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ORIGINAL RESEARCH

Big data-driven optimization for sustainable reverse logistics network design

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Abstract

The reverse logistics network (RLN) design for sustainable supply chain management is a strategic decision in network configuration, and is higher influenced by uncertainty. This paper applies a bi-level stochastic multi-objective model to design an RLN for a disposable product recycling management system. The goal is to balance the overall network cost against the associated environmental risks. An LP-metric based sample average approximation is formulated to solve the optimization problem. The model is validated numerically through a disposable product firm.

Keywords Sustainable-resilient reverse logistics · Recycling · Sample average approximation · Big data

1 Introduction

Numerous strategies are used to address the sustainability problem in Supply Chain Management (SCM), notably the detrimental environmental influence (Gholizadeh and Fazlollahtabar 2020). Deeper consumer-industry engagement has led to win–win interactions in SCM with improved social welfare and higher consumer surplus. Indeed, the traditional maxims of low cost and superior quality control no longer suffice as requisite competitive advantage for firms. With growing competition and awareness of environmentalism, the design of a circular economy through reverse logistics engenders new challenges that have a substantial role in economic development through repurposing products and keener competition (Fathollahi-Fard et al. 2021). The goals of implementing such a system include lower costs, higher service levels, and better awareness of the social and environmental dimensions (Gholizadeh et al. 2021). Put simply, the imperative for firms today is to design an end-to-end supply chain which acknowledges and complies with the environmental and social yardsticks (Singh et al. 2019). As such, recycling is widely accepted and practised, either willingly or through regulatory compliance. The recycling process seeks to achieve the optimal use of resources by converting waste into alternative materials to satisfy the economic and environmental aspects in a supply chain (Zhu et al. 2021). In this regard, disposable plastic products, while offering user convenience, actually pose more risk for people and the environment. Along with the culture of reducing the use of disposable products, recycling these products can help to reduce the risks to public health as well as yield cost savings, for instance, polystyrene wastes such as the disposable cutlery found in fast food and styrofoam packaging found in consumer electronics respectively. Currently, such polystyrene products are reprocessed in unhealthy, unauthorized workshops in developing countries, creating

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hazards downstream, and with a large amount of polystyrene discarded throughout the supply chain.

In the recycling of polystyrene products, beyond the economic considerations, the technical and process aspects are also key elements. By controlling the operating conditions and using catalysts to increase the quality of the products, the recovery of polystyrene waste can help to mitigate the destructive environmental effects and improve the economic aspects. Thus, designing an RLN for polystyrene-based disposable products can help to foster sustainability in the product eco-system. In such a system, the return flows are managed by exploiting the product, as much as possible, its components at the end of their life, promoting the best use of resources with the least environmental impact. That said, the RLN design of a disposable products system is a complicated multi-stage decision making problem involving several specifications related to the treatment site and size, recycling of the disposable products among the various facilities. Furthermore, RLN design is a strategic decision making under uncertainty, affecting the recycling of the disposable products, the cost of transportation, the consumption rate of the products, which can complicate the decision-making process. Hence, we introduce a bi-level stochastic multi-objective model for the RLN design of a disposable product recycling system under uncertainty.

This paper provides a modeling framework for the design of a Sustainable Resilient RLN (SRRLN) for disposable polystyrene appliances in Iran. The objective is to aid in the long-term decision-making of a multi-level sustainable RLN for disposable products within an uncertain environment using big data.

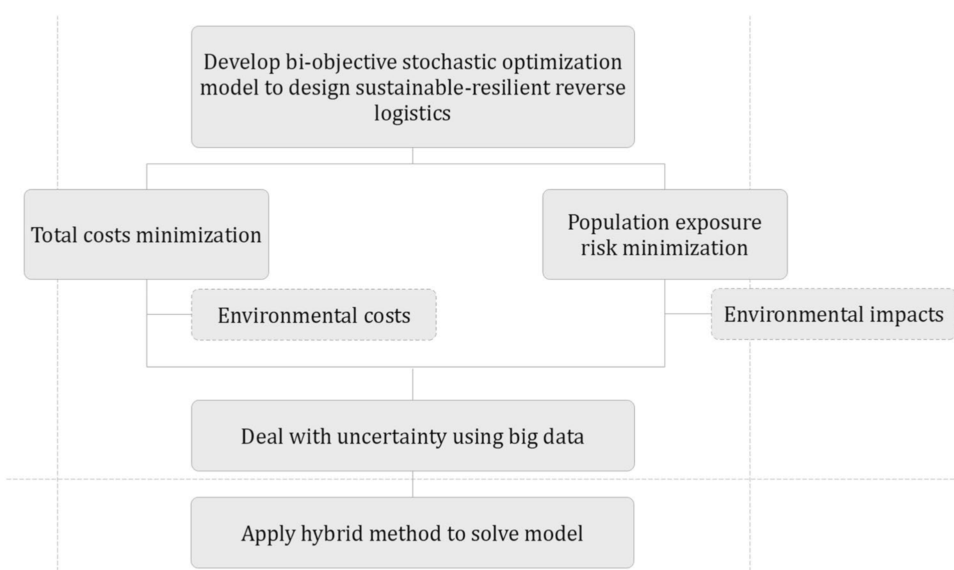
Specifically, we address the following research questions:

- How does the proposed approach lead the uncertainty of input information with big data characteristics in the design of the network to a better solution?
- How can all economic and environmental criteria be balanced at the same time with the stochastic model?

This paper offers several contributions. First, whilst there are several papers in the supply chain network design literature that integrate environmental costs, this study presents a new framework for integrating sustainability and resilience, and RLN disposable products that considers GHG emissions costs (environmental cost). Second, while there are several papers considering various forms of uncertainty, our model takes uncertainty into account in all of the main parameters associated with an RLN. Third, we entertain the question of the degree of redundancy needed in the facilities when deliberating on a robust RLN. Fourth, a solution approach using stochastic optimization and a hybrid algorithm, the SAA-LP, for the multi-objective RLN model, involving multi-levels, multi-periods, multi-products, and multi-carriers, is cast to speak to an actual problem on the ground. Figure 1 shows the research framework. The proposed structure for the 5 V data representation is presented through intra-data heterogeneity and the V's. Pilka Plast Haraz (PPH) which produces disposable products in a northern city of Iran is used as the case firm.

The rest of this paper is set as follows. The research gap in the literature review is presented in Sect. 2. The proposed solution methodology is presented in Sect. 3. The computational experiments are contained in Sect. 4. Section 5 provides the managerial implications. Section 6 concludes with future research directions.

