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Modeling risk and uncertainty in designing reverse logistics problem

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Increasing attention to environmental problems and social responsibility lead to appear reverse logistic (RL) issues in designing supply chain which, in most recently, has received considerable attention from both academicians and practitioners. In this paper, a multi-product reverse logistic network design model is developed; then a hybrid method including Chance-constrained programming, Genetic algorithm and Monte Carlo simulation, are proposed to solve the developed model. The proposed model is solved for risk-averse and risk-seeking decision makers by conditional value at risk, sum of the excepted value and standard deviation, respectively. Comparisons of the results show that minimizing the costs had no direct relation with the kind of decision makers; however, in the most cases, risk-seeking decision maker gained more return products than risk-averse ones. It is clear that by increasing returned products to the chain, production costs of new products and material will be reduced and also by this act, environmental benefits will be created.

1. Introduction

Nowadays, designing reverse logistics plays an important role in gaining competitive advantages (Tonanont et al., 2008). There are different definitions for reverse logistics but According to Salema et al. (2007) reverse logistics (RL) is defined as “The process of planning, implementing and controlling the efficient, effective inbound flow and storage of secondary goods and related information opposite to the traditional supply chain directions for the purpose of recovering value and proper disposal”.

It is worth to mention that, unlike traditional supply chain, RL has an uncertainty inherent such as quality, price, time and amounts of return products (Soleimani & Govindan, 2014). These nature uncertainties imposes a high degree of complexity in RL design (Babazadeh et al., 2015). In order to optimize networks, there are some methods that include RL under uncertainty represented in Table 1.

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Table 1
Some methods of dealing with uncertainty in the networks which include RL

Reference	Methods
(Lee & Dong, 2009)	Stochastic programming and simulated annealing
(Pishvaee et al., 2011)	Robust optimization
(Jindal et al., 2015)	Fuzzy
(Khatami et al., 2015)	Benders' decomposition
(Vahdani & Mohammadi, 2015)	Interval-stochastic robust optimization

Beamon (1999) and Fleischmann, et al. (2000) are some of fundamental papers in reverse logistics. Beamon proposed a conceptual framework for different types of chain (forward, reverse and CLSC) and evaluated environmental factors in RL and CLSC and also introduced customer satisfaction, service or responsiveness and costs as important performance measures in evaluating the supply chain. Fleischmann, et al. (2000) studied product recovery networks and identified general characteristics and compared them with others logistics networks. They also stated that existing uncertainty in these networks are the major distinct between these networks and traditional one. Pokharel and Mutha (2009) and Govindan et al. (2015) proposed a comprehensive review to draw a framework of the past papers until 2013. They also stated that RL networks must be designed with the goal of gaining returned products in expected time, price and quantities to the chain. Based on Govindan et al. (2015), price, demand and costs are important parameters used frequently in related studies as uncertainty parameters and there is a lack of reverse logistics models with various risk parameters.

Table 2
Network structure codes

Layers of network	Code	Layers of network	Code
Inspection	I	Raw material market	R.M.M
Disassembling	Da	Recovery	Rec
Refurbishing	Rf	Customer zone	Cu.Z
Recycling	R	Customer	Cu
Plastic recycling	P.R	Return	Ret
Steel recycling	S.R	Manufacture	M
Disposal	Di	Remanufacture	Rm
Regions	Re	Processing	P
Collection	C	Market	Ma
Sorting	S	Second market	S.M
Refinery	Ref	Distribution	Dis
Warehouse	W	Factory	F
Disposer market	D.M	Reuse market	Ru.M
Reprocessing	R.P		

Nikolaou et al. (2013) developed a framework to measure reverse logistics social responsibility based on the Triple Bottom Line approach. Benedito and Corominas (2012) formulated a Markov decision problem in order to minimize total cost with regard to stochastic demand and return and limited manufacturing and storage capacities. To structure the literature review of RL problem and in order to show difference of this paper from the others, Table 4 is prepared. The codes of this Table are given in Table 2 and Table 3. By investigating Table 3 research gaps can be found in the papers that have been published in reverse logistics field, for example, this table indicates that minimizing total costs or maximizing profit is the main goal that is pointed to in most of the papers and maximizing return products to the chain rarely be considered in literature. Most of the papers have designed RL in certain mode or have considered uncertain parameters such as demand, Return quantity and quality in their model and few of them have evaluated risks in their RL network.

