A resilient closed-loop supply chain network design through integrated sourcing and pricing strategies

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Abstract

Sourcing resilience has become a primary concern in most closed-loop supply chains (CLSC). Companies face the option of sourcing their raw materials from suppliers or recycling centers though the latter can be disrupted sometimes. In this study, a multi-stage, stochastic programming (MSSP) model is developed to analyze how a company can proactively employ sourcing strategies along with pricing policies to enhance sourcing resilience in a CLSC, where the return of end-of-life (used) products into recycling centers is stochastic and sensitive to the purchasing price. The stochastic return is modelled using a scenario-tree-based approach. Since the sample average approximation algorithm (SAA) in scenario generation can lead to an increased number of scenarios and make the model hard to solve, a backward scenario reduction algorithm is employed to efficiently reduce the problem size. The findings indicate that an effective pricing policy can help determine the resilient sourcing strategy in the CLSC network design problem and, therefore, maximize the total profit and mitigate the disruption risks.

Keywords: Close loop supply chain; Pricing policy; Sourcing resilience; Stochastic programming, Automotive battery industry.

1. Introduction

Nowadays, because of the increased risks of business environments and limited natural resources, designing CLSCs has become a necessity, especially on a global scale [1]. Recycling in CLSC reduces the need for virgin raw materials, with lower energy consumption and environmental pollution [2]. It is, thus, vital to provide conditions to recycle such materials to attain sustainability benefits.

As recycling in CLSC contributes to the economic and environmental aspects of sustainability, it is essential to deal with the risks of sourcing through recycling [3]. The recycling centers may sometimes be disrupted due to the fluctuations in the return flows of used products. Here, the most critical risk is customers' reluctance to return the used products to the intended collection centers. According to the existing literature, sourcing resilience is an important criterion for enhancing the security of the supply of critical materials against disruption risks and improving the long-term performance of a CLSC in today's turbulent and competitive environments (e.g. [4, 5]). Recycling capacity expansion in CLSCs is a widely-used sourcing resilience strategy for cheap and safe sourcing [6]. This strategy enables companies to use materials generated from the return flows of the used products in the CLSC instead of solely using virgin materials sourced from suppliers [7]. Consequently, manufacturers will have two sourcing options: (1) cheaper but less reliable recycling centers, or (2) more reliable external suppliers who demand higher prices for their products.

A proper pricing policy in the supply chain can attract new customers and increase the market share of companies [8, 9]. To mitigate the risks related to the return flow of used products, companies can offer attractive prices to encourage customers to return their used products to recycling centers [10]. Since a fair pricing policy for used products can reduce the impact of recycling disruptions, the importance of pricing policy for the success of sourcing strategy should be taken into account in the CLSC network design problem (e.g. [8]). In addition, since a pricing policy can encourage the return of used products and result in increased return costs, firms need to balance these two possible outcomes in developing a return policy. In this respect, this study aims to provide insights into incorporating the sourcing strategy and pricing policy. Thus, we pose the research questions as follows:

1) What is the effective sourcing strategy for mitigating supply disruption risks according to the above-described sourcing options?
2) How should the capacity expansion strategy of recycling facilities, as a proactive and resilient strategy, be applied in designing the CLSC network?
3) For the success of the sourcing strategy, how should the pricing policy be developed to enhance sourcing resilience through recycling?

To the best of our knowledge, this research is the first to apply a mathematical programming approach to address the effect of pricing policy on the sourcing resilience strategy in recycling disruption risk management under the CLSC design problem. We analyze how pricing policy can determine the optimal sourcing strategy for manufacturers to mitigate disruptions. We use price adjustment of new and used products at the beginning of each period as a proactive and practical policy for mitigating the return disruptions of used products that the recycling centers face. For this purpose, we apply a MSSP approach to incorporate the sourcing and pricing decisions into the CLSC design problem for an automotive battery manufacturing company.

The remainder of the article is organized as follows. Section 2 presents a review of the related researchs on sourcing resilience and pricing policy in CLSC network design problem. In Section 3, the mathematical model for designing the CLSC network is developed. In Section 4, the computational results, sensitivity analysis, and managerial insights are provided. The conclusions and future directions are presented in Section 5.

2. Literature review

In this section, we concisely review the most relevant literature on resilience strategies and pricing policy in supply disruption risk management under the CLSC network design problem.

2.1. *Sourcing resilience under supply disruption in CLSC*

In this subsection, we first address the disruption risks of raw materials sourcing and then focus on the used-product return disruptions in CLSCs. The existing literature on supply risk management suggests different resilience strategies for supply risk reduction, which include: 1) multiple sourcing [5, 11], 2) contracting with backup suppliers [12, 13], 3) fortification/protection of suppliers [14], 4) pre-positioning emergency inventory [4, 5], and 5) acceptance [12]. Another resilience strategy in supply chain design is the capacity expansion in facilities such as suppliers, factories, warehouses, distribution and recycling centers (e.g. [4, 15]). The capacity expansion strategy in recycling can mitigate the effects of disruption in the supply chain by increasing the flexibility level of the facilities and, thus, can guarantee the reliable supply of raw materials [7]. Santillán-Saldivar et al. [16] considered the risk-mitigating potential of domestic recycling. They concluded that recycling should be ideally carried out domestically, recycled material should be reinserted into the domestic economy, and the import supply mix should be considered. Cheramin et al. [17], aiming to alleviate the risk of supply shortage for magnets, critical materials and rare-earth elements, used a risk-averse stochastic programming approach to design a resilient magnet recycling supply chain and logistics network, taking the impacts of the COVID-19 pandemic into account. Some studies have evaluated the effect of the design decisions on disruptions related to processing, return and demand volumes. Notably, they have considered the effect of suppliers' investment in capacity expansion or restoration on supply disruption (e.g. [4]). However, to the best of our knowledge, the effect of capacity expansion in collection and recycling centers, as a resilience strategy, on reducing the risk of supply disruption has not been investigated in the literature.

Few studies has suggested different policies such as pricing [18], discount offers [8] and advertising [19] to motivate consumers to return the used products to be recycled. Pricing as a proactive policy can help supply chains manage raw material supply disruptions that mainly occur in the return flow of the used products in CLSCs. However, its effect on sourcing resilience has not been investigated in the literature so far.

Few studies have considered the interaction between sourcing resilience strategy and pricing policy under uncertainty (e.g. [20, 21, 22, 23]). Gupta and Ivanov [24] developed a game-theoretic model to examine the impact of risk aversion, demand volatility, and supply disruption on sourcing decisions and pricing policies under supply disruption. In addition, Mogale et al. [25] developed a multi-objective model for a sustainable CLSC network problem to show the positive effects of incentive pricing on returned goods in the reverse logistics network. To address the research gaps in the literature, this study analyzes pricing policy and capacity expansion of collection and recycling centers in the CLSC network design problem to address the used-product return disruption.

2.2. *Multi-stage stochastic programming in supply chain design*

The stochastic programming methods are divided into two main groups: two-stage stochastic program (TSSP) and multi-stage stochastic program (MSSP) [26]. MSSP allows for sequential and proactive decisions in the supply chain design problem under evolving uncertainties over time (see [27]). In the MSSP approach, the uncertainty in parameters over the planning horizon can be modelled by constructing a scenario tree (see [26, 28]). One of the main issues in MSSP models is that the number of scenarios rises exponentially as the number of periods increases, making it intractable. Researchers have extensively applied the SAA method, proposed by [27], to construct and reduce the size of the scenario tree without sacrificing the solution quality. An SAA technique, like the Latin Hypercube Sampling (LHS) method, is more efficient and can cover more domain space of stochastic processes for the same number of samples than other techniques [29]. However, scenario generation by SAA can also exponentially increase the number of scenarios, making the stochastic CLSC model highly complex. To deal with this problem, forward and backward scenario reduction techniques (FSR and BSR), proposed by [30], have been widely used in the supply chain network design literature as two popular scenario reduction techniques [31].

