Exploring the opportunities in establishing a closed-loop supply chain under uncertainty

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Abstract

Reverse supply chains (RSC) may provide the benefits of reducing pollution, creating new jobs, and generating income from the recyclable materials. At the same time, their implementation comes with higher risks and less predictable outcomes. The model presented in this paper aims to help managers to better evaluate risks and opportunities while deciding on the design of a RSC in order to manage the reverse flow of end-of-life (EOL) products in an existing supply chain. The goal is to set up the disassembly and recovery facilities and organize the flows between them while seeking to maximize total network profit. We propose a two-stage mixed-integer programming model with multiple periods where the budget available for decisions at each period depends on the outcomes of previous periods. We consider that the demand for EOL products, the quantity of products returned as well as the time required to reprocess these products are uncertain. To incorporate this uncertainty into the decision making process, a discrete set of scenarios is defined. In order to take into account the decision maker's behavior in the areas of risks and opportunities, we propose to use R_* criterion to select the final solution. To demonstrate the significance and applicability of the developed model and the relevance of R_* criterion, never used before for design problems in logistics, we conduct numerical investigations on an adapted case study from the literature and do a comparison with classic well-known criteria.

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1. Introduction

The American Reverse Logistics Executive council defines reverse logistics (RL) as "the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal" [Rogers and Tibben-Lembke, 1998]. With increasing awareness about the environmental impacts of manufacturing such as greenhouse gas impacts, the acceleration in resource depletion as well as the increase in solid waste, several countries are promoting the development of collection and recycling systems by encouraging Reverse Supply Chains (RSC). These are intended to reduce environmental pollution, boost the economy by creating new jobs, and generate income from the recyclable materials. At the same time, new economic risks arise out of less predictable reverse flows of EOL products coming from the customer in terms of quantity but also quality of returned products, a wider variety of flow sources, more complex functions in terms of cost, services and environmental impacts, and unexplored market opportunities [Hanafi et al., 2007]. The reverse flow is not only more difficult to predict but also more difficult to control. [Agrawal et al., 2018] showed on four case studies of companies involved in RL processes that all aspect of RL management have to be accurately investigated in order to make the reprocessing of EOL products beneficial, from the prediction of the customer's behaviour to the legislation including the business model of the company. Thus, the existing models used for forward supply chain design have to be adapted in order to integrate a more complex network structure of RSC. The combination of both is referred to as Closed-Loop Supply Chains (CLSC) defined by [Guide Jr and Van Wassenhove, 2009] as "systems 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 times" (see Figure. 1).

A significant number of recent publications have been devoted to the design problem for RSC and CLSC. This fact reflects the importance and relevance of this problem in Supply Chain Management (SCM). Comprehensive reviews of existing approaches can be found in [Fleischmann et al., 2000, Govindan et al., 2017]. The focus on CLSC is more relevant for OEM (Original Equipment Manufacturer) since designing the forward and reverse flows

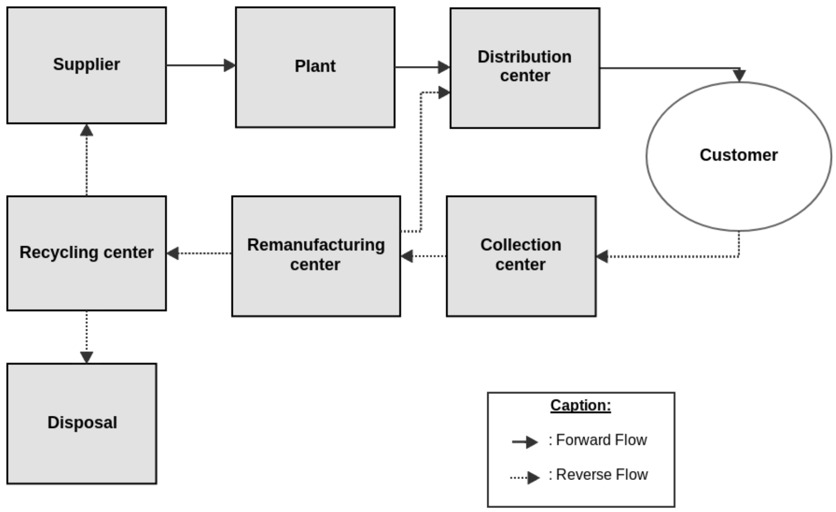

Figure 1: Illustration of a CLSC

separately results in sub-optimal solutions [Chen et al., 2015, Fleischmann et al., 2001, Üster et al., 2007].

The literature acknowledges uncertainty as being the most challenging factor in design of CLSC and describes various sources of uncertainty [Govindan et al., 2017]. However, existing models dealing with uncertainty have mainly been designed in a risk-oriented context [Jabbarzadeh et al., 2018, Zeballos et al., 2016]. As a result, they omit the psychological evidence that decision makers, in many cases, do not consider uncertainty in the same light depending on whether it is perceived as a risk or an opportunity [Grabisch, 2006]. Therefore, the scope for opportunities remains under-explored and potential economic benefits are often underestimated in the decision making process.

In order to help Decision Makers (DM) to better investigate the opportunities offered by the creation of a RSC, we propose to use a novel R_* criterion to select the final solution instead of conservative minmax criterion. Recently, the theoretical properties of R_* have been studied for qualitative sequential decision problems with the focus on the qualitative aspect of this aggregate function [Fargier and Guillaume, 2018a]. However, this criterion has never been used in linear programming for design problems in logistics. In this contribution, we show how it can be applied in the context of creating of a CLSC and what benefits it can bring to the decision makers.

We consider a closed-loop supply chain with three echelons in the forward direction (i.e. suppliers, plants, and distribution centers) and five echelons in the backward direction (i.e. collection center, dismantler, repair center, recycling center and disposal). This configuration matches a Reuse Recycle Recover (3R) framework. Such a structure is the most frequently used in the literature [Kirchherr et al., 2017] and can be adapted for various industrial environments and sectors.

We develop a multi-period model where the budget available for expansion at each period depends on the decisions taken in previous periods and the profit accumulated. Although rarely addressed in the literature [Badri et al., 2017, Dubey et al., 2015], this setting corresponds to the strategies of OEM who are often cautious about reverse logistics and its outcomes [Ko and Evans, 2007, Lee and Dong, 2009].

As several studies strongly suggest (see Table 1), the most influential factors of uncertainty in CLSC are considered to be the initial demand, the quantity and the quality of returned products. Thus, the uncertainty in the decision making process of the presented model is related to these factors. It is easy to see that in comparison to the forward supply chain where the main uncertain factor is the initial demand, the reverse flow brings two additional uncertainty factors related to the quantity and quality of the returned products. In order to be able to take into account the quality of returned products in a quantitative approach, we consider that the time required to reprocess EOL products can be related to their quality, accounting the fact that it will be easier and faster to treat good quality products than products of poor quality. Taking into account these uncertainties, a discrete set of scenarios is defined. The objective is to maximize the total network profit.

The paper is organized in the following way. Section 2 reviews the mathematical models and solution approaches proposed in the literature to design CLSC. In Section 3, we recall the notions of two-stage programming and frequently used two-stage programming methods. In Section 4, we expose the idea behind R_* criterion. Section 5 presents the two-stage MIP formulation for the optimization problem considered. In Section 6, we describe the developed mathematical model. Section 7 deals with computational experiments applied to a case study of a lead/acid battery CLSC network [Subulan et al., 2015]. The obtained results are used to derive managerial insights. Firstly, we compare R_* criterion with classic criteria from the literature. Then, we show its benefits for the DM. Particularly, we demonstrate that it allows the DM to configure the CLSC in a way to make the most of possible opportunities while controlling the level of potential risk. Section 8 provides conclusions as well as future research options.

2. Literature review

The literature review is organized in the following way: firstly, CLSC design is discussed, secondly, models addressing the uncertainty are analyzed.

Research on the design of CLSC was initiated in the 1990s. It was driven by new laws and policies introduced by governments in order to limit the environmental impact of EOL products. The first publications on CLSC provided mostly case studies [Jayaraman et al., 1999, Krikke et al., 2001].

During last decades, the CLSC design problem has been receiving an increasing amount of attention in the academic world resulting in an important number of models being developed for different settings. The impact of different logistics structures on the profitability of re-manufacturing systems has been studied. Because of the extensive literature available, the following review is focused on particular settings relevant to our study.

[Geyer et al., 2007] analyzed the economic effect of product life cycle and component durability on the cost saving potential of CLSC and showed that production cost structure, collection rate, product life cycle and component durability must be carefully coordinated in order to maximize cost savings in CLSC network.

[Guide Jr et al., 2006] demonstrated that companies facing large and increasing flows of EOL products should have a different RL network structure than the ones with a low rate of returned products.

[Atasu et al., 2008] showed that the profitability of RL systems strongly depends on the product life cycle as well as on the competition faced by OEMs. They also demonstrated that there exists a cost threshold that makes re-manufacturing a profitable alternative.

A strategic vision of the expansion of the CLSC has been introduced through multi-period models where facilities can be set up at any period of time [Badri et al., 2017, Dubey et al., 2015]. [De Rosa et al., 2013] considered a multi-period CLSC network design problem in which facility capacities could be increased or decreased dynamically over time for all echelons. Facility and depot locations could be changed and the type of depots and their general size could be modified. More examples of recent dynamic CLSC models are available in [Khatami et al., 2015, Mirmajlesi and Shafaei, 2016].

