



HAL
open science

Lexicographic R^* Criterion For Decision Making Under Uncertainty in Reverse Logistics

Zoé Krug, Romain Guillaume, Olga Battaïa

► **To cite this version:**

Zoé Krug, Romain Guillaume, Olga Battaïa. Lexicographic R^* Criterion For Decision Making Under Uncertainty in Reverse Logistics. 9th IFAC Conference on Manufacturing Modelling, Management and Control (MIM 2019), IFAC, Aug 2019, Berlin, Germany. pp.499-504. hal-03621765

HAL Id: hal-03621765

<https://hal.science/hal-03621765>

Submitted on 28 Mar 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Lexicographic R_* Criterion For Decision Making Under Uncertainty in Reverse Logistics

Zoé Krug^{*,**} Romain Guillaume^{**} Olga Battaïa^{*}

^{*} ISAE-SUPAERO, Université de Toulouse, 10 av. E. Belin - 31055 Toulouse Cedex 4, France (e-mail: {zoe.krug,olga.battaia}@isae.fr).

^{**} Université de Toulouse-IRIT, 5, Allée A. Machado 31058 Toulouse Cedex 1, France (e-mail: romain.guillaume@irit.fr)

Abstract: Reverse supply chains (RSC) deal with End-Of-Life products (EOL). They provide the benefits of reducing solid waste, creating new jobs, and generating income from the sales of re-manufactured products and savings in raw materials. At the same time, their design is more challenging in comparison with forward supply chains because of hardly predictable reverse flows of EOL products. Conventional approaches to address the uncertainty are usually risk-oriented and do not consider eventual opportunities. In order to overcome this drawback, we propose to use the R_* criterion in the decision making process in a context of complete ignorance with a discrete set of equally possible scenarios. This criterion integrated in a new lexicographic algorithm is used in order to take the Decision-Maker's (DM) behavior into account in different ways regarding if the uncertainty is considered as a risk or as an opportunity. Its performances are evaluated on the case study of facility location problem in reverse logistics.

Keywords: Supply chain, Uncertainty, Reverse logistics

1. INTRODUCTION

When information about the distribution of uncertain parameters is not available, it is common to define a set of possible scenarios, each of them corresponding to a possible realization of the uncertain parameters. Robust approach is then applied in the case of a discrete set of equally possible scenarios. Its goal is to maximize the minimum profit over all scenarios. It is very conservative in the way that too much weight is given to the worst case scenario, preventing from finding satisfying solutions when good case scenarios happen (Bertsimas and Sim (2004)). In this paper, we propose to use a different criterion in order to consider the DM optimism while searching for opportunistic solutions.

Several criteria have been proposed in the literature in order to consider the DM's optimism in the case of discrete scenarios. The most common ones are the Hurwicz criterion (Hurwicz (1951)) and the Ordered Weighted Average (OWA) criterion (Yager (2004)). With the OWA criterion, costs of the scenarios are ranked from the best one to the worst one, then a weighted average is calculated on the ranked costs (the weights depend on the ranking). Hurwicz criterion is a special case of OWA when the best case scenario has a weight equals to α and the worst case scenario has a weight equals to $1 - \alpha$ and all other scenarios weights equal 0. These two criteria are compensatory, i.e. a good case scenario will soften the effect of a bad case scenario and reciprocally.

In order to take into account the psychological evidence that a DM will not react to uncertainty in the same way

if considered as a risk or as an opportunity (Grabisch (2006)), we are interested in considering the DM optimism with a non compensatory criterion, in order to distinguish areas of risks and opportunity.