The literature on sourcing resilience and pricing policy which employ stochastic programming approaches are compared in table 1. First, despite efforts to improve resilience in supply chain design problems, there is still a research gap in this area, especially when the supply chain structure is considered closed-loop. As shown in this table, based on the present study, only [17] considered sourcing resilience through recycling in the CLSC design problem, and no study has addressed resilient CLSC design under the return disruption of used products. Additionally, given that only Renjbar et al. [23] simultaneously considered the resilience strategies and pricing policy in the CLSC design problem, there is still a research gap in this area. Recycling capacity development as one of the resilience strategies, despite its direct relevance to resilient CLSC, has not been addressed in the literature.

Contributions of the present study in finding answers to the above research questions are summarized as follows:

1. One of the contributions of the present study is simultaneous consideration of the return disruptions, price-sensitive return and establishment of recycling centers. We determine the optimal sourcing strategy and pricing policy to strengthen the resilience of the CLSC under the non-return of used products.

2. We develop a multi-stage stochastic programming model for coping with the return uncertainty of used products while maximizing total profit in the CLSC. To the best of our knowledge, this is the first study to develop a multi-stage stochastic programming model for a CLSC design problem under the risk of price-sensitive return.
3. We use an efficient approximation method called LHS to closely imitate the real world where the high number of scenarios prevents exact algorithms from solving the problem. This approximation method can consider the return scenarios of the used products in the CLSC design problem with a high accuracy level.

3. Model development

The CLSC considered in this research includes different suppliers, plants, distributors and customer zones in the forward channel. In the reverse channel of the CLSC, the consumers leave the used products at stations called initial collection points and replace them with new ones. The collected used products are transported to the centralized collection point, where they should be inspected for possible quality failure. Then, the decision is made on whether to recycle or dispose of them. Once the inspection is completed, reusable products are sent to recycling centers, where the new raw material is provided under an eco-friendly recycling process. Finally, the recycled material is transported to the plants, where it is used together with the virgin raw material. In each period, products are transported from plants to distributors and finally to customer zones to meet customer demand. The CLSC is mapped in Fig. 1.

3.1. Scenario tree for stochastic data

A scenario tree is a way of discretely approximating the probability distribution of stochastic variables over a time horizon. In the considered CLSC problem, we approximate the uncertainties related to random variables using a scenario tree. Assume that random variables can have two possible realizations for each period (i.e., high or low), as shown in Fig. 2. A possible realization of stochastic variables is presented by an arc on the tree and is denoted mathematically as $\xi_t \in \Xi_t$, where a probability of realization $\overline{p}^{\xi_t}$ is associated with it in the scenario tree. A scenario is denoted by ω_t for period *t* ($\omega_t \in \Omega_t$) and indicates a unique sequence of uncertainty realizations $\{\xi_0, \xi_1, ..., \xi_t\}$ from the root (i.e., the beginning of the planning horizon) to the considering node; ω_t is illustrated by a node at stage *t* on the tree. For the consistency of the notation, at stage 0, no uncertainty is realized, and the 0-stage scenario ω_0 is an artificial scenario with $p^{\omega_0} = 1$. Note that every t-stage scenario ω_t in the scenario tree has a unique ancestor (t−1)-stage scenario ω_{t-1}, denoted by $a(\omega_t)$. It should be noted that the probability of the t-stage scenario ω_t, denoted by p^{ω_t}, is determined as the product of probabilities of the arcs from the root node to the considered node.

To deal with the uncertainty on the return, we adopt the capacity expansion and pricing policies as two proactive strategies before the realization of random return to hedge against the evolving uncertainty related to the return flow of the used products. Similarly, location decisions of collection and recycling centers are made at the beginning of the planning horizon, and decisions about the sale price of new products and the purchase price of the used products are made at the beginning of each stage before any uncertainty is revealed. Other decisions, such as the production amount and flow of the materials and products in CLSC, are made during each stage once the uncertainties have been realized.

3.2. Assumptions and notations

3.2.1. Assumptions

The main assumptions of the CLSC network design problem considered in the present study are as follows:

- In each period, the demand of each customer zone and the return amount for all products depend respectively on the selling and purchasing prices defined as linear price-response functions.
- The return amount of the used products for each product is assumed to be stochastic in each period and is defined with regard to a finite number of possible scenarios.
- The cost parameters (i.e., fixed cost for opening the facilities, material, transportation, processing, distribution, collection and recycling costs) and demand are known.
- The transportation cost per unit of the used product from the initial collection point to the collection centers is already included in the collection cost.
- Unsatisfied demand of the customer zones is penalized.

3.2.2. Notations

Indices and sets:

I	Set of suppliers, $i = 1, \ldots, \lvert I \rvert$
J	Set of fixed locations for plants, $j = 1, \ldots, \lvert J \rvert$
K	Set of fixed locations for distribution centers, $k = 1, \ldots, \lvert K \rvert$
M	Set of fixed locations of customer zones, $m = 1, \ldots, \lvert M \rvert$
H	Set of potential locations for collection centers, $h = 1, \ldots, \lvert H \rvert$
O	Set of potential locations for recycling centers, $o = 1, \ldots, \lvert O \rvert$

T Set of time periods, $t = 1,2,\ldots,|T|$

P Set of product types, $p = 1,2,\ldots,|P|$

Ω_t Set of all scenarios in period t; $\omega_t = 1,\ldots,|\Omega_t|$

Model parameters:

$De^{t}_{m,p,l}$ The demand of customer zone m at level l in period t for product p,

$pn^{t}_{m,p,l}$ Price per unit of product p at level l for customer zone m in period t,

$R^{t,\omega_t}_{m,p,l}$ Potential return amount of used product p at level l from costumer zone m in period t under scenario ω_t

$pr^{t,\omega_t}_{m,p,l}$ Price per unit of used product p at level l from customer zone m in period t under scenario ω_t

$Ru^{t}_{m,p}$ Maximum offer price to a customer zone per unit of product

$Rl^{t}_{m,p}$ Minimum offer price to a customer zone per unit of product

ps^{t}_{i} Purchase price of virgin raw material in kilograms from supplier i in period t

FC_h Fixed cost of opening collection center h

FR_o Fixed cost of opening recycling center o

$ts^{t}_{i,j}$ Cost of transporting virgin material in kilograms from supplier i to plant j in period t

$tp^{t}_{j,k,p}$ Transportation cost per unit of product p from plant j to distribution center k in period t

$td^{t}_{k,m,p}$ Transportation cost-per-unit of product p from distribution center k to customer zone m in period t

$tc^{t}_{h,o,p}$ Transportation cost-per-unit of used product p from collection center h to recycling centers o in period t

$tr^{t}_{o,j,p}$ Cost of transporting recyclable material in kilograms from recycling center o to plant j in period t

$mc^{t}_{j,p}$ Manufacturing cost-per-unit of product p at plant j in period t

$cc^{t}_{h,p}$ Collection cost-per-unit of used product p for collection center h in period t

rc^{t}_{o} Recycling cost of material in kilograms at recycling center o in period t

$hc^{t}_{k,p}$ Holding cost-per-unit of product p at distribution center k in period t

