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An optimization model for a sustainable closed-loop supply chain considering efficient supplier selection and total quantity discount policies

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This paper addresses the sustainable closed-loop supply chain (SCLSC) design problem regarding selecting a supplier under total quantity discount with demand uncertainty and logistic flow uncertainty. The proposed model considers the three pillars of sustainability: the economic, environmental, and social realms. The model deals with the costs incurred by products-related manufacturing and minimizes the carbon dioxide emissions resulting from different manufacturing processes, as well as the attendant rate of injuries among the workers. Python edition 2019-07 software with the SCIPY solver was used to solve the model, using a sequential least squares programming algorithm (SLSQP) to obtain optimal solutions. A numerical study was conducted to validate the model. A sensitivity analysis was conducted to address the effects of both types of uncertainty on the optimal solution. It was found that the effect of a high rate of demand uncertainty is more severe than the effect of the uncertainty of the flow logistics in the reverse direction since the former generated a lower value of the optimal solution than the worst-case scenario generated by the uncertainty budget. Moreover, the higher the weight of environmental and social objectives, the higher the proportion of recycled products from the total production. This study proposes a robust optimization model for an SCLSC that considers two types of uncertainty: the uncertainty budget that is used for the logistics flow in the reverse direction for refurbished and redesigned products and the box of uncertainty that is used to address the demand uncertainty.

1. Introduction

In today's highly competitive world, all companies are seeking to improve their production to meet the customers' expectations and enhance their satisfaction such that the company can achieve its goals and targets. Within this context, supply chain management (SCM) is one of the most effective management tools a company can use to optimize its operations and maximize profits (Li, Ragu-Nathan, Ragu-Nathan, & Rao, 2006). In brief, supply chain management (SCM) can be considered as an integration of all activities related to transforming raw materials into finished products while considering the flow of material, money, and information in both directions to give the company its competitive advantage. As the common goal for all industries is cost minimization and, consequently, profit maximization, supplier selection is a crucial factor. This importance is attributed to the high cost of raw materials since studies have shown that a typical manufacturer spends 60% of the total revenue on purchased items. Moreover, the suppliers must be selected efficiently, especially in the hugely competitive world of today, in which the number of suppliers is increasing daily. As such, suppliers are making huge efforts to attract

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manufacturers by providing a number of incentives—such as discounts and free shipping—to increase their chances of being selected.

When considering the environment within the supply chain context, numerous aspects must be investigated, including gas emissions, waste reduction, and biodiversity. Demartini et al. (2018) investigated the current state of soft drink supply chains in terms of sustainability by reviewing the literature on the best practices and key performance indicators and considered two case studies to ascertain whether there is a positive correlation between the reported findings and practical activities. Elsewhere, it is recommended that greenhouse gas emissions should be reduced by 50% of the 1990 level by 2050 to increase the probability of preventing a global temperature increase of 2°C (Meinshausen et al., 2009). Transportation and production are two of the main sources of carbon dioxide (CO_2) emissions, accounting for approximately 45% of the total emissions (Dekker, Bloemhof, & Mallidis, 2012), with the former being one of the most considered factors in green logistics research. Various social-related aspects, such as job creation, number of injuries in the production plants, number of working hours, and discrimination, have also been studied (Hussain, Awasthi, & Tiwari, 2016). Adding the social factor to the supply chain makes it more realistic and more directed toward protecting the most valuable aspects of life, namely, money, the environment, and humankind. In fact, this has led to the establishment of a sustainable closed-loop supply chain (CLSC), with both researchers and practitioners in most industries focusing more on achieving and maintaining sustainable practices within the area of SCM (Chanchaichujit, Pham, & Tan, 2019). Here, researchers have investigated both the forward chain and the reverse chain, with the main incentive in the reverse path pertaining to the economic aspect (Tahoori, Rosnah, & Norzima, 2014). However, a review of the relevant literature indicates that there is an extremely limited number of studies that consider the social aspects of supply chains in relation to dynamism and the complexity of human behavior. As Demartini, Tonelli, and Bertani (2018) stated, sustainable industrial systems are complex, both in terms of detail and dynamics, and the only way to capture a realistic view is by following an integrated approach. In the process, considering the number of injuries resulting from different processes of the supply chain, maintaining the rate at the minimum is a crucial factor. This consideration of the social aspects would help with the development of a sustainable model that considers the three pillars of sustainability, namely, the economic, the environmental, and the social realms.

Ideally, the raw materials will be smoothly imputed into the supply chain activities to produce final products that fully meet customer demand while taking into account the exact number of products that will be returned. However, an ideal scenario is unlikely to ever be achieved given the existing uncertainties pertaining to each aspect of the supply chain, which include uncertainties in demand, supply, process, reverse logistics, shipment cost, and raw materials (Taleizadeh, Haghighi, & Niaki, 2019). In fact, the uncertainties in supply and demand are two major sources of doubt in the field of SCM (Al-Rawashdeh et al., 2023;). Demand uncertainty is defined as an inexact forecasting demand or as volatile demand. Moreover, the uncertain return factor cannot be neglected since it plays an important role in the uncertainty on the reverse logistics side (Brandenburg, Govindan, Sarkis, & Seuring, 2014). The presence of this type of uncertainty is a developing reality that must be addressed in designing a CLSC through robust optimization mathematical modeling (Barbosa-Póvoa, da Silva, & Carvalho, 2018). The uncertainty budget would lead to a less conservative solution and the formulation of a tractable robust counterpart through strong duality. However, the uncertainty budget is not effective when only one parameter is uncertain in each constraint (Taleizadeh et al., 2019). As the proposed model is a CLSC model, two types of uncertainties are considered in this study to address the effect of uncertainty in both the forward direction and the reverse direction. Specifically, the demand and returned product uncertainties are considered through the use of a robust optimization model.

Nowadays, the focus of both academic researchers and companies is the management and design of sustainable supply chains that form part of new sustainable strategies and production practices aimed at maximizing the profits and minimizing CO_2 emissions (Turki & Rezg, 2019). As such, there is an urgent need for research on the economic, environmental, and social aspects (Govindan & Cheng, 2015), and the current study contributes to the existing research in several ways. First, a comprehensive model is developed that considers the three sustainability pillars (economic, environmental, and social), as well as supplier selection and the forward and reverse directions, under two types of uncertainty in both directions along with a total quantity discount policy. Second, a robust optimization model for a CLSC is designed, which considers two major types of uncertainty: the uncertainty budget that is used for the logistics flow in the reverse direction for refurbished and redesigned products, and the box of uncertainty that is used to address the demand uncertainty. Python edition 2019-07 software with a SCIPY solver is adopted to solve the model using an SLSQP algorithm.

Based on the above, the following points are the main motivations for conducting this study:

The suppliers must be selected efficiently, especially in this highly competitive world, in which the number of suppliers is increasing daily.

Transportation and production are two of the main sources of CO_2 emissions, accounting for approximately 45% of the total emissions.

A review of the relevant literature indicates that there is an extremely limited number of studies that consider the social aspects of SCM in relation to dynamism and the complexity of human behavior.

Investigating the impact of quantity discounts in an uncertain situation is a potentially fruitful area of research(Shekarian, 2020).

The remainder of this paper is organized as follows. Section 2 presents the review of the relevant literature before the research problem and the proposed mathematical model are presented in section 3. Section 4 then illustrates a numerical example and the hypothetical dataset in addition to a discussion of the results, with the results of the sensitivity analysis presented in section 5. Section 6 then discusses the managerial implications of the results before section 7 concludes the paper with the conclusions and several future research directions.

2. Literature Review

In the 1990s, a supply chain revolution emerged, inevitably entwining the environment with supply chain activities. The notion of green (G)SCM thus surfaced and gained a great deal of attention among researchers, with numerous studies conducted to emphasize the importance of this greener approach (Iris & Asan, 2012). Integrating green practices in the supply chain presents a competitive advantage, with profits potentially increased by conserving resources and improving productivity. Darnall, Jolley, and Handfield (2008) asserted, this would encourage companies to adopt GSCM within their operations, an assertion supported by (Chiou, Chan, Lettice, & Chung, 2011), who demonstrated that implementing GSCM would achieve a better performance both in economic and environmental terms. Elsewhere, Roy and Whelan (1992) studied the process of recycling through value-chain collaboration, while green purchasing was found to benefit a company if it has a long-term relationship with the supplier (Zhu & Geng, 2001). Meanwhile, Arena, Mastellone, and Perugini (2003) discussed the process of solid management and its reflection on the environment to identify the best tool for quantifying all the related environmental impacts under different suggested scenarios. Overall, it presents good business sense, with improved revenues, which, in turn, can be considered as enhancing profits, not the cost. A multi-objective Mixed-Integer Programming (MIP) model was designed that works in two directions, the economic and the environmental, to minimize the costs and the effects of the production process on the environment (Wang, Lai, & Shi, 2011).

Within the environmental context, CO_2 emissions have particularly drawn the attention of researchers. For example, study proposed a disassembly system design while considering the CO_2 rate and the idea of recycling to identify an alternative solution for harmonizing the CO_2 emissions(Igarashi, Yamada, Gupta, Inoue, & Itsubo, 2016). Transportation is one of the major sources of CO_2 emissions and numerous researchers have investigated this factor, including (Validi, Bhattacharya, & Byrne, 2015), who addressed a routing problem while considering the CO_2 emissions resulting from transportation in a two-layer sustainable green supply chain distribution model. In addition, study designed a bi-objective model for order allocation and supplier selection to minimize the costs and the effects on the environment by choosing the minimum distance (Govindan, Jafarian, & Nourbakhsh, 2015). Moreover, CO_2 emissions have also been optimized as a part of maritime logistics in studies analyzing operational strategies, such as peak shaving, operations optimization, technology usage, alternative fuels, and energy management systems for improving the energy efficiency and environmental performance of ports and terminals (Iris & Asan, 2012). For example, study addressed the well-known "berth allocation problem" to assign berthing times and positions to the vessels in container terminals by introducing a novel mathematical formulation that extends the classical BAP to cover multiple ports in a shipping network under the assumption of strong cooperation between the shipping lines and the terminals (Venturini, Iris, Kontovas, & Larsen, 2017).