Table 3
Parameters codes

Parameters	Code	Parameters	Code
Return quantity	R.Qn	Fixed cost	F.C
Return quality	R.Qa	Amount of return	AOR
Sorting ratio	S.R	Remanufacturing rate	Rm.R
Transportation cost	T.C	Recycling rate	R.R
Demand	D	disposal rate	Di,R
Rate of return	ROR	Return	R
Timing of returned products	T.R		

To the best of the authors' knowledge there has been no paper that simultaneously considering uncertainty and risk parameters in the modeling RL. Therefore, the present paper focuses on designing and planning a reverse logistic network with the goal of maximizing return products to the chain and minimizing total cost, influenced by uncertainty rate of return, quality and quantity of returned products and risks related to demand, remanufacturing, recycling and disposal rate. To this end a combination of chance constraining, genetic algorithm, and Monte Carlo simulations is used. This method was first provided by Dai and Zheng (2015) to solve their closed-loop supply chain under uncertainty of final product price. In fact, the reason for choosing this hybrid method is assessment capabilities that are existing in chance-constraint and Monte Carlo simulations method. In order to create a comprehensive model, this paper considered two kinds of decision maker that means risk seeking and risk averse.

Table 4
Modeling approach and network structure of the reviewed works

Reference	Objective Function		Parameters		Chain centers	
	Max	Min	Uncertain	Risk	single	Hybrid
(Min et al., 2006)	-	Total cost	-	-	(Cu), C, (Ret)	-
(Salema et al., 2007)	-	Total cost	D, R	-	F, W, (Cu), (Da)	(F/Di)
(Lieckens & Vandaele, 2007)	-	Total cost	(R.Qn), (R.Qa), (T.R)	-	(Ru.M), (D.M), (Rec),	-
(Kara & Onut, 2010)	profit	-	D, (AOR)	-	R, (Di), (Cu)	-
(Tuzkaya et al., 2011)	weighted product volume	Total cost	-	-	(Cu), C, (Ret), M, (Ma), (Di), (S.M)	-
(Alumur et al., 2012)	profit	-	-	-	R	(I/Da), (Rm/Rf)
(Diabat et al., 2013)	-	Total cost	-	-	(Cu), C, (Ret)	-
(Roghanian & Pazhoheshfar, 2014)	-	Total cost	D	-	M, R, P, (Da), (Ret)	-
(Ene & Öztürk, 2014)	profit	-	-	-	(Cu), C, (R.P), (Di), R, (S.M), M	-
(Ayvaz et al., 2015)	profit	-	(R.Qn), (S.R), (T.C)	-	(Re), C, S, R, (Ref), (R.M.M), (Di)	-
(Babazadeh et al., 2015)	-	CVaR in the total cost	(R.Qn), (R.Qa)		(Rec), C, (Cu.Z), (Di)	-
(Govindan et al., 2016)	Social responsibility	Present value of cost and environmental impacts	D, (ROR), (F.C)	-	(Cu.Z), C, (P.R), (S.R)	-
This paper	return products to the chain	Total costs	(ROR), (R.Qn), (R.Qa)	D, (Rm.R), (R.R), (Di.R)	(Cu.Z), R, (Rm), (Di)	C, (Da), (Dis)

The remainder of the paper is structured as follow: section 2 presents mathematical model for designing RL network. The proposed hybrid solution approach and computational sensitivity analysis is provided in section 3. Finally, the paper is concluded in section 4.