Several modeling approaches have been used in the literature in order to address uncertainty which is one of the most challenging issues in CLSC design [Govindan et al., 2017]. The most commonly used approach is the stochastic programming applied under the hypothesis of the known probability distributions of uncertain parameters. [Soleimani and Govindan, 2014] proposed a two-stage stochastic programming approach in order to design an RSC. The conditional value at risk (CVaR) was used as a risk estimator and the return amounts and prices of returned products were considered as two stochastic parameters. Other recent examples of stochastic programming for RL can be found in [Amin et al., 2017, Ayvaz and Bolat, 2014, Ayvaz et al., 2015, Habibi et al., 2017, Zhang and Unnikrishnan, 2016].

However, the data about probability distribution is often missing or not reliable. In this case, the use of the stochastic method does not guarantee suitable results. To overcome this difficulty, fuzzy programming is relatively frequently used [Zadeh, 1999]. Fuzziness helps to model vague information. Two main families of fuzzy approaches coexist in the literature. In the first case, a defuzzification is first performed and the deterministic optimization methods are used to solve the problem obtained. In the second case, the possibility theory is used to express the objective. [Subulan et al., 2015] proposed a fuzzy possibilistic programming model for designing a forward-reverse logistics network with hybrid facilities in the presence of uncertainty on demand quantities and quality of returns as well as the uncertainty of variable costs and random facility disruptions. The fuzzy goal programming model with different priorities was used to solve the developed model. A case study from the lead/acid industry in Turkey was presented. For more examples of fuzzy approach, see [Fallah et al., 2015, Govindan et al., 2016, Hatefi et al., 2015,b, Niknejad and Petrovic, 2014, Özceylan, 2016, Tosarkani and Amin, 2018].

Finally, if there is no available information about the uncertain parameters, a robust optimization can be used to search for a reliable solution even for the worst case scenario, a scenario being one of the possible realizations of the uncertain parameters. For instance, [Ramezani et al., 2013] presented a robust design model for a generic multi-product, multi-echelon CLSC. The uncertainty in demand and the return rate was described in the model by a finite set of possible scenarios. The scenario relaxation algorithm was employed to reduce the solution time. Another robust model was studied by [De Rosa et al., 2013] who considered a multi-stage, multi-period, capacitated, CLSC design problem with discrete uncertainty. The problem was solved by minimizing the expectations of relative regrets compared to a deterministic model. For more detail about this formulation see Section 3.4. More examples of the use of robust optimization for CLSC design can be found in [Pishvaee et al., 2011].

The robust approach is known to be very conservative in the sense that too much weight is given to the worst case. To make it less conservative, the set of scenarios can be reduced with different methods. For instance, [Soyster, 1973] proposed a linear optimization model to construct a solution that is feasible for all data that belong to a convex set. [Ben-Tal and Nemirovski, 1998] considered uncertain parameters that are elliptic, this involves solving the robust counterparts of the nominal problem in the form of conic quadratic problems. However, this approach leads to nonlinear models, which demand more computational time. [Bertsimas et al., 2011] proposed to flexibly adjust the level of conservatism of the robust solutions in terms of probabilistic bounds of constraint violations. These three approaches have been compared by [Dubey et al., 2015] for the problem of a multi-period and multi-product responsive sustainable supply chain design. The parameter-sensitive analysis showed that Soyster's approach was still too conservative, and confirmed that Ben-Tal and Nemirovski's approach and Bertsimas and Sim's approach enhanced the results (with Bertsimas and Sim's approach being slightly faster in the experiments performed).

A summary of the main contributions in 2014-2018 for the CLSC design under uncertainty is presented in Table 1. The anterior work was analyzed in the review of [Govindan et al., 2017]. Column 2 corresponds to the uncertain parameters considered in the model, Columns 3 to 5 correspond to the type of model they used to take into account those uncertain parameters, Column 6 reports the solution method employed.

All the models found in the literature are risk-oriented and never distinguish hazard from opportunity. In order to overcome this drawback, in this paper, we introduce R_* criterion for the CLSC design problem. It assumes that the DM is pessimistic in an hazardous zone and optimistic in an opportunity zone. This is considered under the assumption that the probability distributions of such uncertain parameters as product return quantity and demand and time of reprocessing EOL products are unknown.

Article	Uncertainty	S	F	R	Solution method
[Amin and Zhang, 2013]	R, DR, AF	x			MIP
[Amin et al., 2017]	D, R	x			MIP
[Ayvaz and Bolat, 2014]	R	x			MIP
[Ayvaz et al., 2015]	R, C, PA	x			MIP + SAA
[Badri et al., 2017]	D, R	x			MIP
[Dubey et al., 2015]	R, D			x	MIP
[Fallah et al., 2015]	R, C, CA		x		MIP
[Govindan et al., 2016]	D, C, CA, S		x		improved GA
[Habibi et al., 2017]	D	x			MIP
[Haddadsisakht and Ryan, 2018]	R, D, CT	x		x	Bender's decomposition
[Hatefi et al., 2015]	D, R, C, CA		x		MIP
[Hatefi et al., 2015b]			x		MIP
[Jeihoonian et al., 2016]	R	x			Bender's decomposition
[Jeihoonian et al., 2017]	D, R, C	x			L-shaped method
[Keyvanshokooh et al., 2016]	R, C	x		x	Bender's decomposition
[Khatami et al., 2015]	R	x			Bender's decomposition
[Niknejad and Petrovic, 2014]	R, D		x		MIP
[Özceylan, 2016]	D, CA, DR		x		MIP
[Sadjadi et al., 2014]	R	x	x	x	Memetic based heuristic
[Soleimani and Govindan, 2014]	D, BP, SP	x			MIP
[Subulan et al., 2015]	D, R, C, AF		x		MIP
[Subulan et al., 2015b]	D, R, C, AF	x	x		MIP
[Tosarkani and Amin, 2018]	R, D, C		x		MIP
[Zhalechian et al., 2016]	R, D, C, DS	x	x		MIP + Meta-heuristic
[Zhang and Unnikrishnan, 2016]	D	x			MIP
Our paper	R, D, RT			x	MIP

Table 1: An overview of the state-of-the-art

Parameters. R: Product Return quality and/or quantity, D: Demand, C: Cost, CA: Capacities, DR: Disposal Rate, PA: Proportion of returned products for different activities, SP: Selling Price, AF: Availability of Facilities, BP: Buying Price, CT: Carbon Tax, DS: Distances, S: Social Parameters, RT: Reprocessing time of products
Type of models. S: Stochastic, F: Fuzzy, R: Robust

3. Background

To provide a better understanding of the mathematical model defined in Section 4, we recall some general notions in this section. In particular, we give a brief description of two-stage programming and provide examples of its application.

3.1. Two-stage programming

In two-stage programming, the decision process is conceptually divided into two stages. In the first one, the values for decision variables (y) are chosen before the realization of the scenario is revealed. The values of the second stage decision variable (x) are calculated for the known values of uncertain parameters.

Let Γ be a set of discrete scenarios with $\Gamma = 1...S$, $s \in \Gamma$. The general formulation of two-stage programming in the case of maximization of profit can be written in the following way:

$$\begin{aligned} & \max_{y \in Y}[f^1(y) + g(Q_1(y), ..., Q_S(y))] \\ \text{Where} \quad & Q_s(y) = \max_{x \in X^{y,s}} f_s^2(x) \qquad \forall s \in \Gamma \end{aligned} \tag{1}$$

$f^1(y)$ is the evaluation function taking into account scenario-independent variables (or first-stage variables), $f_s^2(x)$ is the evaluation function considering the scenario-dependent variables (or second-stage variables) and g is an aggregation function. For more information about two-stage programming concepts and properties, the reader can refer to [Shapiro et al., 2009].

Two-stage programming is widely applied in the field of RL because it faithfully reproduces the logic of RSC implementation: the facility location problem often being the first stage problem and the allocation problem the second stage one. Indeed, opening and closing a facility is both an expensive and time-consuming process. On the other hand, the quantity of flows between facilities can be easily adapted to the choice of facility location. For instance, [Kara and Onut, 2010] proposed a two-stage programming model for the location-allocation problem in a paper recycling RSC.

3.2. Robust formulation

In a two-stage robust formulation, the aggregation function g is the maximum and the function Q_s is the minimum. In this way, the minimum profit is maximized over all scenarios [Ramezani et al., 2014]:

$$\begin{aligned} & \max_{y \in Y}[f^1(y) + \min_{s \in \Gamma} Q_s(y)] \\ \text{Where} \quad & Q_s(y) = \max_{x \in X^{y,s}} f_s^2(x) \qquad \forall s \in \Gamma \end{aligned} \tag{2}$$

3.3. Average formulation

In a two-stage average formulation, the aggregation function g is the average of the different profits over all scenarios. Each scenario has an equal weight in the final solution. The objective of a two-stage average formulation can be written as follows:

$$\begin{aligned} & \max_{y \in Y} f^1(y) + \tfrac{1}{S} * \textstyle\sum_s (Q_s(y)) \\ \text{Where} \qquad & Q_s(y) = \max_{x \in X^{y,s}} f_s^2(x) \qquad \forall s \in \Gamma \end{aligned} \tag{3}$$

This formulation is used in stochastic programming when the probability distribution is uniform.

3.4. Regret Average formulation

The two-stage regret average formulation searches for a optimal solution for each scenario separately and then minimizes the average relative regret overall scenarios compared to the optimal solutions. This formulation is used in [De Rosa et al., 2013] and can be written as follows:

$$\begin{aligned} & \max_{y \in Y} \textstyle\sum_{s \in \Gamma} \frac{f^1(y) + Q_s(y)}{F_s} \\ \text{Where} \quad & F_s = \max_{y \in Y}[f^1(y) + Q_s(y)] \quad \forall s \in \Gamma \end{aligned} \tag{4}$$

Here, F_s is the total profit of scenario s for the optimal solution.