In the case of the design of a RSC, the DM has to deal with a lot of uncertainty: on the demand for reprocessed products, the quantity of EOL products returned, the quality of the products, etc... Since the concept of RSC is relatively new, there is a lack of knowledge preventing from efficient probability distribution of possible scenarios. Many studies have already been conducted in this area (Govindan et al. (2017)), but existing models are most of the time risk-oriented and neglect the opportunities that can exist. However, it is very important to take into account these opportunities in order to build more realistic models and show the benefits the RSC may provide. Recent studies show the positive impact of the reverse logistics on economy. For instance, the McKinsey Center for Business and Environment has demonstrated that the choice of a circular economy could reduce the cost of raw materials in Europe by 2030 by 1,800 billion Euro (25%). Economic benefits can be obtained by the reuse of materials and/or components (Toffel (2004)). Furthermore, the management of EOL products improve the image of the company and protect its market which is an indirect source of additional economic benefits (de Brito and Dekker (2003)).

In order to help the DM to explore the opportunities of RSC, we develop a new lexicographic R_* criterion. This criterion is a "bipolar" operator able to take into account uncertainty in the form of risk but also in the form of

opportunity. The classic R_* criterion's formulation is given in Section 2. The Lexicographic algorithm with R_* is detailed in Section 3. In Section 4, it is applied to a facility location problem for a RSC. The conclusions of the study are presented in Section 5.

2. BACKGROUND

As aforementioned, there is a psychological evidence that in many cases the DM does not consider uncertainty in the same manner if it is perceived as a risk or an opportunity. To take into account this fact, bipolar operators have been introduced by Grabisch (2006). They consider a neutral value (for instance 0 or e) below which a score is considered as "bad" and above which a score is considered as "good". Then, "good" and "bad" scores are not aggregated in the same way.

Yager and Rybalov (1996) presented the family of Uninorm operators which are a subgroup of bipolar operators and are defined as follows:

A Uninorm R is a mapping $R : \mathbb{R}^+ \times \mathbb{R}^+ \rightarrow \mathbb{R}^+$ having the following properties:

- (1) $R(a, b) = R(b, a)$ (Commutative)
- (2) $R(a, b) \leq R(c, d)$ if $a \leq c$ and $b \leq d$ (Monotonous)
- (3) $R(a, R(b, c)) = R(R(a, b), c)$ (Associative)
- (4) There exists some element $e \in \mathbb{R}^+$, called the identity element, such that for all $x \in \mathbb{R}^+$ $R(x, e) = x$

On $[0, e]$ a Uninorm behaves like a t-norm, and on $[\overline{e}, +\infty[$ like a t-conorm. We can thus consider that $[0, e]$ is an interval of hazards while $[\overline{e}, +\infty[$ is an interval of opportunities. The threshold e therefore corresponds to the optimism level of the DM.

In the considered context of RSC, we are particularly interested in the Uninorm which takes the minimum for t-norm and takes the maximum for t-conorm. The objective is to minimize the risks and maximize the opportunities. This Uninorm is called R_* and is defined as following:

Let $F(x, s)$ be the evaluation of the objective function for solution x over a scenario $s \in S$,

$$R_*((F(x, s))_{s \in S}, e) = \begin{cases} \min_{s \in S} F(x, s) & \text{if } \exists F(x, s) \leq e \\ \max_{s \in S} F(x, s) & \text{otherwise} \end{cases} \quad (1)$$

The solution space of the R_* criterion in the case of the maximization of the profit and two scenarios is shown in Fig. 1. $f(x, s_1)$ is the profit when scenario s_1 happens and $f(x, s_2)$ when scenario s_2 happens. We consider x_1, x_2 two solutions. The zone of hazards is represented in grey and the zone of opportunities in white. In the first figure, both solutions x_1 and x_2 are in the zone of hazards. In that case, to select the final solution we choose the one with the maximum minimum scenario (here x_2) called robust. In the second figure, one solution is in the zone of hazards and another is in the zone of opportunities. In this case, the solution in the zone of opportunities (here x_1) will always be preferred. If all the solutions are in the zone of opportunities, the final solution selected is the one with the maximum value of the objective function (or optimistic solution).