Fig. 1 Research framework



2 Literature review

As the importance of and concern for sustainability grow, research have sought to simultaneously improve the social and environmental factors in supply chain design on top of the economic factors. Therefore, the influence of the environmental and social elements and models of reverse logistics problems are pertinent. One aspiration is to create a model that can treat the economic, social and environmental factors collectively. Recent research inform that sustainable supply chain management (SSCM) is critical to decreasing the environmental contamination (Ansari et al. 2017). Moreover, establishing SSCM has resulted in better profit, lower cost, stronger consumer relationship, and improved brand equity (Sauer and Seuring 2018). Govindan et al. (2019) proposed a hybrid SMAA-ELECTRE I to obtain the best reverse logistics service provider. Independently, Maric and Opazo-Basaez (2019) have considered a green servitization strategy for RL, one which provides for greater flexibility and sustainability. Doing so, industry can then realise a sustainable recovery for their end-of-life products. More recently, Zarbakhshnia et al. (2020) combined fuzzy analytic hierarchy process with gray multi-objective optimization by ratio analysis (MOORA-G) to obtain the weight of each criterion, and to rank the alternatives including uncertainty to optimally choose a third-party RL provider for an auto parts firm. Trochu et al. (2020) developed a multi-objective stochastic model for RLN planning in the recycling of materials in Canada, so as to lift the expected profit and control the environmental aspects in an uncertain environment. They combined Sampling Average Approximation (SAA) with the ε-constraint method to solve their model. Agrawal and Singh (2019) had applied the partial least squares path technique to a sample of 700 electronics firms to show the effects of the recycling strategies on the triple bottom line in India's electronics sector. Further, Dutta et al. (2020) used multi-objective optimization on an RLN of the Indian e-commerce market involving product returns, considering all the factors of sustainability so as to decrease the cost and control the environmental issues. Moghaddam et al. (2019) had studied the effects of demand changes on profitability in the context of perishable products with the objective to increase the financial rewards, raise customer satisfaction, and decrease the environmental effects and network costs. Sepeher et al. (2019), recognizing that drivers such as social responsibility, demand uncertainty, environmental influences, and technological change, can lead to product risk and challenges in reverse logistics, have argued for newer ways to manage uncertainty. Keshavarz and Toloo (2019) assessed the proficiency of the RL providers operating under uncertainty. Rahimi and Ghezavati (2018) developed a CVaR model for recycling manufacturing waste in a sustainable RLN under uncertainty. Similarly, Entzaminia et al. (2016) designed a robust optimization solution to identify the candidate facilities based on demand uncertainty and the cost to run, and applied the solution to an actual case.

Indeed, designing a resilient RLN has been identified as an important constituent of SSC and GSC in assuring sustainability (Mohammed et al. 2019; Jabbarzadeh et al. 2018; Zahiri et al. 2017). There are several recent studies on resilient RLN design (Ghavamifar et al. 2018; Dehghani et al. 2018; Rezapour et al. 2017). Most of these studies focus on mitigating the disruption risk (Ghavamifar et al. 2018; Rezapour et al. 2017; Hasani and Khosrojerdi 2016; Klibi and Martel 2012) while others studied the RLN seeking to maximize the resiliency and minimize the total cost (Mohammed et al. 2019; Jabbarzadeh et al. 2018; Zahiri et al. 2017; Fattahi et al. 2017; Mari et al. 2016; Fahimnia and Jabbarzadeh, 2016). Mehrjerdi and Lotfi (2019) introduced a two-stage, mixed integer linear programing (MILP) and robust counterpoint modeling in a closed loop supply chain network to cope with demand uncertainty considering resilience, sustainability, and robustness. They used the LP-metric method on a NEOS server to study the automobile assembly industry. Jabbarzadeh et al. (2018) proposed a hybrid method involving fuzzy clustering to evaluate supplier performance in a sustainable supply network dealing with resilience and random disruptions. Their objective was to minimize the overall cost and maximize the sustainability for PVC pipe production. Also, Rajesh (2018) applied the positioning of partition lines to investigate the sequence of evolution of sustainability and flexibility in SSC networks. Kaur and Singh (2019) extended a study on cost under carbon emissions limits in resilient logistics chains by applying a cap-and-trade method. Moosavi et al. (2022) suggested disruption management strategies for use in supply chains with RLN problems.

With large data sets available at various levels of the SC, supply chain managers today seek to capitalize on using data analytics to improve supply chain performance (Gholizadeh et al. 2020a, b). In this regard, Bag et al. (2020) applied the dynamic capability theory to assess the capability of big data analytics in supporting green product development and the sustainable supply chain in South Africa. Mishra and Singh (2020a, b) examined dynamic facility allocation in sustainable RL to decrease the carbon emissions from catastrophes and combined big data with a random dataset. Recently, Gholizadeh et al. (2020a, b) developed a multi-objective fuzzy hybrid model using big data and with environmental constraints and sustainable transportation. Kaur and Singh (2018) proposed a big-data driven SSC model for greenhouse gas emissions. Govindan et al. (2018)'s survey explored opportunities for advancing big data analytics for SCM applications. They report that big data enhance business decisions by infusing intelligence into the analysis. Other studies on using big data analytics include supply chain agility, sustainability, and resilience (Wang et al. 2016).

Lotfi et al. (2022a) proposed strategies to manage inventory costs under uncertainty. They considered fuzzy robust data-driven optimization for the supply chain of sustainable resuscitation and healthcare using a Vendor-Managed Inventory (VMI) policy to improve stock management, under uncertainty and disruptions. Their results suggest varying levels of confidence in conservative decisions, including flexibility, robustness, and cost. Recently, big data sharing, blockchain-based transactions, and data redundancy have been studied, and a framework that offers transaction security and data reliability when trading in blockchain is proposed (Yang et al. 2020; Li et al. 2021).

Aside, Lotfi et al. (2022b) presented a robust multi-objective model of data-driven optimization for renewable energy location. The goal was to minimize risk and maximize profit. They used the improved augmented ε-constraint approach to produce a Pareto frontier. Govindan and Gholizadeh (2021) developed a robust optimization model for sustainable-resilient RLN using big data for end-of-life vehicles. A scenario-based Cross-Entropy (CE) algorithm was proposed to solve the model on a large scale. Their results show that changing the scenario significantly affects the optimal environmental and social costs. Soleimani et al. (2022) proposed a sustainable RLN under energy efficiency. Their model maximizes the total profit and job opportunities while minimizing the energy consumption and carbon emissions. They used two heuristics to obtain feasible solutions and they proposed an efficient reformulation model to find the most optimal solution. Seydanlou et al. (2022) studied a sustainable closed-loop supply chain model to consider the total cost, environmental pollution, and job opportunities for Iran's olive industry. Two hybrid metaheuristics were used to compare with other algorithms while validating the ε-constraint method. Gholizadeh et al. (2022) presented a robust MINLP optimization model for sustainable-green integrated RLN in polystyrene disposable appliances. They used three heuristics, namely, the cross-entropy algorithm, genetic algorithm, and simulated annealing to solve their model. Then, they used the best–worst method to evaluate the performance against the robust optimization method.

Supplementary Table 1, as found in Supplementary Materials Part A, provides a compendium of the papers relevant to this research topic. Most of the recent studies have used robust optimization to deal with uncertainty. In our work, we analyze big data using a combined SAA-LP method. In addition, arising from the literature review, this paper offers a stochastic optimization model for an SRRLN that minimizes the network cost and the environmental risk of disposable products, to holistically account for uncertainty in the parameters and decision variables.

