td>
<td>170</td>
<td>240</td>
<td>0.6063</td>
<td>0.5559</td>
<td>0.5862</td>
<td>0.4935</td>
<td>0.5783</td>
</tr>
<tr>
<td>0.8</td>
<td>15,084,712</td>
<td>8,192,518</td>
<td>242</td>
<td>165</td>
<td>244</td>
<td>0.5856</td>
<td>0.5522</td>
<td>0.5287</td>
<td>0.4286</td>
<td>0.6265</td>
</tr>
<tr>
<td>0.9</td>
<td>15,135,416</td>
<td>8,147,932</td>
<td>245</td>
<td>165</td>
<td>236</td>
<td>0.5624</td>
<td>0.6091</td>
<td>0.4943</td>
<td>0.4286</td>
<td>0.5301</td>
</tr>
<tr>
<td>1</td>
<td>15,128,432</td>
<td>8,256,813</td>
<td>251</td>
<td>161</td>
<td>230</td>
<td>0.5656</td>
<td>0.4701</td>
<td>0.4253</td>
<td>0.3766</td>
<td>0.4578</td>
</tr>
</tbody>
</table>

As it can be inferred from Table 5.6, Table 5.7, and Table 5.8, the objective functions are improved by increasing the $\beta$ value. The objective values of minimum function decreased and maximum functions increased by increasing the value of $\beta$. The obtained results indicate that the TH method gave the best objective function values.

The results of the sensitivity analysis demonstrate that the TH approach is the most suitable method to solve FMOMILP model of sustainable CLSC network design problem compared to the other interactive fuzzy programming approaches, at least for the examined problem. Consistent solutions can be obtained by TH approach by decision maker’s preferences. The TH method is less sensitive to $\gamma$ values than LZL and SO methods. The TH method has flexibility in comparison with other interactive fuzzy programming approaches. The TH method is more robust and reliable than the LZL and SO methods. In addition, the results obtained from LZL and SO methods are unbalanced and poorly compromised while they take into account efficient solutions. These solutions are not acceptable by decision makers.
5.6. Conclusions

This Chapter introduced an FMOMILP model for sustainable CLSC network design problem under uncertainty. A two-phase procedure was presented: (1) a weighted average method (Lai and Hwang, 1992) to convert the FMOMILP model into an equivalent auxiliary crisp MOMILP model; (2) fuzzy programming approaches were implemented and analyzed: the LZL approach of Li et al. (2006), the SO of Selim and Ozkarahan (2008), and TH of Torabi and Hassini (2008). The obtained results demonstrated the TH approach achieve more appropriate solutions than other fuzzy programming methods.

Various sources of uncertainties were taken into account: customer demand, return rates, and facilities’ capacity. Three conflicting objective functions (cost, environmental, and societal) were considered simultaneously. Three commonly used fuzzy programming approaches were employed and compared. Furthermore, a comprehensive sensitivity analysis was carried out on basic parameters of these fuzzy programming approaches.

Even with significant practical and theoretical advantages of the proposed approach, there are some limitations. The software package (CPLEX) (IBM) was employed to solve a small experiment which is not applicable in large-scaled problems cannot be applicable. Hence, the development of an efficient meta-heuristic algorithm to solve this model explored. The implementation of the proposed model and solution approach to a real industrial case should also be considered. For further studies, it is recommended that other fuzzy programming approaches be compared with reference to the practiced methods in this paper to solve sustainable CLSC network design problem. Using other membership functions are also recommended for future investigation.
In Chapters 4 and 5, small-sized experiments were solved using commercial software (CPLEX). The problems of sustainable CLSC network design in large systems cannot be solved by analytical methods and commercial software due to NP-hardness of problem. The next Chapter presents a meta-heuristic algorithm to solve large cases.
CHAPTER SIX: USING MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS TO SOLVE LARGE PROBLEMS OF SUSTAINABLE CLOSED-LOOP SUPPLY CHAIN NETWORK DESIGN

6.1. Introduction
In Chapter 3, a deterministic mixed integer linear integer programming was proposed to optimize a CLSC network design. In Chapter 4, sustainability and uncertainty were added to this problem. A Fuzzy multi objective mixed integer linear programming model was proposed for designing a sustainable CLSC network. In Chapter 5, three fuzzy programming approaches were utilized to solve an FMOMILP model and the performance of those were analyzed. In Chapters 3, 4, and 5, commercial software (CPLEX) was employed to find solutions for small cases. However, this commercial software is not effective in solving large-sized problems, because it cannot yield solutions efficiently for an NP-hard (nondeterministic polynomial-time hard) problem (Soleimani and Kannan 2015). CPLEX relies on linear programming. For a large problem, it becomes difficult to meet all the objectives and constraints, and even if they can be met the computing demands, in terms of storage and processing time, become excessive. This Chapter attempts to overcome this difficulty by relying on meta-heuristic solution methods.

The expansive nature of closed loop supply chain networks design lends it to being as an NP-hard problem (Soleimani and Kannan 2015), i.e. Achieving reliable and efficient solutions within a practical time becomes more important when dealing with real industrial problems. As indicated by Athan and Papalambros (1996) and Chen et al.
(2000), for this kind of problem there is a set of Pareto (near) quasi-optimal solutions. All Pareto quasi-optimal solutions lie on the boundary of the feasible criterion space.

Meta-heuristic approaches are commonly used for the NP-hard problems. Therefore, multi-objective meta-heuristic approaches are found suitable for solving problem of sustainable CLSC network design. Since all objectives cannot be optimized simultaneously; a Pareto set of quasi (near) optimal solutions (objective functions) is obtained. In Multi-Objective Evolutionary Algorithms (MOEA) (Coello et al., 2007), such solution set is just called Pareto optimal solutions, and the entire set of solutions are considered “sufficiently good” for the problem. Normally, a decision maker selects from the Pareto set a solution based on some secondary criteria related to the problem being considered.

In this Chapter, an Non-dominated Sorting Genetic Algorithm (NSGA-II) (Deb et al., 2002) algorithm is adopted to find the Pareto-optimal sets for problem of sustainable CLSC network design. This method is used because of its simplicity and efficiency, in comparison to analytical methods and other meta-heuristics algorithms. The NSGA-II is currently one of the most popular MOEAs, used for different multi-objective problems (Pasandideh et al., 2015; Memari et al., 2017; Rahmati et al., 2014; Sadeghi et al., 2014; Mousavi et al., 2016; Kayvanfar et al., 2011). The complexity of this algorithm is, at most $O(MN^2)$, where $M$ is number of objectives and $N$ is population size. One of the other advantages of this algorithm is it ensures diversity among non-dominated solutions (Deb et al., 2002). For the purpose of validating the results another Non-dominated Ranking Genetic Algorithm (NRGA) (Rabiee et al., 2012) is developed and the results are compared. This validation method is suggested by Pasandideh et al. (2015), Memari
et al. (2016), Rahmati et al. (2014), Sadeghi et al. (2014), and Mousavi et al. (2016). To demonstrate the effectiveness of the method, numerical examples are presented. The validation of results are examined utilizing simple additive weighting and T-test methods based on measures of objective function values, spacing index, number of Pareto solutions, and CPU time index. Moreover, also a small example is solved by the CPLEX software. Here, a solution from the CPLEX set of quasi Pareto-optimal solutions is chosen based on additional criteria; i.e. a satisfaction degree condition. Then, the obtained Pareto quasi optimal set from the NSGA-II algorithm is compared with the selected solution (the “best” one) from the CPLEX. This comparison is somewhat extreme, in the sense that is done by comparing an entire set of solutions from the NSGA-II (without considering any additional criteria) with respect to only one from the CPLEX that is selected based on additional criteria.

6.2. Problem formulation

Figure 6.1 demonstrates the proposed structure of the multi echelon, multi period CLSC network studied in this Chapter. Four layers in the forward logistics, suppliers, producers, distributors, and customer centers are taken into account. In addition, in the reverse logistics, there are four layers, collection & inspection, disposal, recycling, and repairing centers. The assumptions in Section 4.2 were also adopted for this network. The notations, parameters, and decision variables of presented model in this Chapter are represented in Appendix D.
6.2.1. Objective functions

Three objective functions, minimize cost \((Z_1)\), minimize environmental impacts \((Z_2)\), and maximize social impacts are established for the proposed multi-echelon and multi-period CLSC model. These objective functions are presented by the following equations:

\[
\text{Min } C = \sum_{p} \sum_{t} FC_p OP_{tp} + \sum_{d} \sum_{t} FC_d OD_{td} + \sum_{i} \sum_{t} FC_i OL_{ti} + \sum_{m} \sum_{t} FC_m OM_{mt} + \sum_{t} \sum_{l} FC_l OL_{tl} + \sum_{k} \sum_{t} FC_k OK_{tk} + \sum_{p} \sum_{d} \sum_{t} MC_{tp} QS_{tpd} + \sum_{i} \sum_{t} \sum_{l} RC_{ti} QS_{til} + \sum_{k} \sum_{i} \sum_{t} BC_{tk} QS_{tki} + \sum_{m} \sum_{t} \sum_{l} DC_{im} QS_{tim} + \sum_{d} \sum_{t} \sum_{c} TC_{pd} QS_{pd} + \sum_{i} \sum_{t} \sum_{l} TC_{dc} QS_{dci} + \sum_{k} \sum_{l} \sum_{t} TC_{ci} QS_{ci} + \sum_{i} \sum_{m} \sum_{t} TC_{im} QS_{im} + \sum_{i} \sum_{l} \sum_{t} TC_{il} QS_{ili} + \sum_{i} \sum_{k} \sum_{t} TC_{ik} QS_{iki} + \sum_{i} \sum_{d} \sum_{t} TC_{kd} QS_{kdi} + \sum_{s} \sum_{p} \sum_{t} TC_{sp} QS_{sp} \]

\[(6.1)\]
The first objective function calculates total cost of the CLSC model. This objective function consists of fixed costs of establishing facilities (first six terms), manufacturing, recycling, repairing, and disposal costs (seventh to tenth terms), and transportation costs (eleventh to eighteenth terms). The second function is related to environmental impacts objective function of the CLSC network. The first and second terms are the environmental impacts producing goods by producers and disposing of returned products by disposal centers. The rest terms in this objective function stand for the environmental impacts of shipping products between facilities. The social impacts of CLSC network design is formulated by the third function. Fixed and variable job opportunities are measures we considered for social impact objective function. In this objective function,
the seventh to twelfths terms stand for the created variable jobs. It should be noted that variable jobs depend on the applied capacity of facilities.

6.2.2. Constraints

\[
\sum_{p} Q_{sp}^t \leq O_{s}^t \bar{C}_{s}^t \quad \forall s, t \tag{6.4}
\]

\[
\sum_{d} Q_{pd}^t \leq O_{p}^t \bar{C}_{p}^t \quad \forall p, t \tag{6.5}
\]

\[
\sum_{p} Q_{pd}^t + Q_{kd}^t \leq O_{d}^t \bar{C}_{d}^t \quad \forall d, t \tag{6.6}
\]

\[
\sum_{c} Q_{ci}^t \leq O_{l}^t \bar{C}_{l}^t \quad \forall i, t \tag{6.7}
\]

\[
\sum_{i} Q_{im}^t \leq O_{m}^t \bar{M}_{m}^t \quad \forall m, t \tag{6.8}
\]

\[
\sum_{s} Q_{ls}^t \leq O_{l}^t \bar{L}_{l}^t \quad \forall l, t \tag{6.9}
\]

\[
\sum_{p} Q_{sp}^t = \sum_{d} Q_{pd}^t \quad \forall p, t \tag{6.10}
\]

\[
\sum_{k} Q_{kd}^t + \sum_{p} Q_{pd}^t = \sum_{c} Q_{dc}^t \quad \forall d, t \tag{6.11}
\]

\[
\sum_{c} Q_{ci}^t = \sum_{m} Q_{im}^t + \sum_{l} Q_{li}^t + \sum_{k} Q_{ik}^t \quad \forall i, t \tag{6.12}
\]

\[
\sum_{i} Q_{il}^t = \sum_{c} Q_{ci}^t R_{Y}^t \quad \forall i, t \tag{6.13}
\]

\[
\sum_{i} Q_{il}^t = \sum_{s} Q_{ls}^t \quad \forall l, t \tag{6.14}
\]

\[
\sum_{k} Q_{ik}^t = \sum_{c} Q_{ci}^t R_{V}^t \quad \forall i, t \tag{6.15}
\]

\[
\sum_{i} Q_{ik}^t = \sum_{d} Q_{kd}^t \quad \forall k, t \tag{6.16}
\]

\[
\sum_{m} Q_{im}^t = \sum_{c} Q_{ci}^t R_{D}^t \quad \forall i, t \tag{6.17}
\]
$$\sum_d QS_{dc}^t = \bar{D}E_c^t \quad \forall c, t$$  \hfill (6.18)

$$\sum_i QS_{ci}^t = \bar{D}E_i^t \ast \bar{y}_c^t \quad \forall c, t$$  \hfill (6.19)

$$\sum_s OS_s^t \leq S \quad \forall t$$  \hfill (6.20)

$$\sum_P OP_p^t \leq P \quad \forall t$$  \hfill (6.21)

$$\sum_d OD_d^t \leq D \quad \forall t$$  \hfill (6.22)

$$\sum_l OL_l^t \leq I \quad \forall t$$  \hfill (6.23)

$$\sum_m OM_m^t \leq M \quad \forall t$$  \hfill (6.24)

$$\sum_l OL_l^t \leq L \quad \forall t$$  \hfill (6.25)

$$\sum_k OK_k^t \leq K \quad \forall t$$  \hfill (6.26)

$QS_{sp}^t, QS_{pd}^t, QS_{dc}^t, QS_{ci}^t, QS_{im}^t, QS_{it}^t, QS_{ik}^t, QS_{il}^t, QS_{kd}^t \geq 0 \quad \forall i, j, k, l, m, p, t, c, d$  \hfill (6.27)

$OS_s^t, OP_p^t, OD_d^t, OL_l^t, OM_m^t, OL_l^t, OK_k^t \in \{0,1\} \quad \forall i, j, k, l, m, p, s, t, d$  \hfill (6.28)

Constraint (6.4) guarantees that the capacity of suppliers meet the sum of the flow exiting from suppliers to all producers, in each period. Constraint (6.5) shows that, in each period, the sum of the flow exiting from producers to distributors does not exceed the production capacity of plants. Constraint (6.6) ensures that in each period the sum of the flow entering from producers and repairing centers to distributors does not exceed the relevant capacity. Constraint (6.7) states that the all returned products from customer centers which are entered to collection and inspection centers do not exceed the relevant capacity. Constraint (6.8) ensures that the sum of the flow entering from collection and
inspection centers to disposal centers does not exceed the disposing capacity of disposal centers. Constraint (6.9) guarantees that the sum of the flow exiting from recycling centers to suppliers does not exceed the recycling capacity of recycling centers. Constraint (6.10) shows that the flow entering from suppliers to producers is equal to sum of the existing from plants to distributors at each period. Constraint (6.11) guarantees that in each period, the sum of the flow entering from plants and repairing centers to distributors is equal to sum of the existing from distributors to customer centers. Constraint (6.12) states that in each period, the sum of the flow entering from customer centers to collection and inspection centers is equal to existing from collection and inspection centers to recycling, repairing, and disposal centers. Constraints (6.13) and (6.14) guarantees that in each period, all collected products from customer centers which are entered to recycling centers after required activities are delivered to suppliers. Constraints (6.15) and (6.16) ensures that in each period, all collected products from customer centers which are entered to repairing centers after required repair activities are sent to distributors. Constraint (6.17) states that in each period, all returned products which are sent to disposal centers are disposed. Constraints (6.18) ensure that all customer demands should be met in customer centers. Constraint (6.19) shows the amount of returned products which are collected from customer centers. Constraints (6.20)–(6.26) limit the maximum number of allowable locations. In fact, these constraints do not allow the supply chain to have more nodes than relative possible limitations. Constraints (6.27) and (6.28) represent the non-negativity and integrality of variables.
6.3. Auxiliary MOMILP

As seen from the proposed model for CLSC network design in Section 6.2, fuzzy parameters were employed in objective functions and constraints. For this reason, to solve this model, it should be firstly changed to deterministic model. In this Section, the method of Section 4.3 (Weighted Average Method) is employed to convert the FMOMILP model into an equivalent auxiliary crisp Multiple Objective Mixed Integer Linear Programming (MOMILP) model. The fuzzy objective function of social impacts (Eq. 6.3) is converted to the three crisp objectives:

Min \( (SI^m - SI^p) = Z_3 \)

\[
= \sum_{p} \sum_{t} F_{lp} OP_{pt}^f + \sum_{d} \sum_{t} F_{ld} OD_{dt}^f + \sum_{i} \sum_{t} F_{li} OI_{it}^f + \sum_{m} \sum_{t} F_{lm} OM_{mt}^f + \sum_{l} \sum_{t} F_{lj} OL_{lt}^f \\
+ \sum_{k} \sum_{t} F_{lk} OK_{kt}^f + \sum_{p} \sum_{d} \sum_{t} V_{lp} QS_{pd}^t / (CP_p^{t,m} - CP_p^{t,p}) + \sum_{d} \sum_{c} \sum_{t} V_{ld} QS_{dc}^t / (CD_d^{t,m} - CD_d^{t,p}) \\
- \sum_{c} \sum_{i} \sum_{t} V_{li} QS_{ci}^t / (CL_i^{t,m} - CL_i^{t,p}) + \sum_{k} \sum_{i} \sum_{t} V_{lk} QS_{ik}^t / (CK_k^{t,m}) \\
- CK_k^{t,p}) \tag{6.29}
\]

Max \( SI^m = Z_4 \)

\[
= \sum_{p} \sum_{t} F_{lp} OP_{pt}^f + \sum_{d} \sum_{t} F_{ld} OD_{dt}^f + \sum_{i} \sum_{t} F_{li} OI_{it}^f + \sum_{m} \sum_{t} F_{lm} OM_{mt}^f + \sum_{l} \sum_{t} F_{lj} OL_{lt}^f \\
+ \sum_{k} \sum_{t} F_{lk} OK_{kt}^f + \sum_{p} \sum_{d} \sum_{t} V_{lp} QS_{pd}^t / (CP_p^{t,m} - CP_p^{t,p}) + \sum_{d} \sum_{c} \sum_{t} V_{ld} QS_{dc}^t / CP_d^{t,m} \\
+ \sum_{c} \sum_{i} \sum_{t} V_{li} QS_{ci}^t / CL_i^{t,m} + \sum_{m} \sum_{t} \sum_{i} \sum_{t} V_{lm} QS_{im}^t / CM_m^{t,m} + \sum_{i} \sum_{t} \sum_{t} \sum_{t} V_{li} QS_{it}^t / CL_i^{t,m} \\
+ \sum_{k} \sum_{i} \sum_{t} V_{lk} QS_{ik}^t / CL_i^{t,m} \tag{6.30}
\]
\[
\text{Max} (S_I^o - S_I^m) = Z_5
\]

\[
= \sum_{p} \sum_{t} \sum_{d} F_{1d} O_{Pd}^t + \sum_{i} \sum_{t} F_{1i} O_{Ii}^t + \sum_{m} \sum_{t} F_{1m} O_{Mm}^t + \sum_{l} \sum_{t} F_{1l} O_{Ll}^t \\
+ \sum_{k} \sum_{t} F_{1k} O_{Kk}^t + \sum_{p} \sum_{d} \sum_{t} V_{1p} Q_{Sd}^t / (C_{Pd}^{t,o} - C_{Pd}^{t,m}) + \sum_{c} \sum_{d} \sum_{t} V_{1c} Q_{Sd}^t / (C_{Cd}^{t,o} - C_{Cd}^{t,m}) \\
+ \sum_{l} \sum_{d} \sum_{t} V_{1l} Q_{Sd}^t / (C_{Ld}^{t,o} - C_{Ld}^{t,m}) + \sum_{k} \sum_{c} \sum_{t} V_{1k} Q_{Sd}^t / (C_{Kd}^{t,o} - C_{Kd}^{t,m})
\]

The corresponding auxiliary crisp inequalities of constraints (6.4 – 6.9) and (6.18 – 6.19) are obtained based on the method presented in Section 4.3.1. In Chapters 4 and 5, the fuzzy programming approaches were used to solve the MOMILP model and solutions were provided by CPLEX software. Here, a multi-objective meta-heuristic algorithm is used to solve the MOMILP model for large cases, as explained below.

### 6.4. Solution approach

Two approaches can be used for solving complicated multi-objective optimization problems using evolutionary algorithms. In the first approach, a multi-objective problem is turned into a single-objective problem. The second approach creates multiple best (Pareto optimal) solutions for each objective and then finds the best solution among them.

The first approach, uses some multi-criteria decision making algorithm to transfer the problem into a single objective one (Hwang and Masud, 1979). Methods such as Genetic Algorithms (GA), simulated annealing (SA), imperialist competition algorithm (ICA), harmony search algorithm (HAS), and particle swarm optimization (PSO), can be used in this stage (Deb et al. 2000). In the second approach multi-objective evolutionary algorithms (MOEA), such as non-dominated sorting genetic algorithm (NSGA-II), non-dominated ranking genetic algorithm (NRGA), and multi-objective particle swarm
optimization (MOPSO), can be used to arrive at the solution set (Al Jadaan et al., 2006). MOEAs are preferred over SOEAs due to the speed of simulation; single simulation run is required to reach a solution (Pasandideh et al., 2015). Diversity and convergence distinguish the MOEAs from single-objective optimization algorithms. Diversity maintains variety among the Pareto-optimal set of solutions, while convergence aims at directing a solution to the optimal Pareto set (Deb et al., 2000). In this section, a multi-objective evolutionary algorithm (MOEA) is presented, among the MOEAs, the non-dominated sorting genetic algorithm (NSGA-II) is preferred. NSGA-II is commonly used for similar problems, (Mousavi et al. 2016). To validate the results, since no benchmark algorithms are available, this study applies a different GA-based algorithm, namely a non-dominated ranking genetic algorithm (NRGA). The validation process used in this work was suggested by Pasandideh et al. (2015), Memari et al. (2016), Rahmati et al. (2014), Sadeghi et al. (2014), and Mousavi et al. (2016).

6.4.1. NSGA II

NSGA II, developed by Deb et al. (2002), is an extension of the non-dominated sorting genetic algorithm (NSGA), (Srinivas and Deb, 1994), in which an extra sorting criterion was introduced. Both algorithms were developed to deal with multi-objective optimization problems, and both use Goldberg’s (Deb et al. 2002) non-domination criterion to rank the solutions. NSGA uses a fitness sharing parameter to control the diversity of solutions and is found to be highly sensitive to this parameter. Therefore, in NSGA II a crowding distance parameter, which is a second-order sorting criterion, was introduced to improve the efficiency of this method. NSGA-II is found to be faster and more reliable than NSGA. The detailed description of NSGA-II is as follows. First, it
generates a mating pool with binary tournament selection. Second, all the members go through a mutation and crossover processes. Third, a larger population is generated by merging the old solutions with the newly generated solutions. Fourth, the population is sorted based on the members’ rank and crowding distances. Finally, selected members that are sorted higher are kept and the rest are deleted. The previous steps are repeated until the stopping condition is met. The final non-dominated members create the Pareto frontier set for the multi-objective optimization problem. Figure 6.2 is a schematic representation of the described steps.

![Non-dominating sorting](Figure 6.2. Graphical representation of NSGA-II (Deb, 2001))

6.4.2. NRGA

The non-dominated ranking genetic algorithm (NRGA) is a commonly used MOEA algorithm, developed to deal with multi-objective optimization problems by creating a Pareto front optimal set (Rabiee et al., 2012). The NRGA mechanism is similar to that of
NSGA-II, except for the step in which the older members merge with the new generation in the mating pool. The selection process of old members in NRGA integrates a Pareto based population-ranking algorithm with a ranked-based roulette wheel (RBRW) selection process (Al Jadaan et al. 2009). By applying the RBRW operation, one of the fronts is selected and then within the selected front the same procedure is repeated. Therefore, the probability of the chosen front belonging to the best non-dominated set of the first front is the highest. Similarly the probability of selecting the solutions within a set of second front is higher than the third and so on.

6.4.3. Generic operators for GA-based algorithms

- Chromosome representation

In a genetic algorithm, a chromosome consist of a series of genes that are arranged sequentially where genes represent decision variables (James et al. 2005). The value of each gene is called “allele”. The code form is a significant part of GA which describes the chromosome. In this work, the matrix format is employed to represent the chromosome. Based on the proposed CLSC network structure, nine connections are defined to connect the utilities in this network. To produce each chromosome nine linear programming problems are solved. The purpose of solving the linear programming problems is to ensure that the chromosome is within a feasible region. For instance, a network with 3 suppliers and 4 producers, is defined by a 3*4 dimension matrix. (the numbers of rows (3) = number of suppliers and the numbers of columns (4) = numbers of producers). Figure 6.3 displays a graphical representation of the chromosome.
• Selection Strategy

The selection strategy in NSGA-II uses fast non-dominated sorting, density estimation, and crowded comparison operators (Deb et al. 2002). To classify the members in non-dominance levels, the fast non-dominated sorting operator is used. To find the density of solutions around a specific member in the population, the density estimation operator is used. And finally to ensure that members are selected from a uniform Pareto front the crowded comparison operator is applied (Deb et al. 2002). The binary tournament selection strategy is applied based on described operators to find solutions. In this process the rank and crowding distance of each member is considered for the selection.

