Industrial Engineering and Applications
L.-C. Tang (Ed.)

doi:10.3233/ATDE230043

Optimization of Closed-Loop Supply Chain Network Design Under Uncertainty: Considering Electric Vehicle Battery Recycling

Peng LI [a], Ziting HUAI [a] and Jiaxue JIANG [a,1]
[a] *School of Economics and Management, Xian University of Technology (XUT), Xi'an, China*

Abstract. In recent years, the market of electric vehicles (EVs) has developed rapidly across the world, and recycling a large number of their spent power batteries has become an urgent challenge today. The resulting closed-loop supply chain (CLSC) have been considerably studied under different aspects. However, there is a lack of research investigating electric vehicle batteries (EVBs) network design under uncertainty. This paper focuses on the issues of quantitative modelling for the network design of a CLSC of used EVBs consisting of power battery manufacturers, EV retailers, collection centers, recycling centers, echelon utilization centers and disposal centers, where power battery manufacturers can remanufacture used EVB products. We investigate a two-stage stochastic mixed-integer programming (SMIP) model to design the network and the model is solved using the Benders Decomposition (BD) method to derive optimal solutions. Numerical experiments show that the SMIP model can effectively hedge against high uncertainty.

Keywords. Electric vehicle, power batteries, supply chain network design, stochastic mixed-integer programming (SMIP), Benders Decomposition

1. Introduction

In recent years, the growing concern with energy structure transition and environmental protection has promoted the fast development of Electric Vehicles (EVs). According to the statistics, the accumulated sales of EVs are projected to reach 5 million in 2020[1]. Along with the rapid growth of the EV market and the applications of power batteries, a huge number of used EV batteries (EVBs) will intensively face the retirement. According to the China Automotive Technology and Research Centre, 120-170 thousand tons of used EVBs were retired by 2020. It is well known that all materials used for making EVBs are extremely hazardous to both the environment and human health. Therefore, how to properly deal with used EVBs has become an urgent challenge today.

Due to the economic benefit and environmental activism, many manufacturers are willing to take back used EVBs to produce remanufactured products in closed-loop supply chain (CLSC), which consist of decisions related to both forward flow of brand-new products and reverse flow of returned/remanufactured products. To deal with the

[1] Corresponding Author: Jiaxue JIANG, email: 17713680573@163.com.

uncertainties associated with CLSC operations, it is important to generate a proper network design to address the system risk [2]. In the literature, study of network design of CLSC has gained great attention of both academic research and industrial practitioners [3]. Demand and return rate are the two parameters that are most frequently taken as uncertain in the related work [4]. In addition, some studies also consider other types of uncertain as well, such as transportation costs [5], quality [6], manufacturing cost [7], selling price [8] and recovery rate [9].

Through analysis of the model and the main results, we have drawn some meaningful points in this research. First of all, the majority of the existing models on CLSC are mainly focused on pricing decisions and channels coordination, there is a lack of quantitative network design models that represent advanced applications in recycling industries; Secondly, there is not much literature relating to EVB recycling network, also few studies on the research of investigating EVB recycling at the enterprise level. Thirdly, except demand and return rate, there are few studies that consider price, cost and recovery rate as uncertainty in their mathematical model.

To fill this gap, this paper develops a stochastic mixed integer programming (SMIP) model to optimize recycling networks for EVBs. In our model, we consider three potential strategies to handle used EVBs, including recycling, remanufacturing, and disposal. To make the model more suitable, we incorporate the uncertainty of demand, recycling price and cost in the model. The goal is to maximize the network profit by strategically locating participants within the CLSC network. To efficiently solve the model, an enhanced Benders Decomposition (BD) algorithm is proposed, a effectiveness of the solution method is validated by numerical experiments.

2. Preliminaries

In this study, we consider a CLSC network structure of recycling EVBs, which is composed of seven members--power battery manufacturers, EV retailers, customer zones, collection centers, recycling centers, echelon utilization centers and disposal centers. In this network, power battery manufacturers produce new EV products, and then distributed in markets by EV retailers. The used EVBs are collected from customers to EV retailers, then transfer them to collection centers. After proper inspection and grading at collection centers, the used EVBs will be classified and distributed via different reverse channels. Most used EVBs which can be repaired or remanufacturing will be sent to recycling centers, whereas a small number of scrapped EVBs will be transported to disposal centers for refuse disposal. The used EVBs in recycling centers that can be reused are transported to echelon utilization centers, as well as the rest are transformed into power battery manufacturers to remanufacture and reassembled into new EVBs. Overall, the notations are defined and summarized in Table 1.