3 Problem formulation

Our model is intended to balance the overall cost of the network and the environmental risk posed by recycling the disposable products. A bi-level decision making approach is taken to plan the recycling process. First, strategic decisions are adopted for designing the structure of the network by siting the location of the facilities. Next, allocation in terms of the tactical route planning are set as operational decisions to inform how the network for the recycling process should be performed. Figure 2 shows the network structure of the SRRLN for disposable products. The used disposable polystyrene containers are

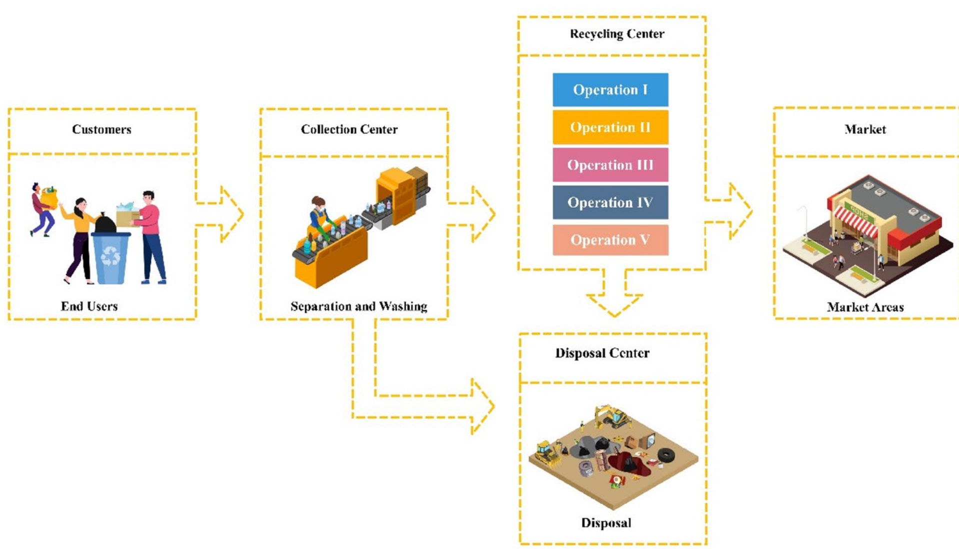


Fig. 2 Typical SRRLN

collected and sent to the collection centers. At the collection centers, the containers are visually inspected and separated, depending on the type of polymer and color. After separation and washing, these containers are sent to the recycling centers to process the recycling. The five recycling operations at the recycling centers then produce three types of products: granules, primary polystyrene, and monomers. Product #1 (granules) is obtained in the fourth recycling operation. Product #2 (polystyrene) is obtained from the second recycling operation. Product #3 (monomers) is produced in the fifth recycling operation. Sometimes, the containers cannot be recycled. For example, when containers are crushed, they come into contact with other contaminants and cannot be repurposed. The non-recyclables are disposed of. Also, some recycling centers are incapable of processing the entire set of operations. This then requires the operations to be transferred to the other recycling centers.

With uncertainty on the parameters of the SRRLN, the lack of information can complicate the decision making. As such, a stochastic optimization model based on discrete scenarios, where the probability of the occurrence of an event can be formulated for various situations, and decisions are made based on the expected uncertainty in the future. Thus, the choice of models to arrive at a decision should be robust or resilient (Gholizadeh et al. 2020a, b; Govindan, and Gholizadeh, 2021). The strategic decisions to be made during the first stage are infrastructural, i.e., where to site the centers. In the second stage, the tactical and operational decisions are resilient and are thus formulated based on the scenarios considered for maximizing the overall performance of the SRRLN. Thus, obtaining the vales of the decision variables of the network structure in the first stage affects the outcome of the second stage decisions.

Figure 3 shows how the proposed structure for large 5 V data (variety, volume, velocity, veracity, and value) relate to the model parameters, in particular the relationship to parameters such as cost, demand, capacity, and hazards.

Many stochastic models employ scenario assumptions and neglect the scenario generation process itself. So, using the SAA guarantees that our result is stable no matter which scenario tree is used. This probably can be better managed with big data. Therefore, in this study, big data is used for the sustainable management of SAA to generate a scenario (Zhuang et al. 2021). The 5 V big data attributes for each model limit are described as follows.

Variety: As the model treats different aspects of uncertainty, evident through attributes that include multi-stage, multi-period, multi-product, multi-echelons, multi-carriers, the parameters of capacity, risk, cost, and demand, will depend on time, population density, and transportation system. So, it is necessary to address the various data perspectives at different levels of the SSRLN network.

Volume: As the volume of disposable products made is large, the volume of information generated is correspondingly great and increases over time. As a result, a significant amount of data must be analyzed.

Velocity: Policies towards disposable product recycling are flexible. This then requires the model parameters to consider how the rate of change will affect the final decision in real time.

Value: The SRRLN contains large chunks of information (data) in various dimensions, and is thus valuable for informed decision making with regard to the importance of

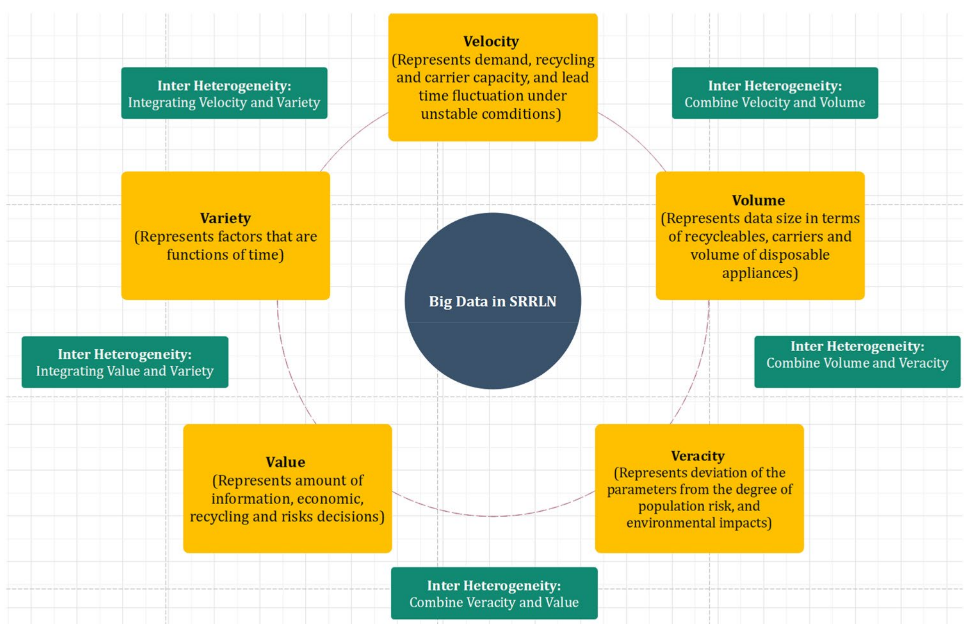


Fig. 3 5 V's for big data SRRLN

sustainability on the economic, environmental and social fronts.

Veracity: Veracity denotes the accuracy of data that is hard to control. In the model, accuracy of the data pertinent to the environmental risk is studied.

This study applies several assumptions. First, the input parameters are uncertain a priori especially in the big data set. Second, the collection, recycling, and disposal centers are known and capacitated. Third, resilience is defined based on the additional capacity afforded by a facility. Supplementary Materials Part B contains the notation of the parameters and variables used in the model. The model is now shown below.