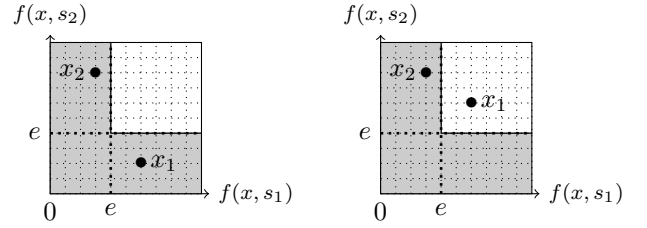


Fig. 1. R_* criterion solution space

R_* is an interesting non compensatory criterion, but it only takes into account the best case and worst case scenarios and neglects all scenarios in between. It means that two solutions with the same best and worst case scenario won't be differentiated by this criterion. We propose a lexicographic approach of R_* in order to fix this drawback.

The lexicographic R_* ($lexiR_*$) approach is the combination of a lexicographic maximum ($leximax$) approach and of a lexicographic minimum ($leximin$) approach. The former searches to maximize not only the largest profit but also to maximize the second largest profit, the third largest, and so on. The latter searches to maximize not only the smallest profit but also to maximize the second smallest profit, the third smallest and so on... (see Ogryczak (1997); Ogryczak and Sliwiski (2003)). In $lexiR_*$ approach, we use $leximin$ in the areas of hazards and $leximax$ in the areas of opportunities.

In a more formal way, it can be written as follows (we denote $S^- = \{s \in S | F(x, s) \leq e\}$ and $S^+ = S \setminus S^-$):

$$LexiR_*((F(x, s))_{s \in S}, e) = \begin{cases} Leximin_{s \in S^-} F(x, s) \\ \text{Then} \\ Leximax_{s \in S^+} F(x, s) \end{cases} \quad (2)$$

In order to make the process of resolution more clear for the reader, we present an example below.

Example 1. Let S be a discrete set of scenarios with $S = \{s_1, s_2, s_3, s_4\}$. Let $F(x, s) = (2, 3, 8, 10)$ (resp $F(y, s) = (2, 5, 7, 10)$) be a vector of objective values for solution x (resp y) of a decision problem regarding the set of scenario S . In order to lighten the notation, we note $F_s^x = F(x, s)$ and $F_s^y = F(y, s)$ in the rest of the example. Our goal is the maximization of the objective. The two vectors cannot be differentiated with R_* as they both have the same worst case scenario (i.e. 2) and the same best case scenario (i.e. 10). We will study the resolution of the problem with $LexiR_*$ criterion for 3 different cases:

- (1) In the first case, we consider $e = 12$. In that case, the DM is pessimistic and both solutions have all their objective values in the area of hazards. Thus, a $leximin$ is applied in order to choose the solution (see Fig.2(a)). The evaluation of the objective in the worst case scenario being the same for the two solutions, they cannot be differentiated at the first iteration. Yet, at the second iteration, $F_{s_2}^y$ is higher than $F_{s_2}^x$. In this case, solution y is chosen.
- (2) In the second case, we consider $e = 1$. In that case, the DM is optimistic and both solutions have all

their objective values in the opportunity area. Thus, a *leximax* is applied in order to choose the solution (see Fig.2(b)). The evaluation of the objective in the best case scenario is the same for the two solutions, they are differentiated at the second iteration, where $F_{s_3}^x$ is better than $F_{s_3}^y$.

- (3) In the last case, we consider $e = 6$. The DM is neither optimistic nor pessimistic. Two objective values of each solution are in the area of hazards, and two are in the opportunity area (see Fig.2(c)). In that case, *LexiR** starts by considering the risky scenarios with *leximin*. The evaluation of the objective in the second worst case scenario is in the risky area for both solutions, however, it is better with y than with x , thus, solution y is chosen. If F_s^y and F_s^x had been equal for all risky scenarios then the differentiation of the solution would have been on the opportunity area with *leximax*.