Table 1. Notations.

	Descriptions
i	customer zones, i=1,2,…, I
j	candidates for locations of EV retailers, j=1,2,…, J
k	candidates for locations of collection centers, k=1,2,…, K
l	candidates for locations of recycling centers, l=1,2,…, L
m	power batteries manufacturers, m=1,2,…,M
n	candidates for locations of disposal centers, n=1,2,…, N
q	candidates for locations of recycling centers, q=1,2,…,Q
r	echelon utilizations, r=1,2,…, R
a	set of raw materials, a=1,2,…,A
s	scenarios, s=1,2,…,S
p_e	unit retail price of new EVBs
p_r	unit recycling price of used EVBs
c_w	unit wholesale price of new EVBs
α	potential market size
β	sensitivity of customers to the retail price of power battery
A	the quantities of spent power batteries consumers are willing to return free of charge
k	consumers' sensitivity for recycling price
Δ	unit benefit by recycling
c_m	unit wholesale price of new EVBs
$\tilde{\mu}_1, \tilde{\mu}_2$	fraction of used EVBs transported to recycling centers and echelon utilization center
π_i	population density of customer zone i
f_j, f_k, f_l, f_n	fixed establishing cost of different facilities
C_j, C_k, C_l, C_n	capacity of different facilities
$\tilde{c}_j, \tilde{c}_k, \tilde{c}_l, \tilde{c}_n$	unit fuzzy processing cost of different facility
$d_{mj}, d_{ij}, d_{jk}, d_{kn}, d_{kl}, d_{lr}, d_{lm}$	linear distance among different facilities
$\tilde{e}_{mj}\tilde{e}_{ij}, \tilde{e}_{ji}, \tilde{e}_{jk}, \tilde{e}_{kn}, \tilde{e}_{kl}, \tilde{e}_{lr}, \tilde{e}_{lm}\tilde{e}_{mj}$	unit fuzzy transportation cost among different facilities
v_j	binary variable which equals '1' if j is open, and '0' otherwise
w_k	binary variable which equals '1' if k is open, and '0' otherwise
x_l	binary variable which equals '1' if l is open, and '0' otherwise
y_q	binary variable which equals '1' if q is open, and '0' otherwise
z_n	binary variable which equals '1' if n is open, and '0' otherwise
$Y_{mjs}^{MJ}, Y_{jis}^{JI}, Y_{ijs}^{IJ}, Y_{jks}^{JK}, Y_{kls}^{KL}, Y_{lrs}^{LR}, Y_{lms}^{LM}, Y_{lqs}^{LQ}, Y_{rqs}^{RQ}, X_{ms}^{MS}, Y_{qmas}^{QMA}$	amount of used EVBs transported among different facilities in scenario s

To handle the problem stated in the above, we propose some key assumptions.

(1) We uniformly use "power battery manufacturers" to represent power battery manufacturers and EV manufacturers;

(2) For power battery, the processes of manufacturing, sale, recycling, echelon utilization and material reusing in remanufacturing are considered in one period.

(3) According to [3], the market demand is a linear function of the power battery retail price and the recycling rate which is $D = a\sqrt{r} - \beta p_e$;

(4) According to our investigation, we assume the amount of recycled power batteries is equal to $G = A + k \times p_r$.

This problem aims to determine the location decisions in the recycling network, such as EV retailers, collection centers, recycling centers and disposal centers, and the number of EVBs that should be transported from one facility to another. The objective of the model is to maximize the total profit in the entire recycling network.

3. Problem Formulation

To formulate the problem, a two-stage stochastic mixed-integer programming (SMIP) model is proposed for the maximization of the total network profit. In two-stage stochastic approach, the decision variables are split into two types: scenario-dependent and scenario-independent. In the first stage, the decisions on the scenario-independent variables like number and location of facilities which are not affected by randomness are made. The amount of used EVBs transported between facilities which vary regard to are determined in second stage based on facilities location and realized uncertainty in each scenario. The total objective function in this approach consists of the sum of the first-stage objective value and the expected value of all scenarios in the second stage.