Objective functions

$$
\begin{aligned}
\text{Min}Z_1 = & \sum_{c\in C} FCC_c \lambda C_c + \sum_{d\in D} FCD_d \lambda D_d + \Bigg[\sum_{i\in I}\sum_{r\in R} FCR_{ri}\lambda R_{ri} + \sum_{r\in R} \sigma \Delta Capr_r + \sum_{s\in S} p_s . \sum_{j\in J}\sum_{e\in E}\sum_{c\in C}\sum_{t\in T}\sum_{v\in V} TC^s_{jectv}.Xec^s_{ject} \\
& + \sum_{j\in J}\sum_{c\in C}\sum_{d\in D}\sum_{t\in T}\sum_{v\in V} TC^s_{jcdtv}.Xcd^s_{jcdt} + \sum_{j\in J}\sum_{c\in C}\sum_{r\in R}\sum_{t\in T}\sum_{v\in V} TC^s_{jcrtv}.Xcr^s_{jcrt} + \sum_{j\in J}\sum_{r\in R}\sum_{m\in M}\sum_{t\in T}\sum_{v\in V} TC^s_{jrmtv}.Xrm^s_{jrmt} \\
& + \sum_{j\in J}\sum_{r\in R}\sum_{d\in D}\sum_{t\in T}\sum_{v\in V} TC^s_{jrdtv}.Xrd^s_{jrdt} + \sum_{j\in J}\sum_{e\in E}\sum_{c\in C}\sum_{t\in T} VCC_{cts}.Xec^s_{ject} + \sum_{j\in J}\sum_{c\in C}\sum_{d\in D}\sum_{r\in R}\sum_{t\in T} VCD_{dts}.(Xcd^s_{jcdt} + Xrd^s_{jrdt}) \\
& + \sum_{j\in J}\sum_{r\in R}\sum_{i\in I}\sum_{t\in T} VCR_{rits}.Xr^s_{jrit} + \sum_{r\in R}\sum_{i\in I}\sum_{j\in J}\sum_{t\in T} ECOR_{rits}.Xr^s_{jrit} + \sum_{j\in J}\sum_{c\in C}\sum_{r\in R}\sum_{d\in D}\sum_{t\in T} ECOD_{dts}\left(Xrd^s_{jrdt} + Xcd^s_{jcdt}\right) \\
& + \sum_{j\in J}\sum_{e\in E}\sum_{c\in C}\sum_{r\in R}\sum_{d\in D}\sum_{t\in T} EC_t.\left(.Xec^s_{ject} + Xrd^s_{jrdt} + Xcd^s_{jcdt} + Xcr^s_{jcrt} + Xrm^s_{jrmt}\right)\Bigg] \\
& + \sum_{c\in C} ECC_c \lambda C_c + \sum_{d\in D} ECD_d \lambda D_d + \sum_{i\in I}\sum_{r\in R} ECR_r \lambda R_{ri}
\end{aligned} \tag{1}
$$

The first objective function (Eq. 1) seeks to minimize the total cost of the RLN, including the fixed costs of opening the facilities, expansion cost for increasing the capacity of the recycling centers, transportation costs generated to move the product between facilities, operating cost of the facilities and the environmental cost.

$$
\begin{aligned}
\text{Min } Z_2 = & \sum\nolimits_{s\epsilon S} p_s \Bigg[\sum_{j\epsilon J}\sum_{e\epsilon E}\sum_{c\epsilon C}\sum_{r\epsilon R \sum_{d\epsilon D}}\sum_{i\epsilon I \sum_{t\epsilon T}}\sum_{v\epsilon V} PR_{vts}(.Xec^s_{ject} + Xrd^s_{jrdt} + Xcd^s_{jcdt} + Xcd^s_{jcrt}Xrm^s_{jrmt}) \\
& + \sum_{c\epsilon C}\sum_{t\epsilon T} PRC_{cts}.\lambda C_c.POC_{cts} + \sum_{c\epsilon C}\sum_{t\epsilon T} PRD_{dts}.\lambda D_d.POD_{dts} + \sum_{c\epsilon C}\sum_{i\epsilon I}\sum_{t\epsilon T} PRR_{rts}.\lambda R_{ri}.POR_{rts}\Bigg]
\end{aligned} \tag{2}
$$

The second objective function (Eq. 2) seeks to minimize the health hazard, namely, the opening of recycling centers and CO_2 emissions when moving the product between facilities.

Network balance constraints

$$\sum_{e\in E}\sum_{c\in C}\sum_{d\in D} Xec^s_{ject}.\delta_{jcds} = \sum_{c\in C}\sum_{d\in D} Xcd^s_{jcdt} \qquad \forall j,t,s \tag{3}$$

$$\sum_{e\in E}\sum_{c\in C}\sum_{d\in D} Xec^s_{ject}.\left(1-\delta_{jcds}\right) = \sum_{c\in C}\sum_{r\in R} Xcr^s_{jcrt} \qquad \forall j,t,s \tag{4}$$

$$\sum_{c\in C}\sum_{r\in R}\sum_{i\in I} Xcr^s_{jcrt}.\alpha_{jris} = \sum_{r\in R}\sum_{m\in M}\sum_{i\in I} Xrm^s_{jrmt} \qquad \forall j,t,s \tag{5}$$

$$\sum_{c\in C}\sum_{r\in R}\sum_{i\in I} Xcr^s_{jcrt}.\left(1-\alpha_{jris}\right) = \sum_{r\in R}\sum_{d\in D}\sum_{i\in I} Xrd^s_{jrdt} \qquad \forall j,t,s \tag{6}$$

$$\sum_{r\in R}\sum_{m\in M}\sum_{i\in I} Xrm^s_{jrmt} = \sum_{r\in R}\sum_{i\in I} Xr^s_{jrit} \qquad \forall j,t,s \tag{7}$$

$$\sum_{r\in R}\sum_{d\in D}\sum_{i\in I} Xrd^{s}_{jrdt}.\left(1-\alpha_{\mathrm{jris}}\right) = \sum_{r\in \mathbf{R}}\sum_{i\in \mathbf{I}} Xr^{s}_{jrit} \qquad \forall j,t,s \tag{8}$$

$$\sum_{j\in J}\sum_{e\in \mathbf{E}}\sum_{t\in \mathbf{T}}\sum_{s\in S} Xec^{s}_{ject} \le InfN.\lambda C_c \qquad \forall c \tag{9}$$

$$\sum_{j\in J}\sum_{c\in C}\sum_{t\in T}\sum_{s\in S} Xcr^{s}_{jcrt} \le InfN.\lambda R_r \qquad r \tag{10}$$

$$\sum_{j\in J}\sum_{r\in R}\sum_{t\in T}\sum_{s\in S} Xrd^{s}_{jrdt} \le InfN.\lambda D_d \qquad \forall d \tag{11}$$

$$\sum_{j\in J}\sum_{c\in C}\sum_{t\in T}\sum_{s\in S} Xcd^{s}_{jcdt} \le InfN.\lambda D_d \qquad \forall d \tag{12}$$

$$\sum_{j\in \mathbf{J}}\sum_{t\in \mathbf{T}}\sum_{s\in S} Xr^{s}_{jrit} \le InfN.\lambda R_{ri} \qquad \forall r,i \tag{13}$$

Constraints (3–8) and (9–13) set the bounds on the product flow. Constraints (3) and (6) guarantee sufficient inflow into a disposal center. Constraints (4) and (5) show the balance between the in- and out-flows for the collection centers. Constraints (7) and (8) set the balance between the in- and out-flows for the recycling centers. Constraints (9–13) ensure that a facility which is open has flows.

Demand constraints

$$\sum_{r\in \mathbf{R}} Xrm^{s}_{jrmt} \le D_{\mathrm{mjts}} \to \forall m,j,t,s \to \tag{14}$$

Constraint (14) shows the relationship between the recycled product sent to the market and its demand.

Capacity constraints

$$MCR_r.BCapr_r \le \Delta Capr_r \le MMR_r.BCapr_r \qquad \forall r \tag{15}$$

$$\Delta Capr_r + BCapr_r = Capr_r \qquad \forall r \tag{16}$$

$$\sum_{j\in J}\sum_{e\in \mathbf{E}}\sum_{t\in \mathbf{T}}\sum_{s\in S} Xec^{s}_{ject} \le CapC_c \qquad \forall c \tag{17}$$

$$\sum_{j\in J}\sum_{c\in C}\sum_{t\in T}\sum_{s\in S} Xcd^{s}_{jcdt} + \sum_{j\in J}\sum_{r\in R}\sum_{t\in T}\sum_{s\in S} Xrd^{s}_{jrdt} \le Capd_d \qquad \forall d \tag{18}$$

$$\sum_{j\in J}\sum_{c\in C}\sum_{t\in T}\sum_{s\in S} Xcr^{s}_{jcrt} \le Capr_r \qquad \forall r \tag{19}$$

$$\mu \Delta Capr_r \ge \rho \qquad \forall r \tag{20}$$

Constraints (15) and (16) set the capacity. Constraints (17–19) guarantee that the product flow between facilities cannot exceed its capacity of a facility. Constraint (20) sets the resilience limit for increasing capacity.