• Crossover

Crossover operations in NSGA-II ensure that the new population is created by inheriting the good genes from the parents for the purpose of improving the chromosome. This happens by exploring the solution area, finding the high quality solutions, and creating a new generation from the parent generation. In this process, two chromosomes are selected to be the parent chromosomes. The previously described crowding selection operator is used for this process. The chance of new generation being the result of crossing the two chromosomes is called crossover chance. Commonly used crossover operators are: single-point, two-point, and multiple-point operators. However there are other methods for cross over operation such as partially mapped crossover (PMX), ordered crossover (OX), Cycle crossover (CX), and Arithmetic crossover (Deb et al.)

\[
\begin{array}{cccc}
S_1 & 200 & 200 & 150 & 100 \\
S_2 & 300 & 150 & 200 & 100 \\
S_3 & 200 & 100 & 150 & 200 \\
\end{array}
\]

Figure 6.3. Chromosome representation
The arithmetic crossover operator is commonly utilized for integer representations. Considering the type of defined problem in this study (Mixed Integer Programming), this operator is used for crossover. This method combines the parent chromosomes linearly to create the new generation using:

\[
\text{Offspring 1} = \alpha \times \text{parent 1} + (1-\alpha) \times \text{parent 2} \tag{6.32}
\]

\[
\text{Offspring 2} = (1- \alpha) \times \text{parent 1} + \alpha \times \text{parent 2} \tag{6.33}
\]

where \(0 < \alpha < 1\).

The chance of crossing the parents is indicated by \(P_c\) and it is considered high for values above 80% (Pasandideh et al., 2013). Figure 6.4. shows a graphical representation of the crossover operation:

- **Mutation**

Mutation happens after the crossover operation in NSGA-II. Similar to the crossover operator, mutation creates an area for further searching. The purpose of this step is to create diversity in the newly generated populations. Therefore, moving from the parent generation to the new generation, the mutation operator searches the new solution space.
This operator selects a chromosome and randomly chooses some genes and changes their values. The probability for this change is the mutation probability, \( P_m \). This process ensures that the new generations are not optimized within a local optimum area and further solutions are not excluded. Random resetting mutation, scramble mutation, flip bit, and uniform, inversion mutation, and mutation for decimal number, shift, and swap are examples of different mutation operators (Greenwell et al. 1995).

6.5. Numerical experiments

For the purpose of verifying the proposed meta-heuristic algorithms in this study, experiments with different properties are designed. Nine designed experiments were considered, ranging from small, medium, to large size problems, to show the performance of adopted meta-heuristics algorithms. The experiments were designed to imitate actual cases. The parameters in each problem were set by assigning values from a uniform distribution with lower and upper limits. Table 6.1 and Table 6.2 present the experiments and their assigned properties. In addition, the population number was 100, the generation number was 200, the crossover probability was 0.9, the mutation probability is 0.05. These parameters were chosen empirically based on trial and error, via a set of parameter-tuning experiments. All computational work was accomplished on a personal computer (32-bit operating system, 2.53 GHz CPU, and 4.00 GB) (Appendix E).
There are various metrics to assess the performance of MOEAs. This study applies three commonly used metrics (Mohtashami et al. 2015; Pasandideh et al. 2015; Memari et al. 2016; Azadeh et al. 2016; Rahmati et al. 2014).

- Spacing Index

This index takes the non-dominated vectors and calculates the variance of the distance of neighboring solutions (Deb, 2001):
\[ SI = \frac{1}{n} \sum_{i=1}^{n} \left| d_i - \bar{d} \right| \]  

(6.34)

with, \( d_i = \min \sqrt{\sum_{m=1}^{5} (f_m^i - f_m^k)} \) and \( \bar{d} = \frac{\sum_{i=1}^{n} d_i}{|n|} \), where \( \bar{d} \) indicates averages of distances and \( n \) indicates the Pareto set solutions, \( f \) represents the objective function values. Accordingly, \(|n|\) represents the cardinality of \( n \) is presented by \(|n|\) by and the number of objectives is presented by \( m \).

✓ Number of Pareto solution (NPS)

The NPS index measures how many Pareto solutions are found by each algorithm.

✓ CPUTI (CPU Time Index)

Measuring the speed of an algorithm with this index is in terms of CPU time needed to find the Pareto-optimal solution.

The NSGA-II and NRGA algorithms were compared based on the objective functions values: \( Z_1, Z_2 \) (Eqs. 6.1 and 6.2), \( Z_1, Z_2, Z_3 \) (Eqs. 6.29, 6.30, 6.31), SI, NPI, and CPUTI indexes. In every run, the algorithm finds a set of Pareto-optimal solutions. The objective functions are compared by taking the minimum values for \( Z_1, Z_2, \) and \( Z_3 \), and the maximum values for \( Z_4, Z_5 \). Table 6.3 Table 6.4 present the results for the 9 experiments by NSGA-II and NRGA.
Table 6.3. The NSGA II results of numerical experiments of Table 6.1

<table>
<thead>
<tr>
<th></th>
<th>$Z_1$</th>
<th>$Z_2$</th>
<th>$Z_3$</th>
<th>$Z_4$</th>
<th>$Z_5$</th>
<th>SI</th>
<th>NPI</th>
<th>CPUTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>24,611,010</td>
<td>1,575,001</td>
<td>469</td>
<td>449</td>
<td>453</td>
<td>72</td>
<td>8</td>
<td>207</td>
</tr>
<tr>
<td></td>
<td>25,192,232</td>
<td>1,513,117</td>
<td>497</td>
<td>471</td>
<td>469</td>
<td>96</td>
<td>12</td>
<td>205</td>
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<tr>
<td></td>
<td>24,817,245</td>
<td>1,561,114</td>
<td>475</td>
<td>445</td>
<td>455</td>
<td>536</td>
<td>7</td>
<td>209</td>
</tr>
<tr>
<td></td>
<td>73,934,328</td>
<td>4,027,728</td>
<td>1,185</td>
<td>1,109</td>
<td>1,173</td>
<td>409</td>
<td>5</td>
<td>267</td>
</tr>
<tr>
<td>Medium</td>
<td>71,819,429</td>
<td>4,011,342</td>
<td>1,019</td>
<td>1,022</td>
<td>1,135</td>
<td>382</td>
<td>13</td>
<td>270</td>
</tr>
<tr>
<td></td>
<td>71,127,814</td>
<td>4,203,279</td>
<td>1,195</td>
<td>1,127</td>
<td>1,163</td>
<td>331</td>
<td>10</td>
<td>275</td>
</tr>
<tr>
<td></td>
<td>152,596,807</td>
<td>8,813,690</td>
<td>2,213</td>
<td>2,077</td>
<td>2,193</td>
<td>2,032</td>
<td>7</td>
<td>327</td>
</tr>
<tr>
<td>Large</td>
<td>175,133,714</td>
<td>8,019,370</td>
<td>2,291</td>
<td>2,113</td>
<td>2,348</td>
<td>1,467</td>
<td>6</td>
<td>320</td>
</tr>
<tr>
<td></td>
<td>178,715,402</td>
<td>8,113,098</td>
<td>2,301</td>
<td>2,193</td>
<td>2,285</td>
<td>487</td>
<td>11</td>
<td>344</td>
</tr>
</tbody>
</table>

Table 6.4. The NRGA results of numerical experiments Table 6.1

<table>
<thead>
<tr>
<th></th>
<th>$Z_1$</th>
<th>$Z_2$</th>
<th>$Z_3$</th>
<th>$Z_4$</th>
<th>$Z_5$</th>
<th>SI</th>
<th>NPI</th>
<th>CPUTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>24,856,211</td>
<td>1,517,229</td>
<td>477</td>
<td>460</td>
<td>451</td>
<td>315</td>
<td>5</td>
<td>331</td>
</tr>
<tr>
<td></td>
<td>24,975,107</td>
<td>1,575,348</td>
<td>491</td>
<td>452</td>
<td>451</td>
<td>319</td>
<td>27</td>
<td>278</td>
</tr>
<tr>
<td></td>
<td>25,134,429</td>
<td>1,631,459</td>
<td>475</td>
<td>452</td>
<td>471</td>
<td>3</td>
<td>19</td>
<td>261</td>
</tr>
<tr>
<td>Medium</td>
<td>74,257,191</td>
<td>4,301,475</td>
<td>1,282</td>
<td>1,173</td>
<td>1,187</td>
<td>212</td>
<td>7</td>
<td>315</td>
</tr>
<tr>
<td></td>
<td>72,517,734</td>
<td>4,157,209</td>
<td>1,122</td>
<td>1,016</td>
<td>1,105</td>
<td>330</td>
<td>5</td>
<td>291</td>
</tr>
<tr>
<td></td>
<td>71,039,875</td>
<td>4,076,342</td>
<td>1,031</td>
<td>1,173</td>
<td>1,183</td>
<td>112</td>
<td>5</td>
<td>297</td>
</tr>
<tr>
<td>Large</td>
<td>155,375,108</td>
<td>7,955,179</td>
<td>2,347</td>
<td>2,015</td>
<td>2,017</td>
<td>767</td>
<td>3</td>
<td>512</td>
</tr>
<tr>
<td></td>
<td>175,917,335</td>
<td>8,243,341</td>
<td>2,375</td>
<td>2,025</td>
<td>2,027</td>
<td>12</td>
<td>10</td>
<td>447</td>
</tr>
<tr>
<td></td>
<td>177,009,375</td>
<td>8,279,351</td>
<td>2,410</td>
<td>2,001</td>
<td>2,255</td>
<td>1,103</td>
<td>10</td>
<td>420</td>
</tr>
</tbody>
</table>

The t-test was selected to examine the hypothesis as a common approach to test the equality of two populations based on parameters (Fisher Box, 1987). In fact, it is a commonly used parametric way to carry out a hypothesis test for the equality of two population means. The hypothesis for this test is that there is not significance difference between the results obtained by NSGA-II and NRGA for the same experiments. The t-test results did not reject the hypothesis, and showed that there was no significance difference between the two algorithms. Because, the $P$-value of all of these tests is larger than our considered significant level ($\alpha = 0.05$); the null hypothesis ($H_0: \mu_1 = \mu_2$) is not rejected. A small $P$-value ($\leq 0.05$) demonstrates strong evidence to reject the null hypothesis. Vice versa, a large $P$-value ($> 0.05$) shows weak evidence to reject the null hypothesis.
Therefore, The NSGA-II results were considered to be validated by comparing to those of NRGA.

| Table 6.5: The p-values of the t-tests on the equality of performance measures for comparison NSGA-II and NRGA |
|---------------------------------|--------|--------|--------|--------|--------|--------|--------|
| Z1    | Z2    | Z3    | Z4    | Z5    | SI     | NPI    | CPUTI  |
| P-value | 0.398 | 0.926 | 0.227 | 0.343 | 0.129  | 0.928  | 0.927  | 0.002  |

The validation of results was further examined using the simple additive weighting (SAW) introduced by Hwang and Yoon (1981), which is a Multi-attribute Decision Making (MADM) method. The SAW method works as follows. First, the decision matrix is normalized. The decision matrix, $D$, consists of 2 columns representing the algorithms (NSGA-II and NRGA) (i) and 8 rows for each index (j) ($Z_1, Z_2, Z_3, Z_4, Z_5, SI, NPI, and CPUTI$ indexes). The desirability of alternative $i$ in respect to index $j$ are the elements of $D$. In this problem, all indices had an equal weight (1/8) (8 is the number of performance measures) for better comparison between these two MOEAs. Then, the sum of each row was calculated and the algorithm with the highest sum was selected. Table 6.6 illustrates the total sum of weights for each algorithm, which suggests the superiority of NSGA-II for all problem indices. However, the results from NRGA are also satisfactory. Therefore, it can be concluded that while both NSGA-II and NRGA provide valid and satisfactory results, the NSGA-II is superior compared to NRGA.
Table 6.6: Simple additive weights (SAW) results for NSGA-II and NRGA algorithms for the problems of Table 6.1

<table>
<thead>
<tr>
<th></th>
<th>NSGA-II</th>
<th>NRGA</th>
<th>Preferred</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>0.9885</td>
<td>0.8059</td>
<td>NSGA-II</td>
</tr>
<tr>
<td></td>
<td>0.9279</td>
<td>0.8674</td>
<td>NSGA-II</td>
</tr>
<tr>
<td></td>
<td>0.8958</td>
<td>0.9615</td>
<td>NRGA</td>
</tr>
<tr>
<td>Medium</td>
<td>0.9829</td>
<td>0.8956</td>
<td>NSGA-II</td>
</tr>
<tr>
<td></td>
<td>0.8891</td>
<td>0.9282</td>
<td>NRGA</td>
</tr>
<tr>
<td></td>
<td>0.9100</td>
<td>0.8564</td>
<td>NSGA-II</td>
</tr>
<tr>
<td>Large</td>
<td>0.9375</td>
<td>0.8986</td>
<td>NSGA-II</td>
</tr>
<tr>
<td></td>
<td>0.9988</td>
<td>0.8754</td>
<td>NSGA-II</td>
</tr>
</tbody>
</table>

6.6. Validation of Results

In this Section, the performance of NSGA-II algorithm is validated for a small problem, solvable by the CPLEX commercial software. The first small example of Section 6.5 is solved by CPLEX (IBM) to ensure that the NSGA-II algorithm is correctly applied. Table 6.1 and Table 6.2 show the information of this small example (the first row of Table 6.1 represents the facilities number of this small example). It has 3 suppliers, 2 plants, 3 distributors, 4 customer centers, 3 collection centers, 2 repairing centers, 2 recycling centers, 2 disposal centers. The CPLEX software was first utilized to solve multi-objective problem of CLSC network design for this small example. A particular solution from the CPLEX set of the Pareto quasi optimal solutions is chosen. Such CPLEX solution is chosen based on an additional satisfaction degree condition. The objective function values of this solution are, \( Z_1 = 23,385,470; \) \( Z_2 = 1,491,358; \) \( Z_3 = 475; \) \( Z_4 = 491; \) \( Z_5 = 471. \) Also, this small example is solved by NSGA-II algorithm and a set of Pareto quasi optimal solutions is obtained. The objective functions values of these quasi-optimal solutions are shown in Table 6.7.
The Deviation Percent of Solutions (DPS) measure (Inghels et al., 2016) was employed to determine the distance between a Pareto-optimal solution and the obtained solution of CPLEX software.

\[
DPS_n = \left( \sum_{i=1}^{m} \frac{1}{m} |Z^n_i - Z^*_i| \right) \times 100
\]  

(6.35)

where \( n \) denotes the number of Pareto-optimal solutions (for this case, asset of 20 Pareto quasi optimal solutions are found (Table 6.7)), \( Z^n_i \) represents the \( i \)th objective function value of solution \( n \) that are calculated by NSGA-II (for example, the value of the first objective function from Pareto quasi optimal solution of \#1 \( Z^1_1 \) is 26,809,373), \( m \) shows the number of objective functions for each Pareto-optimal solution \((m=5\) for this case), and \( Z^*_i \) stands for \( i \)th objective function value which is provided by CPLEX software.

Table 6.7. Comparison of Pareto quasi optimal solutions from the NSGA-II for the small problem of Table 6.1 and CPLEX software (one solution of Pareto quasi optimal set)

<table>
<thead>
<tr>
<th>Pareto-optimal solutions</th>
<th>( Z_1 )</th>
<th>( Z_2 )</th>
<th>( Z_3 )</th>
<th>( Z_4 )</th>
<th>( Z_5 )</th>
<th>DPS(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>26,809,373</td>
<td>1,615,685</td>
<td>537</td>
<td>517</td>
<td>531</td>
<td>10.80</td>
</tr>
<tr>
<td>2</td>
<td>28,806,305</td>
<td>1,575,001</td>
<td>520</td>
<td>501</td>
<td>507</td>
<td>9.62</td>
</tr>
<tr>
<td>3</td>
<td>28,632,289</td>
<td>1,664,205</td>
<td>488</td>
<td>468</td>
<td>491</td>
<td>9.15</td>
</tr>
<tr>
<td>4</td>
<td>26,617,648</td>
<td>1,670,793</td>
<td>476</td>
<td>456</td>
<td>483</td>
<td>7.16</td>
</tr>
<tr>
<td>5</td>
<td>28,557,512</td>
<td>1,643,170</td>
<td>502</td>
<td>482</td>
<td>505</td>
<td>9.42</td>
</tr>
<tr>
<td>6</td>
<td>28,971,145</td>
<td>1,660,207</td>
<td>548</td>
<td>527</td>
<td>541</td>
<td>14.55</td>
</tr>
<tr>
<td>7</td>
<td>26,625,347</td>
<td>1,715,889</td>
<td>484</td>
<td>464</td>
<td>479</td>
<td>7.61</td>
</tr>
<tr>
<td>8</td>
<td>26,248,078</td>
<td>1,751,576</td>
<td>473</td>
<td>452</td>
<td>477</td>
<td>7.87</td>
</tr>
<tr>
<td>9</td>
<td>26,887,779</td>
<td>1,662,599</td>
<td>516</td>
<td>496</td>
<td>501</td>
<td>8.51</td>
</tr>
<tr>
<td>10</td>
<td>26,960,922</td>
<td>1,585,321</td>
<td>521</td>
<td>501</td>
<td>533</td>
<td>9.27</td>
</tr>
<tr>
<td>11</td>
<td>28,826,536</td>
<td>1,706,797</td>
<td>539</td>
<td>518</td>
<td>513</td>
<td>13.12</td>
</tr>
<tr>
<td>12</td>
<td>26,527,504</td>
<td>1,674,493</td>
<td>494</td>
<td>473</td>
<td>487</td>
<td>7.33</td>
</tr>
<tr>
<td>13</td>
<td>28,494,861</td>
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<td>500</td>
<td>480</td>
<td>481</td>
<td>8.71</td>
</tr>
<tr>
<td>14</td>
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<td>546</td>
<td>526</td>
<td>540</td>
<td>14.35</td>
</tr>
<tr>
<td>15</td>
<td>24,611,010</td>
<td>1,717,399</td>
<td>494</td>
<td>474</td>
<td>485</td>
<td>6.17</td>
</tr>
<tr>
<td>16</td>
<td>26,822,404</td>
<td>1,633,188</td>
<td>486</td>
<td>466</td>
<td>492</td>
<td>7.22</td>
</tr>
<tr>
<td>17</td>
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<td>1,674,727</td>
<td>544</td>
<td>523</td>
<td>522</td>
<td>11.78</td>
</tr>
<tr>
<td>18</td>
<td>28,684,880</td>
<td>1,618,782</td>
<td>510</td>
<td>490</td>
<td>497</td>
<td>8.87</td>
</tr>
<tr>
<td>19</td>
<td>28,822,509</td>
<td>1,666,277</td>
<td>528</td>
<td>508</td>
<td>501</td>
<td>11.21</td>
</tr>
<tr>
<td>20</td>
<td>26,663,697</td>
<td>1,580,689</td>
<td>470</td>
<td>450</td>
<td>475</td>
<td>6.08</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>316</strong></td>
<td><strong>352</strong></td>
<td><strong>537</strong></td>
<td><strong>517</strong></td>
<td><strong>531</strong></td>
<td><strong>9.44</strong></td>
</tr>
</tbody>
</table>
(The $Z$ values of CPLEX solution are: $Z_1 = 23,385,470$; $Z_2 = 1,491,358$; $Z_3 = 475$; $Z_4 = 491$; $Z_5 = 471$)

The DPS values shown in Table 6.7 indicate that the set of Pareto quasi optimal solutions of NSGA-II algorithm are sufficiently good with respect to the “best” solution selected from the set yielded by the CPLEX. The average difference between the two solutions is 9.44%. The minimum DPS is related to Pareto-optimal solution #20 (6.08%).

It should be noted that the above comparison between the entire set of Pareto quasi optimal solutions of NSGA-II algorithm with respect to the “best” solution from the set of CPLEX Pareto quasi optimal solutions is somewhat extreme. That is, here an entire set of solutions from the NSGA-II without considering any secondary criteria, has been compared with respect to a “best” solution from the CPLEX set considering an additional criteria. Anyway, the calculated percentage of differences (the last column of Table 6.7) is reasonable.

Based on the above comparison in this Section and Section 6.5 (Comparison results of NSGA-II and NRGA algorithms) the performance of NSGA-II algorithm can be considered satisfactory for the problems of sustainable CLSC network design.

6.7. Conclusions

In this Chapter, a multi-objective genetic algorithm based on NSGA-II algorithm was developed to find Pareto fronts for the problem of sustainable CLSC network design. Since there was no benchmark for this problem, the obtained results were compared with the non-dominated ranking genetic algorithm (NRGA). Nine examples with different sizes of small, medium, and large were provided to demonstrate the efficiency of the algorithms. Eight performance measures ($Z_1$, $Z_2$, $Z_3$, $Z_4$, $Z_5$, SI, NPI, and CPUTI) were
employed to compare the performance of these algorithms. Two-sample tests were implemented to compare the differences between the eight performance measures for these two algorithms. SAW method was also used to determine which method is more preferable. The provided results showed that the NSGA II algorithm had better performance than NRGA. However, there were no significant differences between performance measures. In addition, the provided results by NSGA-II algorithm were compared with a solution of the commercial software CPLEX for a small case. The results showed the NSGA-II algorithm yielded sufficiently close solutions.

Several ways can be suggested to extend this study. At first, it suggested implementing other meta-heuristic algorithms, such as multi-objective harmony search (MOHS), multi objective simulated annealing (MOSA), and MOPSO. Second, using other mutation and crossover operators are also recommended. The implementation of the proposed model and solution approach to a real industrial case would also be a considerable extension of this study. Effect of the parameters and magnitude of uncertainties should be studied as well.

In Chapters 3, 4, 5, and 6, the focus has been on designing and optimizing closed-loop supply chain network. In next Chapter, an approach is proposed to evaluate and rank third-party reverse logistic providers (3PRLP) that play an important role in the performance of closed loop supply chain.
CHAPTER SEVEN: AN INTEGRATED FUZZY APPROACH TO PRIORITIZE THIRD-PARTY REVERSE LOGISTICS BASED ON SUSTAINABLE DEVELOPMENT PILLARS

7.1. Introduction
Reverse logistics is emerging as a useful tool to improve SCM because of the environmental, social as well as economic benefits of used products (Meade et al. 2007). In a Reverse Logistics (RL) process, returned products are collected and their quality and usability is inspected for classification into different categories, and send the used products to suitable centers for recycling, remanufacturing, reuse, or final disposal (Martin et al., 2010). Hence, enhancing efficiency in RL operations is recognized as a significant factor in promoting competitiveness, particularly when done while satisfying the three pillar of sustainable: reducing cost, minimizing environmental impact and meeting social expectations.

An RL processes could be adopted by outsourcing partial or overall RL operations to third-party reverse logistics providers (3PRLPs). Utilizing 3PRLPs can decrease the overall costs, uncertainty that results from some parameters such as return rates, increase flexibility, improve customer responsiveness, and satisfaction enables focusing on core competency, and release more capitals for manufacturers to invest in other sections (Kumari et al., 2015). However, a company has to have access to a reliable 3PRLP for the type of RL network required. In fact, evaluating and selecting the best 3PRLP is recognized as an important subject that can either jeopardize or improve the success of companies (Kafa et al. 2014).
Several studies investigated and prioritized 3PRLPs. Senthil et al. (2014) proposed an integrated approach using analytic hierarchy process (AHP) and fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for prioritizing the 3PRLP in the case of plastic recycling. Khodaverdi and Hashemi (2015) developed a multi-criteria decision making (MCDM) model for ranking third-party reverse logistics service providers, based on financial and environmental criteria. They combined AHP and a gray relational analysis model. An integrated approach of analytical network process (ANP) and balanced score card (BSC) model was introduced by Tjader et al. (2014) for selecting outsourcing strategies. Wang and Zhu (2011) adopted a fuzzy clustering analysis method to evaluate third party providers based on oil consumption, cleaning materials/clean energy use, and carbon emission. They employed this model to evaluate a 3PRLP to whom the transportation of an electronic product company was to be outsourced. A fuzzy AHP-PROMETHE (Preference Ranking Organization Method for Enrichment Evaluations) approach was proposed by Kafa et al. (2014) to evaluate 3PRPs according to sustainability criteria.

the evaluation of reverse logistic provider. The ANP model was employed by Meade and Sarkis (2002) for the selection of reverse logistics.

The above literature indicates that MCDM models used to evaluate and select 3PRLPs are based on quantitative criteria, as well as vague or imprecisely defined qualitative criteria; requiring a comprehensive approach that handles both types of criteria. To accommodate the uncertainty associated with the vagueness of qualitative criteria, fuzzy logic is integrated with MCDM models. High volume of calculations required in order to perform pair comparisons is recognized as the main disadvantage for Fuzzy Multi-criteria Decision-making (MCDM) methods (Orji and Wei, 2015).