CS_i The supply capacity of supplier I

CP_j Production capacity of plant j

CD_k Processing capacity of distribution center k

CC_h The capacity of the collection center h

CR_o	The capacity of recycling centers *o*
α_p	Amount of the raw material needed in kilograms for production of a unit of product *p*
β_p	Amount of the material recycled in kilograms per unit of the returned product *p*
$\pi^t_{m,p}$	Penalty cost per unit of unfulfilled demand of customer *m* for product *p* in period t

Variables:

$R^{t,\omega_t}_{m,p}$	Potential return amount of the used products under the scenario ω_t
$xs^{t,\omega_t}_{i,j}$	Quantity of the transportation of virgin material from entity *i* to entity *j* in period *t* under scenario ω_t
$xp^{t,\omega_t}_{j,k,p}$	Quantity of the product *p* produced at entity *j* and transferred to entity *k* in period *t* under scenario ω_t
$xc^{t,\omega_t}_{k,m,p}$	Quantity of product *p* shipped from entity *k* to customer zone *m* in period *t* under scenario ω_t
$Inv^{t,\omega_t}_{k,p}$	Quantity of ending inventory of product *p* in entity *k* in period *t* under scenario ω_t
$y^{t,\omega_t}_{h,o,p}$	Quantity of the used product *p* shipped from collection center *h to* recycling center *o* in period *t* under scenario ω_t
$z^{t,\omega_t}_{o,j}$	Quantity of the recycled material transported from recycling center *r* to plant *j* in period *t* under scenario ω_t
$\eta^{t,\omega_t}_{m,p}$	Quantity of unsatisfied demand of customer *m* in period *t* under scenario ω_t
w^C_h	1 if a collection center is opened at location *h*, 0 otherwise;
w^R_o	1 if a recycling center is opened at location *o*, 0 otherwise;

3.3. Scenario generation

In this study, a time series called autoregressive (AR(p)) is applied to consider the time dependencies of the stochastic processes in the tree. The potential return quantity in stage *t+1* can be forecasted using the equation $\hat{R}_{t+1} = \alpha + \sum_{i=1}^{P} \beta_i R_{t+1-i}$. In our model, we add a realization of the error term $\varepsilon^{\omega_{t+1}}_{t+1}$, as illustrated in the scenario tree, to the forecast amount in each scenario (node) in the considered problem. Therefore, the forecast in each scenario is based on historical data and the error scenario. The forecasted potential return at period t + 1 (first prediction) under the scenario ω_{t+1} is then obtained by the following formula:

$$\hat{R}^{\omega_{t+1}}_{t+1} = \alpha + \sum_{i=1}^{P} \beta_i R_{t+1-i} + \varepsilon^{\omega_{t+1}}_{t+1}$$

Where α is a constant, β_i is an autoregressive parameter, R_{t+1-i} is the historical return at period *t+1-i*, and $\varepsilon_{t+1}^{\omega_{t+1}}$ is the error term at period t +1 under the scenario ω_{t+1}. Note that forecasting the return for multiple periods can be based on both historical return data and forecasted return, as shown in Fig. 3.

To produce different future scenarios, we apply the LHS sampling technique to generate distinct values for the error terms in each period. Hence, for the respective set of scenarios (nodes) in each time period, we generate the random values of the error term $\varepsilon_{t+j}^{\omega_{t+j}}$ with a (0, σ_ε^2) distribution and obtain the realizations of the stochastic variable through the (AR(p)) method as by following formula . It is assumed that the probability of happening the scenarios are equal.

$$\hat{R}_{t+j}^{\omega_{t+j}} = \begin{cases} \alpha + \sum_{i=1}^{P} \beta_i R_{t+j-i} + \varepsilon_{t+j}^{\omega_{t+j}} & j = 1 \\ \alpha + \beta \hat{R}_{t+j-1}^{a(\omega_{t+j})} + \varepsilon_{t+j}^{\omega_{t+j}} & j > 1 \end{cases}$$

.

A backward scenario reduction algorithm is employed to bound the number of generated scenarios [30].

3.4. *Modelling the relationship between price and the return volume*

In the CLSC model, customers decide whether to return their used products to the collection centers at the announced purchase price or not. It is assumed that a generous return policy by collection centers will lead to more return amounts, and a tighter policy will reduce them. We use a linear function for modelling the relationship between the price and the return quantity of the used products. Linear regression can be used to estimate this relationship. In the considered CLSC model, let $R_{m,p}^{t,\omega_t}$ and $\mathrm{Re}_{m,p}^{t,\omega_t}$ be the potential and realized return amount of collection centers, respectively, and $pr_{h,p}^{t,\omega_{t-1}}$ be the purchase price announced to the customer zone $m \in M$ for one unit of the returned product $p \in P$ at the beginning of the period $t \in T$ such that $Rl_{m,p}^{t} \le pr_{h,p}^{t,a(\omega_t)} \le Ru_{m,p}^{t}$. It is worth noting that the potential return amount, $R_{m,p}^{t,\omega_t}$, has inherent uncertainty regarding customers' inclination to return the used products to collection centers. Fig. 4 shows the relationship between the announced purchase price and the returned used-product volume for product $p \in P$ to customer zone $m \in M$.

Thus, the relationship between the purchase price and the returned used-product volume is defined as:

$$\mathrm{Re}_{m,p}^{t,\omega_t} = R_{m,p}^{t,\omega_t} \left(\frac{pr_{m,p}^{t,a(\omega_t)} - Rl_{m,p}^{t}}{Ru_{m,p}^{t} - Rl_{m,p}^{t}} \right), \; m \in M ,p \in P, t \in T ,\omega_t \in \Omega_t$$

Here, if we assume that a continuous relationship exists between price and return, the developed model for the CLSC design problem will be MINLP due to the nonlinearity of purchasing cost function of the returned products. To deal with this problem, Fattahi et al. [31] applied the effective and easy-to-use approach proposed by [33] to discretize the prices in a dynamic pricing problem. Suppose $L=\{1,2,\ldots,|L|\}$ is a finite set of discrete price levels for buying one unit of used products, so that the purchasing price of used products at period *t*, pr^{t} , is restricted to a discrete set, $pr^{t} \in \Omega_{pr}$, where $\Omega_{pr}=\{pr_{l}^{t}, pr_{2}^{t},\ldots, pr_{|L|}^{t}\}$. Re^{t} means that the realized return amount at period *t* is restricted to $\mathrm{Re}^{t} \in \Omega_{r}$ where $\Omega_{r}=\{\mathrm{Re}_{l}^{t}, \mathrm{Re}_{2}^{t},\ldots, \mathrm{Re}_{|L|}^{t}\}$.