2. The proposed mathematical model

In this section, a RL network problem with hybrid distribution-collection-disassemble (hereafter called HC.C.D.D) is designed based on Fig. 1. In this network, used products from customers are transferred to collection centers and after that, they undergo being disassembled and finally in terms of the quality of used products (A, B and C), are send back to remanufacturing, recycling and disposal centers, respectively.

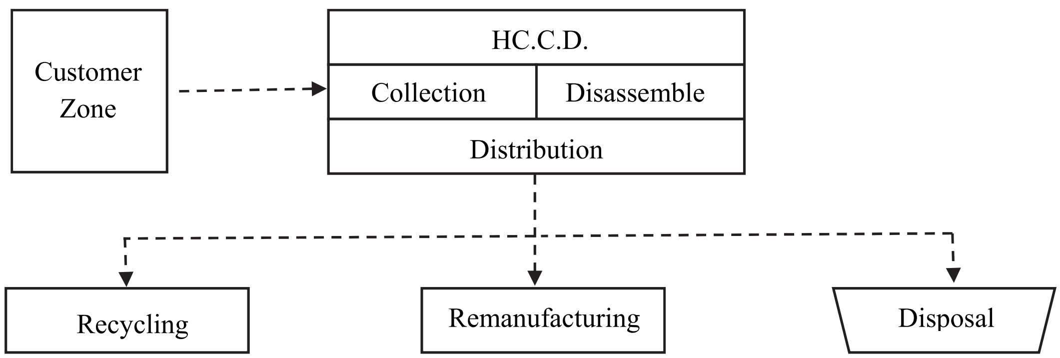

Fig. 1. Proposed structure of closed-loop supply chain network design

Based on Fig. 3, the following notations are introduced for formulating the model.

Sets:

s: Scenarios, s=1,2,...,S
$á$: used products in reverse direction with different quality, á=1,2,...,Á
a: used products that be disassemble on the basis of quality, a=a_1,a_2,a_3
c: customer zone, c=1,2,...,C
d: disposal centers, d=1,2,...,D
h: HC.C.D.D centers, h=1,2,...,H
m: Remanufactures centers, m=1,2,...,M
r: Recycling centers, r=1,2,...,R

Variables:

$X_{chás}$: Quantity of used products ($á$) transferred from customer zone C to HC.C.D.D center h, over scenario s
α_{hma_1s}: Quantity of remanufacturing products (a_1) transferred from HC.C.D.D center h to Remanufactures centers m, over scenario s
β_{hra_2s}: Quantity of recycling products (a_2) transferred from HC.C.D.D center h to Recycling centers r, over scenario s
γ_{hda_3s}: Quantity of disposal products (a_3) transferred from HC.C.D.D center h to disposal center d, over scenario s
$NS_{chás}$: Quantity of non- satisfied demand of customer l
Q_h: Binary variable that show HC.C.D.D center h is open (equals to 1) or close (equals to 0).
Q_m: Binary variable that show Remanufactures centers m is open (equals to 1) or close (equals to 0).
Q_d: Binary variable that show disposal center d is open (equals to 1) or close (equals to 0).

Q_r: Binary variable that show Recycling centers r is open (equals to 1) or close (equals to 0).

Parameters:

$de_{chás}^{T}$: Demand of final products ($\acute{a}$) that customer zone c, request from HC.C.D.D center h, over scenario s

$xr_{chás}^{T}$: Return rate of used products ($\acute{a}$) from customer zone c, to HC.C.D.D center h, over scenario s

Car_{ra_2s}: recycling capacity of center r, for recycling raw material (b_2),over scenario s, in reverse flow

Cam_{ma_1s}: remanufacturing capacity of center m, for remanufacturing products (a_2),over scenario s, in reverse flow

$Cah_{hás}$: collection capacity of HC.C.D.D center h, for used products ($\acute{a}$),over scenario s, in reverse flow

$Cad_{\mathrm{da_3s}}$: Disposal capacity (center d), for returned products ($\mathrm{a_3}$),over scenario t, in reverse flow

FH_h: Fixed cost of opening HC.C.D.D center h

FM_m: Fixed cost of opening Remanufactures centers m

FR_r: Fixed cost of opening Recycling centers r

FD_d: Fixed cost of opening disposal center d

$CNS_{chás}$: Penalty cost per unit of non- satisfied demand of customer zone c, for final products ($\acute{a}$) that request from HC.C.D.D center h, over scenario s.