3.1. The First-Stage Model

$$Max \ \mathbb{E}\left[F_s\left(v_j, w_k, x_l, y_q, z_n\right)\right] - \left(\sum_{j\in J} f_j v_j + \sum_{k\in K} f_k w_k + \sum_{l\in L} f_l x_l + \sum_{q\in Q} f_q y_q + \sum_{n\in N} f_n z_n\right) \tag{1}$$

Subject to:

$$\sum_{j\in J} v_j \geq 1 \tag{2}$$

$$\sum_{k\in K} w_k \geq 1 \tag{3}$$

$$\sum_{l\in L} x_l \geq 1 \tag{4}$$

$$\sum_{q\in Q} y_q \geq 1 \tag{5}$$

$$\sum_{n\in N} z_n \geq 1 \tag{6}$$

$$w_j, x_k, y_l, z_n \in \{0,1\} \ \forall j, k, l, n \tag{7}$$

where the objective Eq.(1) is the expected net profit of entire network, which is obtained by subtracting the fixed cost of construction facilities from the expected profit for all scenarios $s \in S$, where $\mathbb{E}\left[F_s\left(v_j, w_k, x_l, y_q, z_n\right)\right] = \sum_{s\in S} p^s F_s\left(v_j, w_k, x_l, y_q, z_n\right)$ constraints Eqs.(2) ~(6) guarantee that at least one of the potential facilities be selected. Constraint Eq. (7) is binary constraint.

3.2. The Second-stage Model

$$F_s\left(v_j, w_k, x_l, y_q, z_n\right) =$$

$$max \left\{(p_e - c_w) \sum_{m\in M} \sum_{j\in J} Y_{mjs}^{MJ} + \Delta c \sum_{l\in L} \sum_{m\in M} Y_{lms}^{LM} + \xi L \sum_{l\in L} \sum_{r\in R} Y_{lrs}^{LR} + \Delta c' \left(\sum_{l\in L} \sum_{m\in M} Y_{lqs}^{LQ} + \sum_{l\in L} \sum_{m\in M} Y_{rqs}^{RQ}\right) + \sum_{j\in J} h_j W_{js} - \left[\sum_{i\in I} \sum_{j\in J} \tilde{c}_j^J Y_{ijs}^{IJ} + \sum_{j\in J} \sum_{k\in K} \tilde{c}_k^K Y_{jks}^{JK} + \sum_{k\in K} \sum_{l\in L} \tilde{c}_l^L Y_{kls}^{KL} + \sum_{l\in L} \sum_{n\in N} \tilde{c}_n^N Y_{lns}^{LN} + \sum_{l\in L} \sum_{q\in Q} \tilde{c}_q^{LQ} Y_{lqs}^{LQ} + \sum_{r\in R} \sum_{q\in Q} \tilde{c}_q^{RQ} Y_{rqs}^{RQ}\right] - \left[\sum_{m\in M} \sum_{j\in J} \tilde{e}_{mj} \, d_{mj} Y_{mjs}^{MJ} + \sum_{j\in j} \sum_{i\in I} \tilde{e}_{ji} d_{ij} Y_{jis}^{JI} + \right.$$

$$\sum_{i\in I}\sum_{j\in J}\tilde{e}_{ij}d_{ij}Y_{ijs}^{IJ}+\sum_{j\in J}\sum_{k\in K}\tilde{e}_{jk}d_{jk}Y_{jks}^{JK}+\sum_{k\in K}\sum_{l\in L}\tilde{e}_{kl}\,d_{kl}Y_{kls}^{KL}+ \sum_{l\in L}\sum_{r\in R}\tilde{e}_{lr}d_{lr}Y_{lrs}^{LR}+\sum_{l\in L}\sum_{m\in M}\tilde{e}_{lm}d_{lm}Y_{lms}^{LM}+\sum_{l\in L}\sum_{n\in N}\tilde{e}_{ln}d_{ln}Y_{lns}^{LN}+ \sum_{l\in L}\sum_{q\in Q}\tilde{e}_{lq}d_{lq}Y_{lqs}^{LQ}+\sum_{r\in R}\sum_{q\in Q}\tilde{e}_{rq}d_{rq}Y_{rqs}^{RQ}+ \sum_{q\in Q}\sum_{m\in M}\sum_{a\in A}\tilde{e}_{qm}\,d_{qm}Y_{qmas}^{QMA}\Big]\Big\} \tag{8}$$