Then, the price announced at the beginning of period *t*, $pr_{h,p}^{t,\omega_{t-1}}$, and the realized return amount, $\mathrm{Re}_{h,p,l}^{t,\omega_{t}}$, can be obtained by using the following constraints:

$$pr_{m,p,l}^{t,\omega_{t-1}}=Rl_{m,p}^{t}+\left(\frac{l-1}{|L|-1}\right)(Ru_{m,p}^{t}-Rl_{m,p}^{t}), \quad m\in M, p\in P, t\in T, l\in L, \omega_{t-1}\in\Omega_{t-1}$$

$$\mathrm{Re}_{m,p,l}^{t,\omega_{t}}=R_{m,p}^{t,\omega_{t}}\left(\frac{pr_{m,p,l}^{t,a(\omega_{t})}-Rl_{m,p}^{t}}{Ru_{m,p}^{t}-Rl_{m,p}^{t}}\right), \quad m\in M, p\in P, t\in T, l\in L, \omega_{t}\in\Omega_{t}$$

Let $\lambda_{m,p,l}^{t,\omega_{t-1}}$ be binary decision variables that take on the values of zero or one, where the decision variable value 1 means that the price level $l \in L$ is chosen at the beginning of period *t* for buying a unit of the used product $p \in P$ from the initial collection point $m \in M$. Thus, the purchase cost of the used products $RC_{m,p}^{t,\omega_{t}}$, derived from buying all amount of the realized return of the used product $p \in P$ by offering price level $l \in L$ to the initial collection point $m \in M$ in period $t \in T$ under the scenario $\omega_{t} \in \Omega_{t}$, is determined as follows:

$$\sum_{l\in L}\lambda_{m,p,l}^{t,\omega_{t-1}}=1, \quad m\in M, p\in P, t\in T, \omega_{t-1}\in\Omega_{t-1}$$

$$RC_{m,p}^{t,\omega_{t}}=\sum_{l\in L}pr_{m,p,l}^{t,a(\omega_{t})}\,\mathrm{Re}_{m,p,l}^{t,\omega_{t}}\,\lambda_{m,p,l}^{t,a(\omega_{t})}, \ m\in M, p\in P, t\in T, \omega_{t}\in\Omega_{t}$$

Also, we can use the procedure described above to determine the relationship between the selling price and the demand for the new products as follows:

$$\sum_{l\in L}\gamma_{m,p,l}^{t,\omega_{t-1}}=1, \quad m\in M, p\in P, t\in T, \omega_{t-1}\in\Omega_{t-1}$$

$$Inc_{m,p}^{t,\omega_{t}}=\sum_{l\in L}pn_{m,p,l}^{t,a(\omega_{t})}De_{m,p,l}^{t}\gamma_{m,p,l}^{t,a(\omega_{t})}, \ m\in M, p\in P, t\in T$$

3.5. Multi-stage stochastic formulation of CLSC

The objective function in the proposed model (Eq. 1) is to minimize the total expected cost in the CLSC network design problem:

$$\max z = Sal - (Fix + \mathrm{Pr}o + Buy + Tran + HC) \tag{1}$$

Where

$$Fix = \sum_{h \in H} FC_h w_h^C + \sum_{o \in O} FR_o w_o^R, \tag{2}$$

$$\mathrm{Pr}o = \sum_{\omega_t \in \Omega_t} \rho^{\omega_t} \left(\sum_{j \in J} \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} mc_{j,p}^t xp_{j,k,p}^{t,\omega_t} + \sum_{o \in O} \sum_{j \in J} \sum_{t \in T} rc_o^t z_{o,j}^{t,\omega_t} \right) \tag{3}$$

$$Sal = \sum_{\omega_{t-1} \in \Omega_{t-1}} \rho^{\omega_{t-1}} \left(\sum_m \sum_p \sum_t (\sum_{l \in L} (pn_{m,p,l}^{t,a(\omega_t)} De_{m,p,l}^t \gamma_{m,p,l}^{t,a(\omega_t)} - \pi_{m,p}^t \eta_{m,p}^{t,\omega_t}) \right) \tag{4}$$

$$Buy = \sum_{\omega_t \in \Omega_t} \rho^{\omega_t} \left(\sum_{i \in I} \sum_{j \in J} \sum_{t \in T} ps_i^t xs_{i,j}^{t,\omega_t} + \sum_{m \in M} \sum_{p \in P} \sum_{t \in T} \sum_{l \in L} pr_{m,p,l}^{t,a(\omega_t)} \mathrm{Re}_{m,p,l}^{t,\omega_t} \lambda_{m,p,l}^{t,a(\omega_t)} \right), \tag{5}$$

$$Tran = \sum_{t \in T} \sum_{\omega_t} \rho^{\omega_t} \left(\begin{array}{l} \sum_p (\sum_j \sum_k tp_{j,k,p}^t xp_{j,k,p}^{t,\omega_t} + \sum_k \sum_m td_{k,m,p}^t xc_{k,m,p}^{t,\omega_t} + \sum_h \sum_o tc_{h,o,p}^t y_{h,o,p}^{t,\omega_t}) \\ + \sum_i \sum_j ts_{i,j}^t xs_{i,j}^{t,\omega_t} + \sum_r \sum_j tr_{o,j,p}^t z_{o,j}^{t,\omega_t} \end{array} \right) \tag{6}$$

$$HC = \sum_{t \in T} \sum_{\omega_t} \rho^{\omega_t} \left(\sum_{k \in K} \sum_{p \in P} hc_{k,p}^t Inv_{k,p}^{t,\omega_t} + \sum_{h \in H} \sum_{o \in O} \sum_{p \in P} cc_{h,p}^t y_{h,o,p}^{t,\omega_t} \right) \tag{7}$$

The objective function is composed of multiple items such as fixed costs related to the location of facilities (Eq. 2), manufacturing and recycling cost (Eq. 3), sales income-shortage cost (Eq. 4), the purchasing cost of recyclable material and used products (Eq. 5), transportation cost (Eq. 6), and inventory holding and collection cost (Eq. 7).

The objective function is subject to the constraints formulated as follows:

$$\sum_{k \in K} \sum_{p \in P} \alpha_p xp_{j,k,p}^{t,\omega_t} = \sum_{i \in I} xs_{i,j}^{t,\omega_t} + \sum_{o \in O} z_{o,j}^{t,\omega_t} \quad \forall j \in J, t \in T, and \quad \omega_t \in \Omega_t \tag{8}$$

$$Inv_{k,p}^{t-1,a(\omega_t)} + \sum_j xp_{j,k,p}^{t,\omega_t} = Inv_{k,p}^{t,\omega_t} + \sum_m xc_{k,m,p}^{t,\omega_t}, \ \forall k \in K, p \in P, t \in T, and \ \omega_t \in \Omega_t \tag{9}$$

$$\sum_{k \in K} xc_{k,m,p}^{t,\omega_t} + \eta_{m,p}^{t,\omega_t} = \sum_{l \in L} D_{m,p,l}^t \gamma_{m,p,l}^{t,a(\omega_t)}, \ \forall m \in M, p \in P, t \in T, and \ \omega_t \in \Omega_t \tag{10}$$

$$\sum_{h \in H} y_{h,o,p}^{t,\omega_t} = \sum_{l \in L} \mathrm{Re}_{m,p,l}^{t,\omega_t} \lambda_{m,p,l}^{t,a(\omega_t)}, \ m \in M, o \in O, p \in P, t \in T, \omega_t \in \Omega_t \tag{11}$$

$$\sum_{h\in H}\sum_{p\in P}\beta_p y_{h,o,p}^{t,\omega_t}=\sum_{j\in J} z_{o,j}^{t,\omega_t} \quad o\in O, t\in T, \omega_t\in\Omega_t \tag{12}$$

$$\sum_{j\in J} xs_{i,j}^{t,\omega_t}\le CS_i, \quad \forall i\in I, t\in T, and\ \omega_t\in\Omega_t \tag{13}$$

$$\sum_{k\in K} xp_{j,k,p}^{t,\omega_t}\le CP_j, \quad \forall j\in J, t\in T, and\ \omega_t\in\Omega_t \tag{14}$$

$$\sum_{m\in M} xc_{k,m,p}^{t,\omega_t}\le CD_k, \quad \forall k\in K, t\in T, and\ \omega_t\in\Omega_t \tag{15}$$

$$\sum_{o\in O} y_{h,o,p}^{t,\omega_t}\le CC_h w_h^C, \quad \forall k\in K, t\in T, and\ \omega_t\in\Omega_t \tag{16}$$

$$\sum_{j\in J} z_{o,j}^{t,\omega_t}\le CR_o w_o^R, \quad \forall o\in O, t\in T, and\ \omega_t\in\Omega_t \tag{17}$$

$$xs_{i,j}^{t,\omega_t}, z_{o,j}^{t,\omega_t}, xp_{j,k,p}^{t,\omega_t}, xc_{k,m,p}^{t,\omega_t}, Inv_{k,p}^{t,\omega_t}, \eta_{m,p,l}^{t,\omega_t}, y_{h,o,p}^{t,\omega_t}\ge 0, \quad \forall i,j,o,k,m,h,p,t,\omega_t \tag{18}$$

$$w_j^P, w_k^D, w_h^C, w_o^R\in\{0,1\}, \quad \forall j\in J, k\in K, h\in H, o\in O \tag{19}$$