$VX_{chás}$: Unit Variable cost for products ($\acute{a}$) shipped from customer zone c, to HC.C.D.D center h, over scenario s

$V\alpha_{hma_1s}$: Unit Variable cost for products (a_1) shipped from HC.C.D.D center h to Remanufactures centers m, over scenario s

$V\beta_{hra_2s}$: Unit Variable cost for products (a_2) shipped from HC.C.D.D center h to Recycling centers r, over scenario s

$V\gamma_{hda_3s}$: Unit Variable cost for products (a_3) shipped from HC.C.D.D center h to disposal center d, over scenario s

$rom_{hma_1s}^{T}$: Rate of remanufacturing used products (a_1) from HC.C.D.D center h to Remanufactures centers m, over scenario s

$ror_{hra_2s}^{T}$: Rate of recycling used products (a_2) from HC.C.D.D center h to Recycling centers r, over scenario s

$rod_{hda_3s}^{T}$: Rate of disposal used products (a_3) from HC.C.D.D center h to disposal center d, over scenario s

p_s: Occurrence probability of scenario s

The multi-objective, multi-echelon, multi-product reverse logistic network design problem can be modeled by above-mentioned notations under risk and uncertainty parameters that the terms Eqs. (1-20) indicate this modeling.

Objective functions

$$\max \quad {Z_1}^{T} = \sum_c \sum_h \sum_{\acute{a}} \sum_s \left(xr_{chás}^{T} * \left[\left(de_{chás}^{T} - NS_{chás}\right)\right]\right) \tag{1}$$

$$\min \quad Z_2 = \sum_{s=1}^{S} p_s \left[\left(\sum_c \sum_h \sum_{\acute{a}} \sum_s (X_{chás} * VX_{chás})\right) + \left(\sum_h \sum_m \sum_{a_1} \sum_s \left(\alpha_{hma_1s} * V\alpha_{hma_1s}\right)\right) + \left(\sum_h \sum_r \sum_{a_2} \sum_s \left(\beta_{hra_2s} * V\beta_{hra_2s}\right)\right) + \left(\sum_h \sum_d \sum_{a_3} \sum_s \left(\gamma_{hda_3s} * V\gamma_{hda_3s}\right)\right) + \sum_c \sum_h \sum_{\acute{a}} \sum_s NS_{chás} CNS_{chás}\right] + \left(\sum_h FH_h Q_h + \sum_m FM_m Q_m + \sum_r FR_r Q_r + \sum_d FD_d Q_d\right) \tag{2}$$

Constraints

$$X_{chás} = xr^{T}_{chás} * \left[\left(de^{T}_{chás} - NS_{chás}\right)\right] \quad (3)$$
$$\sum_i \alpha_{hma_1s} = \sum_i rom^{T}_{hma_1s} * \sum_l X_{chás} \quad \forall s \quad (4)$$
$$\sum_s \beta_{hra_2s} = \sum_s ror^{T}_{hra_2s} * \sum_l X_{chás} \quad \forall t,j,q_2,\acute{q} \quad (5)$$
$$\sum_k \gamma_{hda_3s} = \sum_k rod^{T}_{hda_3s} * \sum_l X_{chás} \quad \forall t,j,q_3,\acute{q} \quad (6)$$
$$\sum_j rom^{T}_{hma_1s} * \sum_j \alpha_{hma_1s} \leq Cam_{ma_1s} * Q_m \quad \forall i,p_2,q_2,t \quad (7)$$
$$\sum_j ror^{T}_{hra_2s} * \sum_j \beta_{hra_2s} \leq Car_{ra_2s} * Q_r \quad \forall s,r_2,q_3,t \quad (8)$$
$$\sum_j rod^{T}_{hda_3s} * \sum_j \gamma_{hda_3s} \leq Cad_{\mathrm{da}_3s} * Q_d \quad \forall k,q_4,t \quad (9)$$
$$\sum_l X_{chás} \leq Cah_{hás} * Q_h \quad \forall j,\acute{q},t \quad (10)$$
$$\sum_h Q_h \leq H \quad (11)$$
$$\sum_m Q_m \leq M \quad (12)$$
$$\sum_r Q_r \leq R \quad (13)$$
$$\sum_d Q_d \leq D \quad (14)$$
$$\sum_h Q_h \geq 1 \quad (15)$$
$$\sum_m Q_m \geq 1 \quad (16)$$
$$\sum_r Q_r \geq 1 \quad (17)$$
$$\sum_d Q_d \geq 1 \quad (18)$$
$$Q_h, Q_m, Q_r, Q_d \in \{0,1\} \quad (19)$$
$$X_{chás}, NS_{chás} \geq 0 \quad (20)$$
$$\alpha_{hma_1s}, \beta_{hra_2s}, \gamma_{hda_3s} \geq 0$$