3.5. Proposed solution method

We propose to use a new criterion R_* capable of taking the DM perception of risks and opportunities into account. In recent literature, this criterion has been used to solve qualitative sequential decision problems [Fargier and Guillaume, 2018b], but it has never been studied in the context of SCM.

With R_* criterion, the DM can distinguish the areas of risk and opportunity by using a threshold of the expected profit e. If the solution provided by the optimisation is lower than expected, then the DM is in a risky zone, if the value of the profit is greater than expected, the DM is in the opportunity zone. The choice of the best solution for the DM depends on the zone.

Let $F(x, s)$ be the evaluation of the objective function for solution x over scenario $s \in \mathbf{S}$, then mathematically R_* can be defined in the following way:

$$R_*(F(x,.), e) = \begin{cases} \min_{s \in \Gamma} F(x, s) & \textbf{if } \exists\ s \in \Gamma : F(x, s) \leq e \\ \max_{s \in \Gamma} F(x, s) & \textbf{otherwise} \end{cases} \tag{5}$$

R_* specifies that if one of the values of $F(x, s)$ is lower than or equal to e (zone of risk) then the min operator is applied, otherwise the max is applied (zone of opportunity).

To illustrate how the selection works in a simple setting, let us consider a case where a decision is to be made under a discrete set of scenarios S=$\{s_1$,$s_2\}$. Let $f(X, s_1)$ (resp. $f(X, s_2)$) be the value of objective function on scenario s_1 (resp. s_2). Let us consider the case where this value has to be maximized. Let us introduce the parameter e as the risk threshold (or neutral value) and X_1 and X_2 as two possible solutions. Figure 2 shows in red the zones which will be considered by the decision maker as risky and in green the zone of opportunity.

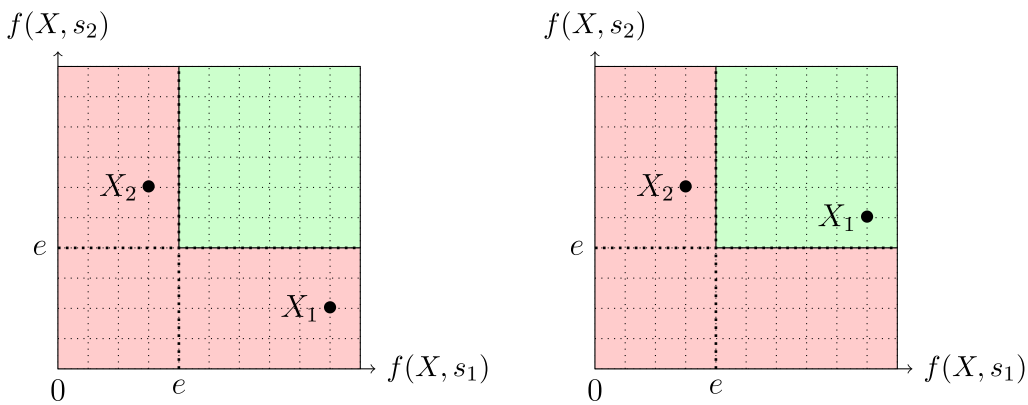

Figure 2: Possible solution spaces for a bipolar operator for two scenarios of uncertainty

On the left, both solutions are in the risky zone. The preferred solution is the more robust in terms of the max-min criterion, i.e. the one with the maximum value of the minimum objective function over scenarios (here X_2). On the right, one solution is in the risky zone and the other in the zone of opportunity. In that case, the solution with the highest maximum scenario in the zone of opportunity (here X_1) is preferred. This approach is capable of taking account not only of risks but also of opportunities for the decision maker. It should be also noted that if e is equal to the value of the robust solution obtained with max-min criterion, by definition R_* will find the robust solution. The DM has to be open to take some risks and loose a pat of profit in the worst case in order to search for opportunities for other scenarios which are not so pessimistic as the worst case.

4. Two-stage MIP formulation for CLSC design problem

In order to integrate R_* criterion in MIP formulation for CLSC design problem, we introduce a new two-stage MIP formulation defined in this section. The uncertainty of reverse flows is modeled with a discrete set of scenarios representing all possible and equally probable cases. Let $\Gamma = 1...S$ be the set of scenarios with $s \in \Gamma$. A two-stage model integrating R_* criterion is defined in the following way. Let $y = y_1, ..., y_n$ be the scenario-independent variables, and $x = x_1, ..., x_n$ the scenario-dependent variables. $f^1(y)$ is thus the evaluation function for the first stage variables and $f^2(x, s)$ for the second stage variables. We apply R_* criterion on both first and second stage variables resulting in the following objective function G for the profit maximization:

$$G = \max_{y \in Y} R_*[f^1(y) + Q_s(y), e] \tag{6}$$

The MIP formulation corresponding to this objective is then as follows: let e be a risk threshold, let Z and z be two continuous variables, let Y_s and δ_s be two binary variables.

$$\max Z + z \tag{7}$$

$$\begin{array}{lcl}
S.t & & \\
(a) & Z \leq f^1(y) + Q_s(y) & \forall s \in \Gamma \\
(b) & Z \leq e & \\
(c) & f^1(y) + Q_s(y) \geq -B * Y_s + e(1 - Y_s) & \forall s \in \Gamma \\
(d) & f^1(y) + Q_s(y) \leq e * Y_s + (1 - Y_s) * B & \forall s \in \Gamma \\
(e) & z \leq (1 - Y_s) * B & \forall s \in \Gamma \\
(f) & \sum_{s=1}^{S} \delta_s = 1 & \\
(g) & z \leq f^1(y) + Q_s(y) + (1 - \delta_s) * B & \forall s \in \Gamma
\end{array}$$

Model (7) implies that if the sum of the profit for the first and second stage (or total profit) is lower than or equal to e in any scenario then the min operator is applied, otherwise the max operator is applied. Thus, Z corresponds to a linearization variable for the min operator and z to a linearization variable for the max operator. Constraints (a) and (b) imply that Z is the minimum total profit over all scenarios unless the total profit is higher than e on all scenarios. In that case, the Z value is set to e: the value of the objective will therefore be too high with the value e, but this is irrelevant on the selection of the best solution (as this will then be performed in the opportunistic manner). Constraints (c) and (d) define the value of Y_s as: $Y_s = 1$ if the total profit is lower than e for scenario s and $Y_s = 0$ otherwise. Constraint (e) sets $z = 0$ if the total profit is lower than or equal to e in any scenario. Constraint (f) translates the fact that the best case scenario can only happen once. Constraint (g) implies that if there is no scenario for which the sum of evaluation functions for the first and second stage variables is lower than or equal to e then z is the maximum total profit over all scenarios.

In the next section, we describe the CLSC location-allocation problem considered for the mathematical model here above.

5. CLSC location-allocation problem

We consider the case of a Supply Chain for an OEM: it comprises suppliers, production and distribution centers. To establish a CLSC, OEM can turn its distribution centers into Hybrid Distribution/Collection centers (HDC) or fully collection centers to gather EOL products. New facilities may also be implemented: new HDCs to take charge of the flow of EOL products, dismantling centers for deconstruction of EOL products, repair centers, recycling centers for procurement of raw materials and disposal (see Figure 3).

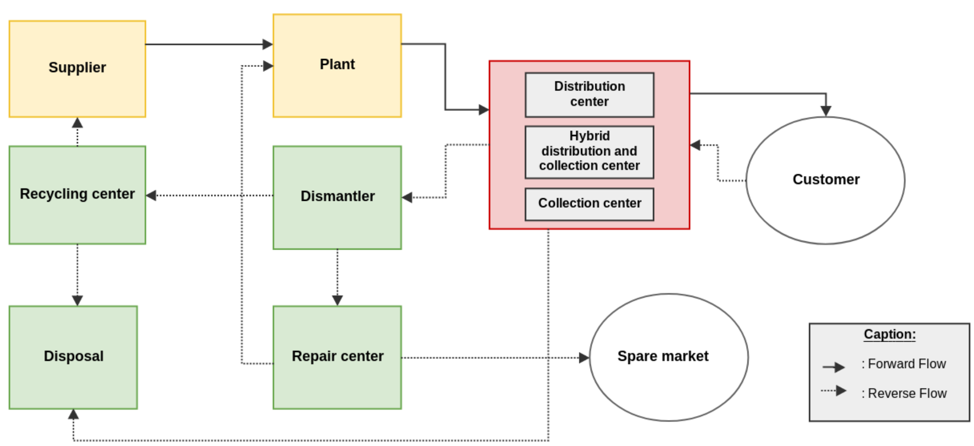

Figure 3: CLSC network

To provide a clearer understanding of the different possibilities for the treatment of a EOL product, let us consider here an example of an item and the way it can move around the CLSC. After being used by a costumer, a product is returned to a collection center. In the collection center, the quality of the product is assessed to see if it is good enough to be repaired or recycled. If yes, the product is brought to a dismantling center (we assume a predefined percentage of EOL products to be dismantled). Otherwise, the product is put in disposal. Once in the dismantling center, the product is disassembled and another quality assessment is done. The better quality products with potential to be repaired move on to a repair center, and the un-repairable products are brought to a recycling center (here again we assume predefined rates of EOL products to be repaired and recycled). After reprocessing in the repair center, the product can either be sold in the form of spare part, or can be re-used in the plant to be re-manufactured. If reprocessed in the recycling center, extracted recycled material is sold to the supplier while residual material is disposed.