The previous level of attention to the environment is no longer sufficient, and the new notion of sustainability takes into account the three main pillars: the economic, the environmental, and the social realms. Social factors can be measured in various ways. Eskandarpour analyzed 87 papers that incorporated economic, environmental, and/or social dimensions to investigate which environmental and social objectives are included, how they are integrated, and which industrial applications and contexts are covered(Eskandarpour, Dejax, Miemczyk, & Péton, 2015). Elsewhere, Pishvaee designed a multi-criteria objective function that assists with various social aspects, including job creation, local communities, consumer risk, and health(Pishvaee, Razmi, & Torabi, 2014), while study created a multi-objective model to optimize the supply chain while considering employee injuries as a measure of health and safety issues (Chen & Andresen, 2014). Meanwhile, Dayhim, Jafari, & Mazurek (2014) translated the social aspects into costs, with the aim of minimizing these costs. For their part, study created a multi-objective model that considers the social pillar by concentrating on employee well-being, which was defined in terms of how far the employees are from the production sites and how much distance will thus be covered (Boukherroub, Ruiz, Guinet, & Fondrevelle, 2015). However, the green aspect is the more dominant factor driving the research, compared with the social aspect (Ciccullo, Pero, Caridi, Gosling, & Purvis, 2018).

Sustainability has been defined in other terms, that is, all the products that are produced will be used (ALNawaiseh et al., 2022; Shibly et al., 2021), disposed of, or recycled in the closed-loop method, defined as closed-loop supply chain management (CLSCM), which pertains to all forward and reverse logistics in the chain (Kumar & Kumar, 2013). These logistics include the procurement of materials, production, distribution, and the collection and processing of the returned products to ensure sustainable recovery (Kumar & Kumar, 2013). Many researchers have studied CLSCs in relation to various problems. For example, Özceylan studied end-of-life vehicle treatment in Turkey via a multi-period closed-loop green supply chain network (Özceylan, Demirel, Çetinkaya, & Demirel, 2017).

Uncertainty in supply chains can be caused by different sources, including uncertainty in supply, demand, and processing. These types of uncertainty affect the planning, design, and control of the supply chain. Various mathematical approaches can be used to deal with the uncertainty in a supply chain; these can be classified into fuzzy, stochastic, and robust optimization. In terms of the fuzzy approach, which considers the ambiguities of the attributes as membership, the function is seen as a means of defining reality. Talaei, Moghaddam, Pishvaee, Bozorgi-Amiri, and Gholamnejad (2016) designed a multi-product CLSC model to resolve the location and allocation problem by addressing demand uncertainty via a robust fuzzy programming-based approach. Other researchers have used the stochastic optimization approach, which deals with uncertainty in such a way that the probability distributions of various uncertain parameters are known. Elsewhere, tudy developed a multi-objective optimization model incorporating carbon emissions and carbon footprints to study the resilience and disruption risk of sustainable chain networks (Mari, Lee, & Memon, 2014). Meanwhile, Manerba studied supplier selection in relation to the capacitated single-period total quantity discount under the uncertainty problem; however, the authors focused on the cases in which only the product price or only the product demand was stochastic, with two frameworks considered: stochastic models and branch-and-cut frameworks (Manerba, Mansini, & Perboli, 2018). For their part, study investigated the uncertain multi-objective shortest path problem for a weighted connected directed graph, where every edge weight is associated with two uncertain parameters—cost and time—by formulating the expected value model and chance-constrained model (Majumder, Kar, Kar, & Pal, 2020). Working within the same context, these authors designed an uncertain multi-objective multi-item fixed charge solid transportation problem while considering a profit maximization and time minimization scheme (Majumder, Kundu, Kar, & Pal, 2019).

After reviewing the literature related to SCM under uncertainty, it was clear that there is a lack of studies that address the uncertainty in SCLSCs, which was confirmed by(Barbosa-Póvoa et al., 2018) , who found that among a set of 220 papers, only 16% considered the issue of uncertainty. Study recommended studying the impact of different types of uncertainty on the different stages of CLSCs (Peng, Shen, Liao, Xue, & Wang, 2020), while Zhen, Huang, & Wang (2019) noted that a joint problem with multi-echelon, multi-objective, multi-product, and stochastic demand for sustainable requirement has not, as yet, been discussed. The latter authors thus developed a bi-objective optimization model with two objectives for CO_2 emissions and total operating cost with demand uncertainty only.

The present study aims to fill the gap in the literature by considering the uncertainty in SCLSCs to solve the supplier selection problem under a discount policy scenario. In addition to building on model (Rad & Nahavandi, 2018), various social aspects represented by choosing a production process that has an acceptable rate of injuries in the workforce were added to the model. Table 1 summarizes the main articles in the existing body of literature related to the present study, presenting the different aspects addressed by these studies.

The model proposed in this study considers many aspects that have not yet been addressed together. More specifically, unlike previous studies, this study seeks to find the optimal decisions that guarantee to increase profits (economic), reduce the pollutants (environmental), and reduce the injury rate (social) by selecting the best supplier with a quantity discount policy under two types of uncertainty. Reviewing the literature helped to identify the research gaps in all the previously-discussed topics and to formulate our research problem and its significance.

3. Model Presentation

The supplier selection problem has attracted the attention of many researchers, with various models developed to help select the best supplier efficiently, mainly in the forward supply chain networks (Barbosa-Póvoa et al., 2018). This study aimed to develop a multi-objective model for developing a multi-product and capacitated sustainable closed-loop logistic network that integrates the pricing problem and supplier's discount policy while considering the three pillars of sustainability (economic, environmental, and social). More specifically, the economic aspect is represented by selecting the best supplier even when there is a discount policy offered from a set of suppliers, as suggested by (Ruiz-Torres, Mahmoodi, & Ohmori, 2019). Regarding the environmental aspect, the model is aimed at minimizing the CO_2 emissions resulting from operations and transportation. Finally, the social aspect involves minimizing the number of injuries suffered by personnel during different operation processes. In the process, two main types of uncertainty related to both the forward and the backward directions are considered: uncertainty in demand and in returned products, as suggested by (Chalmardi & Camacho-Vallejo, 2019). As a result, this comprehensive model could guide organizations in their supplier selection, in determining the volume of products to be produced and stored, and, finally, in terms of the operation method that should be followed, which must be cost-effective (economic), less harmful to the environment (environmental), and more attentive to an acceptable rate of injuries among personnel (social). Establishing such a model that considers all these factors together will contribute to filling the gap in the literature. A full description of the model is given in the following sections.

Table 1
Analysis of the gaps in the related studies

					SC network type		**Sustainability pillar**			**Methodology**	
Study	*Different types of centers*	*Discount policy of Raw material*	*Supplier selection*	*Two types of uncertainty*	*Forward*	*Reverse*	*Social aspects*	*Economic aspects*	*Environmental Aspects*	*Algorithm/Approach*	*Solver*
Chen and Andresen	No	No	No	No	Yes	No	Yes	Yes	Yes	Weighted-sum approach	Branch and Bound Solver of LINGO
Kim et al.	No	No	No	Yes	Yes	Yes	No	Yes	No	Robust optimization method	ILOG 17 CPLEX STUDIO 6.0
Rezaee et al.	Yes	Yes	Yes	No	Yes	Yes	No	Yes	No	Data envelopment analysis–Nash bargaining game	Lingo 14.0
Rad and Nahavandi	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Pareto-optimal	ILOG CPLEX 12.6
Chalmardi & Camacho-Vallejo	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes	Heuristic algorithm	GAMS-IDE
Rahimi et al.	Yes	No	No	Yes	Yes	No	Yes	Yes	Yes	Goal programming techniques	GAMS software
Ghahremani-Nahr et al.	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Robust fuzzy modeling	Whale optimization algorithm/Package
Govindan et al.	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Yes	fuzzy analysis network process multi-objective mixed-linear integer program	GAMS software
Chen et al.	Yes	Yes	Yes	No	Yes	No	No	Yes	No	DEA-TOPSIS, fuzzy mixed integer programming (FMIP)	Not mentioned
Nasr et al.	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Multi-objective mixed integer linear programming	GAMS/24.1.2/Win64 software
Alizadeh et al.	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	a stochastic integrated multi-objective mixed integer nonlinear programming model	ECO-it, GAMS version 24.1.2
Zhu et al.	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes	Fuzzy analysis, cloud model theory	Not mentioned
Ruiz-Torres et al.	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Decision tree model	CPLEX
This Study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Robust optimization method	SLSQP optimizer/ SCIPY solver

3.1. Model Description

In this study, the CLSC model comprises raw material suppliers, a manufacturer, and end customers. Fig. 1 presents the proposed model. Here, the manufacturer uses raw materials that are purchased from a supplier under a total quantity discount policy, materials that can be manufactured in two different ways and assembled to produce different products, which will then be shipped and stored in the storage centers before being shipped to the distribution centers to be sold to the end customers.