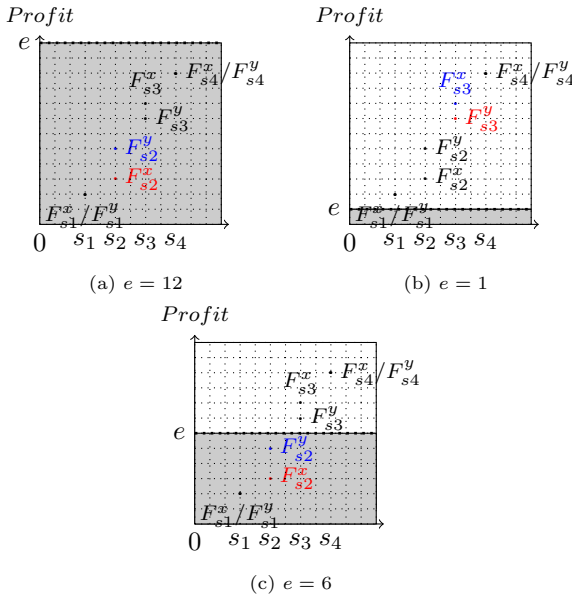


Fig. 2. Examples of resolution with *LexiR** criterion

3. LEXICOGRAPHIC R_* ALGORITHM

Notation	Description	Notation	Description
R_k	Linearization of min	Y_s	Binary variable
r_k	Linearization of max	δ_s^k	Binary variable
k	Number of iteration	γ_s^k	Binary variable
e	Risk threshold	M	Big value

Table 1. Notations

With the use of notations in Table 1, the lexicographic approach can be described as follows. Firstly, the model is solved with R_* to select the first set of solutions. Then, at the first iteration, the scenario on which the selection of the solution has been made (either the maximum best case scenario or the maximum worst case scenario) is recorded and removed. Then, R_* criterion is reapplied to the selected set of solutions with one less scenario. A second set of solutions is thus defined, and the process is repeated until it is possible to differentiate the best solution.

Algorithm 1.

- *Step.0*
 $k \leftarrow 0$
 $N \leftarrow \{s_1, \dots, s_m\}$
 $i = 0..k$

- *Step.1*
Solve Model (3)

$$\max R_k + r_k \quad (3)$$

S.t

$$(a) \quad R_k \leq F((x, y), s) \quad \forall s \in N,$$

$$(b) \quad R_k \leq e$$

$$(c) \quad F((x, y), s) \geq -M * Y_s + e(1 - Y_s) \quad \forall s \in N$$

$$(d) \quad F((x, y), s) \leq e * Y_s + (1 - Y_s)M \quad \forall s \in N$$

$$(e) \quad r_k \leq (1 - Y_s)M \quad \forall s \in N$$

$$(f) \quad \sum_{s=1}^S \delta_s^k = 1$$

$$(g) \quad r_k \leq F((x, y), s) + (1 - \delta_s^k)M \quad \forall s \in N$$

- *Step.2*
If $R_k + r_k \leq e$
then $R_k = R_k^*$, $k = k + 1$ and go to *Step.3*.
Otherwise,
define $R_k = e$, $r_1 = r_k^*$, $k' = 2$ and go to *Step.5*
- *Step.3:*
Solve Model (4)

$$\max R_k + r_k \quad (4)$$

S.t

$$(a) \quad R_i \leq F((x, y), s) + M(1 - \gamma_s^i) \quad \forall s \in N, i \in 1..k$$

$$(b) \quad \sum_{s=1}^S \gamma_s^i = S - i \quad \forall i \in 1..k$$

$$(c) \quad R_k \leq e$$

$$(d) \quad F((x, y), s) \geq -M * Y_s + e(1 - Y_s) \quad \forall s \in N$$

$$(e) \quad F((x, y), s) \leq e * Y_s + (1 - Y_s)M \quad \forall s \in N$$

$$(f) \quad r_k \leq (1 - Y_s)M \quad \forall s \in N$$

$$(g) \quad \sum_{s=1}^S \delta_s^k = 1$$

$$(h) \quad r_k \leq F((x, y), s) + (1 - \delta_s^k) * M \quad \forall s \in N$$

- *Step.4:*
If $S - k = 0$ then go to *Step.7*
Otherwise:
If $R_k \leq e$, then $R_k = R_k^*$, $k = k + 1$ and return to *Step.3*
If $R_k + r_k > e$, then $R_k = e$, $r_1 = r_k^*$ define $k' = 2$ and go to *Step.5*
- *Step.5:*
Solve Model (5)