We consider a multi-period horizon where the CLSC can be expanded progressively. The budget for expansion at each period depends on the decisions taken in previous periods. Uncertainty concerns primary and secondary market demand, the quantity of returned products and their reprocessing time are also uncertain. We assume that the quantity of returned products depends on primary market demand: the higher the demand, the higher the quantity of EOL products collected. Thus, a discrete set of scenarios with all equally probable cases is created. To support the DM in selecting the solution corresponding to his/her level of optimism, we use R_* criterion with the two-stage MIP formulation defined in Section 4.

5.1. Mathematical model

The indexes, parameters, and decision variables of the mathematical model are defined in Appendix A. In order to simplify the presentation of the model, we introduce the following expressions:

- *The total income*: it includes all sales revenues over all periods. It is scenario dependent and noted as $Income_s$.

- *The total operational cost*: it includes all production costs, assembling costs, buying costs, dismantling costs and distribution costs of all centers of the chain. It is scenario dependent and noted as $OpCost_s$.

- *The total fixed cost*: it is the sum of the opening costs of facilities and operational fixed costs for all facilities opened in each period. It is scenario independent and noted as $FixedCost$.

- *The total transportation cost*: it is the sum of travel costs between connected points of the Supply Chain. It is scenario dependent and noted as $TrtCost_s$.

All the mathematical formulations of the different expressions are available in Appendix B. From those expressions we can define the objective of the model which is to maximize the total profit of the CLSC calculated as:

$$TotalProfit_s = Income_s - OpCost_s - FixedCost - TrtCost_s \tag{8}$$

We can decompose the total profit in fixed and variable profits regarding the scenario dependent and independent expressions:

$$TotalProfit_s = FixedProfit + VariableProfit_s \tag{9}$$

$$With$$

$$FixedProfit = -FixedCost$$
$$VariableProfit_s = Income_s - OpCost_s - TrtCost_s$$

Thus, taking into account the definitions of Section 4, we have $f^1(y) = -FixedCosts$ and $f^2(x,s) = VariableProfit_s$, therefore:

$$\begin{array}{ll} G & = \max Z + z \\ G & = \max_{y \in Y} R_*[FixedProfit + Q_s(FixedProfit), e) \\ \text{Where} & Q_s(FixedProfit) = \max_{x \in X^{y,s}}(VariableProfit_s) \quad \forall s \in \Gamma \end{array}$$

To this objective we apply several types of constraints described as follows:

- All capacities of all centers must be respected in all periods and in every scenarios.

- The demand is never over-satisfied. However, the demand can remain unsatisfied and is considered lost in this case.

- The quantity of collected, dismantled, repaired and recycled EOL products are calculated through predefined rates.

- The flows incoming and outgoing each centers are balanced.

- The maximum number of opened centers for a period is restricted depending on the available budget.

- The budget is updated at each period regarding the number of opened centers in the previous period.

- It is forbidden to close opened centers.

All detailed mathematical formulations of the constraints are available in Appendix C. Finally, the additional constraints corresponding to the expression of model 7 are taken into account in (A) to (G).

$$
\begin{array}{lll}
(A) & Z \leq TotalProfit_s & \forall s \in S \\
(B) & Z \leq e_1 & \\
(C) & TotalProfit_s \geq -B * Y_s + e_1(1 - Y_s) & \forall s \in S \\
(D) & TotalProfit_s \leq e_1 * Y_s + (1 - Y_s) * B & \forall s \in S \\
(E) & z \leq (1 - Y_s) * B & \forall s \in S \\
(F) & \sum_{s=1}^{S} \delta_s = 1 & \\
(G) & z \leq TotalProfit_s + (1 - \delta_s) * B & \forall s \in S
\end{array}
$$

6. Numerical investigation

To illustrate the behaviour of the model and the usefulness of the proposed solution methodology, an explicatory numerical investigation has been performed. The obtained results are reported in this section. The data used was adapted from the case study presented in [Subulan et al., 2015] where a lead/acid battery CLSC network design under uncertainty was considered for a Turkish industry. The model of [Subulan et al., 2015] differs from ours since it does not include dismantling centers and only considers one type of center for both recycling and repair, they also only consider three outcomes for the reprocessed EOL products: 1) re-selling them as spare parts, 2) remanufacturing them in the plant, 3) putting them in disposal. They do not consider the re-selling of recycled material to the supplier. Apart from those points, both models consider the flows of products in forward and reverse directions. We adapted the data by adding the lacking distances and costs for the dismantlers and repair centers with the same order of value as those used for the other centers. Ten time periods were considered with 10 suppliers and plants, 10 potential locations for establishing the HDC centers and 10 customers and spare market customers. The number of potential locations for establishing repair centers, or recycling centers, or disposal centers was 10. The maximum number of opened centers was limited by the available budget. Other parameters are reported in Table 2. The transportation costs are defined per product and per 1 kilometer.

Parameters	Range of value	Parameters	Range of value
CapPlant	[28000,56000]	Ca	[0.5,4]
CapHC	[5250,20000]	Cp	[25,65]
Capd	[28000,56000]	Cass	[0.3,0.8]
CapR	[28000,56000]	Coph	[2,5]
CapDec	[28000,56000]	Cdis	[10,12]
Distances	[0,500]	Crep	[7,9]
SP	[40,60]	Cdecr	[0.47,1]
RSP	[5,15]	TC	0.003
Rev	[5,7]	Cohyb	[6000,23000]
Re	70%	Codism	[40000,60000]
Rr	90%	CoRecy	[40000,60000]
CFRep	100	CoDisp	[40000,60000]
CFDisp	100	CoRep	[40000,60000]
CFRecy	100	CFhyb	100
CFDism	100		

Table 2: Nominal data of the model

In the study of [Subulan et al., 2015], 3 uncertain parameters (initial demand, returned fraction of demand and disposal rate) were considered, while we consider 7 uncertain parameters (inital demand, spare market demand, demand for recycled products, return rate, reprocessing time of EOL products at dismantler, repair center and recycling center). For each uncertain parameter, we consider two possible scenarios of realization given as follows: for uncertain demand of customers at primary market D: low level ([1500,1800]) or high level ([2200, 2500]); and secondary markets, spare market Dsm: low level ([350,500]) or high level ([1200,1750]); supplier secondary demand Ds: low level ([250, 400]), high level ([1000,1250]) and for the uncertain return rate of products from consumers R: low level (10% in the first period + 2% per period), high level (40% in the first period + 5% per period) as well as for the uncertain reprocessing time of products $Tdismantler$, $Trecycle$, $Trepair$: long time ([5,6]) or short time ([1,2]). We selected the "low" and "high" level of each uncertain parameter in accordance to the study of [Subulan et al., 2015], the "high" level corresponding to a high range of the values used in their work and the "low" level corresponding to a low range of the values used in their work. We consider the uncertain parameters to be independent and we create eight different scenarios (s_1-s_8), each of them is presented in Table 3. Then, for each scenario, one value for each parameter is randomly selected with the use of a uniform distribution [1] from the intervals presented above. The scenario remains unchanged for the 10 considered periods, i.e. for 10 periods in a scenario with a high demand, 10 values drawn from the high demand range are selected.

Γ	DE	Dsm	Ds	R	Tdismantler	Trecycle	Trepair
s_1	low	low	low	low	long	long	long
s_2	low	low	low	low	short	short	short
s_3	low	low	low	high	long	long	long
s_4	high	high	high	low	long	long	long
s_5	low	low	low	high	short	short	short
s_6	high	high	high	low	short	short	short
s_7	high	high	high	high	long	long	long
s_8	high	high	high	high	short	short	short

Table 3: Uncertain parameters for eight different scenarios

In total, 50 different problem instances were generated. Each problem instance was solved through the process presented in Figure 4.

At the first step, the problem is solved as described in Section 5. Then, the values of the scenario independent variables are recorded. The model is then solved for each scenario separately considering the defined scenario independent variables, in order to find the values of the scenario dependent variables for the maximization of the profit.

The numerical investigation was conducted with IBM-ILOG CPLEX 12.6.3 on an Intel Core 2.60 gigahertz machine with 15 gigabyte RAM. The objective was to compare R_* criterion with the three approaches mentioned in Section 3:

1. The robust approach with the objective to maximize the worst-case scenario.
2. The average approach with the objective to maximize the average over all scenarios with a uniform probability distribution.

[1]The uniform distribution was selected over a normal distribution or a mean value because it better illustrates the lack of information of the decision maker about the behavior of the uncertain parameters.

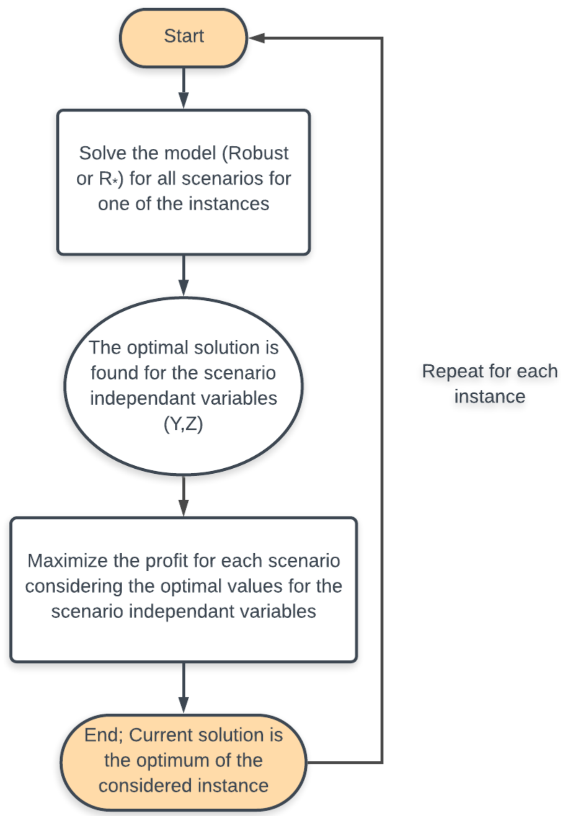

Figure 4: Resolution process

3. The average regret approach with the objective to maximize the average of the regret over all scenarios with a uniform probability distribution.