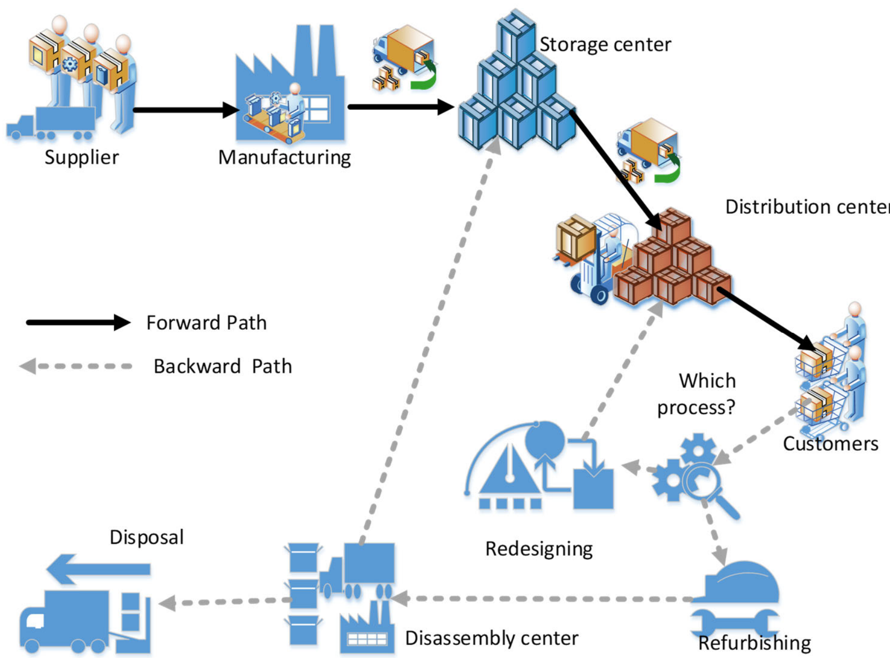

Fig. 1. The proposed CLSC model

Damaged products will be collected from customers for two different types of process: the refurbishment process or the redesigning process, with each process including two different methods of operation. In the initial stages, returned products are collected and shipped to the centers based on the level of damage. The products that need remanufacturing will be then disassembled, remanufactured, reassembled, stored, and distributed again, while others will be redesigned and sent back to the distribution centers or deemed to be defective products. All these processes are integrated to meet demand in the following ways: 1) using the raw materials purchased from a supplier(s) to manufacture new products, 2) using the refurbished products from the refurbishment process, and 3) using the redesigned products from the redesigning process. All the above operations will yield both profits and costs, and this will be expressed in the first objective function. However, pollutants are also produced from the shipping since all the centers are geographically distributed, while each manufacturing method will also involve different amounts of emissions, and this will be illustrated in the second objective function. The third objective function involves determining the acceptable injury rate of each different process and manufacturing method. This model can be applied within different types of industries in which reprocessing and reassembling the products are valid processes, such as the automotive and electronic industries.

3.2. The Mathematical Model

The proposed model is a multi-objective, multi-product, and mixed integer non-linear programming (MINLP) model, which comprises the appropriate objective functions and constraints based on a comprehensive understanding of the research gaps and the required objectives. First, a deterministic model was developed to better understand the characteristics of the model before a robust optimization model was developed to consider two types of uncertainties by developing a dual formulation for the objective functions and constraints.

3.2.1. Model Assumptions

The following assumptions apply:

The demand will be met from the three processes: raw material supply to produce new products, the refurbishment process, and the redesigning process.

Raw material suppliers, refurbishment methods, and redesigning methods have capacity constraints.
One supplier can fulfill the order quantities needed for new products.
The transportation costs depend on the distance between the different centers in addition to the shipped quantity.
For new products, refurbished and redesigned products, the production emissions depend on the chosen method and the produced quantity.
The transportation emissions depend on the shipped quantity, the distance between the centers, and the type of transportation used.
The order quantity from all of the s^{th} raw material suppliers should be consumed before the ($s+1$) order quantity is entered.

3.2.2. Model Preliminaries

This section provides the indices, parameters, decision variables, and assumptions to better define the proposed mathematical model components. Table 2 presents the indices used in the proposed model.

Table 2
The model indices.

Index	Description
s	Raw material supplier
p	Product type
i	Raw material supplied
T	Interval of total discount policy of the raw material supplier
x	Method used for refurbishment
k	Method used for redesign
I	Value of inventory
J	Storage center
W	Distribution center
Z	Disassembly center
m	Method used for manufacturing
o	Severity class of injury (o,…O)

Table 3 presents the parameters used in the proposed model.

Table 3
The model parameters

Parameter	Description
MP_p	Market price for different products p made by raw materials supplied , $\forall p$
ACS_p	Assembly cost of new products p, $\forall p$
cs_p	Cost of shipping the products p to the storage centers, $\forall p$
t_{pJ}	Transportation cost of shipping the products p to the storage centers, J, $\forall p, J$
d_J	Distance traveled to the storage centers J, $\forall J$
cd_p	Cost of shipping the products p to the distribution centers, $\forall p$
t_{pW}	Transportation cost of shipping the products p to the distribution centers, W, $\forall p, W$
D_W	Distance traveled to the distribution centers W, $\forall W$
H_{pm}	# of hours needed to make products p using different methods m, $\forall p, m$
L	Labor cost per hour
cm_p	Manufacturing cost of new products p, $\forall$ p
R_s	Variable cost of products made by raw materials supplier s, $\forall s$
c_s	Ordering cost from each supplier s, $\forall s$
c_{Ts}	Discounted price for each interval T offered by supplier s, $\forall s, T$
n_p	Number of raw materials of each product p, $\forall p$
MP'_p	Market price for different products p made via refurbishment, $\forall p$
ACX_p	Assembly cost of refurbished products p, $\forall p$
R_x	Variable cost of products made via refurbishment method x, $\forall x$
C_{pZ}	Cost of shipping the products p to the disassembly centers Z, $\forall p, Z$
t_{pZ}	Transportation cost of shipping the products p to the disassembly centers Z , $\forall p, Z$
D_Z	Distance traveled to each disassembly centers Z, $\forall Z$
df	Defective percentage of returned disassembled products
h'_p	# of hours needed for refurbished products p, $\forall p$

cm'_p	Manufacturing cost of refurbished products p, $\forall\ p$
Q_x	Capacity of x^{th} refurbishing methods, $\forall x$
c_x	Ordering cost of refurbishment method x selected, $\forall\ x$
MP''_p	Market price for different products made via redesigning, $\forall\ p$
h''_p	# of hours needed for redesigning product p, $\forall\ p$
R_k	Variable cost of products made via redesigning method k, $\forall\ k$
Q_k	Capacity of k^{th} redesigning methods, $\forall k$
Cf_k	Ordering cost of redesigning method k selected, $\forall k$
Pe	Penalty of excess production
I_0	Initial value of inventory
D	Customer demand
I_f	Final value of inventory
invCO	Inventory cost
PDC_p	Pollution caused by shipping products p to the disassembly center per unit of distance, $\forall\ p$
Ph_{pm}	Pollution caused by manufacturing new products p using different methods m, $\forall\ m, p$
PSC_p	Pollution of shipping products p to the storage center per unit of distance, $\forall\ p$
Ph'_p	Pollution caused by refurbishment of products p, $\forall\ p$
$Ph''_{p;}$	Pollution caused by redesign of products p, $\forall\ p$
PDR_p	Pollution of shipping to the distribution center per unit of distance, $\forall\ p$
SE^o_m	Severity function with index o for new products for different methods m, $\forall\ m, o$
SE'_o	Severity function of refurbishment methods for each severity index o, $\forall\ o$
SE''_o	Severity function of redesigning methods for each severity index o, $\forall\ o$
CSC	Capacity of storage centers
CDR	Capacity of distribution centers
CDS	Capacity of disassembly centers
A	Returning goal
b_d	Uncertain demand
C^{*T}_s	Upper bound of the discount interval T offered by supplier s, $\forall\ T, s$
C^T_s	Slightly smaller than C^{*t}_s . $\forall\ T, s$

Table 4 presents the decision variables used in the proposed deterministic model.

Table 4
The decision variables of the proposed deterministic model

Decision Variable	Description
S_s	Binary variable, if the raw material supplier s is selected this = 1, otherwise it = 0, $\forall s$
Y_{Ts}	Binary variable, if the discount interval T for each supplier s is selected, this = 1, otherwise it = 0, $\forall\ T, s$
F_x	Binary variable, if the refurbishment method x is selected, this = 1, otherwise it = 0, ∀x
G_k	Binary variable, if the redesigning method k is selected, this = 1, otherwise it = 0, ∀k
ps_s	Portion of new product of raw material supplied for each supplier s, $\forall s$
pc_x	Portion of refurbished products of each refurbishment method x, $\forall x$
pf_k	Portion of redesigned products of each redesigning method k, $\forall k$
M_m	Binary variable, if the manufacturing method m is used, this = 1, otherwise = 0, $\forall\ m$
SC_J	Binary variable for storage center, if J is selected, this = 1, otherwise it = 0, $\forall J$
DR_W	Binary variable for distribution center, if W is selected, this = 1, otherwise it = 0, $\forall W$
DC_Z	Binary variable for disassembly center, if Z is selected, this = 1, otherwise it = 0, $\forall Z$
oc_{Ts}	Quantity of raw materials in different discount intervals T for each supplier s, $\forall\ s, T$
Q_s	Capacity of the raw material supplier s, $\forall s$

The three objective functions in the model are given as follows, with the first expressed by Eq. (1):