The first objective function (1) seeks to maximize return products to supply chain. The second objective function (2) minimizes total costs of the supply chain. The second objective function includes variable cost, penalty cost of non-satisfied demands and fixed cost of opening the centers of supply chain by the first four terms, the fifth and the last four ones, respectively.

Constraint (3) addresses quantity of the return products that customer zone sent back to HC.C.D.D centers at the end of product's life. Constraints (4-6) refer to the quantity of used products shipped from HC.C.D.D to remanufacturing, recycling and disposal centers, respectively to become recoverable. Constraints (7-10) impose the capacity restrictions on the located facilities. Constraint (11-18) impose the upper and lower bound of locating the centers and finally, Constraint (19 and 20) refer to the binary and decision variables and their restrictions.

3. Experimental results

In this section, validation of the model is determined by GAMS, with regard to input data shown in Table 5, for several random problems produced in Table 6 and finally, the results are represented in Table 7. Note that all of the parameters are assumed to be certain in Table 5. The GAMS results indicate that if constraint of locating centers is applied to model, lost sale will appear and conversely, if constraint of locating centers is not imposed, lost sales will be missed unless the number of HC.C.D.D centers was less than customer zones. Also, due to assumption that considered for Table 5 based on to be certain all the parameters, in each time that the software is run, the quantity of recycling and disposal (that indicates with γ_{hda_3s} and β_{hra_2s}, respectively) are the same and lower than quantity of remanufacturing products (that indicates with α_{hma_1s}).

Table 5
Input data of GAMS software

parameters	The amount attributed	Parameters	The amount attributed
$de^{T}_{chás}$	115	FD_{d_i}	300
$xr^{T}_{chás}$	0.3	$VX_{chás}$	6
Car_{ra_2s}	1200	$V\alpha_{hma_1s}$	5
Cam_{ma_1s}	800	$V\beta_{hra_2s}$	8
$Cah_{hás}$	1000	$V\gamma_{hda_3s}$	6
$Cad_{\mathrm{da_3s}}$	1500	$rom^{T}_{hma_1s}$	0.5
FH_h	500	$ror^{T}_{hra_2s}, rod^{T}_{hda_3s}$	0.25
FM_m	450	$CNS_{cá}$	1000
FR_r	380		

Table 6
General information of the test problem to be solved by GAMS software

Number of problem	Number of centers					Number of scenarios
	Recycling centers	Remanufacturing centers	HC.DA.RD centers	Disposal	Customer zone	
1	3	4	3	3	2	2
2	4	4	5	5	5	2
3	6	5	7	4	7	3
4	4	7	8	3	7	4
5	9	5	9	7	9	3
6	7	7	12	6	13	2

Table 7
Results of deterministic model that solved by GAMS in randomly generated test problems

constraint of locating	Number of problem	result				
		$X_{chás}$	α_{hma_1s}	β_{hra_2s}	γ_{hda_3s}	$NS_{chás}$
yes	1	276	138	69	69	1840
	2	690	345	172.5	172.5	11500
	3	1449	724.5	362.25	362.25	28980
No	4	15456	7728	3864	3864	0
	5	16767	8383.5	4191.75	4191.75	0
	6	19734	9867	4933.5	4933.5	5980

After evaluation and validation of the model under the certain mode, solution method must be proposed in order to solve the developed model under uncertain and risk mode. In 1959, Charnes and Cooper introduced chance-constrained programming to solve optimization problems under the variety uncertainties.