Constraint (8) guarantees that, in each period under each scenario, plants should receive sufficient raw materials from suppliers and recycling centers to produce the requested quantity of products. Constraint (9) guarantees that for each product in each period under each scenario, the sum of the amount of its residual inventory from the previous period and the total quantity of the product entering each distribution center during the current period is equal to the quantity of the product exiting from each distribution center plus the quantity of residual inventory at the end of the current period. According to constraint (10), the demands of customer zones can be fully or partially satisfied, and a shortage is possible. Constraint (11) indicates the quantity of used products which can be transported from customer zones to the collection centers. Constraint (12) guarantees the used product flow balance at each recycling center. Constraints (13)–(17) are capacity constraints on suppliers, plants, distributors, and collection and recycling centers, respectively. Constraints (18) and (19) ensure that corresponding variables are non-negativity and binary, respectively.

4. The model implementation

4.1. Case study

The Saba Battery Co. has more than 40 years of experience producing various kinds of automotive batteries. Recently, the company has been more vulnerable to specific risks in sourcing critical materials. To deal with the above-described problem, the company managers have decided to review their sourcing strategy and pricing policy to mitigate the supply risks.

The company has six suppliers, seven distribution centers, and one plant that can produce different types of automotive batteries in the supply chain under study. We assume that a retailer operates in each customer zone. The company's customer zones are located in 10 provinces. The plant and its central warehouse are located in Tehran province, and the manufactured batteries are transported from the central warehouse to distribution centers and then to retailers in each time period. In addition, the company has a recycling center for providing the required raw material (lead) by recycling the used batteries collected from the customer zones. Recently, Saba Battery has been experiencing low recycling output because of the increase in demand, a significant shortage of used batteries due to the customers' reluctance to sell their used batteries to the collection centers of the company. Therefore, it is essential to invest in establishing new centers for collecting and recycling the used batteries, together with determining an appropriate pricing policy for motivating customers to return their used products to be recycled. According to the managers' assessments, the number of potential locations for establishing the collection and recycling centers is ten and seven, respectively. The model is implemented for a planning horizon of five periods.

4.2. The model solution

In this study, the scenarios are designed using the past records of return amounts existing in the database of the company. Using the available historical data, the managers analyzed the most probable risks and addressed possible levels of uncertainty in the return flow during each period with associated probabilities. For each scenario, the potential return amount of the used products is computed based on the method explained in subsection 3.3. The scenario reduction approach is implemented through the SCENRED2 package in GAMS. In the considered stochastic model, the reduction tree is constructed by determining the exact number of scenarios, where a considered percentage of the original scenarios is 25%, 50%, 75% and 100%. The formulated model is coded and solved in GAMS 23.5/CPLEX 12.2 on a personal computer with Pentium dual-core processor @ 2.10 GHz and 3 GB RAM.

4.2.1. Evaluation of the solution method for the CLSC

In this study, the LHS method is used to generate scenarios, and then the number of scenarios is decreased using a backward scenario reduction technique. When we run the scenario generation procedure several times with the same input parameters, different scenario trees are produced due to the stochastic nature of the LHS. Each scenario generation method should consider two main measures: in-sample stability and out-of-sample stability. In-sample stability means that whichever of these trees is used in the optimization problem, the optimal objective function value will be (approximately) the same. In this study, we generate a scenario tree including 200 scenarios and then decrease the number of scenarios to 20 to solve the CLSC problem. Here, the LHS method produces different scenario trees, including 20 scenarios for 10 instance problems. The optimal objective function values for each of the 10 instance problems are reported in Table 2. In this Table, the in-sample stability error is computed as follows:

$$E_{In-Sample} = \frac{(\text{Max objective - Min objective})}{\text{Average of objective values}} \times 100\%$$

In-sample stability is essential for a reliable scenario generation process, but it alone is not enough [34]. By out-of-sample stability, it is understood that the true objective function values are also the same for first-stage decisions obtained by the different scenario trees. The out-of-sample performance will usually be measured through simulation [34].

Here, to generate scenario trees with more scenarios, an initial scenario tree containing 200 scenarios is simulated and then converted into a scenario tree. In this study, to check the out-of-sample stability, first, the decisions that must be made in the CLSC design problem at the beginning of the planning horizon and will must not change until the end of the planning horizon are obtained by solving the MSSP model. Then, we fix these decisions in the optimization problem and solve it for another scenario tree with more scenarios. The objective function value obtained from the MSSP solution under these conditions can be assumed as a simulation response for the actual objective function value. For each instance problem, the out-of-sample stability error of the scenario tree generation method is calculated as follows:

$$E_{Out-of-Sample} = \frac{(\text{Simulation response - Optimal objective})}{\text{Optimal objective}} \times 100\%$$

Table 2 displays the computational results of in-sample and out-of-sample stability for the scenario tree generation method on various instance problems.

As shown in Table 2, the relative difference between the maximum and minimum objective function values in the scenario trees in each instance problem is relatively small. Therefore, it can be concluded that in-sample stability is achieved with 20 scenarios for our case study. It is also shown in Table 2 that the maximum and minimum values of out-of-stability error are 3.7% and 0.52% in different test samples, respectively. Therefore, our computational results show the efficiency of the scenario tree generation approach in terms of out-of-sample and in-sample stability.

4.3. Sensitivity analysis

4.3.1. The analysis of multi-stage pricing

To prove the efficiency of MSSP, Huang and Ahmed [28] compared it with a TSSP model. To make this comparison, we formulate and solve a two-stage stochastic problem in which the decisions on the price of used and new batteries do not depend on the realizations of the scenarios and cannot hedge against disruptions. By removing the subscript ω_{t-1} from the variables $\gamma^{t,\omega_{t-1}}$ and $\lambda^{t,\omega_{t-1}}$ for the entire time horizon, the MSSP model is converted into a TSSP model. The optimal objective function value of multi-stage (MS) and two-stage (TS) models is denoted by z_{MS} and z_{TS}, respectively. Obviously, every solution to the two-stage model is feasible for the corresponding multi-stage model as well, and thus $z_{TS} \leq z_{MS}$. According to Huang and Ahmed (2009), the value of multi-stage (VMS) relative to two-stage is calculated as $VMS = \frac{z_{MS} - z_{TS}}{z_{TS}}$.

In this subsection, we also consider the impact of return risk on the price of both new and used batteries and the CLSC profit. For sensitivity analysis, we use different sets of return scenarios in the same case by varying the risk level Λ, setting the variance value of stochastic returns (σ_{ε}^2), and then resolving the two models. Thus, we provide the optimal solutions for two-stage and multi-stage models with different levels Λ. The results are reported in terms of the price of used and new batteries, the overall profit of the CLSC problem, and the VMS in table 3 and Figures 5 and 6. Compared with the TSSP model, the MSSP model produces a higher profit for the same values of Λ, especially for the very big ones. Also, it can be seen that prices of both used and new batteries are set higher in the multi-stage model than in the two-stage one. Indeed, the higher the return variance, the higher the price of the used batteries. This way, the return risk of used batteries to the supply chain can be mitigated. The results corresponding to VMS show that a multi-stage model can have a higher effect than a two-stage model on maximizing the total CLSC profit, especially if solved for high levels Λ.