In this Chapter, an approach based on Mamdani Fuzzy Inference System (FIS) is presented to prioritize 3PRLPs which is less computationally demanding than MCDM methods. If-then scenarios are employed to design rules of a FIS model. These scenarios are devised by experts, and such depend on modeling human reasoning and experience. The Experts’ knowledge about the problem is incorporated into the FIS system. This is a significant benefit of the proposed approach, in comparison with approaches which incorporate fuzzy set theory with multi-criteria decision-making models, such as Fuzzy AHP, Fuzzy ANP, and Fuzzy TOPSIS. The proposed approach also relieves decision makers from the high volume of necessary calculations to perform pair comparisons for Fuzzy MCDM models. In addition, the FIS model gives this opportunity to experts to choose different operators such as t-norms, s-norms, and defuzzification operators, which bring flexibility to the system (Orji and Wei, 2015).

The main goal of the present study is to develop a systematic approach to evaluate and select the best 3PRLP in a reverse logistics network which includes two main steps.
First, the Fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) (Dalalah et al. 2011) method is applied to identify the crucial criteria for 3PRLP evaluation. In this study, thirty eight criteria were recognized for sustainability dimensions, derive from existing literature. All criteria for evaluations are not equally influential. Therefore, a fuzzy DEMATEL method is employed to avoid criteria of low influence. The adopted Mamdani FIS model (Mamdani and Assilian, 1975) is then used to evaluate and prioritize 3PRLPs based on the sustainability criteria. Three fuzzy inference systems are designed to calculate the sustainability dimensions scores, FIS 1 for Cost, FIS 2 for Environmental, and FIS 3 for Social dimensions, respectively. Finally, the summation of obtained scores from sustainability dimensions is considered as the final score of 3PRLPs. The providers are prioritized based on these scores. Figure 7.1 displays an overall schematic of the proposed approach.

This approach is implemented for an actual industrial case to demonstrate its practicality, and a sensitivity analysis is performed to examine its robustness. To validate the Fuzzy DEMATEL-FIS approach of this Chapter, the evaluation of this case study is compared to that provided by a commonly used decision-making method (Fuzzy AHP-TOPSIS approach).
Figure 7.1. The framework of proposed approach to evaluate 3PRLPs
7.2. Sustainable reverse logistics criteria

Economic factors such as cost, economies of scale, processing parameters like flexibility, capacity, capability, resource capacity, quality of service, and other strategic, operational and tactical criteria, are commonly employed to evaluate 3PRLPs. Xiangru (2008) applied five criteria and fifteen sub-criteria to evaluate third-party reverse logistics providers: resource capacity, technical indicators, quality of service, experience index, and costs. Govindan and Murugesan (2011) suggested seven criteria; namely third-party logistics services, reverse logistics function, organizational role, user satisfaction, the impact of use of 3PL, organizational performance criteria, Information Technology (IT) applications and thirty-four sub-criteria.

However, sustainability also aims at decreasing the environmental impact of a supply chain system. Environmental criteria of sustainability should be used in decision making processes, supplier selection, supply chain management performance evaluation, and performance of supply chain management practices (Talebzadeh hosseini, 2015). Also, social responsibility must be also considered to meet the triple goals of sustainability. For this reason, triple aspects of sustainability are considered to evaluate 3PRLPs in this study. Different criteria for each dimension of sustainability are summarized in Tables 7.1 to Table 7.3. In Section 7.4.1 the Fuzzy DEMATEL method is utilized to find the most suitable criteria for each of sustainability dimensions (Cost, environmental, social) from among those of Tables 7.1 to 7.3.
### Table 7.1. Cost criteria

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Author</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timeliness of service/responsiveness ($CC_1$)</td>
<td>Senthil, et al. (2014); Govindan and Murugesan (2011); Liu and Wang (2009); Ha and Krishnan (2008)</td>
</tr>
<tr>
<td>Flexibility ($CC_2$)</td>
<td>Senthil, et al. (2014); Govindan and Murugesan (2011)</td>
</tr>
<tr>
<td>Quality of product ($CC_3$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>Customer satisfaction ($CC_5$)</td>
<td>Govindan and Murugesan (2011); Hendrik et al. (2006); Liu and Wang (2009)</td>
</tr>
<tr>
<td>Level of advanced equipment ($CC_6$)</td>
<td>Liu and Wang (2009); Xiangru (2008)</td>
</tr>
<tr>
<td>Transport capacity ($CC_7$)</td>
<td></td>
</tr>
<tr>
<td>Location ($CC_8$)</td>
<td>Senthil, et al. (2014);</td>
</tr>
<tr>
<td>Performance history ($CC_9$)</td>
<td>Senthil, et al. (2014); Xiangru (2008)</td>
</tr>
<tr>
<td>Network capacity ($CC_{10}$)</td>
<td>Xiangru (2008)</td>
</tr>
<tr>
<td>Reliability ($CC_{11}$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>Confidence ($CC_{12}$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>IT application ($CC_{13}$)</td>
<td>Senthil, et al. (2014); Govindan and Murugesan (2011)</td>
</tr>
<tr>
<td>Value-added services ($CC_{14}$)</td>
<td>Agrawal, et al. (2016); Liu and Wang (2009)</td>
</tr>
<tr>
<td>Response to claims ($CC_{15}$)</td>
<td>Liu and Wang (2009); Ha and Krishnan (2008); Xiangru (2008)</td>
</tr>
<tr>
<td>Green purchasing ($CC_{16}$)</td>
<td></td>
</tr>
</tbody>
</table>

### Table 7.2. Environmental criteria

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Author</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pollution control system ($EC_1$)</td>
<td>Agrawal, et al. (2016); Kafa et al. (2015); Kafa et al. (2015)</td>
</tr>
<tr>
<td>Environmental budget ($EC_2$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>Environmental certificate (ISO 14000, ..) ($EC_3$)</td>
<td>Agrawal, et al. (2016)</td>
</tr>
<tr>
<td>Green Transportation ($EC_4$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>Volume of wastes, air and water pollution ($EC_5$)</td>
<td>Agrawal, et al. (2016); Kafa et al. (2015)</td>
</tr>
<tr>
<td>Resource consumption (energy, water) ($EC_6$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>Energy usage from renewable sources ($EC_7$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>Employees &amp; customers’ satisfaction awareness on environmental issue ($EC_8$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>Green packaging ($EC_9$)</td>
<td></td>
</tr>
</tbody>
</table>
Table 7.3. Social criteria

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Author</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training programs ($SC_1$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>Employee satisfaction ($SC_2$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>Health and safety ($SC_3$)</td>
<td>Agrawal, et al. (2016); Kafa et al. (2015)</td>
</tr>
<tr>
<td>Knowledge management ($SC_4$)</td>
<td></td>
</tr>
<tr>
<td>Corporate image ($SC_5$)</td>
<td>Agrawal, et al. (2016)</td>
</tr>
<tr>
<td>Communities influence ($SC_6$)</td>
<td>Agrawal, et al. (2016)</td>
</tr>
<tr>
<td>Enterprise Alliance ($SC_7$)</td>
<td>Senthil, et al. (2014); Kafa et al. (2015)</td>
</tr>
<tr>
<td>Overall working relations ($SC_9$)</td>
<td></td>
</tr>
<tr>
<td>Employee moral ($SC_9$)</td>
<td>Govindan and Murugesan (2011); Hendrik et al. (2006)</td>
</tr>
<tr>
<td>Green reputation ($SC_{10}$)</td>
<td>Kafa et al. (2015)</td>
</tr>
<tr>
<td>Employment opportunities for local community ($SC_{11}$)</td>
<td>Xiangru (2008); Ha and Krishnan (2008)</td>
</tr>
<tr>
<td>Employment gender ratio ($SC_{12}$)</td>
<td>Ha and Krishnan (2008)</td>
</tr>
<tr>
<td>Direct &amp; indirect employees ratio ($SC_{13}$)</td>
<td>Ha and Krishnan (2008)</td>
</tr>
</tbody>
</table>

7.3. Fuzzy Inference System (FIS)

Fuzzy set theory allows partial set membership, rather than crisp set membership or non-membership (Zadeh, 1978). The method is useful for representing human reasoning (Ordoobadi, 2008). It is also recognized as a problem-solving methodology that enables decision makers to reach conclusions from imprecise, vague and uncertain information (Dweiri & Kablan, 2006). The fuzzy inference system (Mamdani and Assilian 1975) is one of the most practical tools proposed within the context of fuzzy set theory to employ nonlinear, but ill-defined, modeling of input variables to some output ones. The FIS model is implemented in a wide variety of industrial and management problems, which could not be solved using purely mathematical and purely logic-based approaches in system design. For example, Lin and Chen (2010) employed FIS model to monitor ecologically sensitive ecosystems in a dynamic semi-arid landscape from satellite imagery. Chen et al. (2010) recommended FIS as a powerful applicant for analysis of structural systems under external excitations. Lin et al. (2012) used FIS model to
potential hazard analysis and risk assessment of debris flows. Amindoust et al. (2012) presented a method based on fuzzy inference for ranking suppliers based on sustainably criteria. An integrated approach of FIS and life cycle assessment techniques was used to guess the environmental impacts in an environmental management system by Liu et al. (2013). Talebzadehhosseini (2015) employed fuzzy inference system to evaluate the sustainability performance of five supply chain management practices.

The basis of FIS is described as the output fuzzy variables derived from input fuzzy variables on the basis of a set of logic inference rules in linguistic terms. The rules of FIS model are adapted from the knowledge base of a fuzzy system (Mamdani and Assilian 1975; Chandima Ratnayake, 2014). In the FIS model, the input space and output space are defined as $U = U_1 \times U_2 \times \ldots \times U_n \subset R^n$ and $V \subset R$, respectively. A fuzzy rule base contains a set of fuzzy IF-THEN rules. The If-Then rules are recognized as the core of the FIS, and all other components such as membership functions implement these rules in a logical, practical and well-organized manner.

In the FIS model, to describe a mapping from fuzzy sets in the input universe of discourse $U \subset R^n$ to fuzzy sets in the output universe of discourse $V \subset R$, the fuzzy if-then rules are employed. In fact, these are defined based on fuzzy logic principles. The fuzzy IF-THEN rules are presented as (Balal et al., 2016):

$$R^{(1)}: \text{IF } x_1 \text{ is } F_1^l \text{ and } \ldots \text{ and } x_n \text{ is } F_n^l \text{ ; THEN } y \text{ is } G^l$$

(7.1)

where $F_i^l$ and $G^l$ are fuzzy sets in $U_n \subset R^n$, respectively, and $x = (x_1, x_2, \ldots, x_n)^T \in U$, and $y \in V$ are the input and output linguistic variables of the FIS. These linguistic variables are related to the input and output universes, respectively. It should be noted that the fuzzy
If-Then rules provide a suitable framework to integrate human experts’ knowledge. In Eq. (1), each fuzzy If-Then rule displays fuzzy set $F_1^l, F_2^l, \ldots, F_M^l \rightarrow G^l$ for $l = 1, 2, \ldots, M$; in the product space $U \times V$, where $M$ is the number of rules in the fuzzy rule base ($l = 1, 2, \ldots, M$) (Guimaraes and Lapa 2004). The fuzzy if-then rules also facilitate decision makers to integrate qualitative and quantitative data in a uniform manner (Bocaniala et al. 2004). In engineering systems, a fuzzifier and a defuzzifier model are added to FIS inputs and outputs, respectively. The fuzzifier maps crisp points in $U$ to fuzzy sets in $U$, and the defuzzifier maps fuzzy sets in $V$ to crisp points in $V$.

7.3.1. Mamdani FIS

The linguistic models (Mamdani-type) (Mamdani and Assilian 1975), the relational equation models (Pedrycz, 1983), and the Takagi–Sugeno–Kang models (Sugeno, 1985) are the main fuzzy logic modeling techniques. The antecedent and the consequence of Mamdani model are defined as fuzzy sets but those of Takagi–Sugeno–Kang models are defined as fuzzy and linear equations, respectively. Also, the Takagi–Sugeno–Kang models require a comprehensive knowledge from system to create a model with trustable solutions. The training process for Takagi–Sugeno–Kang models is not as easy as that of the Mamdani model (Pedrycz and Gomide, 2007). Hence, in this Chapter Mamdani-type is utilized for evaluating 3PRLPs. The details of Mamdani FIS method is presented in Appendix F.

7.4. Proposed approach

As seen from Figure 7.1, this approach is composed of two main steps. In the first step, a Fuzzy DEMATEL method is implemented to identify the important criteria for 3PRLPs evaluation considering defined industrial case in Section 7.5. In the second step, an
adopted Mamdani FIS model is proposed to evaluate and prioritize 3PRLPs based on the sustainability criteria.

7.4.1. Fuzzy DEMATEL

In this work, 38 criteria were recognized as the three sustainability dimensions (16 cost, 9 environmental, and 13 social criteria). All these criteria may not effective in evaluating 3PRLPs. Therefore, a fuzzy DEMATEL method is employed to identify which of these criteria is effective for ranking 3PRLPs. The original DEMATEL method is integrated by fuzzy logic in order to enable it to solve problems with imprecise values and high uncertainty (Dalalah et al. 2011). In this study, a modified fuzzy DEMATEL approach adapted from Dalalah et al. (2011) is employed.

The linguistic assessment terms provided by experts are expressed in terms of an \((n \times n)\) matrix, \(\tilde{Z}\) where \(n\) is the number of criteria. Linguistic terms are given in Table 7.4. The direct relation matrices are all calculated by holding a pair-wise comparison among the criteria themselves, in which, \(\tilde{Z}_{ij}\) displays the degree to which criterion \(C_i\) affects criterion \(C_j\):

\[
\tilde{Z} = \begin{bmatrix}
C_1 & \tilde{Z}_{12} & \cdots & \tilde{Z}_{1n} \\
\tilde{Z}_{21} & C_2 & \cdots & \tilde{Z}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{Z}_{n1} & \tilde{Z}_{n2} & \cdots & C_n
\end{bmatrix}
\]

(7.2)

where \(\tilde{Z}_{ij} = (z_{ij1}, z_{ij2}, \ldots, z_{ijn})\). Then, the normalized direct-relation fuzzy matrix \((\tilde{X})\) is given by Eq. (7.3):
Table 7.4. Linguistic terms for sustainability criteria ratings

<table>
<thead>
<tr>
<th>Linguistic variables</th>
<th>Fuzzy Numbers</th>
<th>Linguistic Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>No influence</td>
<td>1</td>
<td>(1, 1, 2)</td>
</tr>
<tr>
<td>Very low influence</td>
<td>3</td>
<td>(2, 3, 4)</td>
</tr>
<tr>
<td>Low influence</td>
<td>5</td>
<td>(4, 5, 6)</td>
</tr>
<tr>
<td>High influence</td>
<td>7</td>
<td>(6, 7, 8)</td>
</tr>
<tr>
<td>Very high influence</td>
<td>9</td>
<td>(8, 9, 10)</td>
</tr>
</tbody>
</table>

\[
\bar{X} = \begin{bmatrix}
\bar{x}_{11} & \bar{x}_{12} & \cdots & \bar{x}_{1n} \\
\bar{x}_{21} & \bar{x}_{22} & \cdots & \bar{x}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\bar{x}_{n1} & \bar{x}_{n2} & \cdots & \bar{x}_{nn}
\end{bmatrix}
\]

where

\[
\bar{x}_{ij} = \frac{\tilde{Z}_{ij}}{\bar{R}} = \left(\frac{Z_{ij,l}}{r_l}, \frac{Z_{ij,m}}{r_m}, \frac{Z_{ij,u}}{r_u}\right),
\]

\[
\bar{R} = (r_l, r_m, r_u) \text{ and }
\]

\[
rc = \max \left(\sum_{j=1}^{n} \tilde{Z}_{ij,s}\right) \quad \forall s = l, m, u
\]

A total-relationship fuzzy matrix \(\bar{T}\) is then formulated as (Dalalah et al., 2011):

\[
\bar{T} = \lim_{w \to \infty} (\bar{X} + \bar{X}^2 + \cdots + \bar{X}^w) = \bar{X}(I - \bar{X})^{-1}
\]

The \(\bar{T}\) matrix is expressed as:

\[
\bar{T} = \begin{bmatrix}
\bar{t}_{11} & \bar{t}_{12} & \cdots & \bar{t}_{1n} \\
\bar{t}_{21} & \bar{t}_{22} & \cdots & \bar{t}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\bar{t}_{n1} & \bar{t}_{n2} & \cdots & \bar{t}_{nn}
\end{bmatrix}
\]

where \(\bar{t}_{ij} = (t_{ij,l}, t_{ij,m}, t_{ij,u})\) is the overall influence rating of DM for each factor \(i\) against factor \(j\). Then, the sum of rows \(\bar{D}_i\) and sum of columns \(\bar{R}_i\) of the sub-matrices \(T_l, T_m, T_u\) are calculated (Dalalah et al., 2011):

\[
\bar{D}_i = \sum_{j=1}^{n} \bar{t}_{ij} \quad (i = 1, 2, \ldots, n)
\]

\[
\bar{R}_i = \sum_{j=1}^{n} \bar{t}_{ij} \quad (j = 1, 2, \ldots, n)
\]
The defuzzification of $\tilde{D}_i$ and $\tilde{R}_i$ ($\tilde{D}_i^{def}$ and $\tilde{R}_i^{def}$ respectively) are obtained according to the method of Yao and Wu (2000). Then, a diagram is formulated by mapping the ordered pairs of $(\tilde{D}_i^{def} + \tilde{R}_i^{def})$ and $(\tilde{D}_i^{def} - \tilde{R}_i^{def})$. The significance of the factors is express as:

$$\omega_i = \left\{ \left( \tilde{D}_i^{def} + \tilde{R}_i^{def} \right)^2 + \left( \tilde{D}_i^{def} - \tilde{R}_i^{def} \right)^2 \right\}^{\frac{1}{2}}$$

(7.8)

The final criteria weights can be calculated by the normalized values (Dalalah et al., 2011):

$$W_i = \frac{\omega_i}{\sum_{i=1}^{n} \omega_i}$$

(7.9)

The $\tilde{Z}$ matrix is constructed using linguistic assessment terms provided by experts, such as those listed in Table 7.4. Then, the normalized direct-relation matrix for the criteria is obtained using Eq. (7.3). Subsequently, Eq. (7.4) is used to construct the $\tilde{T}$ matrix. After calculation of $\tilde{D}_i$ and $\tilde{R}_i$, their defuzzification ($\tilde{D}_i^{def}$ and $\tilde{R}_i^{def}$ respectively) is obtained using Eq. (7.8). Then, a diagram is calculated by mapping the ordered pairs of $(\tilde{D}_i^{def} + \tilde{R}_i^{def})$ and $(\tilde{D}_i^{def} - \tilde{R}_i^{def})$. The weights of the cost criteria are obtained using Eqs. (7.8). Table 7.5 displays the prominence, relation and respective weights of the cost criteria. The same procedure is implemented to calculate and select the most significant environmental and social criteria for 3PRLPS evaluation.
Table 7.5: Total relationship matrix of cost criteria calculated based on Fuzzy DEMATEL

<table>
<thead>
<tr>
<th>Criteria</th>
<th>$R_{i1}^{def}$</th>
<th>$R_{i1}^{ref}$</th>
<th>$D_{i1}^{def} + R_{i1}^{ref}$</th>
<th>$D_{i1}^{def} - R_{i1}^{def}$</th>
<th>$W_i$</th>
<th>Selected criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CC_1$</td>
<td>8.3</td>
<td>7.3</td>
<td>15.6</td>
<td>1.0</td>
<td>0.062901</td>
<td></td>
</tr>
<tr>
<td>$CC_2$</td>
<td>7.8</td>
<td>6.9</td>
<td>14.7</td>
<td>0.9</td>
<td>0.059262</td>
<td></td>
</tr>
<tr>
<td>$CC_3$</td>
<td>8.8</td>
<td>8.1</td>
<td>16.9</td>
<td>0.7</td>
<td>0.068062</td>
<td>$CC_{r1}$</td>
</tr>
<tr>
<td>$CC_4$</td>
<td>8.3</td>
<td>7.8</td>
<td>16.1</td>
<td>0.5</td>
<td>0.064816</td>
<td></td>
</tr>
<tr>
<td>$CC_5$</td>
<td>6.7</td>
<td>6.8</td>
<td>13.5</td>
<td>-0.1</td>
<td>0.054324</td>
<td></td>
</tr>
<tr>
<td>$CC_6$</td>
<td>9.3</td>
<td>7.4</td>
<td>16.7</td>
<td>1.9</td>
<td>0.067632</td>
<td>$CC_{r4}$</td>
</tr>
<tr>
<td>$CC_7$</td>
<td>9.4</td>
<td>7.5</td>
<td>16.9</td>
<td>1.9</td>
<td>0.068432</td>
<td>$CC_{r3}$</td>
</tr>
<tr>
<td>$CC_8$</td>
<td>6.9</td>
<td>7.5</td>
<td>14.4</td>
<td>-0.6</td>
<td>0.057994</td>
<td></td>
</tr>
<tr>
<td>$CC_9$</td>
<td>8.0</td>
<td>7.4</td>
<td>15.4</td>
<td>0.6</td>
<td>0.062015</td>
<td></td>
</tr>
<tr>
<td>$CC_{10}$</td>
<td>8.1</td>
<td>7.4</td>
<td>15.5</td>
<td>0.7</td>
<td>0.062434</td>
<td></td>
</tr>
<tr>
<td>$CC_{11}$</td>
<td>7.8</td>
<td>6.1</td>
<td>13.9</td>
<td>1.7</td>
<td>0.056349</td>
<td></td>
</tr>
<tr>
<td>$CC_{12}$</td>
<td>7.6</td>
<td>6.8</td>
<td>14.4</td>
<td>0.8</td>
<td>0.058033</td>
<td></td>
</tr>
<tr>
<td>$CC_{13}$</td>
<td>7.9</td>
<td>8.1</td>
<td>16.0</td>
<td>-0.2</td>
<td>0.064387</td>
<td></td>
</tr>
<tr>
<td>$CC_{14}$</td>
<td>9.2</td>
<td>7.8</td>
<td>17.0</td>
<td>1.4</td>
<td>0.068637</td>
<td>$CC_{r2}$</td>
</tr>
<tr>
<td>$CC_{15}$</td>
<td>8.1</td>
<td>6.6</td>
<td>14.7</td>
<td>1.5</td>
<td>0.059458</td>
<td></td>
</tr>
<tr>
<td>$CC_{16}$</td>
<td>8.5</td>
<td>7.7</td>
<td>16.2</td>
<td>0.8</td>
<td>0.065266</td>
<td></td>
</tr>
</tbody>
</table>

Table 7.5 shows the cost criteria as ranked by the Fuzzy DEMATEL method based on weights. It should be noted this ranking is done by expert (thesis’ author) using Fuzzy DEMATEL method. We used Fuzzy DEMATEL to find the significant criteria for evaluating 3PRLPs. The obtained results from the cost criteria evaluation by Fuzzy DEMATEL method shows that four criteria have the highest effects on 3PRLPs evaluation according to experts’ opinions: “quality of product” ($CC_{r1}$), “value added services” ($CC_{r2}$), “transport capacity” ($CC_{r3}$), and “level of advanced equipment” ($CC_{r4}$). The same procedure was applied to find the important criteria for the environmental and social dimensions. Accordingly, “pollution control system” ($EC_{r1}$), “green transportation” ($EC_{r2}$), “environmental certificate” ($EC_{r3}$), and “energy usage from renewable sources” ($EC_{r4}$) were selected among criteria of environmental dimension. For the social dimension, “training programs” ($SC_{r1}$), “employment opportunities for local community” ($SC_{r2}$), “employment gender ratio” ($SC_{r3}$), and “employee moral” ($SC_{r4}$), were recognized as crucial criteria for prioritizing 3PRLPs.
7.4.2. FIS model

The operational steps of Mamdani FIS model to prioritize 3PRLPs are explained in the following sections.

Fuzzification

Several functional forms of the membership functions can be used to display fuzziness; for example, linear, concave, and exponential shaped functions. In this study, the linear triangular and linear trapezoidal membership functions, which are generally used in most studies (Pourjavad and Mayorga, 2017), are employed for fuzzification of inputs. It should be noted that the membership functions in this study are established based on the experts’ knowledge, data, and information extracted from previous assessments and existing documentation (Pourjavad and Mayorga, 2017).