The average solution times for the models tested for the case of 2 (s_1 and s_8) and 8 scenarios are reported in Table 4. The results show that while for 2 scenarios the solution times for robust and R_* models are quite similar, for 8 scenarios it is approximately twice longer for R_*.

6.1. Scenario reduction

The results obtained for 8 scenarios (reported in Table 5) showed the existence of clusters of similar scenarios. The scenarios belonging to the same cluster are indicated by the same colour in Table 5. The values of e are calculated as a percentage of the value of the "MaxMin" solution. The payoff

Model	Number of scenarios	Average solution time(s)
Robust	2	1 623
Average	2	177
R_*	2	1 714
Robust	8	15 900
Average	8	2 077
R_*	8	33 217

Table 4: Solution time regarding models and number of scenarios

values reported are the $TotalProfit$ made by the CLSC when scenario s_1 to s_8 occur. The following observations can be made.

Model	s_1(€)	s_2(€)	s_3(€)	s_4(€)	s_5(€)	s_6(€)	s_7(€)	s_8(€)
Robust	3 319 100	3 404 364	1 363 587	5 315 179	3 063 511	5 479 111	1 125 648	6 453 565
Average	3 418 763	3 508 855	1 320 371	5 368 389	3 167 903	5 596 203	879 353	6 524 019
R_*, e=99%	3 351 986	3 412 147	1 316 274	5 327 129	3 101 006	5 492 417	1 125 453	6 496 221
R_*, e=85%	3 349 895	3 418 813	1 331 187	5 296 488	3 084 977	5 526 364	962 056	6 506 497

Table 5: Total profits for all combinations of scenarios and models (reveal clusters in the results)

Observation 1. Scenario s_8 (in green) is the best case scenario with maximal $TotalProfit_s$. It corresponds to the scenario where demands (DE, Dsm and DS) and return rate of EOL products (R) are high and the reprocessing times of products ($Tdismantler$, $Trepair$ and $Trecycle$) are short. In this situation, we can assume that the company is able to respond to the high demands due to the high flow of EOL products coming back from the consumers in addition with a high reprocessing capacity due to the short times of reprocessing EOL products. Therefore, the number of reprocessed products sold is high and generates considerable profit for the company.

Observation 2. Scenario s_3 and s_7 (in red) are the worst case scenarios with minimal $TotalProfit_s$. They correspond to the cases where the rate of return (R) is high, but the reprocessing times of EOL products ($Tdismantler$, $Trepair$ and $Trecycle$) are long. The number of reprocessed products sold is low and thus generates less profit than in the other cases.

Observation 3. Scenario s_4 and s_6 (in blue) are "medium high" scenarios, and correspond to the situation where demands (DE, Dsm and Ds) are high, but return rate (R) is low. In this case, because of the low rate of return, the company doesn't need a lot of reprocessing facilities to process all the EOL product, thus, the reprocessing times have no impact on the profit. All the reprocessed product are sold, creating profit, but a part of the demand is lost as the flow of reprocessed product is not high enough to respond to the high demand.

Observation 4. Scenario s_1, s_2 and s_5 (in orange) are "medium low" scenarios. They represent the case where the demand is low, and where either the return rate is high and the reprocessing time of EOL products is short, or the return rate is low and the reprocessing time of EOL products is long, or the return rate is low and the reprocessing time of EOL products is short. In those cases, the company is able to reprocess all the returned EOL products without additional costs generated from products put in disposal. However, at the same time, the company is unable to resell all the reprocessed products as the demand is low, and so no considerable profit is possible.

On the basis of these results, the set of scenarios was reduced to 4, keeping only one scenario of each group (i.e. s_1, s_6, s_7 and s_8). This setting requires less computational time and provides the same level of managerial insights. In the next sections, we compare the performances of three models (robust, average, R_*) for these 4 scenarios and for all possible pairs of them.

6.2. Robust model vs R_*

The robust model is the one conceptually closest to R_* since it considers a set of equally possible scenarios. In order to compare their behaviour, the value of risk threshold e was set up to the value of "MaxMin" criterion minus 1% or 3%. The obtained results for 4 scenarios are presented in Table 6, where column 1 shows the model used, the values reported are the $TotalProfit$ made by the CLSC when scenario s_1 to s_8 occur. They are colored in green when the R_* solution brings an improvement compared to the Robust solution and in red otherwise. The standard deviation σ (i.e the square root of the variance) among the scenarios is given in the last column.

Model	s_1	s_6	s_7	s_8	σ
Robust	3 334 384	5 244 279	1 253 605	6 218 444	1 903 483
R_*, e=99%	3 330 883	5 239 336	1 250 748	6 231 859	1 905 423
R_*, e=97%	3 331 035	5 238 529	1 229 414	6 248 992	1 918 007

Table 6: Compared $TotalProfit_s$ between Robust and R_* for the case of 4 scenarios

The obtained results show that R_* may provide better opportunities to the decision maker at price of low risks, especially for the case of $e = 99\%$ of the robust value.

When taking more risks (lowering the value of e) the DM invests more in the implementation of new centers at each period. Thus, if a good case scenario happens (for instance high demand, high returns and short reprocessing time of OEL products), the CLSC is able to collect and reprocess more products resulting in better total profit. Contrariwise, if a bad case scenario happens, the additional investment made by the DM won't be profitable.

To deepen the analysis, we compare the results obtained for each pair of 4 scenarios reported in Table 7. The values reported are the relative percentage of the best $TotalProfit$ made by the CLSC in each scenario, depending on the solution method.

Model	s_1	s_8	σ
Robust	100%	73,36%	475 179
R_*, e= 99%	98,96%	90,97%	1 047 111
R_*, e= 97%	97,05%	100%	1 365 222
Model	s_6	s_8	σ
Robust	100%	88,52%	2 619
R_*, e=99%	99,08%	95,93%	261 659
R_*, e=97%	97,28%	100%	440 992
Model	s_1	s_6	σ
Robust	100%	98,10%	974 108
R_*, e=99%	98,97%	99,63%	1031 542
R_*, e=97%	97,13%	100%	1 080 937
Model	s_8	s_7	σ
Robust	99,43%	100%	2 402 857
R_*, e= 99%	99,84%	99,07%	2 421 540
R_*, e= 97%	100%	97,47%	2 436 837
Model	s_1	s_7	σ
Robust	99,68%	100%	1 042 445
R_*, e=99%	99,83%	99,13%	1 050 470
R_*, e=97%	100%	97,19%	1 065 418
Model	s_6	s_7	σ
Robust	99,51%	100%	2 011 897
R_*, e=99%	99,85%	98,58%	2 024 368
R_*, e=97%	100%	96,63%	2 040 881

Table 7: Comparison of profit obtained with Robust and R_* for the case of 2 scenarios

The following observations can be made on the obtained results.

Observation 1. The R_* model is efficient in comparison to the robust model where both scenarios are not too pessimistic, i.e. opportunities are possible on at least one of the scenarios (see for instance s_1 versus s_8 or s_6 versus s_8.) By allowing a relatively low degradation for the worst case scenario, a significant improvement can be found for the best case. Decreasing e leads to better opportunities, but also to more important losses, however, the gain is superior to the loss in the considered setting. From a practical point of view, when taking more risks, the DM invests more in the implementation of new centers, therefore when scenario s_8 happens, the CLSC is able to reprocess more EOL products and thus to better respond to the demand which brings more profit to the company. At the contrary, when scenario s_1 or s_6 happens, either the demand is low, or the flow of returned products is low, or the reprocessing capacity of the CLSC is low. In all these cases, the CLSC is unable to make a considerable profit. Nevertheless, taking a little risk and implementing more new centers helps to keep a satisfying level of profit compared to a robust approach.

Observation 2. When the models are compared on the best case scenario (s_8) with the worst case one (s_7), or on two middle case scenarios (s_1 and s_6), the opportunities are still possible but the DM has to be very careful about the level of risk to take. Indeed, when we consider the case where the best case scenario (s_8) is faced with the worst case one (s_7), taking more risks in the investment of new centers may bring more profit if s_8 happens, as the CLSC will be able to better respond to the demand. However, this profit is not always compensated by the loss occurred if s_7 happens. When we consider the situation where the two middle cases (s_1 and s_6) are confronted to each other, the room for opportunities is thin in both scenario, as the CLSC may encounter difficulties to respond to the demand. Thus, implementing new centers may lead to better opportunities in one of the two cases but does not necessarily worth the risk in the other case.

Observation 3. Finally, R_* model cannot help to find new opportunities unless by taking much higher risks where both scenarios are not optimistic (the worst case scenario (s_7) and either s_1 or s_6). For such a situation, the robustness should be preferred in order to limit the losses. Here, from a production perspective, taking more risks and thus implementing new centers will probably not lead to more opportunities. Indeed, when the worst case scenario (s_7) happens, the costs generated by the implementation of new centers are not compensated by the reprocessing more EOL products. When one of the middle case scenarios happens (s_1 or s_6) the CLSC is unable to make a considerable profit because of either low demand, a low flow of returned products, or a low reprocessing capacity. Thus, taking risk and implementing more centers than with a robust solution will not provide substantially better profit in this case.