4 Solution approach

A stochastic optimization model is suited for modeling problems which contain uncertain information, and it can be modeled non-linearly (Yu and Solvang 2018, 2020). As many scenarios can be played out in reality, the SAA method is used to solve the stochastic model using Monte Carlo simulation (Ayvaz et al. 2015; Schütz et al. 2009). Also, the SRRLN is multi-objective in nature, to concurrently balance the total cost and the health risks posed by the operations at the facility and during transportation, the LP-metric method is used to solve the problem to optimality. The LP-metric method minimizes the deviation of the objective function from its ideal solution, which is a global optimum point for all goals. In the LP-metric method, the distance metric measures the proximity of a solution to the ideal solution.

4.1 SAA-LP method

Many stochastic models employ scenario assumptions and neglect the scenario generation process itself, so using the SAA guarantees that our result is stable no matter which scenario tree is used. The SAA method assesses the quality and reliability of the result based on the size of the sample that was examined. Two indicators are applied—the lower and upper bound estimators. The lower bound estimators examine the consistency of the samples, that is, when we generate a number of test instances with the same sample size from the same possibility distribution, the objective values are constant over all the test instances (with sufficiently small standard deviations). The upper bound estimators evaluate the quality of the solution of the SAA to the primary problem. The size of the problem is demonstrated by the reference sample. As the decision in the first-stage has been found a priori, the problem would be an LP that can be easily solved. The difference among the lower bound and the upper bound sets the level of confidence of the SAA solution to the problem. If the quality requirement is not achieved, then the sample size or number of iterations is increased and the estimators are re-computed. To solve a multi-objective optimization problem, we first identify the relevant single objective problems using SAA, and then define the appropriate sample size and perform the repetitions. The outputs are the optimal values of each single objective optimization problem, which will become the target values of each objective function in the LP-metric. The LP-metric is solved and the SAA represents a suitable sample size to approximate the value of the original stochastic problem. If all the quality criteria are met, the model needs to be run with the offered sample size only once.

The notation and terms for the SAA-LP algorithm used in this study are in Supplementary Materials part C. The steps for the SAA-LP method are as follows:

Step 1: Form the multi-objective stochastic model as follows.
Objective function (total cost): Eq. (1) and Constraints (3–20)
Objective function (health hazard): Eq. (2) and Constraints (3–20).
Step 2: Adjust and generate the scenarios, number of iterations, and sample size based on the probability distribution of the parameters, set as Sample R and scenario Q respectively.
Step 3: Solve each goal iteratively and evaluate the results using Suplementary Eqs. (23–28).
Step 4: Appraise the efficiency of the estimators with respect to Q and R for both objective functions. If the requirements are met, go to step 5; otherwise, increase the sample size and repeat Steps 2–4.
Step 5: Obtain the best first-stage decision selection for the single-objective model defined in Step 1 by testing each of the candidates in the reference sample.
Step 6: Set the goals for each objective function of the stochastic optimization problem.
Step 7: Find the weight vector of the objective functions and convert the main bi-objective stochastic problem into an LP-metric using Eq. (29).
Step 8: Optimize the LP-metric for various scenarios Q using specific weights over R repetitions. Use the problem objectives for each optimal solution according to Supplementary Eqs. (23–28) to assess the performance of the objectives.
Step 9: Appraise the efficiency. If it is met, goto step 10. Otherwise, repeat Steps 2–9 using a larger sample.
Step 10: Select the optimal first-stage decision variables for locating the facilities. Obtain the deviation of each objective by solving the reference sample by combining the weighted LP-metric.

On the two-stage part, it is common for an SRRLN problem, where first-stage binary variables determine the locations (how to set up the network configuration) and second-stage variables determine how to use the network. The two-stage decisions have different sensitivities to the planning horizon. The second stage decisions such as allocation, inventory policy, and routing can be easily re-optimized with the change in the external environment.

5 Numerical example

The case study focuses on Pilka Plast Haraz (PPH), a polymer player located in the North of Iran. PPH makes disposable products and polystyrene sheets for the dairy and food companies. PPH wants to recycle polystyrene ethically but due to market uncertainty, the company has to decide on the best course of action to balance the cost economics and obligations to the environment. Procuring petrochemical raw materials and selling products cheap in a competitive market