As shown in Figure 7.1, three fuzzy inference systems (FIS 1, FIS 2, FIS 3) are allotted to sustainability dimensions. Four fuzzy sets of membership functions are taken into account for fuzzification of inputs of these FISs. The linguistic rating variables assigned to each of these input fuzzy sets are “very low”, “low”, “medium” and “high”, as shown in Table 7.6. Also, the linguistic rating variables assigned to output fuzzy sets of FISs are defined as “Worst”, “Very Poor”, “Poor”, “Fair”, “Good”, “Very Good”, and “Excellent”, as tabulated in Table 7.7.
Table 7.6. The linguistic terms for FISs inputs

<table>
<thead>
<tr>
<th>Linguistic variable</th>
<th>Fuzzy number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Low (VL)</td>
<td>(0, 0, 0.2, 0.4)</td>
</tr>
<tr>
<td>Low (L)</td>
<td>(0.2, 0.4, 0.4, 0.6)</td>
</tr>
<tr>
<td>Moderate (M)</td>
<td>(0.4, 0.6, 0.6, 0.8)</td>
</tr>
<tr>
<td>High (H)</td>
<td>(0.6, 0.8, 1, 1)</td>
</tr>
</tbody>
</table>

Table 7.7. The linguistic terms for 3PRLPs performance

<table>
<thead>
<tr>
<th>Linguistic variable</th>
<th>Fuzzy number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worst (W)</td>
<td>(0, 0, 0.05, 0.15)</td>
</tr>
<tr>
<td>Very poor (VP)</td>
<td>(0.1, 0, 0.2, 0.3)</td>
</tr>
<tr>
<td>Poor (P)</td>
<td>(0.2, 0.35, 0.35, 0.5)</td>
</tr>
<tr>
<td>Fair (F)</td>
<td>(0.3, 0.5, 0.5, 0.7)</td>
</tr>
<tr>
<td>Good (G)</td>
<td>(0.5, 0.65, 0.65, 0.8)</td>
</tr>
<tr>
<td>Very good (VG)</td>
<td>(0.7, 0.8, 0.8, 0.9)</td>
</tr>
<tr>
<td>Excellent (E)</td>
<td>(0.85, 0.95, 1.0, 1.0)</td>
</tr>
</tbody>
</table>

Defining fuzzy rules

Fuzzy rules are defined after the input variables membership functions are constructed, based on experts’ knowledge. Such rules are usually more suitably formulated in linguistic rather than in numerical terms, and they are often expressed as ‘If-Then’ rules, which are easily employed by fuzzy conditional statements. The If-Then fuzzy rules are of two sections; the phrases following the If statements are named premises while the Then section of the rule is named the conclusion. The fuzzy AND operator is implemented to join the premise variables. The combined premises generate the degree of membership and are the adaptability of the premises to the conclusion of the rule (Kaufmann et al. 2009). The conclusion of rules is a distinct numerical value that is a fuzzy singleton (Kaufmann et al., 2009). All rules that have any truth in their premises contribute to the fuzzy conclusion set. Each rule contributes to a degree that is a function of the degree to which its antecedent matches the input. This imprecise matching makes a basis for the interpolation between possible input states and serves to minimize the
number of the rules required to define the input-output relation (Pourjavad and Mayorga, 2017). The number of rules in the FIS model is calculated according to \( x^n \), in which \( x \) is the number of the input variables membership functions, and \( n \) is the number of input variables (Cornelissen et al. 2001). Based on the fuzzy sets of membership functions and input numbers of FISs, 256 rules are defined for each FIS of the current model.

Defuzzification
Integration of the identified fuzzy sets, based on the fuzzy rule and the related fuzzy area individually is done by the fuzzy interface engine. The proposed FIS model implements the ‘min-max inference’ process to compute the rule conclusions according to the system input values. This process provides a continuous output function and is easy to utilize. Another advantage of this process is its computational simplicity (Dweiri & Kablan, 2006). The obtained results from inference process are ‘fuzzy conclusions’. A defuzzification process is implemented to convert the fuzzy output into the crisp output. The center of area (COA), bisector of area (BOA), mean of maximum (MOM), smallest of maximum (SOM) and the largest of maximum (LOM) methods are used in the defuzzification process. In this work, the COA method is used for all FISs due to its simplicity. The COA method is mostly used for defuzzification process (Lin and Chen, 2010; Chen et al. 2010; Lin et al. 2012; Amindoust et al. 2012). The output membership functions are constructed using zero to one target range. The zero and one values are indicative of low and high values for sustainability dimensions, respectively.
7.5. Case study

The above approach was applied to evaluate 3PRLPs based on sustainability criteria through a case study an pipe & fitting outlet. Kooshan Etesal (KE) Company established in 1986 in the city of Isfahan, Iran. It produces propylene piping and fittings products to convey water. Sustainability rules and legislations were recognized by this company as important factors for its success due to increasing environmental concerns and pressures by customers. Consequently, this company decided to outsource some RL activities to 3PRLPs that meet sustainability criteria. Ten third-party reverse logistics providers (P1,….P10) were chosen by supply chain managers for evaluation based on sustainability criteria. Three academic experts and five senior industrial supply managers were asked to investigate these 3PRLPs, according to cost criteria (FIS 1), environmental criteria (FIS 2), and social criteria (FIS 3). The obtained results are displayed in Table 8. This table demonstrates the inputs of FIS 1, 2, and 3. It should be noted that the values of Table 7.8 are related to the KE Company. These values are based on supply chain managers’ opinions.

<table>
<thead>
<tr>
<th>Inputs</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
<th>P9</th>
<th>P10</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIS 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCr₁</td>
<td>0.59</td>
<td>0.57</td>
<td>0.63</td>
<td>0.59</td>
<td>0.54</td>
<td>0.48</td>
<td>0.60</td>
<td>0.55</td>
<td>0.39</td>
<td>0.46</td>
</tr>
<tr>
<td>CCr₂</td>
<td>0.55</td>
<td>0.40</td>
<td>0.57</td>
<td>0.35</td>
<td>0.48</td>
<td>0.46</td>
<td>0.51</td>
<td>0.38</td>
<td>0.51</td>
<td>0.39</td>
</tr>
<tr>
<td>CCr₃</td>
<td>0.49</td>
<td>0.44</td>
<td>0.37</td>
<td>0.27</td>
<td>0.36</td>
<td>0.48</td>
<td>0.54</td>
<td>0.36</td>
<td>0.41</td>
<td>0.50</td>
</tr>
<tr>
<td>CCr₄</td>
<td>0.54</td>
<td>0.49</td>
<td>0.60</td>
<td>0.46</td>
<td>0.53</td>
<td>0.39</td>
<td>0.55</td>
<td>0.37</td>
<td>0.33</td>
<td>0.48</td>
</tr>
<tr>
<td>FIS 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ECr₁</td>
<td>0.48</td>
<td>0.49</td>
<td>0.43</td>
<td>0.60</td>
<td>0.41</td>
<td>0.50</td>
<td>0.40</td>
<td>0.53</td>
<td>0.33</td>
<td>0.41</td>
</tr>
<tr>
<td>ECr₂</td>
<td>0.58</td>
<td>0.55</td>
<td>0.69</td>
<td>0.47</td>
<td>0.47</td>
<td>0.49</td>
<td>0.65</td>
<td>0.58</td>
<td>0.36</td>
<td>0.51</td>
</tr>
<tr>
<td>ECr₃</td>
<td>0.59</td>
<td>0.43</td>
<td>0.63</td>
<td>0.47</td>
<td>0.51</td>
<td>0.55</td>
<td>0.63</td>
<td>0.31</td>
<td>0.29</td>
<td>0.37</td>
</tr>
<tr>
<td>ECr₄</td>
<td>0.43</td>
<td>0.44</td>
<td>0.50</td>
<td>0.49</td>
<td>0.38</td>
<td>0.45</td>
<td>0.48</td>
<td>0.44</td>
<td>0.39</td>
<td>0.40</td>
</tr>
<tr>
<td>FIS 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SCR₁</td>
<td>0.61</td>
<td>0.49</td>
<td>0.44</td>
<td>0.51</td>
<td>0.42</td>
<td>0.37</td>
<td>0.51</td>
<td>0.54</td>
<td>0.31</td>
<td>0.49</td>
</tr>
<tr>
<td>SCR₂</td>
<td>0.33</td>
<td>0.32</td>
<td>0.49</td>
<td>0.49</td>
<td>0.50</td>
<td>0.50</td>
<td>0.38</td>
<td>0.58</td>
<td>0.49</td>
<td>0.51</td>
</tr>
<tr>
<td>SCR₃</td>
<td>0.60</td>
<td>0.44</td>
<td>0.38</td>
<td>0.43</td>
<td>0.39</td>
<td>0.48</td>
<td>0.46</td>
<td>0.58</td>
<td>0.29</td>
<td>0.61</td>
</tr>
<tr>
<td>SCR₄</td>
<td>0.46</td>
<td>0.54</td>
<td>0.61</td>
<td>0.55</td>
<td>0.47</td>
<td>0.29</td>
<td>0.34</td>
<td>0.46</td>
<td>0.38</td>
<td>0.64</td>
</tr>
</tbody>
</table>
The obtained results from show that provider 3 has the best performance based on “quality of product”, “value added services”, and “level of advanced equipment” criteria from cost dimension of sustainability and “green transportation”, “environmental certificate”, and “energy usage from renewable sources” criteria from environmental dimension. These results also reveal that for “quality of product”, “transport capacity”, and “level of advanced equipment” criteria, providers 7 and 1 got the second and third scores, respectively. But for “value added services” criterion, these two providers have a reverse ranking. In fact, the providers 7 and 1 have the third and second scores for this criterion. It should be noted that provider 4 has the worst performance for this criterion based on experts’ opinions.

For the criteria of “green transportation”, “environmental certificate” from the environmental dimension, providers 7 and 1 were ranked second and third respectively. As inferred from Table 7.8, provider 9 has the worst performance for “pollution control system”, “green transportation”, and “environmental certificate” criteria of environmental dimension. According to experts’ opinions, providers 4 and 5 obtained the highest and lowest scores for “pollution control system”, and “energy usage from renewable sources” respectively.

Also, the achieved results from evaluating the providers based on the social criteria indicate that provider 10 got the best performance for “employment gender ratio” and “employee moral” criteria. The highest scores for “training programs” and “employment opportunities for local community” criteria are allocated to providers 1 and 8 respectively. Also, the lowest scores for “training programs” and “employment gender ratio” are devoted to provider 9. These results also disclose that providers 2 and 6 have
the worst performance for “employment opportunities for local community” and “employee moral” according to experts’ opinions.

In accordance to the scheme of Figure 7.1, the obtained values from sustainability criteria (Table 7.8) were used as inputs of FISs. Then, the scores of sustainability dimensions were calculated based on designed FIS 1, 2, and 3. These scores display the performance of 3PRLPs based on cost as well as environmental and social dimensions (Table 7.9). Finally, the overall score of 3PRLPs was calculated using the summation of sustainability dimensions scores. Prioritizing the providers is done according to the overall score.

### Table 7.9. Final scores of sustainability dimensions (output of FISs) for ranking 3PRLPs of KE Co.

<table>
<thead>
<tr>
<th>Output</th>
<th>FIS 1</th>
<th>FIS 2</th>
<th>FIS 3</th>
<th>Final scores</th>
<th>Ranks</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>0.482</td>
<td>0.502</td>
<td>0.470</td>
<td>1.454</td>
<td>3</td>
</tr>
<tr>
<td>P2</td>
<td>0.398</td>
<td>0.439</td>
<td>0.420</td>
<td>1.257</td>
<td>7</td>
</tr>
<tr>
<td>P3</td>
<td>0.541</td>
<td>0.514</td>
<td>0.469</td>
<td>1.524</td>
<td>1</td>
</tr>
<tr>
<td>P4</td>
<td>0.461</td>
<td>0.501</td>
<td>0.462</td>
<td>1.424</td>
<td>4</td>
</tr>
<tr>
<td>P5</td>
<td>0.317</td>
<td>0.338</td>
<td>0.402</td>
<td>1.057</td>
<td>9</td>
</tr>
<tr>
<td>P6</td>
<td>0.361</td>
<td>0.387</td>
<td>0.416</td>
<td>1.164</td>
<td>8</td>
</tr>
<tr>
<td>P7</td>
<td>0.511</td>
<td>0.539</td>
<td>0.412</td>
<td>1.462</td>
<td>2</td>
</tr>
<tr>
<td>P8</td>
<td>0.471</td>
<td>0.428</td>
<td>0.477</td>
<td>1.376</td>
<td>5</td>
</tr>
<tr>
<td>P9</td>
<td>0.367</td>
<td>0.301</td>
<td>0.367</td>
<td>1.035</td>
<td>10</td>
</tr>
<tr>
<td>P10</td>
<td>0.402</td>
<td>0.419</td>
<td>0.519</td>
<td>1.340</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 7.9 displays the obtained outputs of FIS 1, 2, and 3 which present the performance of 3PRLPs based on cost, environmental, social dimensions. The achieved results from the summation of these scores show that provider 3 has the highest score among all providers. In fact, it ranked first among the providers. The favorable performance of this provider based on cost and environmental dimensions justifies its high rank. These results rank providers 7 and 1 as second and third respectively. Based
on obtained results, provider 7 ranked the highest for the environmental dimension. Provider 9 performed the worst and received the lowest scores in environmental and social dimensions. These results also disclose that provider 10 got the highest score in social dimension.

7.6. Sensitivity analysis
The effect of increasing the input values of model FISs (criteria of sustainability dimensions) on the 3PRLPs ranking was analyzed. The criteria values of the three pillars of sustainability, cost (FIS 1), environmental (FIS 2), and social (FIS 3) are increased twice with a 15%. Twenty four experiments were carried out for this sensitivity analysis. For instance, in experiment 3, the value of $C_{r3}$ and “transport capacity” was increased by 15% and the remaining criteria were not affected. Likewise, in experiment 18, the value of $E_{r2}$ “green transportation” was increased by 30%, while other criteria were unchanged. Table 7.10 and Figure 7.2 demonstrate the results of these experiments.
Table 7.10. Sensitivity analysis of sustainability criteria for ranking 3PRLPs

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Inputs</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
<th>P7</th>
<th>P8</th>
<th>P9</th>
<th>P10</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CCr1</td>
<td>1.468</td>
<td>1.260</td>
<td>1.524</td>
<td>1.428</td>
<td>1.069</td>
<td>1.182</td>
<td>1.472</td>
<td>1.376</td>
<td>1.065</td>
<td>1.345</td>
</tr>
<tr>
<td>2</td>
<td>CCr2</td>
<td>1.475</td>
<td>1.301</td>
<td>1.634</td>
<td>1.488</td>
<td>1.121</td>
<td>1.194</td>
<td>1.501</td>
<td>1.403</td>
<td>1.077</td>
<td>1.389</td>
</tr>
<tr>
<td>3</td>
<td>CCr3</td>
<td>1.451</td>
<td>1.269</td>
<td>1.525</td>
<td>1.471</td>
<td>1.109</td>
<td>1.180</td>
<td>1.481</td>
<td>1.381</td>
<td>1.061</td>
<td>1.377</td>
</tr>
<tr>
<td>4</td>
<td>CCr4</td>
<td>1.456</td>
<td>1.258</td>
<td>1.524</td>
<td>1.425</td>
<td>1.066</td>
<td>1.171</td>
<td>1.470</td>
<td>1.379</td>
<td>1.040</td>
<td>1.348</td>
</tr>
<tr>
<td>5</td>
<td>ECr1</td>
<td>1.475</td>
<td>1.292</td>
<td>1.619</td>
<td>1.460</td>
<td>1.108</td>
<td>1.191</td>
<td>1.491</td>
<td>1.420</td>
<td>1.092</td>
<td>1.370</td>
</tr>
<tr>
<td>6</td>
<td>ECr2</td>
<td>1.481</td>
<td>1.298</td>
<td>1.625</td>
<td>1.471</td>
<td>1.118</td>
<td>1.198</td>
<td>1.495</td>
<td>1.410</td>
<td>1.089</td>
<td>1.395</td>
</tr>
<tr>
<td>7</td>
<td>ECr3</td>
<td>1.481</td>
<td>1.281</td>
<td>1.529</td>
<td>1.453</td>
<td>1.110</td>
<td>1.187</td>
<td>1.480</td>
<td>1.421</td>
<td>1.055</td>
<td>1.375</td>
</tr>
<tr>
<td>8</td>
<td>ECr4</td>
<td>1.461</td>
<td>1.256</td>
<td>1.525</td>
<td>1.431</td>
<td>1.059</td>
<td>1.169</td>
<td>1.475</td>
<td>1.409</td>
<td>1.048</td>
<td>1.379</td>
</tr>
<tr>
<td>9</td>
<td>SCr1</td>
<td>1.460</td>
<td>1.258</td>
<td>1.525</td>
<td>1.429</td>
<td>1.059</td>
<td>1.164</td>
<td>1.465</td>
<td>1.376</td>
<td>1.035</td>
<td>1.344</td>
</tr>
<tr>
<td>10</td>
<td>SCr2</td>
<td>1.461</td>
<td>1.260</td>
<td>1.527</td>
<td>1.433</td>
<td>1.069</td>
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<td>1.475</td>
<td>1.381</td>
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<td>11</td>
<td>SCr3</td>
<td>1.455</td>
<td>1.257</td>
<td>1.525</td>
<td>1.424</td>
<td>1.059</td>
<td>1.171</td>
<td>1.463</td>
<td>1.379</td>
<td>1.035</td>
<td>1.340</td>
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<td>12</td>
<td>SCr4</td>
<td>1.454</td>
<td>1.260</td>
<td>1.528</td>
<td>1.424</td>
<td>1.057</td>
<td>1.166</td>
<td>1.463</td>
<td>1.377</td>
<td>1.035</td>
<td>1.340</td>
</tr>
</tbody>
</table>

As inferred from Table 7.10 and Figure 7.2, the cost and environmental criteria have more effect on ranking 3PRLPs. It can also be concluded that social criteria are not so important for ranking 3PRLPs according to experts’ opinions. The results obtained from this analysis also detail criteria importance of each dimension. According to Table 7.10 and Figure 7.2, the “value added service” criterion has the highest impact on 3PRLPs ranking among cost criteria. In addition, the “level of advanced equipment” has the lowest effect on this ranking. For environmental criteria, the “green transportation” and “energy usage from renewable sources” have the highest and lowest effects on 3PRLPs evaluation based on the experts’ opinions. These findings show increasing values of the
“employment opportunities for local community” and “employment moral” criteria from the social dimension cause the highest and lowest change on 3PRLP ranking.

7.7. Model verification
A commonly used decision-making method was utilized to validate FIS model introduced in this Chapter. The Fuzzy AHP-TOPSIS approach was used for this comparison. It is a pair-wise comparison-based model used to evaluate/rank decision making in several studies (Gumus, 2009; Choudhary and Shankar, 2012; Patil and Kant, 2014; Taylan et al. 2014; Vinodh et al., 2014). This approach is based on Fuzzy AHP and Fuzzy TOPSIS methods.
AHP (Saaty, 1980) is a quantitative technique which organizes a multi-attribute, multi-person and multi-period problem hierarchically to facilitate solutions. A fuzzy extension of AHP was developed to solve hierarchical fuzzy problems (Chamodrakas et al., 2010). The fuzzy AHP method, which is utilized in this Section, is based on the steps of Ayag (2005). Details of this method are presented in Appendix E.

The Fuzzy TOPSIS method was developed by Chen and Hwang (1992), with reference to Hwang and Yoon (1981). The fuzzy TOPSIS method is an integrated model that is used to solve actual application problems under a fuzzy environment (Baykasoglu et al., 2013). The steps of fuzzy TOPSIS method are explained in Appendix G.

The applied integrated Fuzzy AHP-TOPSIS approach in this Section includes several steps. Fuzzy DEMATEL was employed to find out the significant sustainability criteria by avoiding low influences. A hierarchy structure was formed such that the objective (select the best 3PRLPs) was at the first level, sustainability criteria at the second level, and third-party reverse logistic providers to outsource reverse activities at the third level. Then, the weights of the sustainability criteria were estimated by fuzzy AHP. Pair-wise comparison matrixes of experts’ evaluations were used to calculate criteria’ weights using triangular fuzzy numbers. Finally, the Fuzzy TOPSIS method was implemented to investigate and rank 3PRLPs based on sustainability criteria. The 3PRLPs were ranked based on closeness coefficients (CCi) values, calculated by Fuzzy TOPSIS in descending order. The CCi’s measure the distances to the fuzzy positive ideal solution and the fuzzy negative ideal solution, simultaneously. Table 7.11 shows the obtained results of fuzzy AHP-TOPSIS approach for ranking 3PRLPs.
Table 7.11. Results of Fuzzy AHP-TOPSIS approach for ranking 3PRLPs of KE Co

<table>
<thead>
<tr>
<th>Provider</th>
<th>$CC_i$</th>
<th>Ranks</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>0.9837</td>
<td>3</td>
</tr>
<tr>
<td>P2</td>
<td>0.9702</td>
<td>7</td>
</tr>
<tr>
<td>P3</td>
<td>0.9853</td>
<td>1</td>
</tr>
<tr>
<td>P4</td>
<td>0.9755</td>
<td>6</td>
</tr>
<tr>
<td>P5</td>
<td>0.9684</td>
<td>9</td>
</tr>
<tr>
<td>P6</td>
<td>0.9699</td>
<td>8</td>
</tr>
<tr>
<td>P7</td>
<td>0.9844</td>
<td>2</td>
</tr>
<tr>
<td>P8</td>
<td>0.9791</td>
<td>4</td>
</tr>
<tr>
<td>P9</td>
<td>0.9621</td>
<td>10</td>
</tr>
<tr>
<td>P10</td>
<td>0.9783</td>
<td>5</td>
</tr>
</tbody>
</table>

As seen Table 7.11 the provider #3 ranked the first, i.e. this provider has the best performance between providers for reverse operations. Providers 7 and 1 got the second and third ranks, respectively. The results from fuzzy AHP-TOPSIS approach also show providers 5 and 9 have the worst performance based on sustainability criteria.

A comparison between the results of Fuzzy AHP-TOPSIS and Fuzzy DEMATEL-FIS is shown in Table 7.12. The normalized values of $CC_i$ (Fuzzy AHP-TOPSIS approach) and FIS scores (Fuzzy DEMATEL-FIS approach) along with ranks are presented in Table 7.12.

Table 7.12. Comparison of Fuzzy DEMATEL-FIS and Fuzzy AHP-TOPSIS approaches for ranking 3PRLPs of KE Co.

<table>
<thead>
<tr>
<th>Provider</th>
<th>Normalized $CC_i$</th>
<th>Ranks</th>
<th>Normalized FIS score</th>
<th>Ranks</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>0.10082</td>
<td>3</td>
<td>0.11105</td>
<td>3</td>
</tr>
<tr>
<td>P2</td>
<td>0.09944</td>
<td>7</td>
<td>0.09601</td>
<td>7</td>
</tr>
<tr>
<td>P3</td>
<td>0.10098</td>
<td>1</td>
<td>0.11640</td>
<td>1</td>
</tr>
<tr>
<td>P4</td>
<td>0.09998</td>
<td>6</td>
<td>0.10876</td>
<td>4</td>
</tr>
<tr>
<td>P5</td>
<td>0.09925</td>
<td>9</td>
<td>0.08073</td>
<td>9</td>
</tr>
<tr>
<td>P6</td>
<td>0.09941</td>
<td>8</td>
<td>0.08890</td>
<td>8</td>
</tr>
<tr>
<td>P7</td>
<td>0.10089</td>
<td>2</td>
<td>0.11166</td>
<td>2</td>
</tr>
<tr>
<td>P8</td>
<td>0.10035</td>
<td>4</td>
<td>0.10509</td>
<td>5</td>
</tr>
<tr>
<td>P9</td>
<td>0.09861</td>
<td>10</td>
<td>0.07905</td>
<td>10</td>
</tr>
<tr>
<td>P10</td>
<td>0.10027</td>
<td>5</td>
<td>0.10234</td>
<td>6</td>
</tr>
</tbody>
</table>
As Table 7.12 shows, Provider #3 has the first rank based on both approaches. Also, provider #9 has the last rank among providers for these two approaches. These results show Providers 1, 2, 3, 5, 6, 7, and 9 have the same rank based on both approaches. Fuzzy AHP-TOPSIS and Fuzzy DEMATEL-FIS resulted in different rankings for 3 of the providers. Based on Fuzzy AHP-TOPSIS approach, Providers 4, 8, and 10 are ranked sixth, fourth, and fifth respectively, while by Fuzzy DEMATEL-FIS approach these providers are ranked fourth, fifth, and sixth. However, the calculated regression for normalized values (R-value = 0.94) show that there is not a significant difference between these two approaches for ranking 3PRLPs of KE company.

7.8. Managerial Implications
Several managerial implications for supply chain managers can be extracted from this study. Collaboration among 3PRLPs can be beneficial. The best practices of the successful unit can be shared among providers to improve their success rates. The proposed approach provides decision-makers with the opportunity of evaluating the sustainability criteria impact on ranking 3PRLPs. The obtained results of sensitivity analysis exhibit an insight into which criteria have the most crucial role in 3PRLPs investigation. The proposed approach is capable of taking into uncertainties managerial perceptions.

7.9. Conclusions
In this Chapter, an integrated approach was proposed for prioritizing 3PRLPs based on sustainability criteria using fuzzy DEMATEL and Mamdani FIS model. The fuzzy DEMATEL method was applied first to select the most important sustainability criteria. Then, an adopted Mamdani FIS model was performed to rank 3PRLPs. Three fuzzy
inference systems were modeled to calculate dimensions’ scores of sustainability. FIS 1, 2, and 3 were applied for cost, environmental, social dimensions respectively. For each FIS, four criteria were taken into account as inputs of the model. Finally, the summation of obtained scores from sustainability dimensions was assigned as final scores of 3PRLPs based on which the providers were ranked. The proposed approach was applied by a case study in which ten providers were evaluated for the reverse chain operations of a pipe and fitting manufacturer. Also, sensitivity analysis was performed to discuss and explain the proposed approach results. The achieved results revealed that the cost and environmental criteria have more impact on 3PRLPs’ ranking than on social criteria. Moreover, the achieved results of fuzzy DEMATEL-FIS approach in this Chapter were validated by Fuzzy AHP-TOPSIS approach. The obtained results showed there is small deviation among these two approaches for ranking 3PRLPs.