In conclusion, the solutions found with R_* criterion show a greater number of implemented reverse centers compared to the robust solution. Taking more risk is synonym to investing more for the implementation of new centers at the beginning of each period, and thus being able to reprocess and sell more products when a good case scenario happens. When the two scenarios are not too pessimistic, a good case scenario is very likely to occur. Consequently, choosing a solution where more reverse centers are opened will lead to a good probability of increased profit compared to a safer solution where less centers are opened. On the contrary, if all possible scenarios are quite pessimistic, the risk taken by the investment for implementation of additional centers compared to the robust solution will probably not result in a better profit.

6.3. Average and Regret Average models vs R_*

Since the stochastic models are the most used in the literature for the CLSC problem, it seems legitimate to compare them with our model even if they do not take uncertain parameters into account in the same way (a stochastic model considers a distribution of probability (here uniform) for the scenarios. The results obtained for the case of 4 scenarios are presented in Table 8. The comparison of scenarios two by two showed the same results, we do not present them here. The table is organized in the same way as previously, with a new column "*Av*" for the mean value over all scenarios. There is also new Column "*Reg*" corresponding to the value of the sum of regret over all scenarios. The risk threshold e is still equal to the value of "MaxMin" criterion minus 0% (i.e. the robust solution), or -1% and -3%.

Model	s_1	s_6	s_7	s_8	Av	Reg	σ
Average	3 374 146	5 287 225	1 190 523	6 262 269	4 028 541	1 102 861	1 940 129
Regret	3 374 215	5 287 219	1 190 381	6 262 349	4 028 541	1 102 861	1 942 797
R_*, e=100%	3 334 384	5 244 279	1 253 605	6 218 444	4 012 678	1 166 311	1 903 483
R_*, e=99%	3 330 883	5 239 336	1 250 748	6 231 859	4 013 207	1 164 197	1 905 423
R_*, e=97%	3 331 035	5 238 539	1 229 414	6 248 992	4 011 992	1 169 054	1 918 007

Table 8: Comparison of the profits found with the two stochastic models and R_*

It can be observed that the solutions given by the two stochastic models are almost equivalent. For this reason, only gaps between R_* model and average model are reported. Positive gaps are in green and negative ones are in red. The solutions given by R_* are more robust than the stochastic solutions and opportunities can still be found, even if they are less important than in comparison with the robust model. The mean of $TotalProfit_s$ over all scenarios is in the same order of values for all models. Regarding the regret value for each scenario and for each model, the two stochastic models have both the lowest regret. The value of the regret seems to increase while the value of e decreases. However, the regret stays in the same magnitude for all models.

These results show that R_* model allows more robustness by controlling the worst case scenario and still considering opportunities as the best case is comparable with stochastic solutions. Thus, R_* offers a compromise between the "MaxMin" solution which is too conservative and a stochastic solution which is not robust enough.

6.4. Variance analysis

Figure 5 reports the standard deviation for all tested 50 problem instances of the case of 4 scenarios for average model, robust model and R_* model for two values of e. The deviation of the regret average model is not reported because of its quasi equivalence to the average model.

It can be seen that the variances of robust and R_* models are very close while the deviation of the average model is relatively dispersed.

Figure 6 shows the value obtained for the best case scenario by the tested models for all 50 problem instances. Robust model provides the minimal value. R_* model is sensible to the value of e: while it decreases, the value for the best case scenario improves. The values returned by R_* criterion are always higher than with the Robust model, confirming the fact that R_* criterion allows to better explore opportunities. Finally, average model is not constant in providing a good value, thus, it does not guarantee the maximization of opportunities, but it is largely the best one for 18 instances from 50 (i.e. in about 36% of the cases).

Figure 7 shows the value obtained for the worst case scenario by the tested models for all 50 problem instances. Here, unsurprisingly, the robust model provides the best value. R_* model is again sensible to the value of e: the profit decreases when the value of e decreases, nevertheless it remains very close to the value found with the Robust criterion. Average model is again

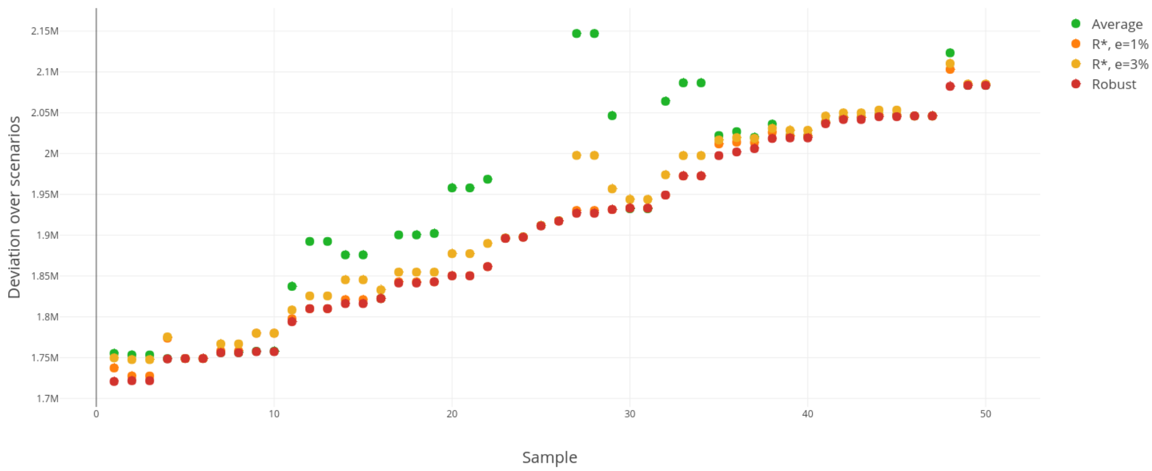

Figure 5: Standard deviation provided by the tested models

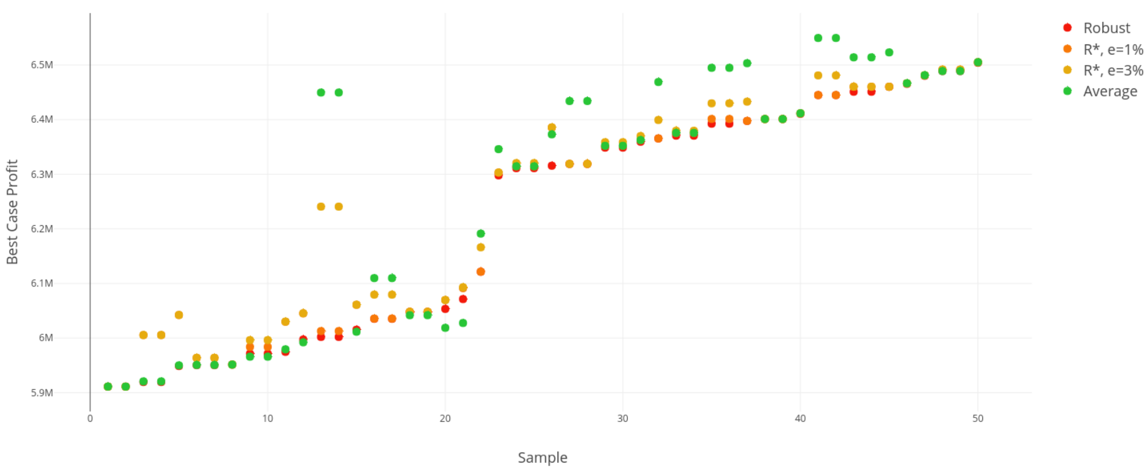

Figure 6: The value for the best case scenario provided by the tested models

inconstant, it could provide a value as good as the robust model or to be largely worse (16 instances from 50 i.e. about 32%). Thus, it does not allow the control of the risk taken by the DM.

When the two figures are considered at the same time, we can see that

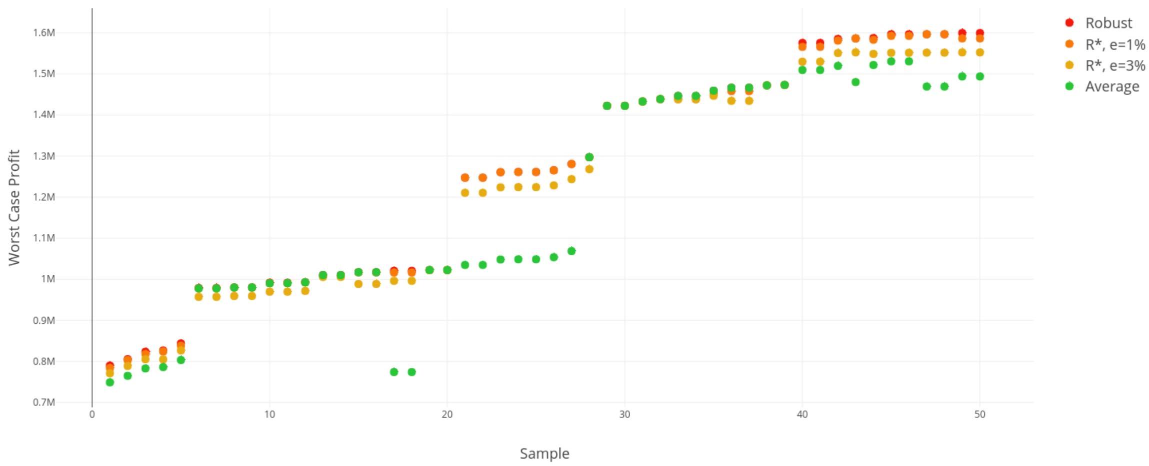

Figure 7: The value for the worst case scenario provided by the tested models

the R_* criterion offers a compromise between a robust solution with no opportunities or an average solution with no control over the robustness.