- Profit maximization in deterministic form:

$$f_1 = MAX \sum_s (\sum_p (MP_p - ACS_p - \sum_J ((cs_p + t_{pJ} * d_J) * SC_J) - \sum_W ((cd_p + t_{pW} * d_W) * DR_W) - \sum_m (H_{pm} * l * M_m) - cm_p - R_s) * \sum_p \sum_T ((oc_{Ts}/n_p * Y_{Ts}) * ps_s)) - \sum_s Q_s * c_s * S_s + \sum_x (\sum_p (MP''_p - ACX_p - R_x - \sum_J ((cs_p + t_{pJ} * d_J) * SC_J) - \sum_W ((cd_p + t_{pW} * d_W) * DR_W) - \sum_Z ((cds_p + t_{pZ} * d_Z) * DC_Z) + df/(1-df) \sum_Z ((cds_p + t_{pZ} * d_Z) * DC_Z) - (h'_p * l) - cm'_p) * ((1-df) * Q_x * pc_x)) - \sum_x c_x * F_x + \sum_k (\sum_p (MP''_p - \sum_W ((cd_p + t_{pW} * 2d_W) * DR_W) - (h''_p * l)) - R_k * (pf_k * Q_K)) - \sum_k (cf_k * G_k) - Pe * (I_0 + \sum_s Q_s ps_s + ((1-df) \sum_x Q_x pc_x + \sum_k (Q_k pf_k) - D - I_f) - invCO * I_f. \quad (1)$$

Description of Eq. (1): Maximizes the summation of the profits from selling the new products, refurbished, and redesigned products. The first objective function maximizes the profit of the manufacturer by calculating the income from the market price of each method s, x and k and then subtracting it from all the operational costs, which include the assembly cost of products in each method, the variable cost of each method, the transportation costs, and the labor costs. This will assist in maximizing the profit by determining the portion of each method, the quantity of raw material that should be purchased, which center should be used, and which manufacturing method should be dealt with. In this objective function, the term, $\sum_p \sum_T ((oc_{Ts}/n_p * Y_{Ts}))$, has not previously been addressed in the literature. It considers the discount policy for each supplier by considering the amount of raw material purchased from and converted to x number of products. The supplier discount policy interval is selected by the decision variable Y_{Ts}, which determines which discount interval is selected for each supplier. In addition, this term was expressed in the model later as Q_s.

The following equation expresses the first objective function under uncertainty:

Dual formulation for profit maximization:

$$\max v^1 + \Gamma_1 + \sum_x u_x^1 * y_x^1 - \sum_x l_x^1 * q_x^1 + f^1 + \Gamma_2 + \sum_k u_k^1 * g_k^1 - \sum_k l_k^1 * j_k^1 + \sum_s (\sum_p (MP_p - ACS_p - R_s - \sum_J ((cs_p + t_{pJ} * d_J) * SC_J) - \sum_W ((cd_p + t_{pW} * d_W) * DR_W) - \sum_m (h_{pm} * l * M_m) - cm_p * (\sum_p \sum_T (oc_{sT}/n_p * Y_{Ts}) * ps_s) - \sum_s Q_s * c_s * S_s - \sum_x c_x * F_x - \sum_k (cf_k * G_k) - Pe * I_0 + Pe * I_f - invCO * I_{f.} \quad (2)$$

Description of Eq. (2): The dual formulation of maximizing the summation of the profits from selling new, refurbished, and redesigned products when uncertainty is presented and found in the reverse path for the refurbishment and redesigning processes.

Pollution minimization in deterministic form.

Description of Eq. (3): Minimizes the summation of the pollution caused by transportation and manufacturing operations. The second objective function minimizes the pollution caused by shipping the products between different centers (storage, distribution, and disassembly centers), which are widely geographically distributed. As such, the amount of pollution will depend on the distance and the quantity shipped from each method s, x and k. In addition to transportation, the pollution pertaining to the manufacturing method is calculated, since different manufacturing methods result in different amounts of emissions. This will help in minimizing the pollution by determining the portion caused by each method, each center, and each manufacturing method.

$$f_2 = MIN\Bigg(\sum_s(\sum_p(\sum_J(PSC_p * SC_J * d_J) + \sum_{dr}(PDR_p * d_{dr} * DR_{dr})) * Q_s * ps_s) + \sum_x(\sum_p(\sum_J(PSC_p * d_J * SC_J) + \sum_W(PDR_p * d_W * DR_W) + \sum_Z(PDC_p * d_Z * DC_Z) - df/(1-df) * \sum_Z(PDC_p * d_Z * DC_Z)) * ((1-df) * Q_x * pc_x)) + \sum_k\left(\sum_p(\sum_W(PDC_p * 2d_W * DR_W)) * (Q_k * pf_k)\right) + \sum_s\sum_p\sum_m(Ph_{pm} * Q_s * ps_s * M_m) + \sum_x\sum_p(Ph'_p * Q_x * pc_x) + \sum_k\sum_p Ph''_p * (Q_k * pf_k)\Bigg). \tag{3}$$

Eq. (4) expresses the second objective function under uncertainty:

Dual formulation for pollution minimization:

$$\min v^3 + \Gamma_1 + \sum_x u_x^3 * y_x^3 - \sum_x l_x^3 * q_x^3 + f^3 + \Gamma_2 + \sum_k u_k^3 * g_k^3 - \sum_k l_k^3 * j_k^3 - \left(\sum_s(\sum_p(\sum_J(PSC_p * SC_J * d_J) + \sum_W(PDR_p * d_W * DR_W) + \sum_m(Ph_{pm} * M_m)) * Q_s * ps_s)\right). \tag{4}$$

Description of Eq. (4): The dual formulation for minimizing the summation of the pollution caused by the transportation and manufacturing of new, refurbished, and redesigned products when uncertainty is presented and found in the reverse path for the refurbishment and redesigning processes.

Injury severity minimization in deterministic form:

$$f_3 = MIN \sum_m(\sum_{o=1}^{O} M_m * e^{o-\Sigma_O^o} \; SE_m^o) * \frac{200000}{\sum_s\sum_p \; H_{pm} * Q_s * ps_s} + \sum_{o=1}^{O} e^{o-\Sigma_O^o} * SE'_o * \frac{200000}{\sum_x\sum_p \; h'_p * (1-df) * Q_x * pc_x} + \sum_{o=1}^{O} e^{o-\Sigma_O^o} \; SE''_o * \frac{200000}{\sum_k\sum_p \; h''_p * Q_k * pf_k}. \tag{5}$$

Description of Eq. (5): Minimizes the summation of the severity of the injury rate pertaining to different manufacturing methods and different processes. The third objective function minimizes the injury/illness incidence rate of each process *s, x* and *k*, which is formulated as follows:

$$Incidence\ rate = \frac{(No.of\ injuries\,\&\,illnesses) * 200{,}0000}{Employee\ worked\ hours}. \tag{6}$$

In Eq. (6), it is assumed that 100 employees are working 40 hours per week, which gives a total of 200,000 hours in a year (50 weeks per year) and provides the standard base for the incidence rates. In the proposed model, an exponential function will be applied, since having a higher class of severity will lead to more unwanted consequences, thus facilitating the selection of the production method or the process that will cause the least severity. Furthermore, by using the exponential function, minor incidences can be accepted to a certain degree. However, in terms of new products, different manufacturing methods have different severity functions and the refurbishment and redesigning processes involve a different amount of severity functions. This will help in minimizing the severity and in maintaining an accepted rate of injury among all the processes and methods by determining the portion pertaining to each process and identifying the most appropriate manufacturing method.

Eq. (7) expresses the third objective function under uncertainty:

Dual formulation for severity minimization:

$$\min v^4 + \Gamma_1 + \sum_x u_x^4 * y_x^4 - \sum_x l_x^4 * q_x^4 + f^4 + \Gamma_2 + \sum_k u_k^4 * g_k^4 - \sum_k l_k^4 * j_k^4 + \sum_m (\sum_{o=1}^{O} M_m * e^{o - \sum_{O}^{o}} \ SE_m^o * \frac{200000}{\sum_s \sum_p \ Hpm * Q_s * ps_s}). \tag{7}$$

Description of Eq. (7): the dual formulation for minimizing the summation of the severity present due to providing new, refurbished, and redesigned products when uncertainty is presented and found in the reverse path for the refurbishment and redesigning processes.