The approach introduced in this Chapter can help decision makers with the efficient conduct of reverse logistics operations, but it also provides a chance for them to visualize the effect of sustainability criteria on 3PRLPs prioritizing. Specialist’s judgments are kept in the knowledge base by this approach. It also involves both quantitative data and vague or imprecisely defined qualitative information.

While the proposed approach includes significant practical and theoretical advantages, it has some limitations. The proposed approach is rule-based, and adding the number of inputs or evaluation criteria increasingly changes the number of rules. Defining rules is the main limitation of this approach. In this study, 4 inputs were considered for each FIS which resulted in 256 rules. The number of rules will increase to 1024, if only one input is added to each model. In fact, rules increase exponentially if the
number of inputs increases for each model. Twelve criteria and three dimensions of sustainability were employed for prioritizing 3PRLPs, but other criteria can have an effect on the results. It is recommended to develop membership functions in a useful, well-organized and consistent manner with the help of data-driven models such as artificial neural networks. In this Chapter, a fuzzy DEMATEL method was employed to find the important criteria, while other MCDM methods could also be applied for this aim.
8.1. Summary
The objective of this thesis was to optimize the Closed Loop Supply Chain network design, considering sustainability and uncertainty. To this aim, several approaches along with different solution methodologies were proposed. In Chapter 1, the concepts of sustainable closed loop supply chain network design were presented. In Chapter 2, a review of supply chain network design problem was provided. Methods were reported based on five features: (i) Type of network (forward, reverse, closed) and considered components and flows; (ii) sustainability dimensions (considered objective functions); (iii) uncertainty; (v) modelling; (iv) solution methods.

In Chapter 3, a Mixed Integer Linear Programming (MILP) model was used to design a Closed-loop Supply Chain (CLSC) network in an actual industrial case (glass manufacturing) where location of facilities and the material flows in the entire network were determined. Both strategic and tactical decisions were incorporated. The CLSC network included five echelons (namely, suppliers, producers, warehouses, distributors, and customer zones) in the forward direction and seven echelons (i.e. collection & inspection centers, disposal centers, recycling centers, remanufacturing centers, recovering centers, redistributors, and second customers) in the reverse direction. A detailed sensitivity analysis was done to investigate effects of changing demands, capacity, and reverse rates on network total cost. In addition, the created optimum network for this industrial case was compared with the current operating conditions of an industrial case.
In Chapter 4, an Fuzzy Multi Objective Mixed Integer Linear Programming (FMOMILP) model was employed to design a sustainable CLSC network under a fuzzy environment. The model included three objective functions: minimization of total cost, minimization of environmental impacts, and maximization of social benefits. To cope with fuzziness in the model, a two-phase interactive fuzzy programming approach was developed. Two appropriate strategies were implemented to convert the fuzzy programming model into an auxiliary crisp MOMILP. Then, the approach by Torabi and Hassini (2008) was applied to solve this auxiliary model and obtain optimum solutions. Various sources of uncertainties were taken into account, such as demand, return rates, and capacity. Three conflicting objective functions (cost, environmental, and societal) were considered simultaneously, strategic and operational decisions were integrated into the model. To examine the significance of the proposed model and the solution approach, a computational experiment was conducted. In addition, the effect of uncertainty on the problem was studied.

In Chapter 5, three widely used interactive fuzzy programming approaches, Li, Zhang, and Li (LZL) approach (Li et al. 2006), the Selim and Ozkarahan (SO) approach (Selim and Ozkarahan, 2008), and Torabi and Hassini (TH) approach (Torabi and Hassini, 2008), were analyzed and compared.

In Chapter 6, a multi-objective genetic algorithm based on the NSGA-II algorithm was developed to find Pareto quasi (near) optimal solutions. The results were validated with the non-dominated ranking genetic algorithm (NRGA). Nine random examples with different sizes of small, medium, and large were studied. In addition, eight performance measures were employed to compare the performance of these algorithms. Two-sample
tests were implemented to compare the differences between the eight performance measures for these two algorithms. The SAW method was used to determine which method is more preferable. Furthermore, the results provided by the NSGA-II algorithm were compared with a (“best”) solution of the commercial CPLEX software considering an additional secondary condition for a small case.

In Chapter 7, an integrated approach was introduced for prioritizing 3PRLPs based on sustainability criteria using fuzzy DEMATEL and Mamdani FIS model. The fuzzy DEMATEL method was applied first to select the most important sustainability criteria. Then, an adopted Mamdani FIS model was performed to rank 3PRLPs. Three fuzzy inference systems were modeled to calculate dimensions scores of sustainability. FIS 1, 2, and 3 were applied for cost, environmental, social dimensions, respectively. For each FIS, four criteria were taken into account as inputs of the model. Finally, the summation of obtained scores from sustainability dimensions was assigned as final scores of 3PRLPs. The providers were ranked based on these scores. The approach was validated by a case study in which ten providers were evaluated for the reverse chain operations of a pipe and fitting manufacturer. Also, a sensitivity analysis was performed to discuss and explain the results.

8.2. Conclusions
The obtained results of Chapter 3 determined how many facilities (supplier, producers, etc.) should be utilized, which facilities should be opened, how many products should be transferred between facilities for each period. In this Chapter, the changing capacity of disposal, recycling, and recovering centers had no effect on total costs. While increasing the capacity of suppliers decreased the total costs. These conclusions showed that the
recycling ratio had more effect on total cost in comparison with disposal and recovering ratios.

In Chapter 4, the significance of the FMOMILP model and the solution approach was examined by a computational experiment. The results demonstrated the applicability of the approach and the feasibility of the solution methodology. Results showed that the model presents a systematic framework that enables management to obtain a solution by adjusting the search direction. The results of comparing problem solving with fuzzy and crisp numbers showed that considering uncertainty results in different strategical and technical decisions.

The conducted sensitivity analysis on fuzzy programming approaches in Chapter 5 demonstrated the TH approach achieves more appropriate solutions than other fuzzy programming methods for solving sustainable CLSC network design problem.

Chapter 6 showed that the NSGA II algorithm had better performance than the NRGA algorithm to solve problem of sustainable CLSC network design for large cases. In addition, the results of the NSGA-II algorithm were compared with the “best” solution of the commercial CPLEX software for a small case. The results showed there is small deviation among solutions of the NSGA-II algorithm and the ones obtained using the CPLEX software.

In Chapter 7, the achieved results revealed that the cost and environmental criteria have more impact on 3PRLPs’ ranking than on social criteria. The approach, not only helped decision makers to efficiently conduct reverse logistics operations but it also provided them with a chance to visualize the effect of sustainability on 3PRLPs prioritizing. The approach also reduces the time required for calculation and involves
both quantitative data and vague or imprecisely defined qualitative information. Moreover, the achieved results of fuzzy DEMATEL-FIS approach in this Chapter were validated by the Fuzzy AHP-TOPSIS approach. The obtained results showed there is small deviation among these two approaches for ranking 3PRLPs.

Generally, it is concluded that fuzzy approach is a suitable method to address uncertainty for problem of sustainable closed loop supply chain network design. Also, NSGA-II algorithm is identified as an effective solution to find solutions for large cases.

8.3. Future work

In this thesis, three objectives of sustainability (cost and environmental impacts minimization, social impacts maximization) were taken into account. While, supply chain risk is recognized as an important criterion for most companies due to business demands and globalization of the firms’ operations, it is recommended to consider minimization of risk as an objective function in the design CLSC network. The proposed models in this thesis for CLSC network design is a single product model. It is suggested to extend these models for a multi-product supply chain. Several ways can be suggested to extend this study. It is suggested implementing other meta-heuristic algorithms such as multi-objective harmony search (MOHS), multi objective simulated annealing (MOSA), and MOPSO.
References


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Appendix A: CPLEX codes for Case study of Chapter 3

Model

//parameters
int supplier=...; //number of supplier
int producers=...; //number of producers
int Warehouse=...; //number of Warehouses
int distributor=...; //number of Distributors
int Customer =...; //number of customer centers
int Collection =...; //number of Collection and Inspection centers
int disposal =...; //number of Disposal centers
int recycling =...; //number of recycling centers
int recovering =...; //number of recovering centers
int Redistributors=...; //number of Redistributors
int second =...; //number of second customer centers
int period =...; //number of periods

range ss=1..supplier;  
range pp=1..producers;  
range ww=1..Warehouse;  
range dd=1..distributor;  
range cc=1..Customer;  
range ii=1..Collection;  
range kk=1..recovering;  
range ll=1..recycling;  
range mm=1..disposal;  
range nn=1..Redistributors;  
range ff=1..second;  
range tt=1..period;

float cas[ss][tt]=...;  
float cap[pp][tt]=...;  
float caw[ww][tt]=...;  
float cad[dd][tt]=...;  
float cai[ii][tt]=...;  
float cam[mm][tt]=...;  
float cal[ll][tt]=...;  
float cak[kk][tt]=...;  
float can[nn][tt]=...;  

float tcpw[pp][ww]=...;  
float tcpd[pp][dd]=...;  
float tcwc[ww][cc]=...;  
float tcdd[dd][cc]=...;  
float tcci[cc][ii]=...;  
float tcim[ii][mm]=...;  
float tcil[ii][ll]=...;  
float tcik[ii][kk]=...;  
float tcil[ll][ss]=...;  
float tcln[ll][nn]=...;  
float tckn[kk][nn]=...;  
float tcnf[nn][ff]=...;
float fcp[pp]=...;
float fcw[ww]=...;
float fcd[dd]=...;
float fci[i][i]=...;
float fcm[mm]=...;
float fcl[ll]=...;
float fck[kk]=...;
float fcn[nn]=...;

float mc[pp][tt]=...;
float dc[mm][tt]=...;
float rc[ll][tt]=...;
float bc[kk][tt]=...;
float pc[ss][tt]=...;
float def[cc][tt]=...;
float def[ff][tt]=...;
float ry[tt]=...;
float rv[tt]=...;
float rd[tt]=...;
float sc[cc]=...;

//variables
dvar boolean Os[ss][tt];
dvar boolean Op[pp][tt];
dvar boolean Ow[ww][tt];
dvar boolean Od[dd][tt];
dvar boolean Oi[i][ii][tt];
dvar boolean Om[mm][tt];
dvar boolean Ol[ll][tt];
dvar boolean Ok[kk][tt];
dvar boolean On[nn][tt];

dvar float+ Xci[cc][ii][tt];
dvar float+ Xsp[ss][pp][tt];
dvar float+ Xpw[pp][ww][tt];
dvar float+ Xpd[pp][dd][tt];
dvar float+ Xwc[ww][cc][tt];
dvar float+ Xdc[dd][cc][tt];
dvar float+ Xim[ii][mm][tt];
dvar float+ Xil[ii][ll][tt];
dvar float+ Xik[ii][kk][tt];
dvar float+ Xln[ll][nn][tt];
dvar float+ Xls[ll][ss][tt];
dvar float+ Xkn[kk][nn][tt];
dvar float+ Xnf[nn][ff][tt];

//Objective function

minimize sum(p in pp, t in tt)fcp[p]*Op[p][t] + sum(w in ww, t in tt)fcw[w]*Ow[w][tt] + sum(d in dd, t in tt)fcd[d]*Od[d][tt] + sum(i in ii, t in tt)fci[i]*Oi[i][tt] + sum(m in mm, t in tt)fcm[m]*Om[m][tt] + sum(l in ll, t in tt)fcl[l]*Ol[l][tt] + sum(k in kk, t in tt)fck[k]*Ok[k][tt] + sum(n in nn, t in tt)fcn[n]*On[n][tt] + sum(p in pp, w in ww, t in tt)mc[p][t]*Xpcw[p][w][tt] + sum(p in pp, d in dd, t in tt)mc[p][t]*Xpd[p][d][tt] + sum(i in ii, l in ll, t in tt)rc[l][t]*Xil[l][ll][tt] + sum(i in ii, k in kk, t in tt)bc[k][t]*Xik[i][k][tt] +...
forall (s in ss, t in tt)
  sum (p in pp) Xsp[s][p][t] <= Os[s][t] * cas[s][t];

forall (p in pp, t in tt)
  sum (w in ww) Xpw[p][w][t] + sum (d in dd) Xpd[p][d][t] <= Op[p][t] * cap[p][t];

forall (w in ww, t in tt)
  sum (p in pp) Xpw[p][w][t] <= Ow[w][t] * caw[w][t];

forall (d in dd, t in tt)
  sum (p in pp) Xpd[p][d][t] <= Od[d][t] * cad[d][t];

forall (i in ii, t in tt)
  sum (c in cc) Xci[c][i][t] <= Oi[i][t] * cai[i][t];

forall (m in mm, t in tt)
  sum (i in ii) Xim[i][m][t] <= Om[m][t] * cam[m][t];

forall (l in ll, t in tt)
  sum (s in ss) Xls[l][s][t] + sum (n in nn) Xln[l][n][t] <= Ol[l][t] * cal[l][t];

forall (k in kk, t in tt)
  sum (n in nn) Xkn[k][n][t] <= Ok[k][t] * cak[k][t];

forall (n in nn, t in tt)
  sum (l in ll) Xln[l][n][t] + sum (k in kk) Xkn[k][n][t] <= On[n][t] * can[n][t];

forall (p in pp, t in tt)
  sum (s in ss) Xsp[s][p][t] = sum (w in ww) Xpw[p][w][t] + sum (d in dd) Xpd[p][d][t];

forall (w in ww, t in tt)
  sum (p in pp) Xpw[p][w][t] = sum (c in cc) Xwc[w][c][t];

forall (d in dd, t in tt)
  sum (p in pp) Xpd[p][d][t] = sum (c in cc) Xdc[d][c][t];

subject to {
  sum (m in mm, i in ii, t in tt) dc[m][t] * Xim[i][m][t] + sum (w in ww, p in pp, t in tt) tcpw[p][w] * Xpw[p][w][t] + sum (p in pp, d in dd, t in tt) tcpd[p][d] * Xpd[p][d][t] + sum (w in ww, c in cc, t in tt) tcwc[w][c][t] + sum (d in dd, c in cc, t in tt) tcdc[d][c][t] + sum (i in ii, m in mm, t in tt) tcici[c][i][t] + sum (i in ii, l in ll, t in tt) tcil[l][i][l][t] + sum (i in ii, k in kk, t in tt) tcik[i][k][k][t] + sum (l in ll, n in nn, t in tt) tcln[t][n][t][n][t] + sum (k in kk, n in nn, t in tt) tckn[k][n][k][n][t] + sum (f in ff, n in nn, t in tt) tcnf[n][f] * Xnf[n][f][f] + sum (s in ss, p in pp, t in tt) pc[s][t] * Xsp[s][p][t] - sum (l in ll, s in ss, t in tt) pc[s][t] * Xls[l][s][t] + sum (l in ll, s in ss, t in tt) rc[l][t] * Xls[l][s][t] + sum (c in cc, t in tt) de[c][t] * sc[c] - sum (w in ww, c in cc, t in tt) Xwc[w][c][t] * sc[c] - sum (c in cc, d in dd, t in tt) Xdc[d][c][t] * sc[c] + sum (c in cc, i in ii, t in tt) tcci[c][i] * Xci[c][i][t];
}
forall (i in ii, t in tt)
    sum (c in cc) Xci[c][i][t] == sum (m in mm) Xim[i][m][t] + sum (l in ll) Xil[i][l][t] + sum (k in kk) Xik[i][k][t];

forall (i in ii, t in tt)
    sum (c in cc) Xci[c][i][t] * ry[t] == sum (l in ll) Xil[i][l][t];

forall (i in ii, t in tt)
    sum (c in cc) Xci[c][i][t] * rv[t] == sum (k in kk) Xik[i][k][t];

forall (i in ii, t in tt)
    sum (c in cc) Xci[c][i][t] * rd[t] == sum (m in mm) Xim[i][m][t];

forall (l in ll, t in tt)
    sum (i in ii) Xil[i][l][t] == sum (n in nn) Xln[l][n][t] + sum (s in ss) Xls[l][s][t];

forall (k in kk, t in tt)
    sum (i in ii) Xik[i][k][t] == sum (n in nn) Xkn[k][n][t];

forall (n in nn, t in tt)
    sum (l in ll) Xln[l][n][t] + sum (k in kk) Xkn[k][n][t] == sum (f in ff, t in tt) Xnf[n][f][t];

forall (c in cc, t in tt)
    sum (w in wvw) Xwc[w][c][t] + sum (d in dd) Xdc[d][c][t] == de[c][t];

forall (f in ff, t in tt)
    sum (n in nn) Xnf[n][f][t] == def[f][t];

forall (c in cc, t in tt)
    sum (i in ii) Xci[c][i][t] == de[c][t];
}

Data

supplier=3;
producers=2;
Warehouse=2;
distributor=2;
Customer=4;
Collection=2;
disposal=3;
recycling=2;
recovering=2;
Redistributors=2;
second=3;
period=4;

SheetConnection my_sheet ("Data09112017.xlsx");
cas from SheetRead (my_sheet, "cas");
cap from SheetRead (my_sheet, "cap");
caw from SheetRead (my_sheet, "caw");
cad from SheetRead (my_sheet, "cad");
cai from SheetRead (my_sheet, "cai");
cam from SheetRead (my_sheet, "cam");
cal from SheetRead (my_sheet, "cal");
cak from SheetRead (my_sheet, "cak");
can from SheetRead (my_sheet, "can");
tcpw from SheetRead (my_sheet, "tcpw");
tcpd from SheetRead (my_sheet, "tcpd");
tcwc from SheetRead (my_sheet, "tcwc");
tcdc from SheetRead (my_sheet, "tdcc");
tcci from SheetRead (my_sheet, "tcci");
tcim from SheetRead (my_sheet, "tcim");
tcil from SheetRead (my_sheet, "tcil");
tcik from SheetRead (my_sheet, "tcik");
tcls from SheetRead (my_sheet, "tcls");
tcln from SheetRead (my_sheet, "tcln");
tckn from SheetRead (my_sheet, "tckn");
tcnf from SheetRead (my_sheet, "tcnf");
fcp from SheetRead (my_sheet, "fcp");
fcd from SheetRead (my_sheet, "fcd");
fcm from SheetRead (my_sheet, "fcm");
fcl from SheetRead (my_sheet, "fcl");
fck from SheetRead (my_sheet, "fck");fc from SheetRead (my_sheet, "ffc");
mc from SheetRead (my_sheet, "mcp");
dc from SheetRead (my_sheet, "dcn");
rc from SheetRead (my_sheet, "rcl");
bc from SheetRead (my_sheet, "bck");
pc from SheetRead (my_sheet, "pcs");
de from SheetRead (my_sheet, "dec");
ry from SheetRead (my_sheet, "ry");
rv from SheetRead (my_sheet, "rv");
rd from SheetRead (my_sheet, "rd");
def from SheetRead (my_sheet, "def");
sc from SheetRead (my_sheet, "sc");
Appendix B: Parameter values of experiment in Chapter 4

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Corresponding random distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>$tc$</td>
<td>U(4, 8)</td>
</tr>
<tr>
<td>$es$</td>
<td>U(5, 25)</td>
</tr>
<tr>
<td>$ep$</td>
<td>U(4, 5)</td>
</tr>
<tr>
<td>$ed$</td>
<td>U(4, 5)</td>
</tr>
<tr>
<td>$fj$</td>
<td>U(4, 15)</td>
</tr>
<tr>
<td>$vj$</td>
<td>U(0.4, 0.6)</td>
</tr>
</tbody>
</table>
Appendix C: CPLEX codes for experiment of Chapter 4

Model

//parameters
int supplier=...; //number of supplier
int plants=...; //number of plants
int distributor=...; //number of Distributors
int Customer=...; //number of customer centers
int collection=...; //number of collection & inspection center
int disposal=...; //number of disposal center
int repairing=...; //number of repairing center
int recycling=...; //number of recycling center
int period=...; //number of periods

range ss=1..supplier;
range pp=1..plants;
range dd=1..distributor;
range cc=1..Customer;
range ii=1..collection;
range mm=1..disposal;
range kk=1..repairing;
range ll=1..recycling;
range tt=1..period;

float casp[ss][tt]=...;
float casm[ss][tt]=...;
float caso[ss][tt]=...;

float capp[pp][tt]=...;
float capm[pp][tt]=...;
float capo[pp][tt]=...;

float cadp[dd][tt]=...;
float cadm[dd][tt]=...;
float cado[dd][tt]=...;

float caip[ii][tt]=...;
float caim[ii][tt]=...;
float caio[ii][tt]=...;

float cakp[kk][tt]=...;
float cakm[kk][tt]=...;
float cako[kk][tt]=...;

float calp[ll][tt]=...;
float calm[ll][tt]=...;
float calo[ll][tt]=...;

float camp[mm][tt]=...;
float camm[mm][tt]=...;
float camo[mm][tt]=...;

float tcpd[pp][dd]=...;
float tcdc[dd][cc]=...;
float tcci[cc][ii]=...;
float tcim[ii][mm]=...;
float tcil[ii][ll]=...;
float tcik[ii][kk]=...;
float tcls[ll][ss]=...;
float tckd[kk][dd]=...;
float fcp[pp]=...;
float fcd[dd]=...;
float fci[ii]=...;
float fcm[mm]=...;
float fcl[ll]=...;
float fck[kk]=...;
float essp[ss][pp]=...;
float espd[pp][dd]=...;
float esdc[dd][cc]=...;
float esci[cc][ii]=...;
float esim[ii][mm]=...;
float esil[ii][ll]=...;
float esik[ii][kk]=...;
float esls[ll][ss]=...;
float eskd[kk][dd]=...;
float ep[pp]=...;
float ed[mm]=...;
float fjp[pp]=...;
float fjd[dd]=...;
float fji[ii]=...;
float fjm[mm]=...;
float fjl[ll]=...;
float fjk[kk]=...;
float vjp[pp]=...;
float vjd[dd]=...;
float vji[ii]=...;
float vjm[mm]=...;
float vjl[ll]=...;
float vjk[kk]=...;
float mc[pp][tt]=...;
float dc[mm][tt]=...;
float rcc[ll][tt]=...;
float bc[kk][tt]=...;
float pc[ss][tt]=...;
float sc[cc]=...;
float dep[cc][tt]=...;
float dem[cc][tt]=...;
floatdeo[cc][tt]=...;
float ry[tt]=...;
float rv[tt]=...;
float rd[tt]=...;
float rrp[cc][tt]=...;
float rrm[cc][tt]=...;
float rro[cc][tt]=...;

//variables
dvar boolean Os[ss][tt];
dvar boolean Op[pp][tt];
dvar boolean Od[dd][tt];
dvar boolean Oi[ii][tt];
dvar boolean Om[mm][tt];
dvar boolean Ol[ll][tt];
dvar boolean Ok[kk][tt];
dvar float+ Xsp[ss][pp][tt];
dvar float+ Xpd[pp][dd][tt];
dvar float+ Xdc[dd][cc][tt];
dvar float+ Xci[cc][ii][tt];
dvar float+ Xim[ii][mm][tt];
dvar float+ Xil[ii][ll][tt];
dvar float+ Xik[ii][kk][tt];
dvar float+ Xls[ll][ss][tt];
dvar float+ Xkd[kk][dd][tt];

dvar float+ L;

Objective Functions

Cost (Z1)
minimize sum(p in pp, t in tt)fcp[p]*Op[p][t]+sum(d in dd, t in tt)fcd[d][0]*Od[d][t]+sum(i in ii, t in tt)fci[i][0]*Oi[i][t]+sum(m in mm, t in tt)fcm[m][0]*Om[m][t]+sum(l in ll, t in tt)fcl[l][0]*Ol[l][t]+sum(k in kk, t in tt)fck[k][0]*Ok[k][t]+sum(p in pp, d in dd, t in tt)mc[p][t]*Xpd[p][d][t]+sum(i in ii, l in ll, t in tt)rcc[l][t]*Xil[i][l][t]+sum(i in ii, k in kk, t in tt)bc[k][t]*Xik[i][k][t]+sum(m in mm, i in ii, t in tt)dc[m][t]*Xim[i][m][t]+sum(p in pp, d in dd, t in tt)tcpd[p][d][t]+sum(d in dd, c in cc, t in tt)tcdd[c][d]*Xdc[d][c][t]+sum(c in cc, i in ii, t in tt)tcci[i][c][t]*Xci[c][i][t]+sum(i in ii, m in mm, t in tt)tcim[i][m][t]+sum(l in ll, i in ii, l in ll, t in tt)tcil[i][l][t]+sum(i in ii, k in kk, t in tt)tcik[i][k][t]+sum(s in ss, p in pp, t in tt)pc[s][t][t]*Xsp[s][p][t]+sum(s in ss, p in pp, t in tt)esps[p][s][p][t]+sum(s in ss, p in pp, t in tt)espd[p][d][t]+sum(d in dd, c in cc, t in tt)esdc[d][c][t]+sum(c in cc, i in ii, t in tt)esci[c][i][t]+sum(i in ii, m in mm, t in tt)esim[i][m][t]+sum(i in ii, l in ll, t in tt)tckd[k][d][t];