The general framework is as follow: (Mitra et al., 2008)

(1) $\min\{f(x)|h_k(x,\delta) \geq 0\}$

(2) $\min\{f(x)|pr(h_k(x,\delta) \geq 0) > \beta\}$ $\qquad k = 1, \dots, u$

where, $f(x)$, x and δ are objective function, set of decision variables and set of random parameter, respectively and also, probability measure is shown by pr and $p \in (0,1]$ shows probability level that must be satisfied for each constraint ($h_k(x,\delta)$).

Since the paper of Soleimani and Kannan (2015), RL problems are classified as an NP-hard problem, therefore, it is appropriate to use Monte Carlo simulation as an effective tool for estimating expected value of uncertain parameters (Kamjoo et al., 2016) with genetic algorithm, in order to solve such the problems that have no analytical solution or it is gained hardly. Genetic algorithm includes the following main steps:

Initialization, evaluation, parent selection, reproduction and mutation. At the first, initial population must be generated randomly, after that, fitness value must be computed for each individual. In step 3, pairs of individuals are selected and crossover imposed on them. A tiny amount of genetic information is changed by imposing mutation in each child. This process must continue until termination condition is satisfied (Kannan et al., 2010).

Eventually, according to Dai and Zheng (2015), it was decided to use chance constrained programming method, Monte Carlo simulation and genetic algorithm to solve the presented model and this hybrid solution is shown in Fig. 2. Therefore, by using this hybrid method and MATLAB software, the presented model under uncertainty and risk parameters can be evaluated from perspectives of risk-averse and risk-seeking decision makers in random sizes. Due to evaluating different perspectives of decision makers, in this paper, conditional value at risk, sum of the excepted value and standard deviation are used for risk-averse and risk-seeking decision makers, respectively. The results in Table 10 are traceable. It is necessary to say that the calculated results in Table 10 have been obtained from the given data in Table 5 and Table 8 for different problem sizes represented in Table 9.