The weighted total objective function of the model is given by

$$\mathrm{F} = \max\{w_1 f_1 - w_2 f_2 - w_3 f_3\}, \tag{8}$$

where $w_i \geq 0$, $\forall i$ and $\sum_0^{i=3} w_i = 1$

Description of Eq. (8): Optimizes the summation of the target weight w_i for objective function i × the optimal solution of the objective function f_i. In this study, it is assumed that the economic objective is slightly more important than the environmental objective but is moderately more important than the social objective. In addition, the environmental objective is slightly more important than the social objective, which is in line with the assumption made by (Chen & Andresen 2014). Therefore, this research uses the same weights, which are shown in Eq. (9):

$$\mathrm{F} = \max\{0.5396 \, f_1 - 0.2970 \, f_2 - 0.1634 \, f_3\}. \tag{9}$$

The following are the constraints of the deterministic model:

$$Q_s = \sum_T \sum_p (oc_{Ts}/n_p * Y_{Ts}) \ , \forall s. \tag{10}$$

Description of Eq. (10): The capacity of a raw material supplier is equal to the summation of the quantity of the raw materials that combine the different types of products for all the intervals selected by each raw material supplier.

$$Q_s \leq \frac{C^{*T}_{s}}{n_p} * Y_{Ts} \ , \forall s, T. \tag{11}$$

Description of Eq. (11): The capacity of a raw material supplier is smaller or equal to the upper bound of the quantity of the raw materials that combine the different types of products for all the intervals selected by each raw material supplier.

$$Q_s \geq \left(C\,_s^{T-1} \frac{}{n_p} * Y_{Ts} \right) , \forall s, T. \tag{12}$$

Description of Eq. (12): The capacity of a raw material supplier is greater or equal to the value of the quantity of the raw materials in the previous interval that combine the different types of products for all the intervals selected by each raw material supplier.

$$\sum_T \sum_p c_{sT} * Y_{Ts} * n_p = c_s \ , \forall s. \tag{13}$$

Description of Eq. (13): The ordering cost of each supplier equals the discounted price of the raw materials multiplied by the quantity of the raw materials of different types of products.

$$\sum_T Y_{Ts} = 1 \, , \forall s. \tag{14}$$

Description of Eq. (14): The summation of $Y_{s,t}$ for each supplier for all intervals = 1, which means that the supplier can be selected only at one discount interval.

$$\sum_s Q_s * ps_s + (1 - df) \sum_x Q_x * pc_x \leq CSC. \tag{15}$$

Description of Eq. (15): Represents the capacity constraint since the capacity storage of the company is bigger or equal to the quantity of both new products and refurbished products, which will lead to a limitation in terms of the quantity of both *s* and *x*.

$$\sum_{s} Q_s * ps_s + (1 - df) * \sum_{x} Q_x * pc_x + \sum_{k} Q_k * pf_k \leq CDR. \tag{16}$$

Description of Eq. (16): Represents the capacity constraint since the distribution capacity of the company is bigger or equal to the quantity of the mixture of new, refurbished, and redesigned products, which will lead to a limitation in terms of the number of *s, x* and *k* processes.

$$\sum_{x} Q_x * pc_x \leq CDS. \tag{17}$$

Description of Eq. (17): Represents the capacity constraint, since the disassembly capacity of the company is bigger or equal to the number of refurbished products, which will lead to a limitation for the number of refurbished products.

$$pc_s \leq S_S, \forall s. \tag{18}$$

Description of Eq. (18): The portion of new products from the total production for each supplier should be equal to or less than the value of selecting the supplier. This means that if the supplier is not selected, then the portion is zero.

$$pc_x \leq F_x, \forall x. \tag{19}$$

Description of Eq. (19): The portion of the refurbished products from the total production for each refurbishment method should be equal to or less than the value of selecting this method.

$$pf_k \leq G_k \ \forall k. \tag{20}$$

Description of Eq. (20): The portion of the redesigned products from the total production for each redesigning method should be equal to or less than the value of selecting this method.

$$I_0 + \sum_{s} Q_s * ps_s + (1 - df) * \sum_{x} Q_x * pc_x + \sum_{k} Q_k * pf_k - I_f \geq D. \tag{21}$$

Description of Eq. (21): The initial inventory added to the total production—which comprises three processes, excluding the final inventory—should be larger or equal to the total demand.

$$(1 - df) * \sum_{x} Q_x * pc_x + \sum_{k} Q_k * pf_k \geq A * D. \tag{22}$$

Description of Eq. (22): The amount of returned products for all refurbishment and redesigning processes should be larger or equal to the returning goal multiplied by the demand.

Non-negativity constraints:

$$ps_s, pc_x, cf_k \geq 0, \forall s, x, k \tag{23}$$

$$F_x, S_s, G_k, M_m, Y_{Ts}, SC_J, DR_W, DS_Z \in \{0,1\}, \forall s, x, k, m, T, J, W, Z. \tag{24}$$

The following constraints illustrate the constraints for the dual formulation of the robust optimization models:

$$\begin{aligned} v^1 + y_x^1 - q_x^1 \leq & \sum_{p} (MP'_P - ACX_p - R_X - \sum_{J} ((cs_p - t_{PJ} * d_J) * SC_J) - \sum_{W} ((cdr_p - t_{PW} * d_W) * DR_W) \\ & - \sum_{Z} ((cds_p - t_{PZ} * d_Z) * DC_Z) - (h'_p * l) - cm'_p) - Pe)) * ((1 - df) * Q_x * pc_x) \ \forall x \end{aligned} \tag{25}$$

$$f^1 + g_k^1 - q_k^1 \leq (\sum_p (MP''_P - \sum_W ((cd_p - t_{PW} * 2d_W) * DR_W) - (h''_p * l)) - R_k - Pe) * (Q_K * pf_k *)\ \forall k \tag{26}$$

$$I_O + \sum_s Q_s * ps_s + v^2 * \Gamma_1 + \sum_x u_x^2 * y_x^2 - \sum_x l_x^2 * q_x^2 + f^2 * \Gamma_2 + \sum_k u_k^2 * g_k^2 - \sum_k l_k^2 * j_k^2 - I_f \geq b_d \tag{27}$$

$$v^2 * \Gamma_1 + \sum_x u_x^2 * y_x^2 - \sum_x l_x^2 * q_x^2 + f^2 * \Gamma_2 + \sum_k u_k^2 * g_k^2 - \sum_k l_k^2 * j_k^2 \geq A * b_d \tag{28}$$

$$v^2 + y_x^2 - q_x^2 \leq (1 - df) * Q_x * pc_x\ \forall x \tag{29}$$

$$\sum_s Q_s * ps_s + v^2 * \Gamma_1 \sum_x u_x^2 * y_x^2 - \sum_x l_x^2 * q_x^2 \leq CSC \tag{30}$$

$$\textstyle\sum_s Q_s * ps_s + v^2 * \Gamma_1 + \sum_x u_x^2 * y_x^2 - \sum_x l_x^2 * q_x^2 + f^2 * \Gamma_2 + \sum_k u_k^2 * g_k^2 - \sum_k l_k^2 * j_k^2 \leq CDR \tag{31}$$

$$v^2 * \Gamma_1 + \sum_x u_x^2 * y_x^2 - \sum_x l_x^2 * q_x^2 + f^2 * \Gamma_2 + \sum_k u_k^2 * g_k^2 - \sum_k l_k^2 * j_k^2 \leq CDS \tag{32}$$

$$f^2 + g_k^2 - j_k^2 \leq pc_k Q_k, \forall x \tag{33}$$

$$\begin{aligned} v^3 + u_x^3 - q_x^3 \leq & \sum_p \left(\sum_J (PSC_p * d_J * SC_J \right) + \left(\sum_W (PDR_p * d_W * DR_W) \right) + \sum_Z (PDC_p * d_Z * DC_Z) \\ & + \left(\frac{df}{(1-df)} * \sum_Z (PDC_p * d_Z * DC_Z \right) + \sum_p (Ph'_p)) * ((1 - df) * Q_x * pc_x)), \forall x \end{aligned} \tag{34}$$

$$v^3 + y_x^3 - q_x^3 \leq (1 - df) * pc_x Q_x, \forall x \tag{35}$$

$$f^3 + g_k^3 - j_k^3 \leq \left(\sum_p \left(\sum_W (PDC_p * 2d_W * DR_W \right) + \sum_p (Ph'''_p)) * (Q_K * pf_k) \right), \forall k \tag{36}$$

$$f^5 + g_k^5 - j_k^5 \leq Q_k * pf_k, \forall k \tag{37}$$

$$v^4 + u_x^4 - q_x^4 \leq \frac{200000}{\sum_p h'_p * (1 - df) * Q_x * pc_x)}, \forall x \tag{38}$$

$$v^4 + y_x^4 - q_x^4 \leq ((1 - df) * Q_x * pc_x), \forall x \tag{39}$$

$$f^4 + g_k^4 - j_k^4 \leq \frac{200000}{\sum_p h''_p * Q_k * pc_k}, \forall k \tag{40}$$

$$f^4 + g_k^4 - j_k^4 \leq Q_k * pc_k, \forall k. \tag{41}$$

4. Results and Discussion

This section presents a numerical example using random data and datasets obtained from the literature to verify the solvability and validity of the proposed model.

4.1. Numerical Example: Parameter Settings

To test the efficiency of the proposed model, a hypothetical example was devised. Here, the proposed production facility is assumed to produce two different products, with each product comprising 14 raw materials. These materials could be purchased from different raw material suppliers offering a different total quantity discount. The production facility can choose between two different production methods (M1 and M2), and it is assumed that M1 is more expensive than M2 but is safer and more environmentally friendly. Moreover, the company has three types of centers that are geographically distributed, namely, storage, distribution, and disassembly centers. Each of these can be chosen from a set of two, with different distances and costs, while each can be reached via two transportation methods. Meanwhile, the facility has two means other than purchasing raw materials, namely, refurbishment and redesign, with each of these processes comprising two different methods. The used parameters for the model are comprised of cost, pollutant emissions, injuries, and various constraint parameters. All the parameters related to cost should be established. As the proposed model illustrates, the costs comprise material, transportation, and production costs.

Production Costs: Table 5 presents the assembly, variable, ordering, and manufacturing costs for the two products.

Table 5

Assembly, variable, ordering, and manufacturing costs (in USD).

Cost Item	Product 1	Product 2
ACS_p	10	12
ACX_p	4	5
R_s	20	25
R_x	18	14
R_k	10	6
c_x	400	450
cf_k	320	310
cm_p	7	10
cm'_p	3	5

Table 6 presents the total hours needed for each method to produce one unit under the scenario of purchasing raw materials, as well as in terms of the different refurbished and redesigned methods. It is assumed that the hourly wage is $10.

Table 6

Hours needed for each production method: h_m^p

Production Method	Product 1	Product 2
h_1^p	25	28
h_2^p	22	23
h'_p	9	14
h''_p	6	7

Transportation Costs: This is calculated in terms of per kilometer of a single product. The cost of shipping to one of the centers depends on the product and center type, while in terms of transportation, the cost depends on the distance traveled, as shown in Table 7 and Table 8.