In this subsection, we also consider the impact of return risk on the price of both new and used batteries and the CLSC profit. To do the sensitivity analysis, we use different sets of return scenarios in the same case by varying the risk level Λ, setting the variance value of stochastic returns (σ_{ε}^2), and then solving the two models. Thus, we provide the optimal solutions for two-stage and multi-stage models with different levels Λ. The results are presented in table 3, Figures 5 and 6 with regard to the price of the used and new batteries, the overall profit of the CLSC problem, and the VMS. Compared with the TSSP model, the MSSP model produces a higher profit for the same values of Λ, especially for the very big values of Λ. Also, it can be seen that the price of both used and new batteries is higher in the multi-stage model than in the two-stage one. Higher variance in the return flow means a higher purchasing price for the used batteries in order to mitigate the return risk of the used products. The results for VMS show that the multi-stage model can have a high effect than the two-stage model on maximizing the total CLSC profit, especially if solved for high levels Λ.

4.3.2. The analysis of the sourcing strategy

In this subsection, we consider the effect of return risk on sourcing strategy. For this purpose, the CLSC model is solved using TSSP and MSSP approaches, and the results are presented as the average values of the solutions of the model. We repeatedly implement the same procedure on the same case by varying the risk level Λ. The main purpose of solving the same case for different Λ values is to provide insights into sourcing strategies for each risk level. Let SUPQ and RECQ be the sourcing amount from suppliers and recycling centers, respectively. As the variance value $\varepsilon_{t+j}^{\omega_{t+j}}$ in $\Lambda = 0$ is zero, the model becomes deterministic. Computational results are obtained for both TSSP and MSSP approaches in terms of the average quantities of the utilization of two sourcing options, the number of opened collection and recycling centers (C, R), and the expected profit of the considered supply chain. Table 4 presents the results, and Figures 7 illustrates the same results visually.

As observed in both the MSSP and TSSP models, the RECQ decreases with the increase in risk level Λ on return flow, while SUPQ increases with the increase in Λ. Generally speaking, under high risk, the results of the MSSP model suggest that there is less tendency for sourcing from the outside supplier, but the opposite is true for the TSSP model results. However, under low risk, there is no significant difference between the results of the two stochastic programming approaches. This implies that the MSSP model can change the sourcing structure by employing a proactive pricing policy, in which the establishment of extra collection and recycling centers is justified. Also, it can be seen that the number of opened collection and recycling centers in the MSSP model decreases from 4 and 3 to 2 and 2, respectively, with an increase in Λ parameter from 0 to 1.1. Therefore, it can be concluded that, in general, risk level and pricing policy can affect the sourcing strategy.

Managerial insights

This research helps managers properly allocate resources and financial investments by understanding the various disruptions and examining their impacts on supply chain design decisions. Managers and policymakers with a deep understanding of the return risk of used products in the battery supply chain can decide on appropriate resilience strategies for mitigating these risks. By determining the risk value of return disruption for a long-term time horizon, decision-makers can decide on the capacity development of recycling centers and other facilities. On the other hand, we require an appropriate pricing strategy to incentivize customers to return used products to the supply chain; otherwise, the established recycling centers will lack used batteries for recycling. Investment in the establishment of recycling centers can improve the resilience of the battery supply chain only if there is a balanced pricing policy.

When automotive battery manufacturers face return disruption, they need to seek a proactive selling policy to sell their products at higher prices to compensate for the production loss due to lead shortage. However, this policy is usually ineffective in all markets that can be considered to determine its impact on profit. Thus, it is better to consider its impact on profit before deciding on the pricing. In addition, companies facing the used batteries shortage for recycling can offer higher purchase prices to motivate consumers to return their used products. This is particularly useful when the return amount of the used batteries is highly sensitive to price. It can be concluded that the less reliable recycling option can be turned into a more reliable sourcing option by employing an appropriate pricing policy, as they can adjust the pricing decisions according to a pricing policy in the planning horizon. Companies can employ such a pricing policy to announce generous purchase prices for the used batteries at the beginning of each period to proactively deal with return disruptions. In general, it is recommended that companies proactively update their selling and purchasing prices in each period and set new prices in the customer zones after the risk level of return flow is determined.

5. Conclusions and future works

This study developed an MSSP model for the CLSC network design problem regarding the sourcing options and pricing policy under the return disruptions. RHS and backward scenario reduction techniques in the MSSP model were employed to generate a scenario tree and efficiently reduce the problem size, respectively. The results of the MSSP model were compared with that of the TSSP model to provide insights on resilient sourcing by analyzing the interaction between sourcing strategy and pricing policy. The results of the MSSP model indicated that investment in the establishment of recycling centers can improve the resilience of the battery supply chain only if there is a balanced pricing policy. In addition, the MSSP model proved less sensitive to the risk level because the proactive decision-making about pricing in the model at the beginning of each period can act as a hedge against return disruptions. The results indicated that sourcing through recycling centers, though it involves a higher risk of disruption in the return flow of the used products, can be effective if the consumers are encouraged to return the used products by employing an effective pricing policy. When the risk level of return is low, companies can source from low-cost recycling centers and decrease the selling price of the new products and purchasing price of the used products. Hence, in low-risk conditions, companies do not have to incur a cost for improving the reliability of the recycling centers. When the risk level is high, companies can have more sourcing from the recycling centers than the suppliers only if there is a balanced pricing policy. Therefore, the proposed CLSC design model can help managers choose the optimal sourcing strategy and pricing policy to mitigate the return risk of used products in battery CLSC.

Future studies can extend the model proposed in this study to include the cost structure related to the collection and recycling centers and raw material prices offered by suppliers. Moreover, the sourcing strategy can be analyzed with regard to sustainability considerations in CLSC. Finally, developing an efficient solution algorithm for scenario reduction can be another future research direction.

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Table 1. Comparing the literature with regard to CLSC decisions, and supply and return disruptions

Articles	Closed loop	Uncertainty consideration			resilience strategies				Pricing		Modelling technique	solution method	Industry
		Supply	return	demand	Multiple sourcing	Contracting with backup suppliers	Fortification of suppliers	Capacity expansion	New product	Used product			
[20]				✓				✓	✓		TSSP	GAMS	-
[9]		✓			✓				✓		Game theory	GAMS	-
[4]		✓			✓			✓			MSSP	GAMS	-

[21]		✓			✓	✓			✓			GAMS	-
[15]		✓		✓		✓					TSSP	GAMS	waste paper
[32]	✓		✓	✓				✓			TSSP	GAMS	automotive battery
[18]		✓		✓				✓			TSSP	SAA & BRS	Glass
[11]		✓			✓	✓					TSSP	GAMS	-
[23]	✓	✓			✓					✓	TSSP	GAMS	TV
[17]		✓					✓	✓		✓	TSSP	Benders decompositio n	electric vehicles
[25]	✓		✓							✓	TSSP	Genetic Algorithm	household appliance
The present study	✓		✓		✓			✓	✓	✓	MSSP	SAA & BRS	automotive battery