Fig. 4 Data management system of case study

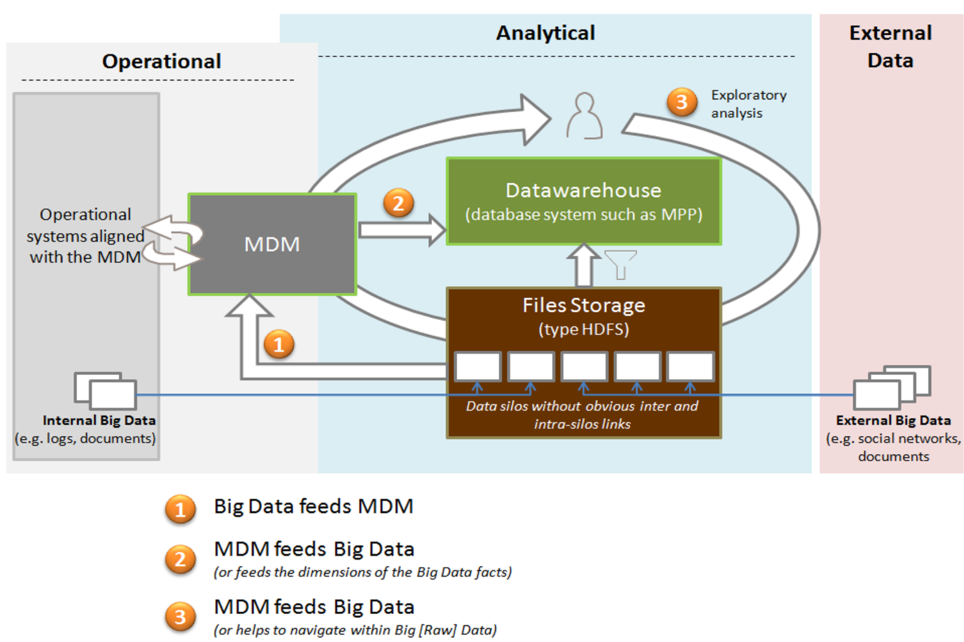


Table 1 SAA results

P. no	Sample size	Repetition	Objective function	Lower bound		Upper bound		Gap estimator		
				Equation (23)	Equation (24)	Equation (25)	Equation (26)	Equation (27)	%	Equation (28)
1	$Q = 10$	$R = 10$	OBJ1	1,505,052	55,675	1,558,700	85,066	6772	0.01576	87,040
			OBJ2	1,700,147	75,050	2,155,123	105,050	15,319	0.01589	106,688
	$Q = 30$		OBJ1	1,310,140	51,228	1,558,700	85,066	7320	0.01681	86,165
			OBJ2	2,102,580	72,400	2,122,345	165,665	7340	0.00752	166,819
	$Q = 50$		OBJ1	1,400,250	49,040	1,558,700	85,066	−144	0	85,548
			OBJ2	2,215,025	67,457	2,200,589	217,400	−5260	−0.0055	218,011
2	$Q = 10$	$R = 10$	OBJ1	2,212,120	62,900	2,410,055	98,100	7810	0.01817	100,376
			OBJ2	2,955,360	95,770	3,576,482	170,401	24,849	0.02577	173,058
	$Q = 30$		OBJ1	2,102,583	59,015	2,410,055	98,100	8442	0.01938	99,367
			OBJ2	3,501,470	88,002	3,517,814	275,800	12,220	0.01251	277,721
	$Q = 50$		OBJ1	2,500,052	53,747	2,531,851	98,100	−166	0	98,656
			OBJ2	3,750,147	84,078	3,709,318	347,022	−8396	−0.00877	347,997
3	$Q = 10$	$R = 10$	OBJ1	3,965,400	80,258	4,010,220	115,299	9179	0.02136	117,975
			OBJ2	5,102,583	122,580	5,780,044	250,369	36,510	0.03787	254,273
	$Q = 30$		OBJ1	3,910,250	75,023	4,010,220	115,299	9922	0.02278	116,789
			OBJ2	5,729,540	100,478	5,751,103	310,478	13,756	0.01409	312,641
	$Q = 50$		OBJ1	4,756,981	70,253	4,775,500	115,299	−195	0	115,952
			OBJ2	6,503,970	95,070	6,491,570	450,852	−10,908	−0.01140	452,119

is critical to PPH's survival. However, PPH is under pressure to recycle the used products. This is aggravated by the data uncertainty arising from sources such as collection, disposal, recycling, and market demand. Using the 5 V's approach, the velocity of demand, expenses, risk, and capacity variety vary a fair bit, and the volume of disposable products is high. As a result, the volume of information produced is exponential. Hence, as the SRRLN has copious amounts of data, the parameters need to be calibrated to match the veracity of the requisite data. In the model, the interactive data logs are transformed into data useful for decision making (Fig. 4). The data warehouse for the SSRLN is formed by extracting, converting and loading the data onto the data archives and processed in the main data management system (Lan et al. 2017).

The model is coded in GAMS 2017. The computations are performed on a PC with Intel(R) Core (TM) i5-5200U CPU @2.20 GHz in Windows 10. Following Mishra and

Table 2 First-stage decisions for objective functions with 10 repetitions ($Q = 50$, $w_1 = w_2 = 0.5$)

P. no	Repetition	OBJ1		OBJ2		First-stage decision			CPU Time (s)
		Value	% Deviation	Value	% Deviation	*C*	*R*	*D*	
2	$R = 1$	2,660,871	0.596152	3,802,794	0.013617	1,2	1,2,5	2	12.3
	$R = 2$	2,729,702	0.353856	3,349,031	0.141119	2,3	1,2,5	2	12.8
	$R = 3$	2,480,659	0.485126	3,853,862	0.137123	2,3	1,2,5	2	13.2
	$R = 4$	2,465,590	0.457232	3,694,291	0.049041	2,3	1,2,5	2	13.6
	$R = 5$	2,301,889	0.237950	3,458,694	0.210460	1,3	1,2,5	2	13.9
	$R = 6$	2,552,492	0.268160	3,680,262	0.217558	1,3	1,2,5	2	14.1
	$R = 7$	2,771,827	0.526987	3,599,343	0.059268	1,2	1,2,5	2	14.4
	$R = 8$	2,304,636	0.428297	3,711,163	0.042200	1,3	1,2,5	2	14.9
	$R = 9$	2,714,827	0.512465	3,436,698	0.081685	2,3	1,2,5	2	15.3
	$R = 10$	2,804,337	0.273262	3,376,018	0.206947	1,2	1,2,5	2	15.6

Table 3 SAA-LP results with 10 repetitions and $Q = 50$, $w_1 = w_2 = 0.5$

P. no	Objective	Lower bound		Upper bound		Percent gap		
		Eq(23)	*Eq*(24)	*Eq*(25)	*Eq*(26)	*Eq*(27)	%	*Eq*(28)
2	OBJ1	2,500,052	53,747	2,531,851	43,190	31,799	0.068	68,950
	OBJ2	3,750,147	84,078	3,709,318	347,022	−40,828	−0.040	357,062

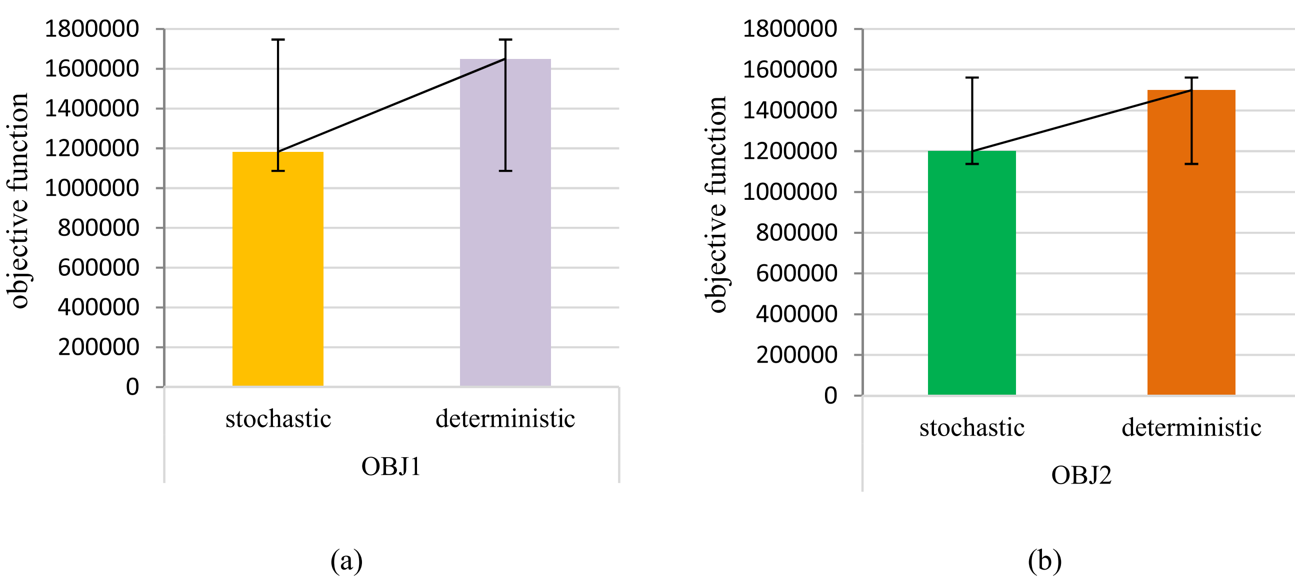


Fig. 5 Comparison of deterministic and stochastic models by objective function

Singh (2020a, b), we choose a uniform distribution to create the data randomly for the case study (Supplementary Table 2). To conduct the SAA-LP method, we conduct a test with various sample sizes with 10, 30, and 50 scenarios, of 10 replications each. The reference sample size is taken as 500 scenarios.

5.1 Computational analysis

To validate the model, 3 tests with various problem sizes are used (Table 1). Supplementary Table 2 provides the estimates of the model parameters as found in Supplementary Materials part D.

To assess the output quality of the first stage, SAA was examined for each of the proposed targets and computed using the equations in Sects. 3 and 4. Table 1 shows the statistical estimates for the lower and upper bounds. As can be seen from Table 2, for only the lower bound, the variance decreases with increasing sample size. Also, considering the estimated optimality gap, it is important to note that by increasing sample size from 10 to 30, the gap was relatively stable, but from 30 to 50, the gap narrowed, which has been relatively stable with increasing problem size.