Table 7

Shipping and transportation costs (in USD)

Cost Item	Facilities	Product1	Product 2
cs_p	---	5	3
cd_p	---	4	2
t_{pJ}	SC1	0.3	0.5
	SC2	0.2	0.3
t_{pW}	DR1	0.5	0.4
	DR2	0.8	0.3
t_{pZ}	DS1	0.2	0.4
	DS2	0.3	0.25

Table 8

Shipping distance to the centers.

Distance Item	Facility Number	Distance (km)
d_J	SC1	8
	SC2	6
d_W	DR1	12
	DR2	7
d_Z	DS1	6
	DS2	4

Regarding pollution, the proposed model incorporates two types: production emissions and transportation emissions.

Production Emissions: This includes the different rate of manufacturing emissions, and any emissions produced by the refurbishment and redesigning methods, which depends on the specific production method, as shown in Table 9.

Table 9

Emitted pollution based on the production method Ph_m^p (in g/ton/km).

Production method	Product 1	Product 2
Ph_1^p	150	170
Ph_2^p	200	210
Ph'_p	170	130
Ph''_p	140	110

Transportation Emissions: There are three types of centers, which are geographically distributed, and it is assumed that traveling to each type of center will involve a specific type of transportation. This includes ship plus rail, which entails 7.798 g/ton/km of emitted CO_2 and ship plus truck, with 9.842 g/ton/km of emitted CO_2 (these amounts were taken from Dekker et al.2007. This will lead to different amounts of emissions, while the distance traveled to each center will play a major role in determining the emission amount, as shown in Table 10.

Table 10
Pollution pertaining to shipping to different centers (g/ton/km).

Pollution caused by shipping to:	Center (1)	Center (2)
PSC_p	7.898	9.842
PDR_p	9.842	7.898
PDC_p	7.898	9.842

Table 11
Description of severity class.

O	O Severity class description
1	1 = Less than a week absent
2	2 = Less than a month absent
3	3 = Less than 3 months absent
4	4 = Less than 6 months absent
5	5 = Less than a year absent

In terms of the social objective function, the attendant parameters mainly depend on the used severity class. To include all the injuries and illnesses, the severity class was categorized as the number of days the worker will be absent due to injury or illness, as shown in Table 11 (the values were taken from (Chen & Andresen, 2014).

In the proposed model, there are two different production methods for producing new products, which have different severity functions, as shown in Table 12.

Table 12
Severity function for new products and *x, k* processes for different methods SE^{o}_{m}.

Production Method	o=1	o=2	o=3	o=4	o=5
Production method M1	17	5	2	1	1
Production method M2	20	6	3	2	1
SE'_o	16	5	4	2	1
SE''_o	12	3	2	1	1

To establish a feasible solution, a set of parameters needed to be set, as illustrated in Table 13.

Table 13
Capacity and general parameters.

Parameter	Value	Unit
Storage capacity (CSC)	500	product
Distribution capacity (CDR)	500	product
Disassembly capacity (CDS)	500	product
Returning goal (A)	0.2	% of demand
Penalty excess (Pe)	300	USD
Initial inventory (I_0)	10	product
Demand (D)	180	product
Final inventory (I_f)	30	product
Inventory cost (invCO)	10	USD
Defective percentage (df)	0.3	% of product
Labor cost (l)	10	USD

Meanwhile, Table 14 shows the capacity limitation for the *x* and *k* processes.

Table 14
Capacity of *x* and *k* processes.

Parameter	Process 1	Process 2
Refurbishing capacity (Q_x)	200	100
Redesigning capacity(Q_k)	200	100

Table 15 illustrates the market price for the two products pertaining to each process.

Table 15
Market price for each process.

Parameter	Product 1	Product 2
Market price of new products (MP_p)	500	416
Market price of refurbished products (MP'_p)	347	320
Market price of redesigned products (MP''_p)	280	224

Table 16 presents the total quantity discount policy for the raw materials at the Interval of discount for each raw material supplier and the bounds quantity for each discount interval, with the assumption that each product requires 12 raw materials $n_p = 12, \forall\, p$.

Table 16
Total quantity discount for raw materials.

	Raw Material Supplier (1)		Raw Material Supplier (2)	
Interval	Quantity (raw material)	Price (c_{Ts}) (USD)	Quantity (raw material)	Price (c_{Ts}) (USD)
1	$0 \le oc_{11} < 2000$	0.67	$0 \le oc_{21} < 1000$	0.73
2	$2000 \le oc_{12} < 4000$	0.43	$1000 \le oc_{22} < 2000$	0.52
3	$4000 \le oc_{13} < 6000$	0.25	$2000 \le oc_{23} < 3000$	0.44

4.2. Optimal Solutions

The proposed model was coded using Python and solved via an SLSQP solver on a laptop ($INTEL^{®}$ $\mathrm{CORE}^{TM} CPU\mathrm{i}5 - 72000\mathrm{U}$ @ $2.50GH_Z$ and 4.00 GB RAM). The model solutions were found in 10 seconds. This section illustrates the results pertaining to solving the previously introduced numerical example.

4.1.1. Deterministic Case

After coding and solving the model using the aforementioned solver and algorithms, for the deterministic model, each objective function was solved independently and all of the attendant decision variables were found. Table 17 presents the decision variables of the economic objective function.

Table 17
Decision variables of the economic objective function

Decision Variable	Option (1)	Option (2)
SC_J	1	1
DR_W	0	0
DC_Z	1	0
M	0	1
ps_s	0.8	0
pc_x	0.1	0
pf_k	0.1	0
Q_s	210	0

Table 18
Decision variables of the environmental objective function

Decision Variable	Option (1)	Option (2)
SC_J	0	0
DR_W	0	0
DC_Z	1	0
M	1	0
ps_s	0.31	0.0020
pc_x	0.098	0
pf_k	0.59	0
Q_s	210	100

Following this, the environment objective function was solved, as shown in Table 18. Table 19 presents the findings related to the social objective function.

Table 19
Decision variables of the social objective function

Decision Variable	Option (1)	Option (2)
M	1	0
ps_s	0.6502	0
pc_x	0.2167	0
pf_k	0.1331	0
Q_s	210	0

Table 20
Decision variables of the total multi-objective function.

Decision Variable	Option (1)	Option (2)
SC_J	0	1
DR_W	0	1
DC_Z	1	0
M	0	1
ps_s	0.675	0
pc_x	0.225	0
pf_k	0.1	0
Q_s	210	0

Table 20 summarizes the decision variable values of the total multi-objective function. As the above tables show, there were clear differences between the values of the individual objective functions and the total multi-objective function. For example, M2 was selected according to the economic objective functions due to the lower attendant costs compared with M1, while in terms of the environment and social objectives, M1 was selected. However, in the multi-objective function, M2 was chosen, which was as expected since the weight for the economic objective was the most superior.

4.1.2. Non-Deterministic Case: Robust Optimization

This section presents the results of reverse flow uncertainty before presenting the results for both the flow uncertainty and the demand side.

Effect of Reverse Logistics Flow Uncertainty

After solving the dual formulation of the deterministic model (Appendix 1), the optimal value of the multi-objective function and all its decision variables were determined for the following Γ_i values. Here, there were differences between the values of the individual objective functions and the total multi-objective function. Table 21 summarizes the optimum value of each objective function. To establish an optimum multi-objective function, a compromise needs to be made between the three functions, as is clear from the different values of the decision variables for each objective, especially for the chosen production method and the proportion for each process. For example, M2 was selected for the multi-objective function despite it posing a higher risk to both humans and the environment, meaning the profit of the economic pillar will be increased alongside an increase in emissions and injuries values.

Table 21
Optimal multi-objective function values under reverse flow uncertainty

Uncertainty budget Γ_i	$\mathbf{f_1}$ (Economic)	$\mathbf{f_2}$ (Environmental)	$\mathbf{f_3}$ (Social)	**F**
2	125280.1	99280.81	891.81	**37969.02**
1.75	125134.3	99545.6	1080.45	**37780.88**
1.5	125005.4	99779.4	1118.848	**37635.61**
1.25	124862.5	100039	1370.246	**37440.32**
1	124719.5	100299.3	1673.7	**37236.27**

As shown in Table 21, the value of f_1 – which denotes the economic pillar—decreased while reducing the value of Γ_i , since the reliability of the reversed processes decreased. To compensate for this, the company will have to produce more products, which will increase the costs and minimize the profits. Meanwhile, in terms of the environmental pillar, the emitted pollutants will increase when decreasing the value of Γ_i since the company needs to have more products to cover the reliability issue, which will result in an increase in the amount of emissions. This also applies to f_3, with the social pillar with a decreasing Γ_i increasing the number of injuries and illnesses due to the increasing amount of work. Regarding the optimum value of the multi-objective function, when the value of Γ_i decreases, the optimum value of the total objective function decreases, since manipulating these values will affect the reliability of the process, which will increase the costs and all other related operations. This, in turn, will lead to the production of more products across the two processes, *x* and *k*. Moreover, this will increase the rate of injuries, which will, overall, reduce the value of the total multi-objective functions. These results are illustrated in Fig. 2.