Table 2. Performance of the simulation for the CLSC problem

Instance problems	Optimal objective function value	Optimal problem objectives related to different scenario trees with 20 scenarios				Expected value of simulation's responses	$E_{In-Sample}$	$E_{Out-of-Sample}$
		Scenario tree 1	Scenario tree 2	Scenario tree 3	Scenario tree 4			
1	1.07E+07	1.08E+07	1.09E+07	1.08E+07	1.09E+07	1.09E+07	0.92	1.87
2	1.21E+07	1.22E+07	1.23E+07	1.20E+07	1.22E+07	1.23E+07	2.46	1.65
3	1.37E+07	1.34E+07	1.36E+07	1.37E+07	1.35E+07	1.38E+07	2.21	0.73
4	1.49E+07	1.47E+07	1.49E+07	1.50E+07	1.48E+07	1.52E+07	2.02	2.01
5	1.51E+07	1.49E+07	1.50E+07	1.49E+07	1.51E+07	1.53E+07	1.34	1.32
6	1.68E+07	1.65E+07	1.62E+07	1.67E+07	1.63E+07	1.69E+07	3.04	0.60
7	1.73E+07	1.70E+07	1.74E+07	1.75E+07	1.72E+07	1.71E+07	2.89	1.16
8	1.77E+07	1.74E+07	1.76E+07	1.79E+07	1.75E+07	1.78E+07	2.84	0.56
9	1.89E+07	1.85E+07	1.89E+07	1.83E+07	1.88E+07	1.82E+07	3.22	3.70
10	1.92E+07	1.89E+07	1.90E+07	1.93E+07	1.91E+07	1.93E+07	2.10	0.52

Table 3. Optimal prices of the used and new battery and VMS

Λ	Price of used battery		Price of new battery		Profit		VMS
	MS	TS	MS	TS	MS	TS	
0	9.92	9.1	85.18	85.18	1.68E+07	1.66E+07	0.010
0.1	11.78	9.9	88.36	86.59	1.63E+07	1.60E+07	0.020
0.2	13.05	10.6	90.27	87.32	1.60E+07	1.54E+07	0.042
0.3	13.42	11.2	91.44	88.74	1.58E+07	1.50E+07	0.053
0.4	13.97	12.2	92.69	89.50	1.58E+07	1.47E+07	0.075
0.5	15.4	13	93.77	90.94	1.58E+07	1.45E+07	0.087
0.6	17.16	13.9	94.49	91.40	1.58E+07	1.44E+07	0.099
0.7	18.5	14.5	95.03	91.70	1.57E+07	1.41E+07	0.111
0.8	19.26	15.5	95.69	92.20	1.54E+07	1.36E+07	0.136

0.9	19.76	16.1	95.98	92.40	1.51E+07	1.31E+07	0.149
1	20.35	16.8	96.32	92.65	1.48E+07	1.30E+07	0.136
1.1	21.4	17.5	96.81	92.87	1.43E+07	1.24E+07	0.149

Table 4. Optimal design and sourcing amount for different levels of risk

	TS				MS			
Λ	(C,R)	SUPQ	RECQ	Profit	(C,R)	SUPQ	RECQ	Profit
0	4,3	0	2728344	1.66E+07	4,3	0	3128344	1.68E+07
0.1	3,3	0	2723910	1.60E+07	3,3	0	3023910	1.63E+07
0.2	3,3	0	2726006	1.54E+07	3,3	0	2926006	1.60E+07
0.3	3,2	900354	1827990	1.50E+07	3,3	0	2927990	1.58E+07
0.4	2,2	908417	1823250	1.47E+07	3,3	0	2823250	1.58E+07
0.5	2,2	902648	1823214	1.45E+07	3,3	0	2723214	1.58E+07
0.6	2,1	894583	1816495	1.44E+07	3,2	804583	2095990	1.58E+07
0.7	1,1	1800707	910542	1.41E+07	3,2	780070	2070000	1.57E+07
0.8	1,1	1790500	903250	1.36E+07	2,2	770500	2062000	1.54E+07
0.9	1,1	1780548	902350	1.31E+07	2,2	768048	2042400	1.51E+07
1	1,1	1775200	890950	1.30E+07	2,2	775200	2010210	1.48E+07
1.1	0,0	2553500	0	1.24E+07	2,2	753500	1992540	1.43E+07

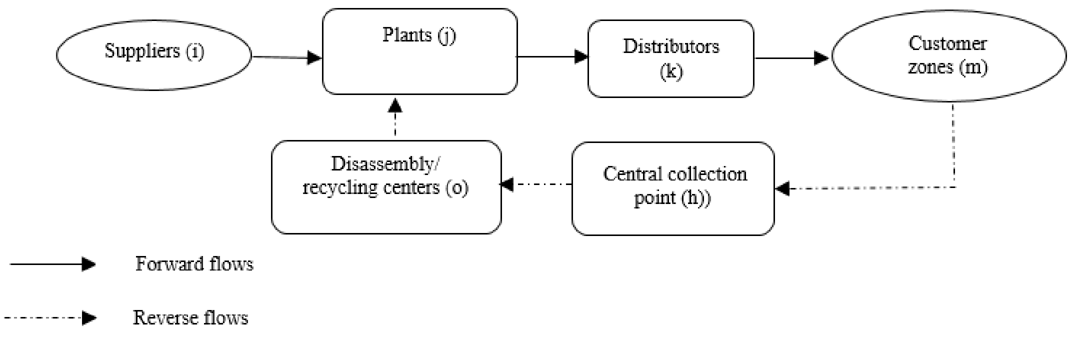


Figure 1. The CLSC map

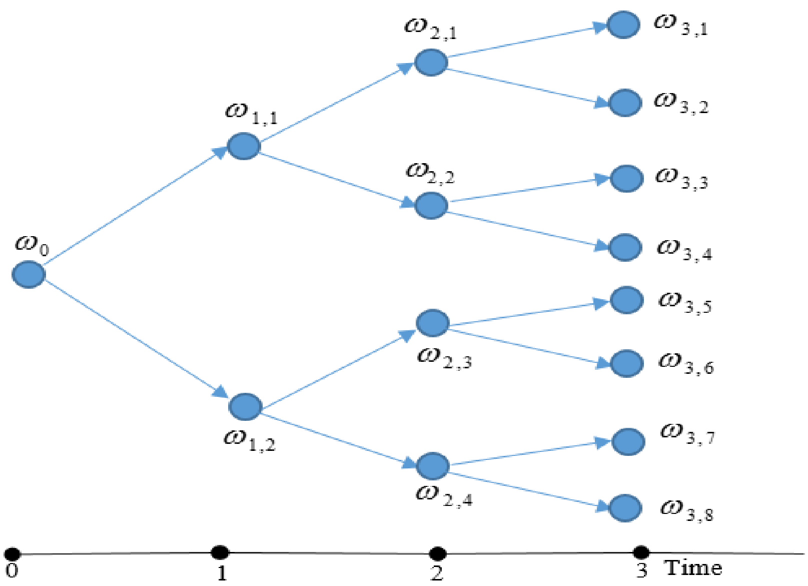
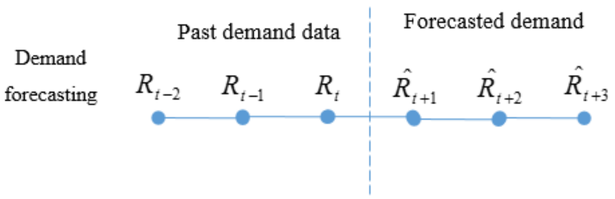


