International Journal of Supply and Operations Management

IJSOM

August 2021, Volume 8, Issue 3, pp. 264-288
ISSN-Print: 2383-1359
ISSN-Online: 2383-2525
www.ijsom.com

Optimal PET Recycling Management; Applying the Conditional Value-at-Risk (CVaR) Approach under Uncertainty for a Real Case

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Abstract

In the pursuit of sustainable development goals, recycling has attracted a high level of attention around the world due to its economic and environmental benefits; however, applying the Conditional Value-at-Risk (CVaR) as an effective risk management approach for optimal Design of reverse supply chain (RSC) has been addressed by a few studies. This study mainly aims to achieve an optimal design for the RSC of recycling of polyethylene terephthalate (PET) bottles due to uncertainties in the market price of recycling materials, logistics costs, and the supply of raw materials. Considering the stochastic nature of the waste RSC parameters, two-stage stochastic programming models are developed in which the CVaR(Shortage) is utilized as a risk criterion to control shortages in demand centers. Moreover, the expected value of profit (E(Profit)) and the CVaR(Profit) are considered as two different objective functions. To evaluate efficiency and applicability, our selected models are implemented with the real data of Tehran's Municipal Waste data. Comparing the empirical results indicate that using the CVaR(shortage) is an appropriate and reasonable approach to tackle the risk of a shortage in demand centers, and can be used to design the supply chain of other case studies. Also, the CVaR(Profit)) is more conservative in the face of the risk of shortage due to the risk-taking feature embedded in the objective function, which can be adjusted based on the decision maker's preference. The results additionally indicate that transportation cost plays an essential role in the cost structure of PET recycling stages.

Keywords: Reverse logistics supply chain; Circular economy; Polyethylene terephthalate (PET) bottles; Conditional value-at-risk (CVaR); Recycling; Uncertainty.

1. Introduction

In a circular economy (CE) products are recycled, reused, or repaired rather than thrown away, and in which waste from one process becomes an input into other processes (Figure 1). The CE is now a core component both of the EU's 2050 Long-Term Strategy to achieve a climate-neutral Europe and of China's five-year plans (Preston et al., 2019). In the current age of business, where the life cycle of products is getting shorter and shorter, product return policies are characterized by fast response times and fast customer service, while there is a greater emphasis on return management, shape change, and re-storage of finished products. Collecting and recycling products after the consumption by customers and returning them to the supply chain or devastating them bring up the supply chain problem (Forouzanfar et al., 2018). New public laws and regulations related to returning products and materials also compel top managers responsible for logistics and supply chain processes to look closely at the reverse logistic (RL) process since the implementation of the RL process at different supply chain levels can increase the value of returned products for factories (Wilcox et al., 2011).

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DOI: 10.22034/IJSOM.2021.3.3