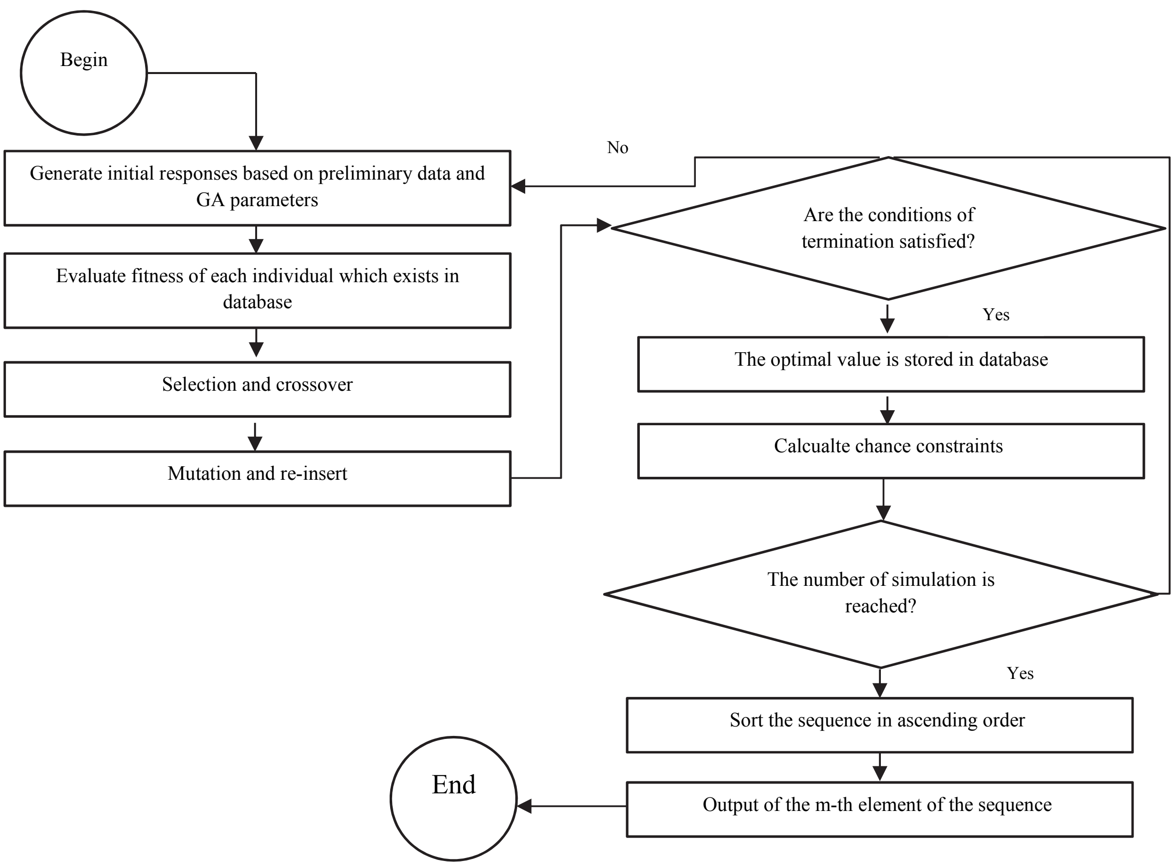

Fig 2. Implementation of the proposed solution algorithm

Table 8

Range of changes for the input stochastic data of MATLAB software

Parameters	The amount attributed	parameters	The amount attributed
$de^{T}_{chás}$	[80-115]	$rom^{T}_{hma_1 s}$	[0,1]
$xr^{T}_{chás}$	[0,1]	$ror^{T}_{hra_2 s}, rod^{T}_{hda_3 s}$	

Table 9
General information of the test problem to be solved by MATLAB software

Number of problem	Number of centers					Number of scenarios
	Recycling centers	Remanufacturing centers	HC.DA.RD centers	Disposal	Customer zone	
1	3	4	3	3	2	2
2	4	4	5	5	5	3
3	10	13	15	10	15	3
4	12	16	21	25	22	4
5	23	28	31	25	31	5
6	38	35	45	40	45	7

Table 10
Results of the presented model under uncertainty and risk solved by MATLAB in different sizes

	constraint of locating	Number of problem	result				
			$X_{chás}$	α_{hma_1s}	β_{hra_2s}	γ_{hda_3s}	$NS_{chás}$
Risk-averse	yes	1	261.5605	32.7405	115.2174	113.6027	1754
		2	526.0582	182.9018	129.3934	213.7630	13133
		3	795.1832	374.9611	348.5060	71.7161	137670
	No	4	201730	24265	110660	66803	0
		5	524060	182560	166600	174900	0
		6	1540800	262720	676180	601950	0
Risk-seeking	yes	1	295.3018	36.9640	130.0804	128.2575	1946
		2	704.5913	244.9748	173.3068	286.3097	14377
		3	1160	547.2351	508.6255	104.6657	152200
	No	4	223070	26832	122370	73870	0
		5	579470	201860	184210	193400	0
		6	1703400	290440	747520	665460	0

The results of Table 9 also follow a trend similar to Table 6 for both kinds of decision makers. Also the results indicate that the risk-seeking decision maker gained more return products than risk-averse ones and it is not covered to any one that used returned products are more profitable and economical instead of producing new ones. Also, regardless of decision makers, the quantity of returned products to each remanufacturing, recycling and disposal centers do not have a specific trend and will be determined based on the quality of the used products, which are assumed to be uncertain, in any time that the program be run. Also total quantities of returned products to the chain were obtained from the summation quantities of remanufacturing, recycling and disposal centers. These results are shown clearly in Fig. 3.