From the realized analysis we can conclude the following.

If e is superior or equal to the value of the robust solution, model R_* will give the equivalent solution. The closer the value of e to the value of the robust model, the closer the solution obtained with R_* is to the robust solution and the smaller is the standard deviation of the profits for different scenarios as well as the gap between the solution's best and worst scenarios. The average and regret average models are the ones with the greatest average over scenarios, but have the worst "worst case scenarios".

7. Conclusion

Establishing CLSC is an essential challenge when shifting from linear to circular economy. A successful CLSC design relies on appropriate modeling of uncertainty in terms of risk, but also opportunities. In this study, we suggest a new modeling approach using R_* to take DM optimism into account in both hazard and opportunity zones. This approach can be used to set up reverse facilities and connect them to an existing forward supply chain. The CLSC can be expanded gradually on the basis of the decisions made in previous periods. The proposed approach is compared to robust and stochastic models in an extensive numerical investigation. The results obtained show that the use of R_* criterion makes it possible to better explore the opportunity zone without loosing control over robustness.

Indeed, it provides the DM with greater control on the investment she/he is willing to make to open new reverse centers, bringing more profit in a good case scenario while still controlling the losses when a bad case scenario occurs. Particularly, we show that in the case where the initial demand is high, the rate of return is high and the reprocessing time of EOL products is short (s_8) versus the case where the demand and the return are low and the reprocessing time is long (s_1), the solution found with R_* criterion allows up to 36% more profit that the robust solution in the fist case for only 3% of losses in the second case.

This study reveals many new research paths. The proposed model can be extended by considering not only the best and worst case scenarios but all scenarios in between. For instance, a Leximax criterion can be applied in order to rank solutions with the same best and worst case scenarios. Another research path lies in examining the case of a discrete set of scenarios with imprecise probabilities. Its extension to a continuous set of scenarios should also be examined.

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Appendix A. Indexes, Parameters and Variables

	Indexes
$i = 1..I$	Index of suppliers
$j = 1..J$	Index of plants
$l = 1..L$	Index of customers
$c = 1..C$	Index of HDC
$p = 1..P$	Index of dismantlers
$q = 1..Q$	Index of repair centers
$m = 1..M$	Index of spare market customers
$f = 1..F$	Index of disposal sites
$d = 1..D$	Index of recycling centers
$t = 1..T$	Index of time periods
$s = 1..S$	Index of scenarios
	Demand parameters
$D_{l,t,s}$	of consumers l for period t and scenario s
$Dsm_{m,t,s}$	of spare market consumers m for period t and scenario s
$Ds_{i,t,s}$	of suppliers i for period t and scenario s
	Capacity parameters
$CapPlant_j$	Production capacity of plant j
$CapHC_c$	Capacity of HDC c
$Capd_p$	Production capacity of dismantler p
$CapR_q$	Production capacity of repair center q
$CapDec_d$	Production capacity of recycling center d
	Distance parameters
$DisSP_{i,j}$	Between supplier i and plant j
$DisPH_{j,c}$	Between plant j and HDC c
$DisCH_{l,c}$	Between costumer l and HDC c
$DisCoDi_{c,p}$	Between HDC c and dismantler p
$DisCoF_{c,f}$	Between HDC c and disposal f
$DisDiDe_{p,d}$	Between dismantler p and recycling center d
$DisDeDis_{d,f}$	Between recycling center d and disposal f
$DisDeS_{d,i}$	Between recycling center d and supplier i
$DisDiR_{p,q}$	Between dismantler p and repair center q
$DisRSM_{q,m}$	Between repair center q and spare market customer m
$DisRPP_{q,j}$	Between repair center q and plant j
	Time parameters
$Tdismantler_s$	Unit dismantling time
$Trecycle_s$	Unit recycling time
$Trepair_s$	Unit repair time

	Variable cost parameters
Ca_i	Unit cost of buying product at supplier i
Cp_j	Unit production cost at plant j
$Cass_j$	Unit assembling cost at plant j
$Coph_c$	Unit operational cost at HDC c
$Cdis_p$	Unit dismantling cost at dismantling center p
$Crep_q$	Unit repair cost at repair center q
$Cdecr_d$	Unit production cost of raw material at recycling center d
$Ceco_c$	Unit environmental tax for non-reprocessed products
TC	Unit transportation cost for 1 kilometer
	Rate parameters
$R_{t,s}$	Rate of return for period t and scenario s
Re	Repairing rate after dismantling
Rr	Recycling ratio after decomposition
	Unit selling price parameters
SP_l	of product at market zone l
RSP_m	of product at spare market m
Rev_i	of recycled product to the supplier i
	Fixed opening cost parameters
$Cohyb_c$	for HDC c
$CoDism_p$	for dismantling center p
$CoRecy_d$	for recycling center d
$CoDisp_f$	for disposal f
$CoRep_q$	for repair center q
	Fixed operational cost parameters
$CFhyb_{c,t}$	for HDC c in period t
$CFDism_{p,t}$	for dismantling center p in period t
$CFRecy_{d,t}$	for recycling center d in period t
$CFDisp_{f,t}$	for disposal f in period t
$CFRep_{q,t}$	for repair center q in period t
C_t	Budget for opening centers in period t
	Positives variables *(Flow from . to . at period t and scenario s)*
$XSP_{i,j,t,s}$	from supplier i to plant j
$XPH_{j,c,t,s}$	from plant j to hybrid center c
$XCHD_{c,l,t,s}$	from HDC c to customer l
$XCHC_{l,c,t,s}$	from customer l to HDC c
$XCODI_{c,p,t,s}$	from HDC c to dismantler p
$XCOF_{c,f,t,s}$	from HDC c to disposal f
$XDIR_{p,q,t,s}$	from dismantler p to repair center q
$XRSM_{q,m,t,s}$	from repair center q to spare market costumer m
$XDIRE_{p,d,t,s}$	from dismantler p to recycling center d
$XREDIS_{d,f,t,s}$	from recycling center d to disposal f
$XPS_{d,i,t,s}$	from recycling center d to supplier i
$XRPP_{q,j,t,s}$	from repair center q to plant j
$h_{c,l,t,s}$	maximum flow between forward and return from costumer l to HDC center c

	Binary variables
$YCH_{c,t}$	HDC c is opened or not at period t
$YP_{p,t}$	Dismantler p is opened or not at period t
$YD_{d,t}$	Recycling center d is opened or not at period t
$YF_{f,t}$	Disposal f is opened or not at period t
$YQ_{q,t}$	Repair center q is opened or not at period t
$ZYCH_c$	1 if HDC c has been opened, 0 otherwise
ZYP_p	1 if Dismantler p has been opened, 0 otherwise
ZYD_d	1 if Recycling center d has been opened, 0 otherwise
ZYF_f	1 if Disposal f has been opened, 0 otherwise
ZYQ_q	1 if Repair center q has been opened, 0 otherwise
	Additional parameters corresponding to the MIP formulation
B	A big enough value
e_1	Risk threshold
	Additional Variables corresponding to the MIP formulation
δ_s	1 if the best case scenario s occurs, 0 otherwise
z, Z	Variables for the linearization of Model (7)

Appendix B. Mathematical formulations of the expressions

$$
\begin{aligned}
Income_s &= \textstyle\sum_{t=1}^{T}(\sum_{l=1}^{L}(\sum_{c=1}^{C}(SP_l * XCHD_{c,l,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{m=1}^{M}(\sum_{q=1}^{Q}(RSP_m * XRSM_{q,m,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{i=1}^{I}(\sum_{d=1}^{D}(Rev_i * XPS_{d,i,t,s})))
\end{aligned} \tag{B.1}
$$

$$
\begin{aligned}
OpCost_s &= \textstyle\sum_{t=1}^{T}(\sum_{j=1}^{J}(\sum_{i=1}^{I}(Ca_i * XSP_{i,j,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{c=1}^{C}(\sum_{j=1}^{J}(Cp_j * XPH_{j,c,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{c=1}^{C}(\sum_{j=1}^{J}(Cass_j * XPH_{j,c,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{l=1}^{L}(\sum_{c=1}^{C}(Coph_c * (XCHD_{c,l,t,s} + XCHC_{l,c,t,s})))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{p=1}^{P}(\sum_{c=1}^{C}(Cdis_p * XCODI_{c,p,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{m=1}^{M}(\sum_{q=1}^{Q}(Crep_q * XRSM_{q,m,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{j=1}^{J}(\sum_{q=1}^{Q}(Crep_q * XRRP_{q,j,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{i=1}^{I}(\sum_{d=1}^{D}(Cdecr_d * XPS_{d,i,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{f=1}^{F}(\sum_{c=1}^{C}(Ceco_c * XCOF_{c,f,t,s})))
\end{aligned} \tag{B.2}
$$

$$
\begin{aligned}
FixedCost &= \textstyle\sum_{c=1}^{C}(Cohyb_c * ZYCH_c) \\
&+ \textstyle\sum_{p=1}^{P}(CoDism_p * ZYP_p) \\
&+ \textstyle\sum_{d=1}^{D}(CoRecy_d * ZYD_d) \\
&+ \textstyle\sum_{f=1}^{F}(CoDisp_f * ZYF_f) \\
&+ \textstyle\sum_{q=1}^{Q}(CoRep_q * ZYQ_q) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{c=1}^{C}(CFhyb_{c,t} * YCH_{c,t})) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{p=1}^{P}(CFDism_{p,t} * YP_{p,t})) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{d=1}^{D}(CFRecy_{d,t} * YD_{d,t})) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{f=1}^{F}(CFDisp_{f,t} * YF_{f,t})) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{q=1}^{Q}(CFRep_{q,t} * YQ_{q,t}))
\end{aligned} \tag{B.3}
$$