Clearly, sample size influences solution quality. Therefore, repeatedly solving the model provides a robust decision for the reference sample, so $Q = 50$ was selected to test the LP problem (Table 2).

We take the optimization of the single objective as LP goals based on minimum cost and risk. The results of minimizing the weight deviation of the objectives for the SAA-LP problem with $Q = 50$ and 10 repetitions are given in Table 2. Table 2 shows the values of the objective functions which are the deviation of the optimal solution of each iteration from the decision obtained in the first stage. The trade-offs between the weighted cost and the risk deviations provide the optimal solution.

From Table 3, the outputs are used to assess the quality of the goals in the SAA-LP problem. Based on these results, and comparing with the single objective optimization, the estimated optimality gap is now higher. However, this guarantees a reasonable solution. In the best solution, the deviations of OBJ1 and OBJ2 are 2.762% and 2.078%, respectively.

From Fig. 5, for the deterministic solution case, due to the limited capacity in the recycling centers and to handle the market demand fluctuations, more centers need to be opened, leading to increased cost and risk. Hence, the stochastic model provides a sharper estimate of the cost and risk values.

The expected value of modelling uncertainty is a benefit indicator arising from using a stochastic model (Yu et al.

Table 4 Sensitivity analysis of SAA-LP results

Weight w_1	Objective function	Lower bound		Upper bound		Gap estimator		
		Eq (23)	Eq (24)	Eq (25)	Eq (26)	Eq (27)	%	Eq (28)
0	OBJ1	5,550,789	302,268	5,622,190	76,518	71,401	0.119	311,803
	OBJ2	1,200,500	8000	1,197,919	106,646	−2580	−0.002	106,945
0.1	OBJ1	4,240,283	286,787	4,571,412	68,929	331,129	0.662	294,954
	OBJ2	1,870,350	15,559	1,854,108	165,073	−16,241	−0.016	165,805
0.2	OBJ1	3,905,630	24,507	3,890,694	66,975	−14,935	−0.031	71,318
	OBJ2	2,150,369	22,591	2,159,100	201,870	8731	0.008	203,130
0.3	OBJ1	3,453,647	21,880	3,440,107	59,146	−13,539	−0.028	63,063
	OBJ2	2,764,010	29,067	2,775,328	259,497	11,318	0.011	261,120
0.4	OBJ1	2,850,147	18,667	2,839,586	48,640	−10,560	−0.022	52,099
	OBJ2	3,300,140	34,837	3,313,239	309,899	13,099	0.013	311,852
0.5	OBJ1	2,500,052	53,747	2,531,851	43,190	31,799	0.068	68,950
	OBJ2	3,750,147	84,078	3,709,318	347,022	−40,828	−0.040	357,062
0.6	OBJ1	2,200,310	5134	2,199,374	39,676	−935	−0.001	40,007
	OBJ2	4,104,200	23,465	4,109,472	386,342	5272	0.005	387,053
0.7	OBJ1	1,850,340	4116	1,849,346	33,192	−993	−0.002	33,446
	OBJ2	4,625,801	24,226	4,628,092	435,496	2291	0.002	436,169
0.8	OBJ1	1,456,966	4034	1,454,439	27,365	−2526	−0.005	27,661
	OBJ2	5,203,001	42,734	4,620,581	434,789	2287	0.002	435,461
0.9	OBJ1	1,136,200	3882	1,131,154	21,264	−5045	−0.011	21,616
	OBJ2	5,650,347	60,788	5,679,084	512,693	28,737	0.024	516,284
1	OBJ1	972,123	1940	972,092	18,192	−30	0	18,295
	OBJ2	6,250,147	50,404	6,247,161	564,783	−2985	−0.002	567,028

Table 5 First-stage decisions for deterministic and stochastic models

Weight w_1	First-stage decision						EVMU %	
	Deterministic			Stochastic				
	C	R	D	C	R	D	OBJ1	OBJ2
1.0	1,3	1,2,5	2	3	1,2,5	2	0	0
0.9	2,3	1,2,5	2	2,3	1,2,5	2	0	0
0.8	1,3	1,2,5	2	1,3	1,2,5	2	0	0
0.7	1,3	1,2,5	2	1,3	1,2,5	2	8.28	9.15
0.6	1,2	1,2,5	1	2,3	1,2,5	1	7.36	8.29
0.5	1,2	1,2,5	1	2,3	1,2,5	1	9.48	7.14
0.4	1,2	1,2,5	1	1,3	1,2,5	1	10.30	10.75
0.3	2,3	1,2,5	1	1,3	1,2,5	1	9.25	−1.50
0.2	2,3	1,2,5	1	1,3	1,2,5	1	9.25	−1.50
0.1	2,3	3,4,5	2	1,2	1,2,5	2	0	0
0.0	2,3	3,4,5	2	1,2	3,4,5	2	0	0

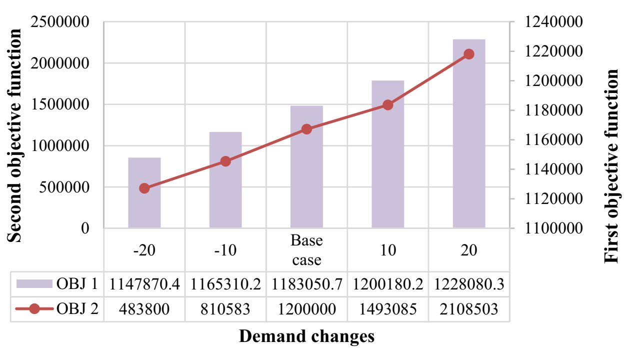


Fig. 6 Sensitivity analysis of demand on objective functions

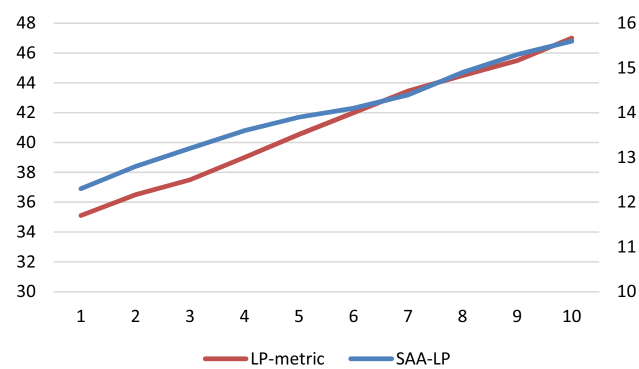


Fig. 8 Solution time comparison

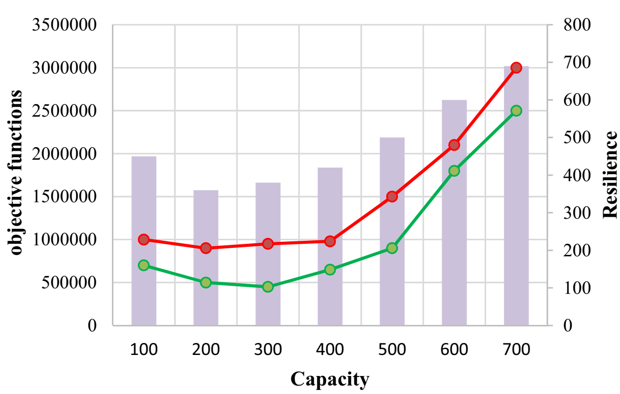


Fig. 7 Effect of capacity resilience on network objectives

2020). The EVMU is found using EVMU = Expected cost with mean-value model − Expected cost with stochastic model. We replace the mean value of the stochastic parameters with the EVMU, and re-solve the problem to get the first-stage decision. Then, using that solution, we re-solve the stochastic problem.