Due to its crucial role in cost of reverse logistic, sensitivity analysis will be discussed on rate of return on the first size of Table 8. The results have been shown in Table 11 indicating that when rate of return increases, the returned products (first objective function) and total costs (second objective function) increase as well.

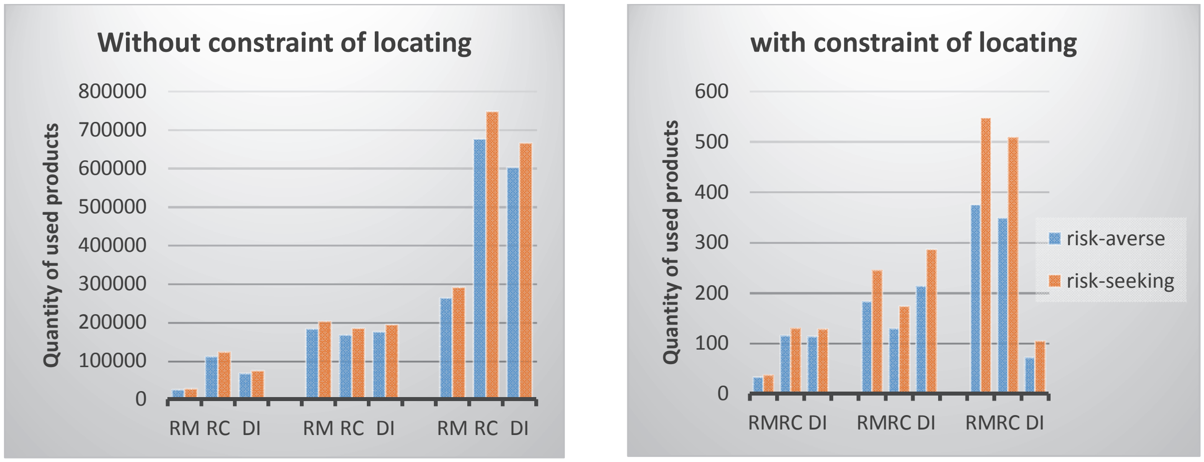

Fig 3. Comparison the quantity of used products shipped to different centers for being recovery, from the perspective of decision makers (*RM=remanufacture, RC=recycling & DI=disposal)

Table 11
Results of rate of return sensitivity analysis for risk-averse and risk-seeking decision makers

	Objective function	Sensitive result					
		0	0.2	0.4	0.6	0.8	1
Risk-seeking	First obj.	0	552	1104	1656	2208	2760
	Second obj.	2630	7808	12986	18163	23341	28519
Risk-averse	First obj.	0	524.4	1048	1573	2098	2622
	Second obj.	2630	7548	12468	17387	22305	27224

4. Conclusion and future research directions

During the last few years, growing interest has been dedicated to reverse logistics, due to some reasons including responsibility about returned products, yielding more economic value and environmental concerns. Reverse logistics problem has always faced with uncertainty and risk due to their uncertain nature. Therefore, this paper considered simultaneously uncertainty and risk parameters in designing RL network. For solving the proposed model, chance constrained, genetic algorithm, and Monte Carlo simulations have been used together. At the end, the results have been evaluated and compared for risk-averse and risk-seeking decision makers by appropriate risk measures. The experimental results showed that reducing the cost has no serious impact on kind of decision makers and in most cases, risk-seeking decision maker gained more returned products than risk-averse ones.

There are some recommendations for further research: The model can be expanded to include others risk or uncertainty parameters such as capacity and variable costs or can compare the risk measures to each other. Future research can expanded this model by adding forward chain to this reverse presented structure to show better relation between the quantities of return products with profitability of chain. As a final offer, utilizing two-stage stochastic method instead of chance-constrained may lead to create valuable results.

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