Environmental (Z2)
minimize sum(p in pp, d in dd, t in tt)ep[p][t]*Xpd[p][d][t]+sum(s in ss, p in pp, t in tt)esp[s][p][t]*Xsp[s][p][t]+sum(s in ss, p in pp, t in tt)espd[p][d][t]+sum(d in dd, c in cc, t in tt)esdc[d][c][t]+sum(c in cc, i in ii, t in tt)esci[c][i][t]+sum(i in ii, m in mm, t in tt)esim[i][m][t]+sum(i in ii, l in ll, t in tt)tckd[k][d][t];
(Z3)

Min $Z_3 = Z^m$

minimize sum(p in pp, t in tt)fjp[p]*Op[p][t]+sum(d in dd, t in tt)fjd[d][t]+sum(i in ii, t in tt)fji[i][t]+sum(m in mm, t in tt)fjm[m][t]+sum(l in ll, t in tt)fjl[l][t]+sum(k in kk, t in tt)fjk[k][t]+Ok[k][t]+sum(p in pp, d in dd, t in tt)vjp[p]*

0p[p][t]*Xpd[p][d][t]/capm[p][t]+sum(d in dd, c in cc, t in tt)vjd[d]*

Od[d][t]*Xdc[d][c][t]/cdm[d][t]+sum(c in cc, i in ii, t in tt)vji[i]*

Oi[i][t]*Xci[c][i][t]/caim[i][t]+sum(i in ii, m in mm, t in tt)vjm[m]*

Om[m][t]*Xim[i][m][t]/camm[m][t]+sum(i in ii, l in ll, t in tt)vjl[l] *

Ol[l][t]*Xil[i][l][t]/calm[l][t]+sum(i in ii, k in kk, t in tt)vjk[k] *

Ok[k][t]*Xik[i][k][t]/cakm[k][t];

Max $Z_4 = (Z^m - Z^p)$

minimize sum(p in pp, t in tt)fjp[p]*Op[p][t]+sum(d in dd, t in tt)fjd[d][t]+sum(i in ii, t in tt)fji[i][t]+sum(m in mm, t in tt)fjm[m][t]+sum(l in ll, t in tt)fjl[l][t]+sum(k in kk, t in tt)fjk[k][t]+Ok[k][t]+sum(p in pp, d in dd, t in tt)vjp[p]*

0p[p][t]*Xpd[p][d][t]/capm[p][t]- capp[p][t]+sum(d in dd, c in cc, t in tt)vjd[d]*

Od[d][t]*Xdc[d][c][t]/cdm[d][t]- cadm[d][t]+sum(c in cc, i in ii, t in tt)vji[i] *

Oi[i][t]*Xci[c][i][t]/caim[i][t]- caip[i][t]+sum(i in ii, m in mm, t in tt)vjm[m]*

Om[m][t]*Xim[i][m][t]/camm[m][t]- camp[m][t]+sum(i in ii, l in ll, t in tt)vjl[l]*

Ol[l][t]*Xil[i][l][t]/calm[l][t]- calp[l][t]+sum(i in ii, k in kk, t in tt)vjk[k] *

Ok[k][t]*Xik[i][k][t]/cakm[k][t]- cakp[k][t];

Min $Z_5 = (Z^o - Z^m)$

minimize sum(p in pp, t in tt)fjp[p]*Op[p][t]+sum(d in dd, t in tt)fjd[d][t]+sum(i in ii, t in tt)fji[i][t]+sum(m in mm, t in tt)fjm[m][t]+sum(l in ll, t in tt)fjl[l][t]+sum(k in kk, t in tt)fjk[k][t]+Ok[k][t]+sum(p in pp, d in dd, t in tt)vjp[p]*

0p[p][t]*Xpd[p][d][t]/capo[p][t]- capm[p][t]+sum(d in dd, d in dd, c in cc, t in tt)vjd[d]*

Od[d][t]*Xdc[d][c][t]/cdm[d][t]- cadm[d][t]+sum(c in cc, i in ii, t in tt)vji[i] *

Oi[i][t]*Xci[c][i][t]/caio[i][t]- caim[i][t]+sum(i in ii, m in mm, t in tt)vjm[m]*

Om[m][t]*Xim[i][m][t]/camo[m][t]- camm[m][t]+sum(i in ii, l in ll, t in tt)vjl[l] *

Ol[l][t]*Xil[i][l][t]/calo[l][t]- calp[l][t]+sum(i in ii, k in kk, t in tt)vjk[k] *

Ok[k][t]*Xik[i][k][t]/cako[k][t]- cakp[k][t]);

Objective function (TH model)

maximize 0.5*L+0.5*(0.4*(6.1-0.00000024*(sum(p in pp, t in tt)fcp[p]*Op[p][t]+sum(d in dd, t in tt)fcd[d][t]+sum(i in ii, t in tt)fci[i][t]+sum(m in mm, t in tt)fcm[m][t]+sum(l in ll, t in tt)fcl[l][t]+sum(k in kk, t in tt)fck[k][t]+Ok[k][t]+sum(p in pp, d in dd, t in tt)mc[p][t]*Xpd[p][d][t]+sum(i in ii, l in ll, t in tt)rcc[l][t]+sum(i in ii, k in kk, t in tt)bc[k][t]+sum(m in mm, i in ii, t in tt)dc[m][t]+sum(i in ii, m in mm, t in tt)bc[m][t]+sum(m in mm, i in ii, k in kk, t in tt)dc[m][t]*Xil[i][l][t]+sum(k in kk, d in dd, t in dd)esk[k][d][t]*Xkd[k][d][t];

200
(1) \( \sum_{s \in ss, t \in tt} \text{rs}(l[l][s][t]) + \sum_{p \in pp, d \in dd} \text{es}(p[p][d][t]) + \sum_{i \in ii, t \in tt} \text{es}(i[i][t]) \leq \sum_{s \in ss, t \in tt} \text{Os}(s[s][t]) \times (\text{casp}(s[s][t]) + \text{casm}(s[s][t]) + \text{caso}(s[s][t])); \)

(2) \( \sum_{p \in pp, t \in tt} \text{es}(p[p][d][t]) + \sum_{i \in ii, t \in tt} \text{es}(i[i][t]) \leq \sum_{c \in cc, t \in tt} \text{Oi}(i[i][t]) \times (\text{caip}(i[i][t]) + \text{caim}(i[i][t]) + \text{caio}(i[i][t])); \)

(3) \( \sum_{m \in mm, t \in tt} \text{es}(i[i][m][t]) \leq \sum_{i \in ii, l \in ll, t \in tt} \text{Ol}(l[l][t]) \times (\text{camp}(l[l][t]) + \text{camm}(l[l][t]) + \text{camo}(l[l][t])); \)

(4) \( \sum_{l \in ll, t \in tt} \text{es}(i[i][l][t]) \leq \sum_{k \in kk, t \in tt} \text{Ok}(k[k][t]) \times (\text{cakp}(k[k][t]) + \text{cakm}(k[k][t]) + \text{cako}(k[k][t])); \)

(5) \( \sum_{p \in pp, t \in tt} \text{vp}(p[p][d][t]) + \sum_{i \in ii, t \in tt} \text{vi}(i[i][t]) \leq \sum_{k \in kk, t \in tt} \text{Vjp}(k[k][t]) \times (\text{capm}(k[k][t]) + \text{caik}(k[k][t]) + \text{camo}(k[k][t])); \)

subject to 
(6) \( \sum_{s \in ss, t \in tt} \text{ds}(s[s][t]) \leq \sum_{p \in pp, d \in dd} \text{es}(p[p][d][t]) + \sum_{i \in ii, t \in tt} \text{es}(i[i][t]) \times (\text{caip}(i[i][t]) + \text{caim}(i[i][t]) + \text{caio}(i[i][t])); \)

(7) \( \sum_{m \in mm, t \in tt} \text{es}(i[i][m][t]) \leq \sum_{i \in ii, l \in ll, t \in tt} \text{Ol}(l[l][t]) \times (\text{caik}(l[l][t]) + \text{cam}(l[l][t]) + \text{calo}(l[l][t])); \)

(8) \( \sum_{k \in kk, t \in tt} \text{es}(i[i][k][t]) \leq \sum_{m \in mm, t \in tt} \text{es}(i[i][m][t]) \times (\text{capm}(m[m][t]) + \text{cajm}(m[m][t]) + \text{camin}(m[m][t])); \)

(9) \( \sum_{p \in pp, t \in tt} \text{vp}(p[p][d][t]) + \sum_{i \in ii, t \in tt} \text{vi}(i[i][t]) \leq \sum_{k \in kk, t \in tt} \text{Vjp}(k[k][t]) \times (\text{capm}(k[k][t]) + \text{caik}(k[k][t]) + \text{camo}(k[k][t])); \)
\[
\sum (s \in ss)X_{sp[s][p][t]} = \sum (d \in dd)X_{pd[p][d][t]};
\]

forall (d \in dd, t \in tt)
\[
\sum (p \in pp)X_{pd[p][d][t]} + \sum (k \in kk)X_{kd[k][d][t]} = \sum (c \in cc)X_{dc[d][c][t]};
\]

forall (i \in ii, t \in tt)
\[
\sum (c \in cc)X_{ci[c][i][t]} = \sum (m \in mm)X_{im[i][m][t]} + \sum (l \in ll)X_{il[i][l][t]} + \sum (k \in kk)X_{ik[i][k][t]};
\]

forall (l \in ll, t \in tt)
\[
\sum (i \in ii)X_{il[i][l][t]} = \sum (s \in ss)X_{ls[l][s][t]};
\]

forall (i \in ii, t \in tt)
\[
\sum (c \in cc)X_{ci[c][i][t]}*ry[t] = \sum (l \in ll)X_{il[i][l][t]};
\]

forall (i \in ii, t \in tt)
\[
\sum (c \in cc)X_{ci[c][i][t]}*rv[t] = \sum (k \in kk)X_{ik[i][k][t]};
\]

forall (i \in ii, t \in tt)
\[
\sum (c \in cc)X_{ci[c][i][t]}*rd[t] = \sum (m \in mm)X_{im[i][m][t]};
\]

forall (k \in kk, t \in tt)
\[
\sum (i \in ii)X_{ik[i][k][t]} = \sum (d \in dd)X_{kd[k][d][t]};
\]

forall (c \in cc, t \in tt)
\[
\sum (d \in dd)X_{dc[d][c][t]} = \text{dep}[c][t] + \text{dem}[c][t] + \text{deo}[c][t];
\]

forall (c \in cc, t \in tt)
\[
\sum (i \in ii)X_{ci[c][i][t]} = \text{dep}[c][t] * \text{rrp}[c][t] + \text{dem}[c][t] * \text{rrm}[c][t] + \text{deo}[c][t] * \text{rro}[c][t];
\]
\[ Z2 \]
\[ L \leq 3.28 - 0.0000046 \cdot (\sum (p \in pp, d \in dd, t \in tt) ep[p] \cdot Xpd[p][d][t] + \sum (s \in ss, p \in pp, t \in tt) esp[s][p] \cdot Xsp[s][p][t] + \sum (p \in pp, d \in dd, t \in tt) esdc[d][c] \cdot Xdc[d][c][t] + \sum (c \in cc, i \in ii, t \in tt) esci[c][i][t] + \sum (i \in ii, m \in mm, t \in tt) esim[i][k][m][t] + \sum (m \in mm, i \in ii, t \in tt) esil[i][l][i][l][t] + \sum (l \in ll, s \in ss, t \in tt) esls[l][s][ll][s][t]) \]
Data
supplier=4;
plants=3;
distributor=2;
Customer=5;
collection=2;
disposal=2;
repairing=2;
recycling=2;
period=4;

SheetConnection my_sheet ("Modeldata4periods.xlsx");
casp from SheetRead (my_sheet, "casp");
casm from SheetRead (my_sheet, "casm");
caso from SheetRead (my_sheet, "caso");
capp from SheetRead (my_sheet, "capp");
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cadm from SheetRead (my_sheet, "cadm");
cado from SheetRead (my_sheet, "cado");
caip from SheetRead (my_sheet, "caip");
caim from SheetRead (my_sheet, "caim");
caio from SheetRead (my_sheet, "caio");
cakp from SheetRead (my_sheet, "cakp");
cakm from SheetRead (my_sheet, "cakm");
cako from SheetRead (my_sheet, "cako");
calp from SheetRead (my_sheet, "calp");
calm from SheetRead (my_sheet, "calm");
calo from SheetRead (my_sheet, "calo");
camp from SheetRead (my_sheet, "camp");
camm from SheetRead (my_sheet, "camm");
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tcci from SheetRead (my_sheet, "tcci");
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tcil from SheetRead (my_sheet, "tcil");
tcik from SheetRead (my_sheet, "tcik");
tcls from SheetRead (my_sheet, "tcls");
tckd from SheetRead (my_sheet, "tckd");
fcp from SheetRead (my_sheet, "fcp");
fcd from SheetRead (my_sheet, "fcd");
fcf from SheetRead (my_sheet, "fcf");
fcm from SheetRead (my_sheet, "fcm");
fcl from SheetRead (my_sheet, "fcl");
fck from SheetRead (my_sheet, "fck");
esssp from SheetRead (my_sheet, "essp");
espd from SheetRead (my_sheet, "espd");
esdc from SheetRead (my_sheet, "esdc");
esci from SheetRead (my_sheet, "esci");
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ep from SheetRead (my_sheet, "ep");
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fjp from SheetRead (my_sheet, "fjp");
fjd from SheetRead (my_sheet, "fjd");
fji from SheetRead (my_sheet, "fji");
fjm from SheetRead (my_sheet, "fjm");
fjl from SheetRead (my_sheet, "fjl");
fjk from SheetRead (my_sheet, "fjk");
vjp from SheetRead (my_sheet, "vjp");
vjd from SheetRead (my_sheet, "vjd");
vji from SheetRead (my_sheet, "vji");
vjm from SheetRead (my_sheet, "vjm");
vjl from SheetRead (my_sheet, "vjl");
vjk from SheetRead (my_sheet, "vjk");
mc from SheetRead (my_sheet, "mc");
dc from SheetRead (my_sheet, "dc");
rcc from SheetRead (my_sheet, "rcc");
bc from SheetRead (my_sheet, "bc");
pc from SheetRead (my_sheet, "pc");
sc from SheetRead (my_sheet, "sc");
dep from SheetRead (my_sheet, "dep");
dem from SheetRead (my_sheet, "dem");
deo from SheetRead (my_sheet, "deo");
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rv from SheetRead (my_sheet, "rv");
rd from SheetRead (my_sheet, "rd");
rrp from SheetRead (my_sheet, "rrp");
rrm from SheetRead (my_sheet, "rrm");
rro from SheetRead (my_sheet, "rro");
Appendix D: Notations, Parameters, and Decisions Variables of Chapter 6

Notations

\( \overline{C}_{S}^{t} \): Capacity of Supplier ‘s’ at time period ‘t’
\( \overline{C}_{p}^{t} \): Capacity of Plants ‘p’ at time period ‘t’
\( \overline{C}_{d}^{t} \): Capacity of Distributor ‘d’ at time period ‘t’
\( \overline{C}_{i}^{t} \): Capacity of Collection & Inspection Center ‘i’ at time period ‘t’
\( \overline{C}_{m}^{t} \): Capacity of Disposal Center ‘m’ at time period ‘t’
\( \overline{C}_{l}^{t} \): Capacity of Recycling Center ‘l’ at time period ‘t’
\( \overline{C}_{k}^{t} \): Capacity of Repairing Center ‘k’ at time period ‘t’
\( TC_{sp} \): Transportation cost a product from supplier ‘s’ to producer ‘p’
\( TC_{pd} \): Transportation cost a product from plant ‘p’ to distributor ‘d’
\( TC_{dc} \): Transportation cost a product from distributor ‘d’ to customer center ‘c’
\( TC_{ci} \): Transportation cost a product from customer center ‘c’ to collection & inspection center ‘i’
\( TC_{im} \): Transportation cost a product from collection & inspection center ‘i’ to disposal center ‘m’
\( TC_{il} \): Transportation cost a product from collection & inspection center ‘i’ to recycling center ‘l’
\( TC_{ik} \): Transportation cost a product from collection & inspection center ‘i’ to repairing center ‘k’
\( TC_{ls} \): Transportation cost a product from recycling center ‘l’ to supplier ‘s’
\( TC_{kd} \): Transportation cost a product from repairing center ‘k’ to distributor ‘d’
\( FC_{p} \): Fixed cost of opening plant ‘p’
\( FC_{d} \): Fixed cost of opening distributor ‘d’
\( FC_{i} \): Fixed cost of opening collection & inspection center ‘i’
\( FC_{m} \): Fixed cost of opening disposal center ‘m’
\( FC_{l} \): Fixed cost of opening recycling center ‘l’
\( FC_{k} \): Fixed cost of opening repairing center ‘k’
\( EIS_{sp} \): Environmental impacts of shipping a product from supplier ‘s’ to plant ‘p’
\( EIS_{pd} \): Environmental impacts of shipping a product from plant ‘p’ to distributor ‘d’
\( EIS_{dc} \): Environmental impacts of shipping a product from distributor ‘d’ to customer center ‘c’
$EIS_{ci}$: Environmental impacts of shipping a product from customer center ‘c’ to collection & inspection center ‘i’

$EIS_{im}$: Environmental impacts of shipping a product from collection & inspection center ‘i’ to disposal center ‘m’

$EIS_{il}$: Environmental impacts of shipping a product from collection & inspection center ‘i’ to recycling center ‘l’

$EIS_{ik}$: Environmental impacts of shipping a product from collection & inspection center ‘i’ to repairing center ‘k’

$EIS_{ls}$: Environmental impacts of shipping a product from recycling center ‘l’ to supplier ‘s’

$EIS_{kd}$: Environmental impacts of shipping a product from repairing center ‘k’ to distributor ‘d’

$EIP_p$: Environmental impacts of producing at plant ‘p’

$EID_m$: Environmental impacts of disposing at disposal center ‘m’

$FJ_p$: The number of fixed job opportunities created by establishing plants

$FJ_d$: The number of fixed job opportunities created by establishing distributors

$FJ_l$: The number of fixed job opportunities created by establishing collection & inspection centers

$FJ_m$: The number of fixed job opportunities created by establishing disposal centers

$FJ_l$: The number of fixed job opportunities created by establishing recycling centers

$FJ_k$: The number of fixed job opportunities created by establishing repairing centers

$VJ_p$: The number of variable job opportunities created by establishing plants

$VJ_d$: The number of variable job opportunities created by establishing distributors

$VJ_l$: The number of variable job opportunities created by establishing collection & inspection centers

$VJ_m$: The number of variable job opportunities created by establishing disposal centers

$VJ_l$: The number of variable job opportunities created by establishing recycling centers

$VJ_k$: The number of variable job opportunities created by establishing repairing centers

$MC_p^t$: Manufacturing cost at plant ‘p’ at time period ‘t’

$DC_m^t$: Disposal cost at disposal center ‘m’ at time period ‘t’

$RC_l^t$: Recycling cost at recycling center ‘l’ at time period ‘t’

$BC_k^t$: Repairing cost at repairing center ‘k’ at time period ‘t’
\( \bar{DE}_c^t \): Demand of customer center ‘c’ at time period ‘t’

\( RY_t \): Recycling ratio at time period ‘t’

\( RV_t \): Repairing ratio at time period ‘t’

\( RD_t \): Disposal ratio at time period ‘t’

\( \bar{r}_c^t \): Reverse ratio at time period ‘t’

**Decision Variables**

\( OS_s^t \): 1 if a supplier is open in location ‘s’ at time period ‘t’; 0 otherwise

\( OP_p^t \): 1 if a plant is open in location ‘p’ at time period ‘t’; 0 otherwise

\( OD_d^t \): 1 if a distributor is open in location ‘d’ at time period ‘t’; 0 otherwise

\( OI_i^t \): 1 if a collection & inspection center is open in location ‘i’ at time period ‘t’; 0 otherwise

\( OM_m^t \): 1 if a disposal center is open in location ‘m’ at time period ‘t’; 0 otherwise

\( OR_l^t \): 1 if a recycling center is open in location ‘l’ at time period ‘t’; 0 otherwise

\( OK_k^t \): 1 if a repairing center is open in location ‘k’ at time period ‘t’; 0 otherwise

\( QS_{sp}^t \): Quantity shipped from supplier ‘s’ to plant ‘p’ at time period ‘t’

\( QS_{pa}^t \): Quantity shipped from plant ‘p’ to distributor ‘d’ at time period ‘t’

\( QS_{de}^t \): Quantity shipped from distributor ‘d’ to customer center ‘c’ at time period ‘t’

\( QS_{ci}^t \): Quantity shipped from customer center ‘c’ to Collection & Inspection center ‘i’ at time period ‘t’

\( QS_{im}^t \): Quantity shipped from collection & inspection center ‘i’ to disposal center ‘m’ at time period ‘t’

\( QS_{il}^t \): Quantity shipped from collection & inspection center ‘i’ to recycling center ‘l’ at time period ‘t’

\( QS_{ik}^t \): Quantity shipped from collection & inspection center ‘i’ to repairing center ‘k’ at time period ‘t’

\( QS_{ts}^t \): Quantity shipped from recycling center ‘l’ to supplier ‘s’ at time period ‘t’

\( QS_{kd}^t \): Quantity shipped from repairing center ‘k’ to distributor ‘d’ at time period ‘t’
Appendix E: Matlab code of NSGA-II algorithm (Chapter 6)

clc;clear;
format short g;

%%% READING MODEL PARAMETERS
periodN=6;
ratio=xlsread('ratio.xlsx');
reverseR=ratio(:,1);
repairR=ratio(:,2);
recycleR=ratio(:,3);
disposalR=ratio(:,4);

%CAPACITIES AND DEMANDS
for i=1:periodN
ca(:,i,:)=xlsread('ca.xlsx',['Sheet',num2str(i)]);
ca_m(:,i,:)=xlsread('ca_m.xlsx',['Sheet',num2str(i)]);
ca_p(:,i,:)=xlsread('ca_p.xlsx',['Sheet',num2str(i)]);
c_o(:,i,:)=xlsread('ca_o.xlsx',['Sheet',num2str(i)]);
end
sCapacity=ca(:,1,:);
sCapacity_m=ca_m(:,1,:);
sCapacity_p=ca_p(:,1,:);
sCapacity_o=ca_o(:,1,:);
sNumber=find(sCapacity(:,1)>0, 1, 'last ');
sCapacity=sCapacity(1:sNumber,:);
sCapacity_m=sCapacity_m(1:sNumber,:);
sCapacity_p=sCapacity_p(1:sNumber,:);
sCapacity_o=sCapacity_o(1:sNumber,:);

pCapacity=ca(:,2,:);
pCapacity_m=ca_m(:,2,:);
pCapacity_p=ca_p(:,2,:);
pCapacity_o=ca_o(:,2,:);
pNumber=find(pCapacity(:,1)>0, 1, 'last ');
pCapacity=pCapacity(1:pNumber,:);
pCapacity_m=pCapacity_m(1:pNumber,:);
pCapacity_p=pCapacity_p(1:pNumber,:);
pCapacity_o=pCapacity_o(1:pNumber,:);

dCapacity=ca(:,3,:);
dCapacity_m=ca_m(:,3,:);
dCapacity_p=ca_p(:,3,:);
dCapacity_o=ca_o(:,3,:);
dNumber=find(dCapacity(:,1)>0, 1, 'last ');
dCapacity=dCapacity(1:dNumber,:);
dCapacity_m=dCapacity_m(1:dNumber,:);
dCapacity_p=dCapacity_p(1:dNumber,:);
dCapacity_o=dCapacity_o(1:dNumber,:);

cDemand=ca(:,4,:);
cNumber=find(cDemand(:,1)>0, 1, 'last ');
cDemand=cDemand(1:cNumber,:);

iCapacity=ca(:,5,:);
iCapacity_m=ca_m(:,4,:);
iCapacity_p=ca_p(:,4);
iCapacity_o=ca_o(:,4);
iNumber=find(iCapacity(:,1)>0, 1, 'last' );
iCapacity=iCapacity(1:iNumber,:);
iCapacity_m=iCapacity_m(1:iNumber,:);
iCapacity_p=iCapacity_p(1:iNumber,:);
iCapacity_o=iCapacity_o(1:iNumber,:);

mCapacity=ca(:,:,6);
mCapacity_m=ca_m(:,:,5);
mCapacity_p=ca_p(:,:,5);
mCapacity_o=ca_o(:,:,5);
mNumber=find(mCapacity(:,1)>0, 1, 'last' );
mCapacity=mCapacity(1:mNumber,:);
mCapacity_m=mCapacity_m(1:mNumber,:);
mCapacity_o=mCapacity_o(1:mNumber,:);
mCapacity_p=mCapacity_p(1:mNumber,:);

kCapacity=ca(:,:,7);
kCapacity_m=ca_m(:,:,6);
kCapacity_o=ca_o(:,:,6);
kCapacity_p=ca_p(:,:,6);
kNumber=find(kCapacity(:,1)>0, 1, 'last' );
kCapacity=kCapacity(1:kNumber,:);
kCapacity_m=kCapacity_m(1:kNumber,:);
kCapacity_o=kCapacity_o(1:kNumber,:);
kCapacity_p=kCapacity_p(1:kNumber,:);

lCapacity=ca(:,:,8);
lCapacity_m=ca_m(:,:,7);
lCapacity_o=ca_o(:,:,7);
lCapacity_p=ca_p(:,:,7);
lNumber=find(lCapacity(:,1)>0, 1, 'last' );
lCapacity=lCapacity(1:lNumber,:);
lCapacity_m=lCapacity_m(1:lNumber,:);
lCapacity_o=lCapacity_o(1:lNumber,:);
lCapacity_p=lCapacity_p(1:lNumber,:);