Subject to:

$$\sum_{m\in M}\sum_{j\in J}Y_{mjs}^{MJ}\le D(s) \tag{9}$$

$$\sum_{j\in J}Y_{jis}^{JI}\le D(s)\rho_i \quad \forall i\in I, s\in S \tag{10}$$

$$\sum_{j\in J}Y_{ijs}^{IJ}\le G(s)\rho_i \quad \forall i\in I, s\in S \tag{11}$$

$$\sum_{i\in I}Y_{jis}^{JI}=\sum_{m\in M}Y_{mjs}^{MJ} \quad \forall j\in J, s\in S \tag{12}$$

$$\sum_{i\in I}Y_{ijs}^{IJ}=\sum_{k\in K}Y_{jks}^{JK}+W_{js} \quad \forall j\in J, s\in S \tag{13}$$

$$\sum_{j\in J}Y_{jks}^{JK}=\sum_{l\in L}Y_{kls}^{KL} \quad \forall\, k\in K, s\in S \tag{14}$$

$$\sum_{r\in R}Y_{lrs}^{LR}=\mu_0\sum_{k\in K}Y_{kls}^{KL} \quad \forall l\in L, s\in S \tag{15}$$

$$\sum_{m\in M}Y_{lms}^{LM}\le\tilde{\mu}_1\sum_{k\in K}Y_{kls}^{KL} \quad \forall l\in L, s\in S \tag{16}$$

$$\sum_{q\in Q}Y_{lqs}^{LQ}\le\tilde{\mu}_2\sum_{k\in K}Y_{kls}^{KL} \quad \forall l\in L, s\in S \tag{17}$$

$$\sum_{n\in N}Y_{lns}^{LN}\le\tilde{\mu}_3\sum_{k\in K}Y_{kls}^{KL} \quad \forall l\in L, s\in S \tag{18}$$

$$\sum_{q\in Q}Y_{rqs}^{RQ}=\sum_{k\in K}Y_{lrs}^{LR} \quad \forall r\in R\,, s\in S \tag{19}$$

$$\sum_{m\in M}Y_{qmas}^{QMA}\le\mu_a\left(\sum_{l\in L}\tau_aY_{lqs}^{LQ}+\sum_{r\in R}\tau_aY_{rqs}^{RQ}\right) \forall q\in Q, a\in A, s\in S \tag{20}$$

$$X_{ms}^{MS}+\sum_{l\in L}Y_{lms}^{LM}\le\sum_{j\in J}Y_{mjs}^{MJ} \quad \forall\, m\in M, s\in S \tag{21}$$

$$\tau_aX_{ms}^{MS}=\sum_{q\in Q}Y_{qmas}^{QMA} \quad \forall\, m\in M, a\in A, s\in S \tag{22}$$

$$\sum_{i\in I}Y_{ijs}^{IJ}\le C_jv_j \quad \forall j\in J \tag{23}$$

$$\sum_{j\in J}Y_{jks}^{JK}\le C_kw_k \quad \forall k\in K \tag{24}$$

$$\sum_{k\in K}Y_{kls}^{KL}\le C_lx_l \quad \forall l\in L \tag{25}$$

$$\sum_{l\in L}Y_{lqs}^{LQ}+\sum_{l\in L}Y_{rqs}^{RQ}\le C_qy_q \quad \forall q\in Q \tag{26}$$

$\sum_{l\in L} Y_{lns}^{LN} \leq C_n z_n \ \ \forall n \in N$ (27)