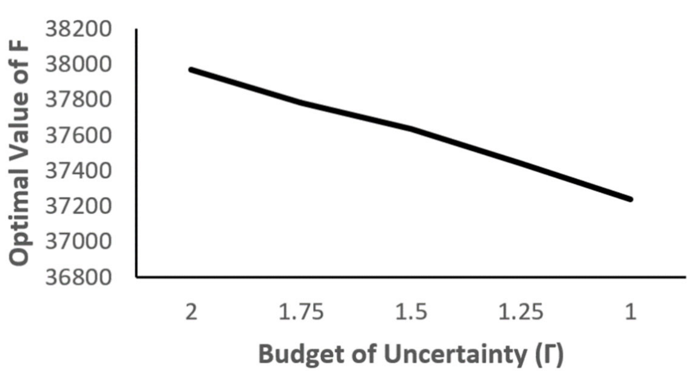

Fig. 2. Effect of the reversed logistics flow uncertainty

The value of the total optimum function decreased as Γ_i decreased because the reliability of the reversed processes decreased, which will decrease the value of the optimum function of the company as the emissions and injuries increase, as reflected in the values of each specific function alone. As a result, the best scenario will be when Γ_i =2, in which case the processes will be 100% reliable.

Effect of Considering Reverse Logistics Flow and Demand Uncertainty

Next, the effect of both the reverse logistics flow uncertainty and the demand uncertainty was studied. This involved changing the values of the demand uncertainty and the uncertainty budget, as shown in Table 22.

Table 22
Effect of considering reverse logistics flow and demand uncertainty

Demand uncertainly	**Uncertainty budget (Γ_i)**	**f_1** (Economic)	**f_2** (Environmental)	**f_3** (Social)	**F**
3%	1.75	125090.4	99588.31	1080.81	**37744.45**
	1.5	124901.4	99820.81	1124	**37566.35**
	1.25	124733.7	99900.51	1170.41	**37444.61**
	1	124575.8	99996.31	1247.2	**37318.41**
5%	1.75	124561.6	100104.71	1267.3	**37275.26**
	1.5	124515.3	100325.01	1354.5	**37170.60**
	1.25	124365.4	100424.21	1404.45	**37052.09**
	1	124185.5	100524.41	1459.7	**36916.23**
10%	1.75	123158.4	101500.01	1691.82	**36034.33**
	1.5	122682.3	102093.21	1838.41	**35577.29**
	1.25	122561.3	102263.31	1893.01	**35452.56**
	1	122410.1	102383.81	1937.21	**35327.96**

The values of the economic pillar will be decreased due to the increment in the related costs. The exact decrease is dependent on the percentage of the demand uncertainty that runs alongside the budget uncertainty of reversed flow. Here, with a high percentage of demand, the values decreased significantly as more products were produced. However, the environmental and social function values specifically increased with a high percentage of demand uncertainty. Meanwhile, more emissions and injuries will occur due to the increment in total production aimed at meeting the uncertain demand. As a result, high percentages of demand uncertainty will have a greater effect than the reverse flow uncertainty in all cases. The value of the optimal multi-objective function is affected by changing the value of the uncertainty budget of each refurbishment and redesign, as well as the percentage of demand uncertainty. Table 22 shows the effect of considering both reverse logistics flow and demand uncertainty. In terms of lower uncertainty demand, the optimum value of the total objective function was close to the first case, which means that the effect of demand uncertainty was low. Meanwhile, in the case of a higher rate of uncertainty demand, the effect of reverse flow uncertainty was lower than the worst-case scenario, which will, in turn, weaken the effect of reverse flow uncertainty. This is illustrated in Fig. 3. In the case of 3% of demand uncertainty alongside reverse logistics flow uncertainty, the values of the optimum functions were extremely close to those in the case with reverse logistics flow uncertainly only. This means that the effect of demand uncertainty is extremely small and barely affects the values of the optimum functions. However, in the case of a demand uncertainty of 10%, the optimum function values dropped significantly, meaning, in this case, the effect of demand uncertainty is worse than the effect of reverse logistics flow uncertainty.

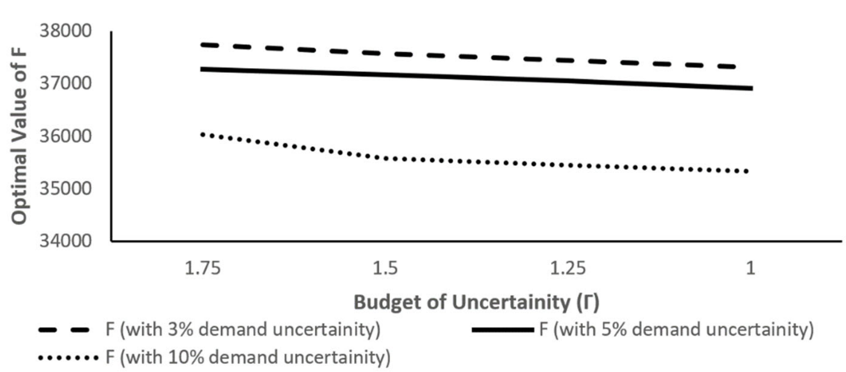

Fig. 3. Effect of considering both reverse logistics flow and demand uncertainty.

5. Sensitivity Analyses

To further confirm the validity of the proposed model and to ensure rational relationships among the parameters, sensitivity analysis was conducted in terms of the value of the uncertainty budget Γ_i. Further sensitivity analysis was then performed to determine the effects of changing the weights of each individual objective function on the final optimal solution for the multi-objective functions.

5.1. Effect of Uncertainty Budget and Demand Uncertainty

The values of the uncertainty budget were uniformly distributed (1.5~1.75), and the percentages of the demand uncertainty were deemed to be 3%, 5%, and 10%. The optimal values are shown in Table 23. The table shows the effect of considering reverse logistics flow and demand uncertainty by taking random numbers of Γ_i between (1.5~1.75) values for the three chosen cases of demand uncertainty. The findings obtained in the previous analysis confirmed the findings of the previous sections, that is, when the value of demand uncertainty is high, it has a greater effect than the reverse flow uncertainty. This will increase the cost of production, meaning the value of the total multi-objective function will decrease due to the reduction in the values of the economic pillar, as the cost of the production processes will increase due to the production of more products. This is related to the percentage of the demand uncertainty; so long as the demand is uncertain, the necessity of producing more products will increase to cover the expected demand. In the same manner, the values of the environmental and social functions will increase with an increase in the demand uncertainty percentage, as greater production will lead to more pollutants and injuries. Clearly, for all the functions, be it in terms of the optimal multi-objective function value or in terms of each individual function, the demand uncertainty will present a worse value than the worst-case scenario of reversed flow uncertainty. For example, when Γ_i= 1, without the demand uncertainty, the value of the optimum function = **37236.27**, while when Γ_i= 1.5~1.75, with a demand uncertainty of 10%, the mean value **= 37095.3**, a 0.38% difference. As such, the optimized value of the multi-objective function and each individual function depends on the value of the budget uncertainty for the reversed processes and the demand uncertainty percentage. The effect of the demand uncertainty percentage on each function is higher than that of the uncertainty for the reversed processes.

Table 23
The effect of changing the results of the uncertainty budget.

Demand uncertainly	**Uncertainty budget**	**Statistical Measure**	$\mathbf{f_1}$(Economic)	$\mathbf{f_2}$(Environmental)	$\mathbf{f_3}$(Social)	**F**
3%	Γ_i= 1.5~1.75	mean	125197.3	99460.83	1105.13	**37836**
		SD*	44.45	58.20	13.86	**29.65**
		max	125320	99541.64	1124.81	**37875**
		min	125105.7	99412.11	1080.91	**37805**
5%	Γ_i= 1.5~1.75	mean	124994.9	99628.64	1306.31	**37644**
		SD	63.15	87.35	32.1	**43.15**
		max	125113.2	99661.19	1354.5	**37690.4**
		min	124912	99523.05	1267.2	**37637.1**
10%	Γ_i= 1.5~1.75	mean	124360.4	100067.8	1771.48	**37095.3**
		SD	147.8	159.65	54.5	**93.21**
		max	124677.5	100252.9	1838.4	**37200.5**
		min	124215.8	100105.8	1745.6	**37010.2**

*SD: standard deviation $=\sqrt{(0{,}5396)^2(SD_{f1})^2+(0{,}2970)^2(SD_{f2})^2+(0{,}1634)^2(SD_{f3})^2}$

5.2. Effect of the Weight of Individual Objective Functions on the Optimal Solution

To ascertain the effect of each individual objective function on the optimal value of the objective functions, the weights were changed. The optimal *F* values for all scenarios are shown in Table 24. Here, for the four cases, each scenario will have a set of different decision variables. In the first three scenarios, the proportion of redesign production greatly increased since this is the safest and most environmentally friendly process, while it is the least profitable, which explains its proportion of the total production. This also applies to the manufacturing method, since increasing the weights of the environment or social pillars will lead to choosing M1 at all times, since it is a safer and more environmentally friendly method than M2. This emphasizes the importance of the formulated model in helping the decision maker to make an appropriate decision by setting up the weight of each objective function based on their priorities. The used mathematical model considers many aspects that have not previously been addressed together, since it has the capacity to find the optimal multi-objective value that guarantees more profit, less pollution, and a lower rate of illnesses and injuries. This is achieved by selecting the best supplier under the discount policy and the correct amounts of reverse logistics, in addition to the appropriate center and production method under the two types of uncertainty.

Table 24
Effect of changing the weights of the different objective functions.