%FIXED COSTS
costFp=xlsread('costF.xlsx','p');
costFd=xlsread('costF.xlsx','d');
costFi=xlsread('costF.xlsx','i');
costFk=xlsread('costF.xlsx','k');
costFl=xlsread('costF.xlsx','l');
costFm=xlsread('costF.xlsx','m');

%TRANSPORTATION COSTS

costTsp=xlsread('costT.xlsx','sp');
costTpd=xlsread('costT.xlsx','pd');
costTdc=xlsread('costT.xlsx','dc');
costTci=xlsread('costT.xlsx','ci');
costTik=xlsread('costT.xlsx','ik');
costTil=xlsread('costT.xlsx','il');
costTim=xlsread('costT.xlsx','im');
costTkd=xlsread('costT.xlsx','kd');
costTls=xlsread('costT.xlsx','ls');
% ENVIRONMENTAL IMPACTS
impactEsp=xlsread('impactE.xlsx','sp');
impactEpd=xlsread('impactE.xlsx','pd');
impactEdc=xlsread('impactE.xlsx','dc');
impactEci=xlsread('impactE.xlsx','ci');
impactEik=xlsread('impactE.xlsx','ik');
impactEil=xlsread('impactE.xlsx','il');
impactEim=xlsread('impactE.xlsx','im');
impactEkd=xlsread('impactE.xlsx','kd');
impactEls=xlsread('impactE.xlsx','ls');
impactEp=xlsread('impactE.xlsx','p');
impactEm=xlsread('impactE.xlsx','m');

% FIXED AND VARIABLE JOBS
jobFp=xlsread('jobF.xlsx','p'); jobVp=xlsread('jobV.xlsx','p');
jobFd=xlsread('jobF.xlsx','d'); jobVd=xlsread('jobV.xlsx','d');
jobFi=xlsread('jobF.xlsx','i'); jobVi=xlsread('jobV.xlsx','i');
jobFm=xlsread('jobF.xlsx','m'); jobVm=xlsread('jobV.xlsx','m');
jobFl=xlsread('jobF.xlsx','l'); jobVl=xlsread('jobV.xlsx','l');
jobFk=xlsread('jobF.xlsx','k'); jobVk=xlsread('jobV.xlsx','k');

% PROCESS COSTS
costPs=xlsread('costP.xlsx','material');
costPp=xlsread('costP.xlsx','manufacturing');
costPk=xlsread('costP.xlsx','repairing');
costPl=xlsread('costP.xlsx','recycling');
costPm=xlsread('costP.xlsx','disposal');

% GENETIC ALGORITHM PARAMETERS
genMax=200;
popN=100;
poolN=100;
cRate=0.9;
mRate=0.05;
changeR=0.05;
reserveN=genMax*popN*mRate;
eps=0.01;

% INITIALIZING THE FIRST GENERATION

tic;

% INITIALIZING POPULATION MATRICES
Xdc=zeros(dNumber,cNumber,periodN,popN);
Xci=zeros(cNumber,iNumber,periodN,popN);
Xiklm=zeros(iNumber,kNumber+lNumber+mNumber,periodN,popN);
Xil=zeros(iNumber,lNumber,periodN,popN);
Xik=zeros(iNumber,kNumber,periodN,popN);
Xim=zeros(iNumber,mNumber,periodN,popN);
Xkpd=zeros(kNumber+pNumber,dNumber,periodN,popN);
Xpd=zeros(pNumber,dNumber,periodN,popN);
Xkd=zeros(kNumber,dNumber,periodN,popN);
Xls=zeros(lNumber,sNumber,periodN,popN);
Xsp=zeros(sNumber,pNumber,periodN,popN);

% LINEAR PROGRAMMING FOR Xdc
Adc=zeros(dNumber,dNumber*cNumber);
AEQdc=zeros(cNumber,dNumber*cNumber);
lb=zeros(1,cNumber*dNumber);
Bdc=zeros(dNumber,1);
BEQdc=zeros(cNumber,1);
for
i=1:dNumber
Adc(i,(i-1)*cNumber+1:i*cNumber)=ones(1,cNumber);
for
j=1:cNumber
AEQdc(j,(i-1)*cNumber+j)=1;
end
end
for
t=1:periodN
Bdc=dCapacity(:,t);
BEQdc=cDemand(:,t);
for
popCounter=1:popN+reserveN
f1=rand(1,cNumber*dNumber)*2-1;
f2=rand(1,cNumber*dNumber)*2-1;
[Xdc1,fval1]=linprog(f1,Adc,Bdc,AEQdc,BEQdc,lb);
[Xdc2,fval2]=linprog(f2,Adc,Bdc,AEQdc,BEQdc,lb);
Xdc1=vec2mat(Xdc1,cNumber);
Xdc2=vec2mat(Xdc2,cNumber);
randN=rand;
Xdc(:,:,t,popCounter)=randN*Xdc1+(1-randN)*Xdc2;
end
end
XdcR=Xdc(:,:,popN+1:popN+reserveN);

%LINEAR PROGRAMMING FOR Xci
Aci=zeros(cNumber+iNumber,cNumber*iNumber);
AEQci=ones(1,cNumber*iNumber);
lb=zeros(1,cNumber*iNumber);
Bci=zeros(cNumber+iNumber,1);
BEQci=zeros(1,1);
for
i=1:cNumber
Aci(i,(i-1)*iNumber+1:i*iNumber)=ones(1,iNumber);
for
j=1:iNumber
Aci(cNumber+j,(i-1)*iNumber+j)=1;
end
end
for
t=1:periodN
Bci=[cDemand(:,t);iCapacity(:,t)];
BEQci=reverseR(t)*sum(cDemand(:,t));
for
popCounter=1:popN+reserveN
f1=rand(1,cNumber*iNumber)*2-1;
f2=rand(1,cNumber*iNumber)*2-1;
[Xci1,fval1]=linprog(f1,Aci,Bci,AEQci,BEQci,lb);
[Xci2,fval2]=linprog(f2,Aci,Bci,AEQci,BEQci,lb);
Xci1=vec2mat(Xci1,iNumber);
Xci2=vec2mat(Xci2,iNumber);
randN=rand;
Xci(:,:,t,popCounter)=randN*Xci1+(1-randN)*Xci2;
end
end
XciR=Xci(:,:,popN+1:popN+reserveN);

%LINEAR PROGRAMMING FOR Xik, Xim, Xil
Aiklm=zeros(kNumber+lNumber+mNumber,iNumber*(kNumber+lNumber+mNumber));
AEQiklm=zeros(iNumber+3,iNumber*(kNumber+lNumber+mNumber));
lb=zeros(1,iNumber*(kNumber+lNumber+mNumber));
Biklm=zeros(kNumber+lNumber+mNumber,1);
BEQiklm=zeros(iNumber+3,1);
for i=1:iNumber
    AEQiklm(i,(i-1)*(kNumber+lNumber+mNumber)+1:i*(kNumber+lNumber+mNumber))=ones(1,kNumber+1Number+mNumber);
    for j=1:kNumber+1Number+mNumber
        Aiklm(j,(i-1)*(kNumber+1Number+mNumber)+j)=1;
    end
    AEQiklm(iNumber+1,1:kNumber)=ones(1,kNumber);
    AEQiklm(iNumber+1,kNumber+lNumber+mNumber+1:2*kNumber+lNumber+mNumber)=ones(1,kNumber);
    AEQiklm(iNumber+1,2*(kNumber+1Number+mNumber)+1:3*kNumber+2*lNumber+2*mNumber)=ones(1,kNumber);
    AEQiklm(iNumber+2,kNumber+1:kNumber+lNumber)=ones(1,lNumber);
    AEQiklm(iNumber+2,2*kNumber+lNumber+mNumber+1:2*kNumber+2*lNumber+mNumber)=ones(1,lNumber);
    AEQiklm(iNumber+2,3*kNumber+2*lNumber+2*mNumber+1:3*kNumber+3*lNumber+2*mNumber)=ones(1,lNumber);
    AEQiklm(iNumber+3,kNumber+lNumber+1:kNumber+lNumber+mNumber)=ones(1,mNumber);
    AEQiklm(iNumber+3,2*kNumber+2*lNumber+mNumber+1:2*kNumber+2*lNumber+2*mNumber)=ones(1,mNumber);
    AEQiklm(iNumber+3,3*kNumber+3*lNumber+2*mNumber+1:3*kNumber+3*lNumber+3*mNumber)=ones(1,mNumber);
end
for t=1:periodN
    Biklm=[kCapacity(:,t);lCapacity(:,t);mCapacity(:,t)];
    for popCounter=1:popN+reserveN
        BEQiklm=[sum(Xci(:,:,t,popCounter))';reverseR(t)*repairR(t)*sum(cDemand(:,:,t));reverseR(t)*recycleR(t)*sum(cDemand(:,:,t));reverseR(t)*disposalR(t)*sum(cDemand(:,:,t))];
        f1=rand(1,iNumber*(kNumber+lNumber+mNumber))*2-1;
        f2=rand(1,iNumber*(kNumber+lNumber+mNumber))*2-1;
        [Xiklm1,fval1]=linprog(f1,Aiklm,Biklm,AEQiklm,BEQiklm,lb);
        [Xiklm2,fval2]=linprog(f2,Aiklm,Biklm,AEQiklm,BEQiklm,lb);
        Xiklm1=vec2mat(Xiklm1,kNumber+lNumber+mNumber);
        Xiklm2=vec2mat(Xiklm2,kNumber+lNumber+mNumber);
        randN=rand;
        Xiklm(:,:,t,popCounter)=randN*Xiklm1+(1-randN)*Xiklm2;
        Xik(:,:,t,popCounter)=Xiklm(:,1:kNumber,t,popCounter);
    end
end
XikR=Xik(:,:,popN+1:popN+reserveN);
XilR=Xil(:,:,popN+1:popN+reserveN);
XimR=Xim(:,:,popN+1:popN+reserveN);
%LINEAR PROGRAMMING FOR Xpd and Xkd
Akpd=zeros(pNumber,(kNumber+pNumber)*dNumber);
AEQkpd=zeros(kNumber+dNumber, (kNumber+pNumber)*dNumber);
lb=zeros(1, (kNumber+pNumber)*dNumber);
Bkpd=zeros(pNumber,1);
BEQkpd=zeros(kNumber+dNumber,1);
for i=1:pNumber+kNumber
    if i<=pNumber
        Akpd(i,(i-1)*dNumber+1:i*dNumber)=ones(1,dNumber);
    end
    if i>pNumber
        AEQkpd(i-pNumber,(i-1)*dNumber+1:i*dNumber)=ones(1,dNumber);
    end
    for j=1:dNumber
        AEQkpd(j+kNumber,(i-1)*dNumber+j)=1;
    end
end
for t=1:periodN
    Bkpd=pCapacity(:,t);
    for popCounter=1:popN+reserveN
        BEQkpd=[sum(Xik(:,:,t,popCounter))';sum(Xdc(:,:,t,popCounter),2)];
        f1=rand(1,(kNumber+pNumber)*dNumber)*2-1;
        f2=rand(1,(kNumber+pNumber)*dNumber)*2-1;
        [Xkpd1,fval1]=linprog(f1,Akpd,Bkpd,AEQkpd,BEQkpd,lb);
        [Xkpd2,fval2]=linprog(f2,Akpd,Bkpd,AEQkpd,BEQkpd,lb);
        Xkpd1=vec2mat(Xkpd1,dNumber);
        Xkpd2=vec2mat(Xkpd2,dNumber);
        randN=rand;
        Xkpd(:,:,t,popCounter)=randN*Xkpd1+(1-randN)*Xkpd2;
        Xpd(:,:,t,popCounter)=Xkpd(1:pNumber,:,t,popCounter);
    end
end
XpdR=Xpd(:,:,popN+1:popN+reserveN);
XkdR=Xkd(:,:,popN+1:popN+reserveN);

%LINEAR PROGRAMMING FOR Xls
Als=zeros(sNumber,lNumber*sNumber);
AEQls=zeros(lNumber,lNumber*sNumber);
lb=zeros(1,lNumber*sNumber);
Bls=zeros(sNumber,1);
BEQls=zeros(lNumber,1);
for i=1:lNumber
    AEQls(i,(i-1)*sNumber+1:i*sNumber)=ones(1,sNumber);
    for j=1:sNumber
        Als(j,(i-1)*lNumber+j)=1;
    end
end
for t=1:periodN
    Bls=sCapacity(:,t);
    for popCounter=1:popN+reserveN
        BEQls=sum(Xil(:,:,t,popCounter));
        f1=rand(1,lNumber*sNumber)*2-1;
        [Xls1,fval1]=linprog(f1,Als,Blsp,AEQls,BEQls,lb);
        Xls(:,:,t,popCounter)=Xls1;
    end
end
XlsR=Xls(:,:,popN+1:popN+reserveN);
f2=rand(1,lNumber*sNumber)*2-1;  
[Xls1,fval1]=linprog(f1,Als,Bls,AEQls,BEQls,lb);  
[Xls2,fval2]=linprog(f2,Als,Bls,AEQls,BEQls,lb);  
Xls1=vec2mat(Xls1,sNumber);  
Xls2=vec2mat(Xls2,sNumber);  
randN=rand;  
Xls(:,::,t,popCounter)=randN*Xls1+(1-randN)*Xls2;
end
XlsR=Xls(:,::,popN+1:popN+reserveN);

%LINEAR PROGRAMMING FOR Xsp  
AEQsp=zeros(pNumber,sNumber*pNumber);  
Asp=zeros(sNumber,sNumber*pNumber);  
lb=zeros(1,sNumber*pNumber);  
Bsp=zeros(sNumber,1);  
BEQsp=zeros(pNumber,1);  
for i=1:sNumber  
Asp(i,(i-1)*pNumber+1:i*pNumber)=ones(1,pNumber);  
for j=1:pNumber  
AEQsp(j,(i-1)*pNumber+j)=1;  
end
end
for t=1:periodN  
Bsp=sCapacity(:,t);  
for popCounter=1:popN+reserveN  
BEQsp=sum(Xpd(:,:,t,popCounter),2);  
f1=rand(1,sNumber*pNumber)*2-1;  
f2=rand(1,sNumber*pNumber)*2-1;  
[Xsp1,fval1]=linprog(f1,Asp,Bsp,AEQsp,BEQsp,lb);  
[Xsp2,fval2]=linprog(f2,Asp,Bsp,AEQsp,BEQsp,lb);  
Xsp1=vec2mat(Xsp1,pNumber);  
Xsp2=vec2mat(Xsp2,pNumber);  
randN=rand;  
Xsp(:,::,t,popCounter)=randN*Xsp1+(1-randN)*Xsp2;
end
end
clc;

XspR=Xsp(:,::,popN+1:popN+reserveN);  
Xdc(:,::,popN+1:popN+reserveN)=[];  
Xci(:,::,popN+1:popN+reserveN)=[];  
Xik(:,::,popN+1:popN+reserveN)=[];  
Xil(:,::,popN+1:popN+reserveN)=[];  
Xim(:,::,popN+1:popN+reserveN)=[];  
Xkd(:,::,popN+1:popN+reserveN)=[];  
Xls(:,::,popN+1:popN+reserveN)=[];  
Xpd(:,::,popN+1:popN+reserveN)=[];  
Xsp(:,::,popN+1:popN+reserveN)=[];

%INITIALIZING COSTS AND CALCULATING OBJECTIVE FUNCTIONS  
TC=zeros(periodN,popN);  
FC=zeros(periodN,popN);  
ManC=zeros(periodN,popN);  
MatC=zeros(periodN,popN);  
RepC=zeros(periodN,popN);
RecC=zeros(periodN,popN);
DisC=zeros(periodN,popN);
EI=zeros(periodN,popN);
FJ=zeros(periodN,popN);
VJ1=zeros(periodN,popN);
VJ2=zeros(periodN,popN);
VJ3=zeros(periodN,popN);

for popCounter=1:popN
  for t=1:periodN

    TC(t,popCounter)=sum(sum(costTsp.*Xsp(:, :, t, popCounter)))+sum(sum(costTpd.*Xpd(:, :, t, popCounter)))+sum(sum(costTdc.*Xdc(:, :, t, popCounter)))+sum(sum(costTci.*Xci(:, :, t, popCounter)))+sum(sum(costTik.*Xik(:, :, t, popCounter)))+sum(sum(costTil.*Xil(:, :, t, popCounter)))+sum(sum(costTim.*Xim(:, :, t, popCounter)))+sum(sum(costTkd.*Xkd(:, :, t, popCounter)))+sum(sum(costTls.*Xls(:, :, t, popCounter)));

    FC(t,popCounter)=costFp'*((Xpd(:, :, t, popCounter)>eps)+eps)+costFd'*((Xdc(:, :, t, popCounter)>eps)+eps)+costFi'*((Xci(:, :, t, popCounter),1)>eps)+costFk'*((Xkd(:, :, t, popCounter),2)>eps)+costFl'*((Xls(:, :, t, popCounter),2)>eps);
    ManC(t,popCounter)=costPp(:, t)'*sum(Xpd(:, :, t, popCounter),2);
    MatC(t,popCounter)=costPs(:, t)'*(sum(Xsp(:, :, t, popCounter),2)-sum(Xls(:, :, t, popCounter)));
    RepC(t,popCounter)=costPk(:, t)'*sum(Xkd(:, :, t, popCounter),2);
    RecC(t,popCounter)=costPl(:, t)'*sum(Xls(:, :, t, popCounter),2);
    DisC(t,popCounter)=costPm(:, t)'*sum(Xim(:, :, t, popCounter),1);

    EI(t,popCounter)=impactEp'*((Xpd(:, :, t, popCounter),2)>eps)+impactEm'*((Xim(:, :, t, popCounter),1)>eps)+sum(sum(impactEsp.*Xsp(:, :, t, popCounter)))+sum(sum(impactEpd.*Xpd(:, :, t, popCounter)))+sum(sum(impactEdc.*Xdc(:, :, t, popCounter)))+sum(sum(impactEci.*Xci(:, :, t, popCounter)))+sum(sum(impactEik.*Xik(:, :, t, popCounter)))+sum(sum(impactEil.*Xil(:, :, t, popCounter)))+sum(sum(impactEim.*Xim(:, :, t, popCounter)))+sum(sum(impactEkd.*Xkd(:, :, t, popCounter)))+sum(sum(impactEls.*Xls(:, :, t, popCounter)));

    FJ(t,popCounter)=jobFp'*((Xpd(:, :, t, popCounter),2)>eps)+jobFd'*((Xdc(:, :, t, popCounter),2)>eps)+jobFi'*((Xci(:, :, t, popCounter),1)>eps)+jobFk'*((Xkd(:, :, t, popCounter),2)>eps)+jobFl'*((Xls(:, :, t, popCounter),2)>eps)+sum(Xim(:, :, t, popCounter),1)>eps)+jobFm;

    VJ1(t,popCounter)=sum(sum(Xpd(:, :, t, popCounter),2).*(jobVp./(pCapacity_m(:, t)-pCapacity_p(:, t))))+sum(sum(Xdc(:, :, t, popCounter),2).*(jobVd./(dCapacity_m(:, t)-dCapacity_p(:, t))))+sum(sum(Xci(:, :, t, popCounter),1).*(jobVi./(iCapacity_m(:, t)-iCapacity_p(:, t))))+sum(sum(Xik(:, :, t, popCounter),1).*(jobVk./(kCapacity_m(:, t)-kCapacity_p(:, t))))+sum(sum(Xil(:, :, t, popCounter),1).*(jobVl./(lCapacity_m(:, t)-lCapacity_p(:, t))))+sum(sum(Xim(:, :, t, popCounter),1).*(jobVm./(mCapacity_m(:, t)-mCapacity_p(:, t))));

    VJ2(t,popCounter)=sum(sum(Xpd(:, :, t, popCounter),2).*(jobVp./(pCapacity_m(:, t)-pCapacity_p(:, t))))+sum(sum(Xdc(:, :, t, popCounter),2).*(jobVd./(dCapacity_m(:, t)-dCapacity_p(:, t))))+sum(sum(Xci(:, :, t, popCounter),1).*(jobVi./(iCapacity_m(:, t)-iCapacity_p(:, t))))+sum(sum(Xik(:, :, t, popCounter),1).*(jobVk./(kCapacity_m(:, t)-kCapacity_p(:, t))))+sum(sum(Xil(:, :, t, popCounter),1).*(jobVl./(lCapacity_m(:, t)-lCapacity_p(:, t))))+sum(sum(Xim(:, :, t, popCounter),1).*(jobVm./(mCapacity_m(:, t)-mCapacity_p(:, t))));

  end
end
+ sum(sum(Xci(:,:,t,popCounter),1)'.*(jobVi./(iCapacity_m(:,t))))+sum(sum(Xik(:,:,t,popCounter),1)'.*(jobVk./(kCapacity_m(:,t))))+sum(sum(Xil(:,:,t,popCounter),1)'.*(jobVl./(lCapacity_m(:,t))))+sum(sum(Xim(:,:,t,popCounter),1)'.*(jobVm./(mCapacity_m(:,t)))));

VJ3(t,popCounter)=sum(sum(Xpd(:,:,t,popCounter),2).*(jobVp./(pCapacity_o(:,t)-pCapacity_m(:,t))))+sum(sum(Xdc(:,:,t,popCounter),2).*(jobVd./(dCapacity_o(:,t)-dCapacity_m(:,t))))+sum(sum(Xci(:,:,t,popCounter),1)'.*(jobVi./(iCapacity_o(:,t)-iCapacity_m(:,t))))+sum(sum(Xik(:,:,t,popCounter),1)'.*(jobVk./(kCapacity_o(:,t)-kCapacity_m(:,t))))+sum(sum(Xil(:,:,t,popCounter),1)'.*(jobVl./(lCapacity_o(:,t)-lCapacity_m(:,t))))+sum(sum(Xim(:,:,t,popCounter),1)'.*(jobVm./(mCapacity_o(:,t)-mCapacity_m(:,t)))));

J1=FJ+VJ1;
J2=FJ+VJ2;
J3=FJ+VJ3;
end
end
Z1=sum(TC,1)+sum(FC,1)+sum(ManC,1)+sum(MatC,1)+sum(RepC,1)+sum(RecC,1)+sum(DisC,1);
Z2=sum(EI,1);
Z3=sum(J1,1);
Z4=sum(J2,1);
Z5=sum(J3,1);

%NON DOMINATION SORTING
pop=[(1:popN);Z1;Z2;Z3;Z4;Z5]';

sortedPop=NDS(pop,5,1);

%% GENETIC ALGORITHM MAIN LOOP
for genCounter=1:genMax
disp(genCounter);
pool=tournement(sortedPop,poolN,2);
poolIndex=pool(:,1);