$Y_{mjs}^{MJ}, Y_{jis}^{JI}, Y_{ijs}^{IJ}, Y_{jks}^{JK}, Y_{kls}^{KL}, Y_{lrs}^{LR}, Y_{lms}^{LM}, Y_{lqs}^{LQ}, Y_{rqs}^{RQ}, X_{ms}^{MS}, Y_{qmas}^{QMA} \geq$
$0, \forall i, j, k, l, m, n, q, r, a, s$ (28)

where equation Eq. (8) is to maximize the manufacturer's profit under any scenario s, where the first term represents the sales of power batteries. The second item is the benefits of echelon utilization of used EVBs and the savings of remanufacturing; The third item is the reward-penalty given by the government; The fourth item represents the recovery cost and processing cost; The fifth item is the cost of transporting used EVBs between facilities; Constraints Eqs.(9) ~ (22) are the balance constraints which confirm the uniformity of input flow and output flow at each facility; Constraints Eqs.(23) ~ (27) assure that the flows to and from each facility could not exceed its capacity; Constraint Eq.(28) is the positive variable constraints.

4. Solution Method

Since the second-stage model involves the analysis of fuzzy parameters we first use fuzzy programming method to transform the SMIP model into a deterministic MIP model. Then, a Benders Decomposition (BD) algorithm is applied to solve the model.

4.1. Model Transformation

According to [10], the above model with fuzzy numbers can be transformed into two equivalent forms, namely linear lower approximation model (LLAM) and linear upper approximation model (LUAM), which are significantly easier to solve.

Since there are fuzzy variables in the objective functions and constraints, we used the expected value and operator and chance constrained operator based on *Me* to deal with the objective functions and constraints, respectively.

Assume that $\tilde{c}_{ij} = \left(c_{ij}, \alpha_{ij}^{c}, \beta_{ij}^{c}\right)$ are positive triangular fuzzy variables, the expected value of the objective function can be computed as

$$E\left[\sum_{j\in J} \tilde{c}_{ij}^{T} x_j\right] = \sum_{j\in J}\left(\frac{(1-\lambda)}{2}\left(c_{ij} - \alpha_{ij}^{c}\right) + \frac{c_{ij}}{2} + \frac{\lambda}{2}\left(c_{ij} + \beta_{ij}^{c}\right)\right) x_j \quad (29)$$

Where λ is the optimistic-pessimistic parameter.

Therefore, the objective function Eq. (8) can be transformed into the following equation by using fuzzy random expected value method.

$$F_s\left(v_j, w_k, x_l, y_q, z_n\right) =$$

$$\max\{(p_e - c_w)\sum_{m\in M}\sum_{j\in J} Y_{mjs}^{MJ} + \Delta c\sum_{l\in L}\sum_{m\in M} Y_{lms}^{LM} + \xi L\sum_{l\in L}\sum_{r\in R} Y_{lrs}^{LR} +$$
$$\Delta c'\left(\sum_{l\in L}\sum_{m\in M} Y_{lqs}^{LQ} + \sum_{l\in L}\sum_{m\in M} Y_{rqs}^{RQ}\right) + \sum_{j\in J} h_j W_{js} - \left[\sum_{i\in I}\sum_{j\in J} E(\tilde{c}_j^{J}) Y_{ijs}^{IJ} +\right.$$
$$\sum_{j\in J}\sum_{k\in K} E(\tilde{c}_k^{K}) Y_{jks}^{JK} + \sum_{k\in K}\sum_{l\in L} E(\tilde{c}_l^{L}) Y_{kls}^{KL} + \sum_{l\in L}\sum_{n\in N} E(\tilde{c}_n^{N}) Y_{lns}^{LN} +$$
$$\left.\sum_{l\in L}\sum_{q\in Q} E(\tilde{c}_q^{LQ}) Y_{lqs}^{LQ} + \sum_{r\in R}\sum_{q\in Q} E(\tilde{c}_q^{RQ}) Y_{rqs}^{RQ}\right] -$$