$$\max r_{k'} \quad (5)$$

S.t

$$(a) R_i \leq F((x, y), s) + M(1 - \gamma_s^i) \forall s \in N, \forall i \in 1..k$$

$$(b) \sum_{s=1}^S \gamma_s^i = S - i, \quad \forall i \in 1..k$$

$$(c) r_i \leq F((x, y), s) + M(1 - \delta_s^i) \forall s \in N, \forall i \in 1..k'$$

$$(d) \sum_{s=1}^S \delta_s^{k'} = k'$$

- *Step.6:*
If $S - k - k' - 1 = 0$ then go to Step.7
Otherwise $r_{k'} = r_{k'}^*$, $k' = k' + 1$, and go to Step.5
- *Step.7:*
Stop.

Algorithm 1 operates in the following way.

Step 0 is the initialization of the algorithm: we define an index k that will be the number of the iteration, a set of all scenarios considered N and an index i .

In Step 1, the model is solved with the R_* criterion (only the best and worst case are considered).

At Step 2, the cases minimax and maximax are distinguished in order to proceed differently at the second iteration: if the found solution is lower than e , we want to optimize the second worst case scenario; in that case we go to Step 3. On the contrary, if the found solution is higher than e , we want to optimize the second best case scenario, thus we go to Step 5.

Step 3 chooses the second maximum minimum scenario, then the third and so on as long as the solution at the previous iteration stays lower than e .

Step 4 makes a transition between a maxmin case and a maxmax case if the solution of Model.4 at the previous iteration become higher than e .

Step 5 and 6 select the second maximum maximum scenario, then the third and so on and so forth as long as the solution at the previous iteration is higher than e .

When there is no more scenario to treat, Algorithm stops in Step 7.

4. CASE STUDY

We apply our Lexi R_* criterion to a RSC design problem. The results obtained are compared with the robust solutions.

4.1 Description of the case study

The application is based on a facility - location - transportation problem applied to RSC design for a third party logistic company.

Our goal is to locate the different facilities (collection center, re-manufacturing center and disposal) and optimize the transport between them. The objective is the maximization of the profit. The uncertainty is related

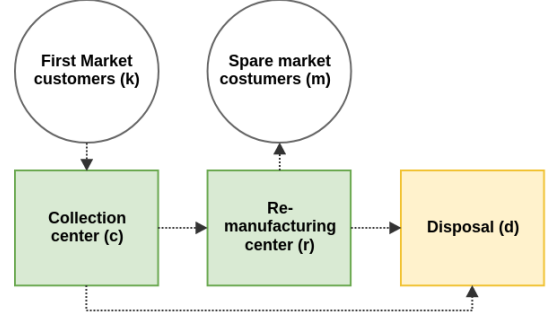


Fig. 3. Reverse Supply Chain

to the quantity of returned EOL products, the quantity of demand for re-manufactured EOL products and the reprocessing time of EOL products.

4.2 Mathematical model

Indexes, parameters and variables are presented here:

	Indexes
$k = 1..K$	Index of customers
$m = 1..M$	Index of spare markets
$c = 1..C$	Index of collection centers
$r = 1..R$	Index of re-manufacturing centers
$d = 1..D$	Index of disposal sites
$s = 1..S$	Index of scenarios
	Demand
$D_{m,s}$	of spare market m for scenario s
	Capacity
$CapC_c$	of collection center c
$CapR_r$	of re-manufacturing center r
	Distance between...
$DKC_{k,c}$	customer k and collection center c
$DCR_{c,r}$	collection center c and re-manufacturing center r
$DCD_{c,d}$	collection center c and disposal d
$DRD_{r,d}$	re-manufacturing center r and disposal d
$DRM_{r,m}$	re-manufacturing center r and spare market m
	Time parameters
$Tremanu_s$	Unit dismantling time
	Unit operational cost
$Coph_c$	at collection center c
$Cdis_p$	at re-manufacturing center p
$Ceco$	tax for non-reprocessed products
TC	transportation cost for 1 kilometer
	Rate parameters
R_s	Quantity of return for scenario s
Rr	Re-manufacturing rate after collection
Rd	Disposal rate after re-manufacturing
	Unit selling price parameters
RSP_m	of product at spare market m
	Fixed opening cost parameters
CFC_c	for collection center c
CFR_r	for re-manufacturing center r
CFD_d	for disposal d
	Positives variables (Flow from . to . for s)
$XKC_{k,c,s}$	customer k to collection center c
$XCR_{c,r,s}$	collection center c to re-manufacturing center r
$XCD_{c,d,s}$	collection center c to disposal d
$XRD_{r,d,s}$	re-manufacturing center r to disposal d
$XRM_{r,m,s}$	re-manufacturing center r to spare market m
	Binary variables
YC_c	collection center c is opened or not
YR_r	re-manufacturing center r is opened or not
YD_d	Disposal d is opened or not

In order to simplify the presentation of the model, we introduce the following expressions.

The total income: it includes all sales revenues. It is scenario dependent and can be formulated as:

$$Income_s = \sum_{m=1}^M \left(\sum_{r=1}^R (RSP_m * XRM_{r,m,s}) \right) \quad (6)$$

The total operational cost: it includes all production costs, assembling costs, buying costs, dismantling costs or distribution costs from/to all centers of the chain. It is scenario dependent and can be defined as follows:

$$\begin{aligned} OpCost_s = & \sum_{k=1}^K \left(\sum_{c=1}^C (Coph_c * XKC_{k,c,s}) \right) \\ & + \sum_{c=1}^C \left(\sum_{r=1}^R (Cdis_r * XCR_{c,r,s}) \right) \\ & + \sum_{f=1}^F \left(\sum_{c=1}^C (Ceco * (XRD_{r,d,s} + XCD_{c,d,s})) \right) \end{aligned} \quad (7)$$

The total fixed cost: it is the sum of the set-up costs of facilities:

$$\begin{aligned} FixedCost = & \sum_{c=1}^C (CFC_c * YC_c) \\ & + \sum_{p=1}^P (CFR_p * YR_p) \\ & + \sum_{d=1}^D (CFD_d * YD_d) \end{aligned} \quad (8)$$

The total transportation costs: it is the sum of travel costs between connected points of the Supply Chain. It is scenario dependent and can be written as:

$$\begin{aligned} TrtCost_s = & \sum_{k=1}^K \left(\sum_{c=1}^C (TC * DKC_{k,c} * XKC_{k,c,s}) \right) \\ & + \sum_{r=1}^R \left(\sum_{c=1}^C (TC * DCR_{c,r} * XCR_{c,r,s}) \right) \\ & + \sum_{d=1}^D \left(\sum_{c=1}^C (TC * DCD_{c,d} * XCD_{c,d,s}) \right) \\ & + \sum_{r=1}^R \left(\sum_{d=1}^D (TC * DRD_{r,d} * XRD_{r,d,s}) \right) \\ & + \sum_{r=1}^R \left(\sum_{d=1}^D (TC * DRSM_{r,m} * XRM_{r,m,s}) \right) \end{aligned} \quad (9)$$

Objective The objective is to maximize the total profit calculated as:

$$TotalProfit_s = Income_s - OpCost_s - FixedCost - TrtCost_s \quad (10)$$

Constraints

$$\begin{aligned} (1) \quad & \sum_{k=1}^K XKC_{k,c,s} \leq CapC_c * YC_c \quad \forall c \in C, s \in S \\ (2) \quad & \sum_{c=1}^C XCR_{c,r,s} * Tremanu_s \leq CapR_r * YR_r \quad \forall r \in R, s \in S \\ (3) \quad & \sum_{c=1}^C XCD_{c,d,s} + \sum_{r=1}^R XRD_{r,d,s} \leq B * YF_f \quad \forall d \in D, s \in S \\ (4) \quad & \sum_{r=1}^R XRM_{r,m,s} \leq D_{m,s} \quad \forall m \in M, s \in S \\ (5) \quad & \sum_{k=1}^K XKC_{k,c,s} \leq R_s \quad \forall k \in K, s \in S \\ (6) \quad & \sum_{k=1}^K XKC_{k,c,s} * Rr = \sum_{r=1}^R XCR_{c,r,s} \quad \forall c \in C, s \in S \\ (7) \quad & \sum_{c=1}^C XCR_{c,r,s} * Rd = \sum_{d=1}^D XRD_{r,d,t,s} \quad \forall r \in R, s \in S \\ (8) \quad & \sum_{k=1}^K XKC_{k,c,s} = \sum_{r=1}^R XCR_{c,r,s} \\ & + \sum_{d=1}^D XCD_{c,d,s} \quad \forall c \in C, s \in S \\ (9) \quad & \sum_{c=1}^C XCR_{c,r,s} = \sum_{d=1}^D XRD_{r,d,s} \\ & + \sum_{m=1}^M XRM_{r,m,s} \quad \forall r \in R, s \in S \end{aligned}$$

Constraints (1) to (3) verify that the capacities of all centers are respected. Constraint (4) verifies that the demand is never over-satisfied. However, the demand can remain unsatisfied and considered lost in this case. Constraint (5) calculates the quantity of collected EOL products. Constraints (6) and (7) calculate the quantity of dismantled, repaired and recycled products. Constraints (8) and (9) are the flow balance constraints.

4.3 Results: Robust model versus LexiR* model

In order to show the advantages of our model, we compare it with a Robust model, and with a classic R_* model as presented in Section 2. The results of the numerical experiment are reported in this section. The scale of the numerical experiment is as follows: the number of potential locations for establishing the collection centers, re-manufacturing centers and disposal is 10, the number of customers and spare market customers is 10. The data used for the resolution are presented in Table 2. The transportation costs are defined per product and per 1 kilometer.

We define four different scenarios from the worst case to the best case. They are presented in Table 3.

The numerical experiment was conducted with IBM-ILOG CPLEX 12.6.3 on an Intel Core 2.60 gigahertz machine with 15 gigabyte RAM. The results from R_* are presented in Table 4 and the results from LexiR* are presented in Table 5. The two tables are built in the same way: Column 1 is the model used to solve the problem, Column 2 is the chosen value for e when the R_* or the LexiR* model

Parameter	Value
<i>CapC</i>	Uniform(55000,200000)
<i>CapR</i>	Uniform(28000,56000)
<i>Distances</i>	Uniform(0,500)
<i>Coph</i>	Uniform(1,6)
<i>Cdis</i>	Uniform(2,8)
<i>Ceco</i>	1
<i>TC</i>	0.003
<i>Rd</i>	80%
<i>Rr</i>	80%
<i>RSP</i>	Uniform(90,120)
<i>CFC</i>	Uniform(10000,90000)
<i>CFR</i>	Uniform(40000,60000)
<i>CFD</i>	Uniform(40000,60000)

Table 2. Deterministic Parameters

Parameter	s_1	s_2	s_3	s_4
<i>D</i> (*1000)	U(22,27.5)	U(12,17.5)	U(22,27.5)	U(22,27.5)
<i>R</i> (*1000)	U(12,17.5)	U(12,17.5)	U(22,27.5)	U(22,27.5)
<i>Tremanu</i>	U(1,2)	U(5,6)	U(5,6)	U(1,2)

Table 3. Uncertain Parameters

are used (they are indicated in relative percentage of the "MaxMin" solution). Column 3 to 6 are the results for each scenario. Every scenario for which the R_* or the $LexiR_*$ model brings an improvement compared to the Robust model are colored in green and every scenario for which the R_* or the $LexiR_*$ model brings a degradation are colored in red.