%IMPLEMENTING CROSSOVER
childXdc=zeros(dNumber,cNumber,periodN,poolN);
childXci=zeros(cNumber,iNumber,periodN,poolN);
childXiklm=zeros(iNumber,kNumber+lNumber+mNumber,periodN,poolN);
childXik=zeros(iNumber,kNumber,periodN,poolN);
childXil=zeros(iNumber,lNumber,periodN,poolN);
childXim=zeros(iNumber,mNumber,periodN,poolN);
childXkd=zeros(kNumber,dNumber,periodN,poolN);
childXsd=zeros(sNumber,pNumber,periodN,poolN);

for i=1:2:poolN-1
if rand<cRate
    beta=rand;
    childXsp(:,;,:,i)=Xsp(:,;,:,poolIndex(i))*beta+Xsp(:,;,:,poolIndex(i+1))*(1-beta);
    childXsp(:,;,:,i+1)=Xsp(:,;,:,poolIndex(i))*(1-beta)+Xsp(:,;,:,poolIndex(i+1))*beta;
    childXpd(:,;,:,i)=Xpd(:,;,:,poolIndex(i))*beta+Xpd(:,;,:,poolIndex(i+1))*(1-beta);
    childXpd(:,;,:,i+1)=Xpd(:,;,:,poolIndex(i))*(1-beta)+Xpd(:,;,:,poolIndex(i+1))*beta;
    childXdc(:,;,:,i)=Xdc(:,;,:,poolIndex(i))*beta+Xdc(:,;,:,poolIndex(i+1))*(1-beta);
    childXdc(:,;,:,i+1)=Xdc(:,;,:,poolIndex(i))*(1-beta)+Xdc(:,;,:,poolIndex(i+1))*beta;
    childXci(:,;,:,i)=Xci(:,;,:,poolIndex(i))*beta+Xci(:,;,:,poolIndex(i+1))*(1-beta);
    childXci(:,;,:,i+1)=Xci(:,;,:,poolIndex(i))*(1-beta)+Xci(:,;,:,poolIndex(i+1))*beta;
else
    childXsp(:,;,:,i)=Xsp(:,;,:,poolIndex(i));
    childXsp(:,;,:,i+1)=Xsp(:,;,:,poolIndex(i+1));
    childXpd(:,;,:,i)=Xpd(:,;,:,poolIndex(i));
    childXpd(:,;,:,i+1)=Xpd(:,;,:,poolIndex(i+1));
    childXdc(:,;,:,i)=Xdc(:,;,:,poolIndex(i));
    childXdc(:,;,:,i+1)=Xdc(:,;,:,poolIndex(i+1));
    childXci(:,;,:,i)=Xci(:,;,:,poolIndex(i));
    childXci(:,;,:,i+1)=Xci(:,;,:,poolIndex(i+1));
    childXik(:,;,:,i)=Xik(:,;,:,poolIndex(i));
    childXik(:,;,:,i+1)=Xik(:,;,:,poolIndex(i+1));
end
childXik(:,:,i+1)=Xik(:,:,poolIndex(i+1));
childXil(:,:,i)=Xil(:,:,poolIndex(i));
childXil(:,:,i+1)=Xil(:,:,poolIndex(i+1));
childXim(:,:,i)=Xim(:,:,poolIndex(i));
childXim(:,:,i+1)=Xim(:,:,poolIndex(i+1));
childXkd(:,:,i)=Xkd(:,:,poolIndex(i));
childXkd(:,:,i+1)=Xkd(:,:,poolIndex(i+1));
childXls(:,:,i)=Xls(:,:,poolIndex(i));
childXls(:,:,i+1)=Xls(:,:,poolIndex(i+1));
end
end

%IMPLEMENTING MUTATION
for i=1:poolN
    if rand<mRate
        randIndex=randi([1,reserveN]);
        childXsp(:,:,i)=childXsp(:,:,i)*(1-changeR)+XspR(:,:,randIndex)*changeR;
        childXpd(:,:,i)=childXpd(:,:,i)*(1-changeR)+XpdR(:,:,randIndex)*changeR;
        childXdc(:,:,i)=childXdc(:,:,i)*(1-changeR)+XdcR(:,:,randIndex)*changeR;
        childXci(:,:,i)=childXci(:,:,i)*(1-changeR)+XciR(:,:,randIndex)*changeR;
        childXik(:,:,i)=childXik(:,:,i)*(1-changeR)+XikR(:,:,randIndex)*changeR;
        childXil(:,:,i)=childXil(:,:,i)*(1-changeR)+XilR(:,:,randIndex)*changeR;
        childXim(:,:,i)=childXim(:,:,i)*(1-changeR)+XimR(:,:,randIndex)*changeR;
        childXkd(:,:,i)=childXkd(:,:,i)*(1-changeR)+XkdR(:,:,randIndex)*changeR;
        childXls(:,:,i)=childXls(:,:,i)*(1-changeR)+XlsR(:,:,randIndex)*changeR;
    end
end

%CALCULATING OBJECTIVE FUNCTIONS
for i=1:poolN
    for t=1:periodN
        TC(t,popCounter)=sum(sum(costTsp.*childXsp(:,:,t,popCounter)))+sum(sum(costTpd.*childXpd(:,:,t,popCounter)))+sum(sum(costTdc.*childXdc(:,:,t,popCounter)))+sum(sum(costTci.*childXci(:,:,t,popCounter)))+sum(sum(costTci.*childXci(:,:,t,popCounter)))+sum(sum(costTc
Tik.*childXik(:,:,t,popCounter)*)+sum(sum(costTil.*childXil(:,:,t,popCounter))) + sum(sum(costTim.*childXim(:,:,t,popCounter)))+sum(sum(costTkd.*childXkd(:,:,t,popCounter)))+sum(sum(costTls.*childXls(:,:,t,popCounter))); FC(t,popCounter)=costFp'*((sum(childXpd(:,:,t,popCounter),2)>eps)+costFd'*(sum(childXdc(:,:,t,popCounter),2)>eps)+costFi'*((sum(childXci(:,:,t,popCounter),1)>eps)+costFk'*((sum(childXkd(:,:,t,popCounter),2)>eps)+costFm'*((sum(childXim(:,:,t,popCounter),1)>eps)); ManC(t,popCounter)=costPp(:,t)'*sum(childXpd(:,:,t,popCounter),2); MatC(t,popCounter)=costPs(:,t)'*(sum(childXsp(:,:,t,popCounter),2)- sum(childXls(:,:,t,popCounter))); RepC(t,popCounter)=costPk(:,t)'*sum(childXkd(:,:,t,popCounter),2); RecC(t,popCounter)=costPl(:,t)'*sum(childXls(:,:,t,popCounter),2); DisC(t,popCounter)=costPm(:,t)'*sum(childXim(:,:,t,popCounter),1); EI(t,popCounter)=impactEp'*sum(childXpd(:,:,t,popCounter),2)+impactEm'* sum(childXim(:,:,t,popCounter),1)+sum(sum(impactEsp.*childXsp(:,:,t,popCounter)))+sum(sum(impactEdc.*childXdc(:,:,t,popCounter)))+sum(sum(impactEci.*childXci(:,:,t,popCounter)))+sum(sum(impactEik.*childXik(:,:,t,popCounter)))+sum(sum(impactEil.*childXil(:,:,t,popCounter)))+sum(sum(impactEim.*childXim(:,:,t,popCounter)))+sum(sum(impactEkd.*childXkd(:,:,t,popCounter)))+sum(sum(impactEls.*childXls(:,:,t,popCounter))); FJ(t,popCounter)=jobFp'*((sum(childXpd(:,:,t,popCounter),2)>eps)+jobFd'*(sum(childXdc(:,:,t,popCounter),2)>eps)+(sum(childXci(:,:,t,popCounter),1)>eps)*jobFi+jobFk'*((sum(childXkd(:,:,t,popCounter),2)>eps)+jobFl'*(sum(childXim(:,:,t,popCounter),1)>eps)*jobFm; VJ1(t,popCounter)=sum(sum(childXpd(:,:,t,popCounter),2).*((jobVp./(pCapacity_m(:,t)- pCapacity_p(:,t))))+sum(sum(childXdc(:,:,t,popCounter),2).*((jobVd./(dCapacity_m(:,t)- dCapacity_p(:,t))))+sum(sum(childXci(:,:,t,popCounter),1).*((jobVi./(iCapacity_m(:,t)- iCapacity_p(:,t))))+sum(sum(childXkd(:,:,t,popCounter),1).*((jobVk./(kCapacity_m(:,t)- kCapacity_p(:,t))))+sum(sum(childXil(:,:,t,popCounter),1).*((jobVl./(lCapacity_m(:,t)- lCapacity_p(:,t))))+sum(sum(childXim(:,:,t,popCounter),1).*((jobVm./(mCapacity_m(:,t)- mCapacity_p(:,t))))); VJ2(t,popCounter)=sum(sum(childXpd(:,:,t,popCounter),2).*((jobVp./(pCapacity_m(:,t))))+sum(sum(childXdc(:,:,t,popCounter),2).*((jobVd./(dCapacity_m(:,t))))+sum(sum(childXci(:,:,t,popCounter),1).*((jobVi./(iCapacity_m(:,t))))+sum(sum(childXkd(:,:,t,popCounter),1).*((jobVk./(kCapacity_m(:,t))))+sum(sum(childXil(:,:,t,popCounter),1).*((jobVl./(lCapacity_m(:,t))))+sum(sum(childXim(:,:,t,popCounter),1).*((jobVm./(mCapacity_m(:,t)))));
VJ3(t, popCounter) = sum(sum(childXpd(:,:,t, popCounter), 2).*(jobVp./(pCapacity_o(:,t)- pCapacity_m(:,t)))) + sum(sum(childXdc(:,:,t, popCounter), 2).*(jobVd./(dCapacity_o(:,t)- dCapacity_m(:,t)))) + sum(sum(childXci(:,:,t, popCounter), 1).*(jobVi./(iCapacity_o(:,t)- iCapacity_m(:,t)))) + sum(sum(childXik(:,:,t, popCounter), 1).*(jobVk./(kCapacity_o(:,t)- kCapacity_m(:,t)))) + sum(sum(childXil(:,:,t, popCounter), 1).*(jobVl./(lCapacity_o(:,t)- lCapacity_m(:,t)))) + sum(sum(childXim(:,:,t, popCounter), 1).*(jobVm./(mCapacity_o(:,t)- mCapacity_m(:,t))));

J1 = FJ + VJ1;
J2 = FJ + VJ2;
J3 = FJ + VJ3;

end

Z1 = sum(TC, 1)+sum(FC, 1)+sum(ManC, 1)+sum(MatC, 1)+sum(RepC, 1)+sum(RecC, 1)+
    sum(DisC, 1);
Z2 = sum(EI, 1);
Z3 = sum(J1, 1);
Z4 = sum(J2, 1);
Z5 = sum(J3, 1);
popChild = [(1:poolN); Z1; Z2; -Z3; -Z4; -Z5]';

% NON DOMINATION SORTING OF PREVIOUS POPULATION AND CHILDREN
interPop = [pop; popChild];
sortedInterPop = NDS(interPop, 5, 1);

% CREATING POPULATION OF THE NEXT GENERATION
nextXdc = zeros(dNumber, cNumber, periodN, popN);
nextXci = zeros(cNumber, iNumber, periodN, popN);
nextXil = zeros(iNumber, lNumber, periodN, popN);
nextXik = zeros(iNumber, kNumber, periodN, popN);
nextXim = zeros(iNumber, mNumber, periodN, popN);
nextXpd = zeros(pNumber, dNumber, periodN, popN);
nextXkd = zeros(kNumber, dNumber, periodN, popN);
nextXls = zeros(lNumber, sNumber, periodN, popN);
nextXsp = zeros(sNumber, pNumber, periodN, popN);
for i = 1:popN
    if sortedInterPop(i, 1) <= popN
        nextXsp(:,:,i) = Xsp(:,:,sortedInterPop(i, 1));
        nextXpd(:,:,i) = Xpd(:,:,sortedInterPop(i, 1));
        nextXdc(:,:,i) = Xdc(:,:,sortedInterPop(i, 1));
        nextXci(:,:,i) = Xci(:,:,sortedInterPop(i, 1));
        nextXik(:,:,i) = Xik(:,:,sortedInterPop(i, 1));
        nextXil(:,:,i) = Xil(:,:,sortedInterPop(i, 1));
        nextXim(:,:,i) = Xim(:,:,sortedInterPop(i, 1));
        nextXkd(:,:,i) = Xkd(:,:,sortedInterPop(i, 1));
        nextXls(:,:,i) = Xls(:,:,sortedInterPop(i, 1));
    else
        nextXsp(:,:,i) = childXsp(:,:,sortedInterPop(i, 1)-popN);
        nextXpd(:,:,i) = childXpd(:,:,sortedInterPop(i, 1)-popN);
nextXdc(:, :, :, i) = childXdc(:, :, :, sortedInterPop(i, 1) - popN);
nextXci(:, :, :, i) = childXci(:, :, :, sortedInterPop(i, 1) - popN);
nextXik(:, :, :, i) = childXik(:, :, :, sortedInterPop(i, 1) - popN);
nextXil(:, :, :, i) = childXil(:, :, :, sortedInterPop(i, 1) - popN);
nextXim(:, :, :, i) = childXim(:, :, :, sortedInterPop(i, 1) - popN);
nextXkd(:, :, :, i) = childXkd(:, :, :, sortedInterPop(i, 1) - popN);
nextXls(:, :, :, i) = childXls(:, :, :, sortedInterPop(i, 1) - popN);
end
end
sortedPop = sortedInterPop(1:popN, :);
Xsp = nextXsp;
Xpd = nextXpd;
Xdc = nextXdc;
Xci = nextXci;
Xik = nextXik;
Xil = nextXil;
Xim = nextXim;
Xkd = nextXkd;
Xls = nextXls;
end
toc;

%WRITING THE RESULTS TO EXCEL
xlswrite('Obj&Rank.xlsx', sortedPop(:, 2:size(sortedPop, 2)));
Appendix F: Mamdani FIS model

In this Appendix, the Mamdani FIS model is presented (Mamdani and Asilian, 1975). In the Mamdani FIS model, the specialist idea is provided for the consequences on the basis of rules (Zadeh 1965). The t-norm (minimum) is usually accepted for the logic connective “and”, as expressed by:

\[ \mu_A(x) \text{ and } \mu_B(x) = \min\{\mu_A(x), \mu_B(x)\} \]  

(1)

For the logic connective “or” s-norm V (maximum) is usually displayed.

\[ \mu_A(x) \text{ OR } \mu_B(x) = \max\{\mu_A(x), \mu_B(x)\} \]  

(2)

The inference machine employs an implication relation R between the fuzzy number resulting from the logic operations, and the consequent, \( \tilde{B} \) for rules. A commonly employed implication operator is the Minimum (Mamdani), expressed as (Altrock 1995):

\[ \mu_R(x,y) = \min\{\mu_A(x), \mu_B(x)\} \]  

(3)

Alternative operators are the Max–Min (Zadeh) and the Multiplication (Larsen), respectively, as expressed (Altrock 1995):

\[ \mu_R(x,y) = \max\{1 - \mu_A(x), \min\{\mu_A(x), \mu_B(x)\}\} \]  

(4)

\[ \mu_R(x,y) = (\mu_A(x) \times \mu_B(x)) \]  

(5)

The composition between a fuzzy singleton and the implication relation is used to demonstrate the output fuzzy number of rules. Several composition operators of fuzzy relations are usually used: Max–Min, Max–prod, and Max–Media. These operators are represented by (Pedrycz and Gomideh 2007):

\[ SoR(x,y) = \max\{\min\{\mu_s(x,y), \mu_R(y,z)\}\} \]  

(6)
\( S.R(x,z) = \text{MAX}\{\mu_s(x,y)^* \mu_R(y,z)\} \) (7)

\( S \oplus R(x,z) = \text{MAX}\{1/2(\mu_s(x,y) + \mu_R(y,z))\} \) (8)

An aggregation of the resulting composition operations for each rule is defined as the final step of FIS model. For the aggregation process, there are several operators, such as arithmetic, geometric or harmonic means, Min and Max (Zadeh 1965; Pedrycz and Gomideh 2007). The Max operator is preferred when compensation between input variables is desirable (Altrock 1995). The Max operator is given by:

\( AG(.) = \text{MAX}(\mu_{R1}(x), \mu_{R2}(x), \ldots, \mu_{Rn}(x)) \) (9)

In the defuzzification interface, the output fuzzy numbers are converted into a crisp number. The Center of Area (CoA) is a commonly applied:

\[
\text{Center of area } Z_{\text{COA}} = \frac{\int z \mu_A(z) dz}{\int \mu_A(z) dz}
\] (10)

where \( n \) is the number of discrete points of the fuzzy set and \( \mu_A(z) \) is the aggregated output MF.
Appendix G: Fuzzy AHP and Fuzzy TOPSIS

The steps of fuzzy AHP approach is presented as follows: (Ayag, 2005)

At first, the fuzzy comparison matrices are built. Triangular fuzzy numbers \( \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} \) are applied to display the relative strength of each pair of elements in the same hierarchy. The fuzzy judgment matrix, \( \tilde{A} \) via pair wise comparison is constructed as given below:

\[
\tilde{A} = \begin{bmatrix}
1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\
\tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{a}_{n1} & \tilde{a}_{12} & \cdots & 1
\end{bmatrix}
\]  

(1)

where \( \tilde{a}_{ij} = 1 \), if \( i \) is equal \( j \), and \( \tilde{a}_{ij} = \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} \) or \( \tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1} \), if \( i \) is not equal \( j \). In the next step, the fuzzy eigenvalues are calculated. A fuzzy eigenvalue, \( \tilde{\lambda} \), is a fuzzy number solution to:

\[
\tilde{A} \tilde{x} = \tilde{\lambda} \tilde{x}
\]

(2)

where \( \tilde{\lambda}_{\text{max}} \) is the largest eigenvalue of \( \tilde{A} \) and \( \tilde{x} \) is a non-zero \( n \times 1 \) fuzzy vector containing fuzzy number \( \tilde{x}_i \). To compute fuzzy multiplications and additions by using the interval arithmetic and \( \alpha \)-cut, the equation \( \tilde{A} \tilde{x} = \tilde{\lambda} \tilde{x} \) is equivalent to:

\[
[a_{i1}^\alpha x_1^\alpha, a_{i1_u}^\alpha x_{1_u}^\alpha] \oplus \cdots \oplus [a_{i n_l}^\alpha x_{n_l}^\alpha, a_{i n_u}^\alpha x_{n_u}^\alpha] = [\tilde{\lambda} x_{i l}^\alpha, \tilde{\lambda} x_{i u}^\alpha]
\]

where,

\[
\tilde{A} = [a_{ij}^\alpha], \tilde{x}^\alpha = (\tilde{x}_1, \ldots, \tilde{x}_n),
\]

\[
\tilde{a}_{ij}^\alpha = [a_{i j l}^\alpha, a_{i j u}^\alpha], \tilde{x}_{ij}^\alpha = [x_{ij l}^\alpha, x_{ij u}^\alpha],
\]

\[
\tilde{\lambda}^\alpha = [\lambda_{l}^\alpha, \lambda_{u}^\alpha]
\]

(3)

for \( 0 < \alpha \leq 1 \) and all \( i, j \), where \( i = 1, 2, \ldots, n \), \( j = 1, 2 \ldots, n \).

The \( \alpha \)-cut is famous to contain the experts or decision maker confidence over his/her preferences. The degree of satisfaction for the judgment matrix \( \tilde{A} \) is calculated by the
index of optimism $\mu$. A larger value of the index $\mu$ shows a higher degree of optimism.

The index of optimism is a linear convex combination defined as:

$$\tilde{a}_{ij}^\alpha = \mu \tilde{a}_{ij}^\alpha + (1 - \mu) \tilde{a}_{ij}^\alpha, \forall \alpha \in [0,1]$$

(4)

When $\alpha$ is fixed, the following matrix can be obtained by setting the index of optimism, $\mu$, in order to estimate the degree of satisfaction:

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix}$$

(5)

After constructing all required pairwise judgment matrices between criteria/sub-criteria levels, for each, the consistency ratio (CR) should be calculated. The deviation from consistency, the measure of inconsistency is named the consistency index (CI) and computed using the following equation:

$$\text{CI} = \lambda_{\text{max}} - 1/n - 1$$

(6)

where $n$ is matrix size.

The CR is applied to calculate directly the consistency of pairwise comparisons, and computed by dividing the CI by a value obtained from a table of random consistency index (RI), the average index for randomly generated weights (Saaty, 1980), as shown in the following equation:

$$\text{CR} = \frac{\text{CI}}{\text{RI}}$$

(7)

If the CR less than 10%, the comparisons are acceptable, otherwise not.

<table>
<thead>
<tr>
<th>Size (n)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
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<td>RI</td>
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<td>0</td>
<td>0.52</td>
<td>0.89</td>
<td>1.11</td>
<td>1.25</td>
<td>1.35</td>
<td>1.40</td>
<td>1.45</td>
<td>1.51</td>
</tr>
</tbody>
</table>
The Fuzzy TOPSIS method consists of the following steps: (Aydogan, 2012)

Step 1: Choose the linguistic rating values for the alternative with respect to criteria

There are m possible alternatives called \( A = \{ A_1, A_2, \ldots A_m \} \) which are to be calculated against the criteria, \( C = \{ C_1, C_2, \ldots C_n \} \). The criteria weights are indicated by \( w_j \) (\( j = 1, 2, \ldots, n \)). The performance ratings of each expert \( D_k \) (\( k = 1, 2, \ldots K \)) for each alternative \( A_i \) (\( i = 1, 2, \ldots, m \)) with respect to criteria \( C_j \) (\( j = 1, 2, \ldots, n \)) are indicated by \( \bar{R}_k = \bar{x}_{ijk} \) (\( i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; k = 1, 2 \ldots K \)) membership function \( \mu \bar{R}K(x) \).

Step 2: Calculate aggregate fuzzy ratings for the alternatives

If the fuzzy ratings of all experts are presented as TFN \( \bar{R}_k = (a_k, b_k, c_k) \), \( k = 1, 2, \ldots K \) then the aggregated fuzzy rating is given by \( \bar{R} = (a, b, c) \) \( k = 1, 2, \ldots K \) where

\[
a_k = \min \{ a_k \}, \quad b_k = \frac{1}{K} \sum_{k=1}^{K} b_k, \quad c_k = \max \{ c_k \},
\]

(1)

If the fuzzy rating of the \( k \)th decision maker are \( \bar{x}_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk}) \), \( i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \), then the aggregated fuzzy ratings \( \bar{x}_{ij} \) alternatives with respect to each criteria are given by \( \bar{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}) \), where:

\[
a_{ij} = \min \{ a_{ijk} \}, \quad b = \frac{1}{K} \sum_{k=1}^{K} b_{ijk}, \quad c = \max \{ c_{ijk} \},
\]

(2)

Step 3: Construct the fuzzy decision matrix

The fuzzy decision matrix for the alternatives \( \bar{D} \) is constructed as follows:

\[
\bar{A} = \left[ \begin{array}{cccc}
\bar{x}_{11} & \bar{x}_{12} & \ldots & \bar{x}_{1n} \\
\bar{x}_{21} & \bar{x}_{22} & \ldots & \bar{x}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\bar{x}_{m1} & \bar{x}_{m2} & \ldots & \bar{x}_{mn}
\end{array} \right] \quad i = 1, 2, \ldots m; j = 1, 2, \ldots, n
\]

(3)
Step 4: Construct the Normalize fuzzy decision matrix

In this step by using linear scale transformation the raw data are normalized to bring the various criteria scales into a comparable scale. The normalized fuzzy decision matrix \( \tilde{R} \) is given by:

\[
\tilde{R} = [r_{ij}]_{m \times n}, \quad i = 1, 2, \ldots; j = 1, 2, \ldots, n
\]  

(4)

where

\[
\tilde{r}_{ij} = \left( \frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+} \right) \quad \text{and} \quad c_j^+ = \max c_{ij} \quad \text{(benefit criteria)}
\]  

(5)

\[
\tilde{r}_{ij} = \left( \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right) \quad \text{and} \quad a_j^- = \min a_{ij} \quad \text{(cost criteria)}
\]  

(6)

Step 5: Construct the weighted normalized matrix

The weighted normalized matrix \( \tilde{v} \) for criteria is computed by multiplying the weights \( W_j \) of evaluation criteria with the normalized fuzzy decision matrix \( \tilde{r}_{ij} \).

\[
\tilde{V} = [\tilde{v}_{ij}]_{m \times n}, \quad i = 1, 2, \ldots; j = 1, 2, \ldots, n \quad \text{where} \quad \tilde{v}_{ij} = \tilde{r}_{ij} W_j
\]  

(7)

Step 6: Determine the fuzzy ideal solution (FPIS) and fuzzy negative ideal solution (FNIS)

The FPIS and FNIS of the alternatives are computed as follows:

\[
A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_m^+) \quad \text{where} \quad \tilde{v}_j^+ = (\tilde{c}_j^+, \tilde{c}_j^+, \tilde{c}_j^+) \quad \text{and} \quad \tilde{c}_j^+ = \max \{ \tilde{c}_{ij} \}
\]  

(8)

\[
A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_m^-) \quad \text{where} \quad \tilde{v}_j^- = (\tilde{a}_j^-, \tilde{a}_j^-, \tilde{a}_j^-) \quad \text{and} \quad \tilde{a}_j^- = \min \{ \tilde{a}_{ij} \}
\]  

(9)

\( \forall i = 1, 2, \ldots, m \quad \text{and} \quad j = 1, 2, \ldots, n \)
Step 7: Calculate the distance of each alternative from FPIS and FNIS

The distance \( (d_i^+, d_i^-) \) of each weighted alternative \( i = 1, 2, \ldots, m \) from the FPIS and the FNIS is calculated as follows:

\[
d_i^+ = \sum_{j=1}^{n} d_\nu(\tilde{\nu}_{ij}, \tilde{\nu}_{ij}^+) \quad i = 1, 2, \ldots, m
\]  \hspace{1cm} (10)

\[
d_i^- = \sum_{j=1}^{n} d_\nu(\tilde{\nu}_{ij}, \tilde{\nu}_{ij}^-) \quad i = 1, 2, \ldots, m
\]  \hspace{1cm} (11)

Step 8: Calculate the closeness coefficient \((CC_i)\) of each alternative

The closeness coefficient \(CC_i\) displays the distances to the fuzzy positive ideal solution \( (A^+)\) and the fuzzy negative ideal solution \( (A^-)\) simultaneously. The closeness coefficient of each alternative is estimated as:

\[
CC_i = \frac{d_i^-}{d_i^+ + d_i^-}
\]  \hspace{1cm} (12)

Step 9: Rank the alternatives

In step 9, the different alternatives are ranked according to the closeness coefficient \((CC_i)\) in decreasing order.