$$[\sum_{m\in M}\sum_{j\in J} E(\tilde{e}_{mj})\, d_{mj} Y_{mjs}^{MJ} + \sum_{j\in j}\sum_{i\in I} E(\tilde{e}_{ji}) d_{ij} Y_{jis}^{JI} +$$
$$\sum_{i\in I}\sum_{j\in J} E(\tilde{e}_{ij}) d_{ij} Y_{ijs}^{IJ} + \sum_{j\in J}\sum_{k\in K} E(\tilde{e}_{jk}) d_{jk} Y_{jks}^{JK} + \sum_{k\in K}\sum_{l\in L} E(\tilde{e}_{kl})\, d_{kl} Y_{kls}^{KL} +$$
$$\sum_{l\in L}\sum_{r\in R} E(\tilde{e}_{lr}) d_{lr} Y_{lrs}^{LR} + \sum_{l\in L}\sum_{m\in M} E(\tilde{e}_{lm}) d_{lm} Y_{lms}^{LM} +$$
$$\sum_{l\in L}\sum_{n\in N} E(\tilde{e}_{ln}) d_{ln} Y_{lns}^{LN} + \sum_{l\in L}\sum_{q\in Q} E(\tilde{e}_{lq}) d_{lq} Y_{lqs}^{LQ} +$$
$$\sum_{r\in R}\sum_{q\in Q} E(\tilde{e}_{rq}) d_{rq} Y_{rqs}^{RQ} + \sum_{q\in Q}\sum_{m\in M}\sum_{a\in A} E(\tilde{e}_{qm})\, d_{qm} Y_{qmas}^{QMA}]\,\} \quad (30)$$

In LLAM model, the constraints of Eqs.(16) ~ (18) with fuzzy numbers can be transformed as Eqs.(31) ~ (33), and Eqs.(34) ~ (36) in LUAM model.

$$\sum_{m\in M} Y_{lms}^{LM} \le [\mu_1 - \delta_l a_1^a] \sum_{k\in K} Y_{kls}^{KL} \quad \forall l \in L \quad (31)$$

$$\sum_{q\in Q} Y_{lqs}^{LQ} \le [\mu_2 - \varphi_l a_2^a] \sum_{k\in K} Y_{kls}^{KL} \quad \forall l \in L \quad (32)$$

$$\sum_{n\in N} Y_{lns}^{LN} \le [\mu_3 - \eta_l a_3^a] \sum_{k\in K} Y_{kls}^{KL} \quad \forall l \in L \quad (33)$$

In LUAM model, the constraints of Eqs. (16) ~ (18) with fuzzy numbers can be transformed as Eqs. (34) ~ (36).

$$\sum_{m\in M} Y_{lms}^{LM} \le [\mu_1 + (1-\delta_l)\beta_1^a] \sum_{k\in K} Y_{kls}^{KL} \quad \forall l \in L \quad (34)$$

$$\sum_{q\in Q} Y_{lqs}^{LQ} \le [\mu_2 + (1-\varphi_l)\beta_2^a] \sum_{k\in K} Y_{kls}^{KL} \quad \forall l \in L \quad (35)$$

$$\sum_{n\in N} Y_{lns}^{LN} \le [\mu_3 + (1-\eta_l)\beta_3^a] \sum_{k\in K} Y_{kls}^{KL} \quad \forall l \in L \quad (36)$$

It is necessary to mention that the above results were obtained based on the following parameters,

$$\lambda = 0.5, 0.5 \le \delta_l \le \varphi_l \le \eta_l \le 1.$$

Therefore, the second-stage model can be transformed into two deterministic models, such as LLAM model with an objective function Eq. (30) and constraints Eqs. (9)～(15), (19)~(28) and (31)~(33), and LUAM model with an objective function Eq.(30) and constraints Eqs.(9)～(15), (19)~(28) and (34)~(36).

4.2. Benders Decomposition (BD) Method

BD is an efficient framework to solve a large-scale MIP model. It separates the problem into two related problems (a master problem and subproblem), these two problems are solved iteratively in a delayed-constraint-generation fashion and finally converge to a global optimal solution.

The procedure of the BD algorithm is summarized as follows:

Step 1: initialize $UB = \infty, LB = +\infty, Gap = \varepsilon$;

Step 2: solve the master problem and obtain solution $\bar{w}_j, \bar{x}_k, \bar{y}_l, \bar{z}_n$ and obtain value z_m, then set $LB = max\{z_m, LB\}$;

Step 3: solve the subproblem, and obtain the optimal objective value z_s,

if all subproblem are optimal, obtain the optimal value z_s, add the optimality Benders cut to the master problem, and $UB = \min\{zs, UB\}$, calculate $GAP = (UB - LB)/UB$;
else
all the feasibility Benders cut to the master problem, go to Step 2;
Step 4: if $GAP < \varepsilon$, Stop, output the optimal value.