Scenario #	w_1	w_2	w_3	f_1 (Economic)	f_2 (Environmental)	f_3(Social)	F
Scenario 1	1/3	1/3	1/3	41760.03	33093.6	297.3	**2789.7**
Scenario 2	1/6	1/6	2/3	20880.01	16546.8	594.5	**325.9**
Scenario 3	1/6	2/3	1/6	20880.01	66187.2	148.6	**−40669.6**
Scenario 4	2/3	1/6	1/6	83520.07	16546.8	148.6	**52879.5**

This study integrates three models proposed in previous studies and provides a comprehensive view of the most important factors in the supply chain. While Chen and Andresen (2014) considered the same three pillars and identified the optimal multi-objective function, they did not consider having different types of centers, nor did they consider the discount policy or any type of uncertainty. Meanwhile, although Kim et al. (2018) considered the two types of uncertainty, this was only in terms of the economic aspect, with neither the environmental nor the social aspects considered. Moreover, these authors did not consider the discount policy or the different types of production methods and production centers. Therefore, the objectives of the current formulated model were not included in any previous model, objectives that will help companies take the right decision in most circumstances.

6. Managerial Implications

The sensitivity analysis results were used to confirm the validity and applicability of the model. The first analysis was conducted to study and analyze the effect of changing the values of the uncertainty budget for each x and k process with the demand uncertainty for the multi-objective function and each individual objective function. Here, decreasing the value of the total budget uncertainty decreased the value of the optimal uncertainty. The reduction in the reliability of the process will help the company to take appropriate decisions, even under uncertain demand or logistics flow in the reverse path, as well as under specific conditions, such as when a raw material supplier offers a discount policy. Further sensitivity analysis was conducted to assess the impact of changing the weight of each individual objective function on the optimal value of the total multi-objective function, an aspect that will help policymakers develop efficient plans that best suit their targets and needs. With the changes, the weights of the individual objective functions will affect the optimal value of the multi-objective function, which will have a major impact on the proportion of each process of production and on the selected production method. Assigning the greatest weight to the economic objectives will lead to an increase in the portion of raw materials, leading to maximum profits. In contrast, increasing the weight of the environmental objective or the social objective will increase the proportion of redesign and refurbishment production within the total production process. Overall, this will help the company make appropriate decisions and review its plan regarding meeting its targets in the economic, environmental, and social realms based on assigned weights that align with its strategic plans. Based on the sensitivity analysis results, the importance of considering the two types of uncertainty related to both directions cannot be neglected for the multi-objective function and each individual function under a discount policy, since the values of the objective functions will fluctuate according to the amount of budget uncertainty in the backward path and the demand uncertainty in the forward path. However, high rates of demand uncertainty will always produce a worse scenario than the reverse flow logistics uncertainty for the multi-objective function and individual objective functions.

7. Conclusions

This study proposed a new model that addresses all the major targets and challenges that a company will face in an SCLSC by introducing two types of uncertainty in both directions. In addition, various characteristics were addressed to enhance the model's efficiency. More specifically, this involved maximizing a firm's profits by introducing all the earnings and related costs for each operation in the forward and backward paths. In addition, the environmental issue was addressed by minimizing all the emissions produced by the transportation and production methods. Furthermore, the social aspect was considered in view of minimizing it optimally by considering all the severity functions related to any given operation. This means that the proposed model addresses the three pillars of sustainability. Overall, the results indicated that the proposed model integrates most of the company operations by considering the environmental and social objectives in addition to the economic objectives. The model was constructed and solved such that all of the three targeted functions, namely, profit maximization, pollutant minimization, and rate of injuries and illnesses minimization, were represented. First, the model focuses on maximizing the total profit of the company, considering this in terms of all the related operation costs, such as the cost of transportation to different centers, which are geographically distributed, as well as the manufacturing and assembly costs. Second, the model is concerned with minimizing the CO_2 emissions produced by the manufacturing process and the transportation between the different types of centers. Moreover, the model addresses the uncertainty in both the forward path and the reverse path by considering the demand uncertainty and the reverse logistics flow pertaining to the two methods. This makes these processes less reliable, meaning more products need to be produced, thus increasing the related costs, the amount of pollutants, and the number of injuries, which will, in turn, decrease the value of the optimal total-multi objective function. Moreover, sensitivity analyses were conducted to assess the effects of demand uncertainty and flow logistics uncertainty, with the results indicating that the higher the demand uncertainty value, the lower the effect of the uncertainty in the backward path. Meanwhile, the effect of the weighting of the objective functions on the total optimal solution was confirmed via further sensitivity analysis. Here, the results indicated that changing the weight of each individual objective function will produce a different set of decision variables, which will lead to a different optimal value that achieves the objective of the superior weight function.

In future studies, using the real conditions of the company policies regarding the new products and recycled products may lead to different plans and suggestions. Meanwhile, although the social aspect was investigated in terms of the severity of the used methods to decrease the rate of illnesses and injuries, other factors could have been considered to improve the efficiency, such as the degree of worker satisfaction and the workers' characteristics and their effect on the total objective function. Moreover, addressing more types of uncertainty will provide a more realistic model, while considering a recoverable robustness concept in the area of uncertainty would fill a further research gap (Buhayenko & den Hertog, 2017; Iris & Lam, 2019). In addition, the model was tested using a hypothetical dataset and it may have been better to use data based on a real case, which would provide a clearer picture of the effects of the model parameters and decision variables such that they could be analyzed more precisely. A further limitation relates to how the model was solved by assuming a choice of two raw suppliers, as well as different types of centers, manufacturing methods, transportation methods, refurbishment methods, and redesigning methods. Furthermore, the proposed model considers two products that consist of the same raw materials provided by raw suppliers offering a total quantity discount. However, incorporating more complex products that involve different amounts of varied raw materials provided by different raw suppliers will enhance the complexity of the model.

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Appendix 1

Dual Formulation

Robust optimization can be constructed as follows:

$$\min C_x$$
$$subject\ to:$$
$$Ax \leq B,$$

where x is a set of decision variables, while A, B, and C are the parameters and C_x is the function of the decision variables. In general, each uncertain parameter consists of a nominal value a set to $\mathbf{E}\hat{a}$ and a variation parameter. To determine the contribution to the actual parameter's realization, the random variable ξ is multiplied by a positive constant $\hat{a}$:

$$\tilde{a} = a + \xi\hat{a}.$$

Based on the previous definition, the following equation can be used when uncertain parameters act linearly on the constraints or the objective functions of the model:

$$\min_{x,y} \sum_j c_j\, x_j$$

$$s.t. \sum_j a_{ij}\, x_i + \max_{\xi_{ij} \in U_{ij}} \left\{ \sum_{j \epsilon J_i} \xi_{ij} \hat{a}_{ij}\, x_i \right\} \leq b_i\,, \forall i,$$

where U_{ij} denotes the uncertainty set. This equation ensures imposing the entire uncertainty set for ξ_{ij} on the model to ensure that there is a feasible optimal solution for all the uncertain realizations in U_{ij}. However, if the inner maximization part is replaced by a finite number of equations, the robust counterpart becomes deterministic. An uncertainty budget Γ_i is included in $[0,|\mathrm{J_j}|]$ for all constraints, which can be used to adjust parameter uncertainty. The robust solution is optimized based on Γ_i since it reflects the level of uncertainty in $|\mathrm{J_j}|$ under the condition that the parameter of variation is $(\Gamma_i - \lfloor \Gamma_i \rfloor)\hat{a}_{it}$. This is expressed by the two following equations:

$$\min cx$$

$$s.t. \sum_j a_{ij}\, x_i + \max_{\{s_i \cup \{t_i\}\}| s_i \subseteq j_{i'} |s_i| \leq |\Gamma_i|, t_i \epsilon j_i \setminus S_i\}} \left\{ \sum_{j \in s_i} \hat{a}_{ij} |x_j| + (\Gamma_i - \lfloor \Gamma_i \rfloor)\hat{a}_{it_i} |x_{t_i}| \right\} \leq b_i\,, \forall i.$$

The second term can be expressed as $\beta_i(x^*, \Gamma_i)$ with decision variable x^* for a given Γ_i, which can thus be formulated as follows:

$$\beta_i(x^*, \Gamma_i) = \max \sum_{j \in J_i} \hat{a}_{ij} |x_j^*|\, z_{ij}$$

$$s.t. \sum_{j \epsilon j_i} z_{ij} \leq \Gamma_i$$

$$0 \leq z_{ij} \leq 1\ \forall j \in J_i.$$

Moreover, this term is also replaced by the dual problem with dual variables and a tractable robust counterpart, p_{ij}, by considering a uncertainty budget as follows:

$$\max cx$$

$$s.t. \sum_j a_{ij}\, x_j + z_i\, \Gamma_i + \sum_{j \epsilon J_i} p_{ij} \leq b_i\,, \forall i$$

$$z_i + p_{ij} \geq \hat{a}_{ij} y_i\ \forall i, j \in J_i$$

$$-y_j \leq x_j \leq y_j, \forall j$$

$$p_{ij} \geq 0\ \forall i\,, j \in J_i$$

$$y_j \geq 0, \forall j$$

$z_i \geq 0, \forall i.$

As explained previously, two types of uncertainty sets can be considered: the box uncertainty and the uncertainty budget, knowing that the largest box uncertainty set is [0, 1], expressing the lower and upper bound reliability, which is expressed as follows:

$$z_x^1 \in [\, l_x^1, u_x^1]$$
$$z_k^1 \in [\, l_k^1, u_k^1].$$

However, the uncertainty budget aspect is applied to obtain a less conservative solution by varying the value of Γ_i , which can be expressed as follows:

$$z_x^1 \in U^1 \equiv \{z_x^1 : l_x^1 \leq z_x^1 \leq u_x^1], \sum_x z_x^1 \geq \Gamma_1\}$$

$$z_k^1 \in U^2 \equiv \{z_k^1 : l_k^1 \leq z_k^1 \leq u_k^1], \sum_k z_k^1 \geq \Gamma_2\}.$$