Figure 2. The structure of the scenario tree model with three periods and two outcomes



$$\hat{R}_{t+j} = \begin{cases} \alpha + \sum_{i=1}^{P} \beta_i R_{t+j-i} & j = 1 \\ \alpha + \sum_{i=1}^{j-1} \beta_i \hat{R}_{t+j-i} + \sum_{i=j}^{P} \beta_i R_{t+j-i} & 1 < j < P \\ \alpha + \sum_{i=1}^{P} \beta_i \hat{R}_{t+j-i} & j > P \end{cases}$$

Figure 3. Forecasting the amount of returned used products

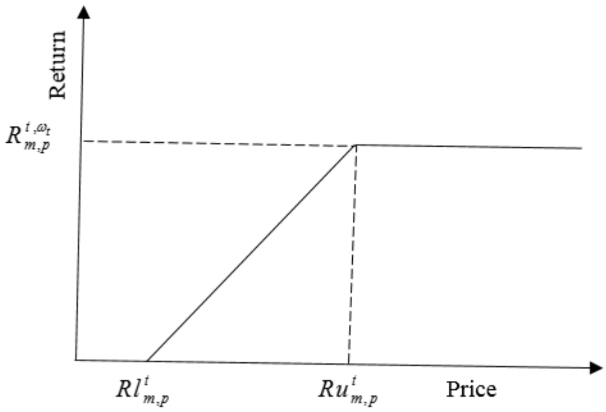
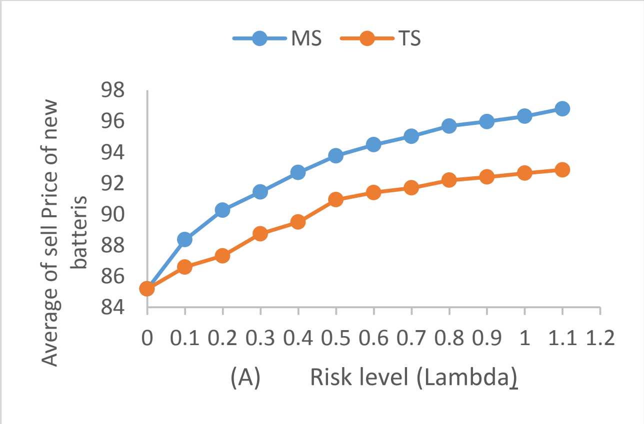


Figure 4. The relationship between the announced purchase price and the return amount of used products



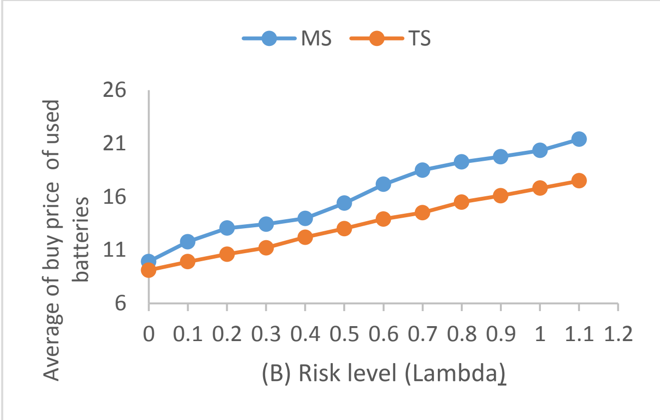


Figure 5. The average price of new (A) and used (B) batteries for different levels of risk

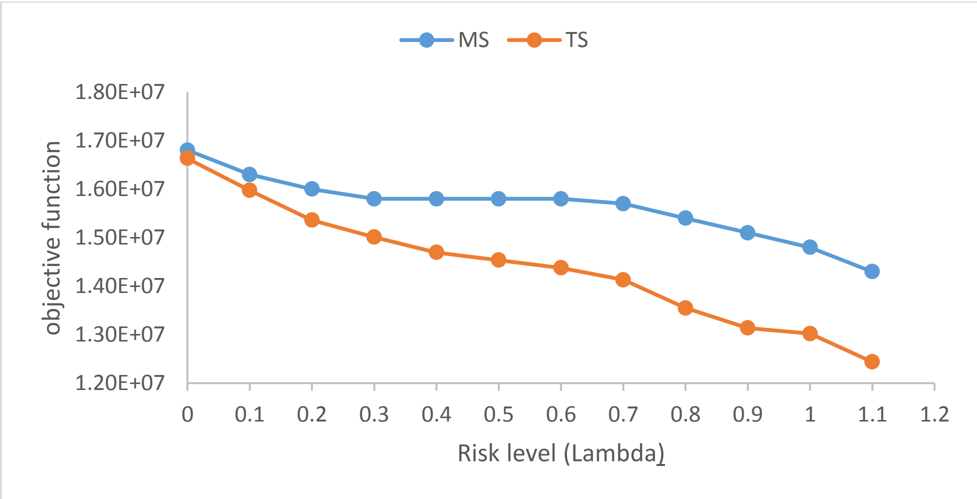
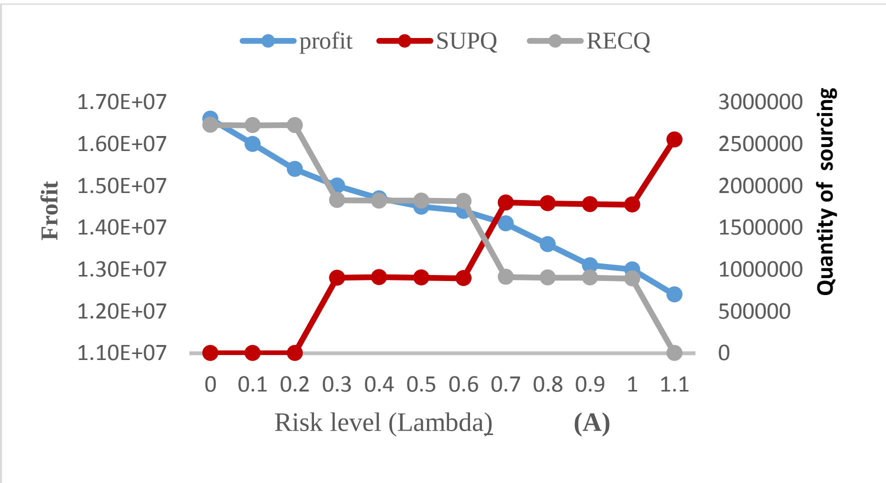


Figure 6. Quantities of the optimal objective functions for different levels of risk



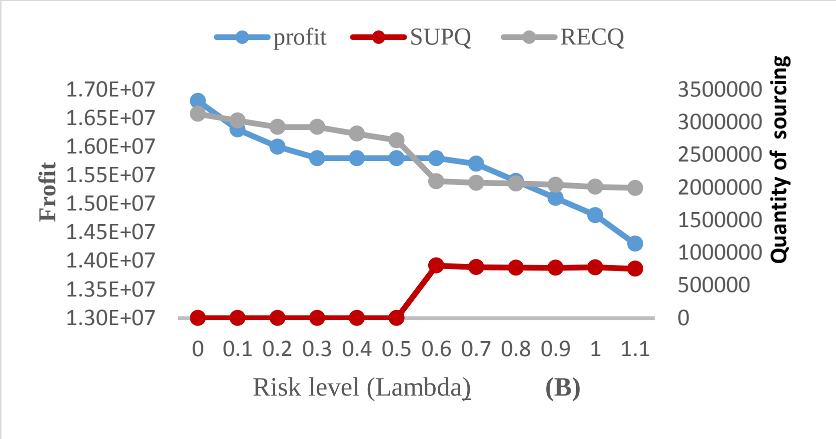


Figure 7. The profit and the average amount of lead provided by the sourcing options in terms of TSSP (A) and MSSP (B)

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