Model	e	s_1 (€)	s_2 (€)	s_3 (€)	s_4 (€)
Robust	-	1552422	1899237	1969349	1981001
R_*	-0%	1552422	1899237	1969349	1981001
R_*	-3%	1538872	1896560	2662113	2902355
R_*	-5%	1482802	1666845	3204561	3212546

Table 4. Compared Profit between Robust approach and R_* approach for the case of 4 scenarios

Model	e	s_1 (€)	s_2 (€)	s_3 (€)	s_4 (€)
Robust	-	1552422	1899237	1969349	1981001
$LexiR_*$	+3%	1552422	1899994	1970978	1981001
$LexiR_*$	-0%	1552422	1899994	1970978	1981001
$LexiR_*$	-3%	1538875	1897844	2663437	2902355
$LexiR_*$	-5%	1482862	1669413	3211150	3212546

Table 5. Compared Profit between Robust and $LexiR_*$ approach for the case of 4 scenarios

The results obtained show that:

- If e is equal to or above the robust "MinMax" solution, the found solution is the same with the Robust model and with the R_* model while the $LexiR_*$ model improves the two middle case scenarios compared to the robust solution. Thus, new opportunities are disclosed without any risks for the DM.
- With the R_* and the $LexiR_*$ models, the more e decreases compared to the "MinMax" solution, the more the two worst case scenarios are degraded but in return, opportunities are revealed in two best case scenarios. The gains are much more important than the losses in all considered cases and are slightly superior with the $LexiR_*$ model than with the R_* model. By choosing the value for e the DM accepts to take a little more risks, but it is possible to keep the control over the robustness of the solution while

the opportunity area is much better explored than with the Robust model.

- The $LexiR_*$ model gives better results for two worst case scenarios compared to the R_* model. Therefore, the risks taken by the DM are better controlled.

5. CONCLUSION

The implementation of RSC is essential in order to reduce waste. A successful RSC design relies on appropriate modeling of uncertainty not only in terms of risks, but also opportunities. In this paper, we suggest a new modeling approach using $LexiR_*$ to take DM optimism into account in both hazard and opportunity zones. The results obtained show that the use of the $LexiR_*$ criterion makes it possible to better explore the opportunity zone compared to a robust model without losing control over robustness. It also provides the possibility to better control the risks taken in comparison to the R_* model without lexicographic approach.

This study reveals many research perspectives. For instance, we are planning to examine the case of a discrete set of scenarios with imprecise probabilities. The presented algorithm could also be improved by considering a fuzzy value for e . Its extension to a continuous set of scenarios should also be examined.

REFERENCES

- Bertsimas, D. and Sim, M. (2004). The price of robustness. *Operations research*, 52(1), 35–53.
- de Brito, M.P. and Dekker, R. (2003). Modelling product returns in inventory control: exploring the validity of general assumptions. *International Journal of Production Economics*, 81, 225–241.
- Govindan, K., Fattahi, M., and Keyvanshokoo, E. (2017). Supply chain network design under uncertainty: A comprehensive review and future research directions. *European Journal of Operational Research*, 263(1), 108–141.
- Grabisch, M. (2006). Aggregation on bipolar scales. In *Theory and applications of relational structures as knowledge instruments II*, 355–371. Springer.
- Hurwicz, L. (1951). Optimality criteria for decision making under ignorance. Technical report, Cowles Commission Discussion Paper, Statistics.
- Ogryczak, W. (1997). On the lexicographic minimax approach to location problems. *European Journal of Operational Research*, 100(3), 566 – 585.
- Ogryczak, W. and Sliwiski, T. (2003). On solving linear programs with the ordered weighted averaging objective. *European Journal of Operational Research*, 148(1), 80 – 91.
- Toffel, M.W. (2004). Strategic management of product recovery. *California management review*, 46(2), 120–141.
- Yager, R.R. (2004). Generalized OWA aggregation operators. *Fuzzy Optimization and Decision Making*, 3(1), 93–107.
- Yager, R.R. and Rybalov, A. (1996). Uninorm aggregation operators. *Fuzzy sets and systems*, 80(1), 111–120.