$$
\begin{aligned}
TrtCost_s \; &= \textstyle\sum_{t=1}^{T}(\sum_{j=1}^{J}(\sum_{i=1}^{I}(TC * DisSP_{i,j} * XSP_{i,j,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{c=1}^{C}(\sum_{j=1}^{J}(TC * DisPH_{j,c} * XPH_{j,c,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{l=1}^{L}(\sum_{c=1}^{C}(TC * DisCH_{l,c} * h_{l,c,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{p=1}^{P}(\sum_{c=1}^{C}(TC * DisCoDi_{c,p} * XCODI_{c,p,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{q=1}^{Q}(\sum_{p=1}^{P}(TC * DisDiR_{p,q} * XDIR_{p,q,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{m=1}^{M}(\sum_{q=1}^{Q}(TC * DisRSM_{q,m} * XRSM_{q,m,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{d=1}^{D}(\sum_{p=1}^{P}(TC * DisDiDe_{p,d} * XDIRE_{p,d,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{f=1}^{F}(\sum_{D=1}^{D}(TC * DisDeDis_{d,f} * XREDIS_{d,f,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{i=1}^{I}(\sum_{d=1}^{D}(TC * DisDeS_{d,i} * XPS_{d,i,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{j=1}^{J}(\sum_{q=1}^{Q}(TC * DisRPP_{q,j} * XRPP_{q,j,t,s}))) \\
&+ \textstyle\sum_{t=1}^{T}(\sum_{f=1}^{F}(\sum_{c=1}^{C}(TC * DisCoF_{c,f} * XCOF_{c,f,t,s})))
\end{aligned} \tag{B.4}
$$

Appendix C. Constraints

Constraints (1) to (6) verify that the different capacities of all centers are respected.

$$
\begin{array}{lll}
(1) & \sum_{i=1}^{I} XSP_{i,j,t,s} + \sum_{q=1}^{Q} XRPP_{q,j,t,s} \leq CapPlant_j & \forall s \in S, t \in T, j \in J \\
(2) & \sum_{j=1}^{J} XPH_{j,c,t,s} + XCHC_{j,c,t,s} \leq CapHC_c * YCH_{c,t} & \forall s \in S, t \in T, c \in C \\
(3) & \sum_{c=1}^{C} XCODI_{c,p,t,s} * Tdismantler_s \leq Capd_p * YP_{p,t} & \forall s \in S, t \in T, p \in P \\
(4) & \sum_{p=1}^{P} XDIR_{p,q,t,s} * Trepair_s \leq CapR_q * YQ_{q,t} & \forall s \in S, t \in T, q \in Q \\
(5) & \sum_{p=1}^{P} XDIRE_{p,d,t,s} * Trecycle_s \leq CapDec_d * YD_{d,t} & \forall s \in S, t \in T, d \in D \\
(6) & \sum_{d=1}^{D} XREDIS_{d,f,t,s} \leq B * YF_f & \forall s \in S, t \in T, f \in F
\end{array}
$$

Constraints (7) to (9) are used to verify that the demand is never over-satisfied. However, the demand can remain unsatisfied and considered lost in this case.

$$
\begin{array}{lll}
(7) & \sum_{c=1}^{C}(XCHD_{c,l,t,s}) \leq D_{l,t,s} & \forall s \in S, t \in T, l \in L \\
(8) & \sum_{q=1}^{Q}(XRSM_{q,m,t,s}) \leq Dsm_{m,t,s} & \forall s \in S, t \in T, m \in M \\
(9) & \sum_{d=1}^{D}(XPS_{d,i,t,s}) \leq Ds_{i,t,s} & \forall s \in S, t \in T, i \in I
\end{array}
$$

Constraint (10) calculate the quantity of collected EOL products.

$$
(10) \quad \sum_{c=1}^{C}(XCHC_{l,c,t,s}) = R_{t,s} * D_{l,t,s} \quad \forall s \in S, t \in T, l \in L
$$

Constraints (11) and (12) calculate the quantity of the dismantled, repaired and recycled products.

$$
\begin{array}{lll}
(11) & \sum_{c=1}^{C} XCODI_{c,p,t,s} * Re = \sum_{q=1}^{Q} XDIR_{p,q,t,s} & \forall p \in P, s \in S, t \in T \\
(12) & \sum_{p=1}^{P} XDIRE_{p,d,t,s} * Rr = \sum_{i=1}^{I} XPS_{d,i,t,s} & \forall d \in D, s \in S, t \in T
\end{array}
$$

Constraints (13) to (18) are the flow balance constraints.

$$(13)\quad \sum_{i=1}^{I}(XSP_{i,j,t,s}) + \sum_{q=1}^{Q}(XRPP_{q,j,t,s}) = \sum_{c=1}^{C}(XPH_{j,c,t,s}) \quad \forall s \in S, t \in T, j \in J$$

$$(14)\quad \sum_{j=1}^{J}(XPH_{j,c,t,s}) = \sum_{l=1}^{L}(XCHD_{c,l,t,s}) \quad \forall s \in S, t \in T, c \in C$$

$$(15)\quad \sum_{l=1}^{L}(XCHC_{l,c,t,s}) = \sum_{p=1}^{P}(XCODI_{c,p,t,s}) + \sum_{f=1}^{F}(XCOF_{c,f,t,s}) \quad \forall s \in S, t \in T, c \in C$$

$$(16)\quad \sum_{c=1}^{C}(XCODI_{c,p,t,s}) = \sum_{q=1}^{Q}(XDIR_{p,q,t,s}) + \sum_{d=1}^{D}(XDIRE_{p,d,t,s}) \quad \forall s \in S, t \in T, p \in P$$

$$(17)\quad \sum_{p=1}^{P}(XDIR_{p,q,t,s}) = \sum_{m=1}^{M}(XRSM_{q,m,t,s}) + \sum_{j=1}^{J}(XRPP_{q,j,t,s}) \quad \forall s \in S, t \in T, q \in Q$$

$$(18)\quad \sum_{p=1}^{P}(XDIRE_{p,d,t,s}) = \sum_{f=1}^{F}(XREDIS_{d,f,t,s}) + \sum_{i=1}^{I}(XPS_{d,i,t,s}) \quad \forall s \in S, t \in T, d \in D$$

Constraint (19) restricts the maximum number of opened centers for a period depending on the available budget.

$$(19)\quad \sum_{c=1}^{C}((YCH_{c,t} - YCH_{c,t-1}) * Cohyb_c) + \sum_{p=1}^{P}((YP_{p,t} - YP_{p,t-1}) * CoDism_p) + \sum_{d=1}^{D}((YD_{d,t} - YD_{d,t-1}) * CoRecy_d) + \sum_{f=1}^{F}((YF_{f,t} - YF_{f,t-1}) * CoDisp_f) + \sum_{q=1}^{Q}((YQ_{q,t} - YQ_{q,t-1}) * CoRep_q) \leq C_t \forall t \in T$$

Constraint (20) updates the budget regarding the number of opened centers in the previous period.

$$(20)\quad C_t = C_1 - \sum_{c=1}^{C}(YCH_{c,t-1} * Cohyb_c) - \sum_{p=1}^{P}(YP_{p,t-1} * CoDism_p) - \sum_{d=1}^{D}(YD_{d,t-1} * CoRecy_d) + \sum_{f=1}^{F}(YF_{f,t-1} * CoDisp_f) - \sum_{q=1}^{Q}(YQ_{q,t-1} * CoRep_q) \qquad \forall t \in T$$

Constraints (21) to (25) calculate the fixed opening costs.

$$(21)\quad ZYCH_c \geq (1/T) * \sum_{t=1}^{T} YCH_{c,t} \quad \forall c \in C$$

$$(22)\quad ZYQ_q \geq (1/T) * \sum_{t=1}^{T} YQ_{q,t} \quad \forall q \in Q$$

$$(23)\quad ZYD_d \geq (1/T) * \sum_{t=1}^{T} YD_{d,t} \quad \forall d \in D$$

$$(24)\quad ZYP_p \geq (1/T) * \sum_{t=1}^{T} YP_{p,t} \quad \forall p \in P$$

$$(25)\quad ZYF_f \geq (1/T) * \sum_{t=1}^{T} YF_{f,t} \quad \forall f \in F$$

Constraints (26) to (30) forbid to close opened centers.

$$
\begin{array}{lll}
(26) & YCH_{c,t+1} \geq YCH_{c,t} & \forall c \in C, t \in T \\
(27) & YQ_{q,t+1} \geq YQ_{q,t} & \forall q \in Q, t \in T \\
(28) & YD_{d,t+1} \geq YD_{d,t} & \forall d \in D, t \in T \\
(29) & YP_{p,t+1} \geq YP_{p,t} & \forall p \in P, t \in T \\
(30) & YF_{f,t+1} \geq YF_{f,t} & \forall f \in F, t \in T
\end{array}
$$

Constraints (31) and (32) are used in order to limit the transportation costs to unidirectional among forward and reverse flows depending on the maximum number of products transported between.

$$
\begin{array}{lll}
(31) & h_{c,l,t,s} \geq XCHD_{c,l,t,s} & \forall c \in C, l \in L, s \in S, t \in T \\
(32) & h_{c,l,t,s} \geq XCHC_{l,c,t,s} & \forall c \in C, l \in L, s \in S, t \in T
\end{array}
$$