5.2 Sensitivity analysis

We analyze the sensitivity associated with the weight, the results of which are given in Table 4. As the weight increases from 0 to 1, the deviation of the cost objective function increases, but the deviation of the risk objective function decreases. When $w_1 = 0 and 0.1$, the level of risk is minimized, but the deviation in the cost objective function is high. When $w_1 = 0.8, 0.9, 1$, the level of cost is close to optimality, but there is much risk deviation in the objective range. This suggests that the choice of weights affects the robustness of the results and the behavior of the system, so informed decisions making is critical to the level of profitability for PPH.

With the bi-level model, a first-stage robust decision can be found. Table 5 compares the first-stage decisions of the deterministic and stochastic models. The network

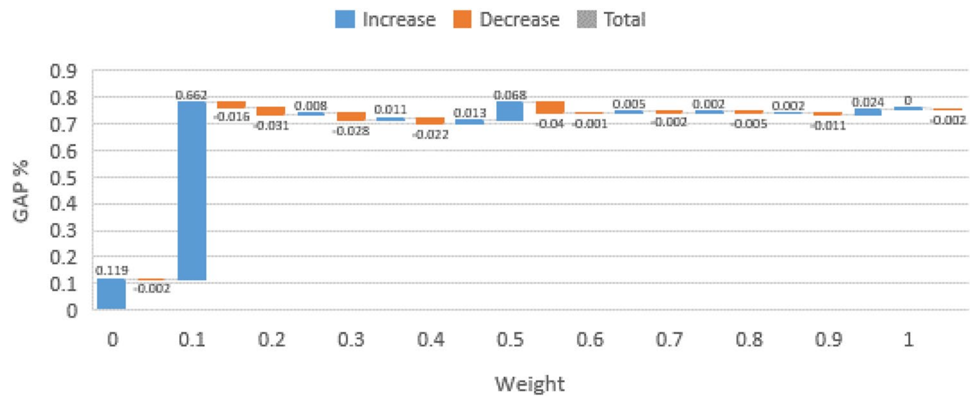


Fig. 9 Gap % against value of weight

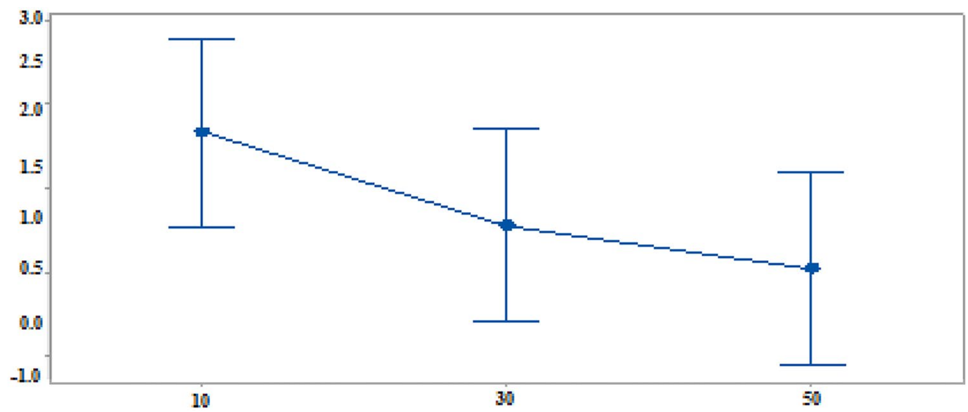


Fig. 10 Standard deviation for different sample sizes

configuration is highly dependent on the system design. Also, for some weights ($w_1 = 0, 0.1, 0.7, 0.8, 0.9, 1.$), the deterministic model yields better first-stage decisions. However, when the equilibrium solution for the deviations of the cost and the risk objective functions is obtained, the stochastic model performs better than the deterministic model. Third, for a multi-objective optimization problem under uncertainty, the performance of the individual goals may yield better outcomes, as shown with $w_1 = 0.2 and 0.3$.

From Fig. 6, clearly, the change in the parameters affects the objective functions. With more demand due to more recycling and more facilities opened, the health hazard is now greater; as the demand grows by 40%, the risk increases by 33%, while the cost increases by 7%.

From Fig. 7, if the capacity of the network is increased, the costs and risk will follow too. Using a stochastic model to increase the capacity of the recycling center by 7.04%, the performance of the disposable products recycling system will net a 12.07% decrease in total cost and a 7.17% decrease in total risk, respectively. Moreover, network capacity can be flexed to handle the demand fluctuations, at the expense of cost and risk. This can be achieved through outsourcing or reducing the service level. Building an SRRLN under uncertainty therefore supports better recycling rates, albeit generating higher costs.

5.3 Statistical comparison

Next, we compare the proposed hybrid method with the traditional LP-metric method as shown in Figs. 8 and 9. We compare the performance of two solution methods on the solution time and complexity of a multi-objective optimization problem. Due to the nature of the test problem, the goals set by both methods is similar. However, the traditional LP-metric method can only find optimal solutions near an ideal solution, while the SAA-LP method can produce optimal solutions by random distributions and the proximity of a solution to a better ideal solution. In addition, from Fig. 10 the SAA-LP method can effectively eliminate the dominant solutions, but the traditional LP-metric method cannot. Therefore, the SAA-LP method performs better. Also, the SAA-LP method performs better on computational efficiency, as the computational time required is less in most cases. However, as the interaction of the decision variables and constraints can cause conflicts in the scenarios, caution should be exercised when solving the model.

5.4 Managerial implications

The results of this study offer several implications. First, while economic costs have decreased by 31.03%, managing product recovery with specific technologies for social responsibility for developing economies like Iran is often overlooked. Thus, using this stochastic model affords a new option for industry particularly on the social obligations. The model informs that most values of the decision variables have improved by 18%. Next, on the aspect of big data, managers can achieve operational efficiency by leveraging on the positive correlation between big data analytics capability and the repurposing of used products. Developing the ability to manage big data in an SRRLN can help firms to develop the desired reverse logistics outcomes. Third, the proposed stochastic model can be used to predict the need for an upsurge in their recycling center capacity at least cost to the environment.

6 Conclusion

The use of disposable products is increasing globally. Therefore, designing a reverse logistics network is essential for reducing waste and protecting the environment. It is a complicated decision-making problem that requires an exchange between the total cost of the system and health hazards. In this study, a scenario-based approach has been used to deal with the uncertainty of some parameters. The SAA-LP method is used as a solution approach. For instance, the economic cost to PPH is 3,800,000 Tomans; our model reports 2,900,000 Tomans, which is an improvement. Furthermore, our stochastic model has measured the risk dimension. Unlike the models that focus mainly on simultaneous strategic decision-making (location) and tactical and operational decisions (allocation, routing, and inventory), our model has applied a robust and flexible decision-making approach to manage disposable product recycling. The first-stage decision under an uncertain environment was on strategic location decisions, which highlighted the optimal network configuration as a more realistic function of cost and risk. The results also suggest providing a flexible network configuration for profitable recycling.

Future research opportunities include the use of a combination of established methods such genetic algorithm with Bender's decomposition, as well as the use of pattern-based formulations. Similarly, the lexicographic weighted Chebychev method could be used as a weighting method in combination with SAA.

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Data availability statement The participants of this study did not agree for their data to be shared publicly, so supporting data are unavailable.

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