5. Numerical Experiments

In this section, we conduct three problems set with different sizes and each set include 10 problem instances. We summarize the values of the parameters that determine the size of our problem instances in Table 2. Note that K1 and K2 are constructed to investigate the impact of the number of scenarios on the performance of the solution methods, and K2 and K3 are constructed to illustrate the impact of other size-determining problem parameters. Our problem instances are generated based on the instances used by [11]. We coded the proposed solution methods in JAVA using CPLEX Concert Technology and executed the numerical experiments on an Intel Core i7 PC with3.10GHz processor and 16GB RAM. We use 0.1% optimality gap and 3-hour time limit as the termination conditions.

Table 2. Problem sets.

	I	J	K	L	M	N	R	Q	A	S
K1	8	5	3	4	2	3	3	4	5	50
K2	8	5	3	4	2	3	3	4	5	250
K3	20	10	5	6	2	4	2	3	5	250

Therefore, the optimal value of net profits of the total system is shown in Table 3.

Table 3. The optimal value of the problem sets.

	K1	K2	K3
1	9435290862	2733911586	2710907444
2	9211177263	2620003588	2661028416
3	9629308934	2754895399	2826882003
4	9518217995	2643446029	2622872451
5	9236811276	2526208161	2655146645
6	9523898589	2821475222	2557095382
7	10689490829	2599435760	2599359153
8	9241658805	2632184998	2701345969
9	10409954171	2758411030	2799289892
10	10241622379	2746660933	2757610860

The above results show that the BD algorithm has a good convergence property and is very efficient in solving large-scale problem.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (Program No.71401133), National Science Basic Research Plan in Shaanxi Province of China (Program No. 2020JM466).

References

[1] K. Subulan, A. Baykasoglu, F.B. Ozsoydan, A.S.Tasan and H.Selim, " A case-oriented ap- proach to a lead/acid battery closed-loop supply chain network design under risk and uncertainty," J. Manuf. Syst., vol. 37, pp.340-61, 2015.

[2] M. Ramezani, M. Bashiri and R.Tavakkoli-Moghaddam, "A new multi-objective stochastic model for a forward/reverse logistic network design with responsiveness and quality level," Appl. Math. Model., vol. *37*, pp.328–344, 2013.

[3] K.Govindan, H. Soleimani and D.Kannan, "Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future,"Eur. J. Oper. Res., vol. 240, pp, 603–626,2015.

[4] L.Zhen, L.Huang and W.Wang,"Green and sustainable closed-loop supply chain network design under uncertainty," J. Clean Prod., vol. *227*, pp,1195–1209, 2019.

[5] E.Keyvanshokooh, S.M.Ryan, and E., Kabir, "Hybrid robust and stochastic optimization for closed-loop supply chain network design using accelerated," Eur. J. Oper. Res., vol. 249(1), pp. 76-92, 2016.

[6] L.J. Zeballos, C.A. Mendez, and A.P. Barbosa-Povoa, "Integrating decisions of product and closed-loop supply chain design under uncertain return flows," Comput. Chem. Eng., vol, 112, pp, 211–238, 2018.

[7] A.M. Fathollahi-Fard, M. Hajiaghaei-Keshteli and S. Mirjalili, "Multi-objective stochastic closed-loop supply chain network design with social considerations," Appl. Soft. Comput. vol.71, pp,505–525, 2018.

[8] S. Baptista, A.P. Barbosa-Povoa, L.F. Escudero, M.I. Gomes and C. Pizarro, " On risk management of a two-stage stochastic mixed 0–1 model for the closed-loop supply chain design problem," Eur. J. Oper. Res., vol. 274(1), pp, 91–107, 2019.

[9] M.Alegoz, O.Kaya and Z.P.Bayindir, "Closing the loop in supply chains: Economic and environmental effects," Comput. Ind. Eng., vol. 142, pp,106366.1-106366.15, 2020.

[10] Xu J, Zhou X. Approximation based fuzzy multi-objective models with expected objectives and chance constraints: Application to earth-rock work allocation[J]. Information Sciences, 2013, 238: 75-95.

[11] Uster H, Memisoglu G. Biomass logistics network design under price-based supply and yield uncertainty [J]. Transportation Science, 2018, 52(2):474-492.