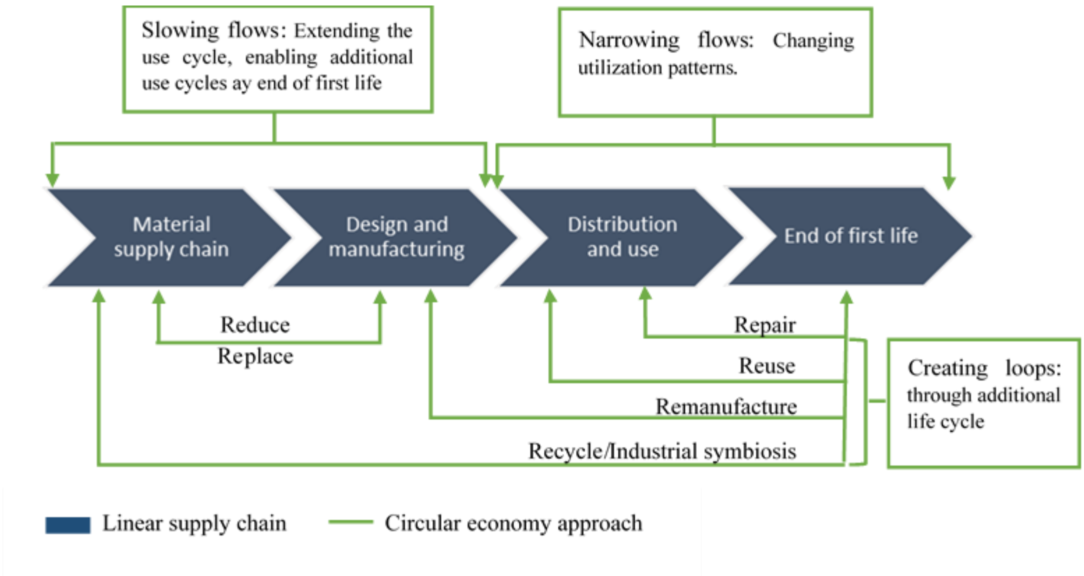

Figure 1. Circular economy activities

According to the statistics published by World Atlas (2018), Tehran is the 40th most populous city in the world with 8.43 million inhabitants. While the world's urban population growth was 1.9% in 2018, the urban population in Iran experienced a 2.1% growth (WDI, 2019). Along with the increase in urbanization growth, municipal solid waste (MSW) production (associated with air, soil, and water pollution) has increased (Chen, 2018); (Han et al., 2019); (Rai and Goswami, 2019). According to the 2018 annual report of the World Health Organization (WHO), waste production per capita is 300g per day. This figure is more than 710g for Iranians, while it is 790g in Tehran, which is 2.5 times the world average. However, the value added to waste recycling accounts for 15% of the Gross Domestic Product (GDP) of some industrialized countries. While an average of 70% of the produced waste is recycled in the world, this figure is optimistically about 20% in Iran.

Solid waste management (SWM), as an important environmental aspect, plays a major role in sustainable development (Rodić and Wilson, 2017);(Mwanza and Mbohwa, 2017); (Ferronato et al., 2018); (Das et al., 2019). In line with sustainable development, waste management is one of the main concerns, and neglecting this issue will inflict irreparable damages on the ecosystem of Iran.

In many countries, several laws and regulations have been passed and implemented in this regard. Nowadays, developed countries do not consider waste as a threat; rather, they see it as an opportunity to promote the development of the country and to supply and produce goods and energy. The adoption of the Law on Waste Management in 2004 was a giant step towards regulating proper waste management in Iran. However, the performance level of waste management in Iran is not very satisfactory. For instance, more than 58 thousand tons of waste (equivalent to 21 million tons per year) were produced in 2018 in Iran, but only 20% of this waste was recycled. Moreover, about 70 weight percent of wastes are landfilled in the metropolises of the country, which produces about 6 million tons of greenhouse gases (IPRC, 2018).

The recycling amount of dry waste in metropolises of Iran is about 9%, and given that about 35% of waste is recyclable dry waste, the amount of recycled dry waste despite its high economic justification is much lower than expected. Currently, landfilling is an ordinary mechanism for Tehran's MSW management. Up to 50% of Tehran's wastes are disposed of in landfills without any separation (Heidari et al., 2019). Considering its extensive use in packaging, soft-drink bottles, fibers, and films, PET has been a main source of plastic pollution in the world (Zhou et al., 2019).

According to Figure 2, the global production rate of PET bottles was 485 billion bottles in 2016, a trend projected to reach 583.3 billion bottles per year by 2021. Iran's annual plastic consumption tops 2.5 million tons (over 31 kilograms per capita). Moreover, according to Figure 3, Plastics and PET constituted 11% of Iran's MSW composition (2009-2019), which means that after organic and food wastes (68%), it has the largest share in the beta MSW composition (Esmaeilizadeh et al., 2020). Just in Tehran, 7,500 tons of waste are produced daily, 1,000 tons of which are plastic, while 100 tons of it are made up of PET bottles (IPRC, 2018). Since recycling and waste separation are not commonplace in Iran, almost all of this plastic waste is disposed of in landfills. This is while recycling one ton of plastic equals saving 11 barrels of crude oil (TURPC, 2018).

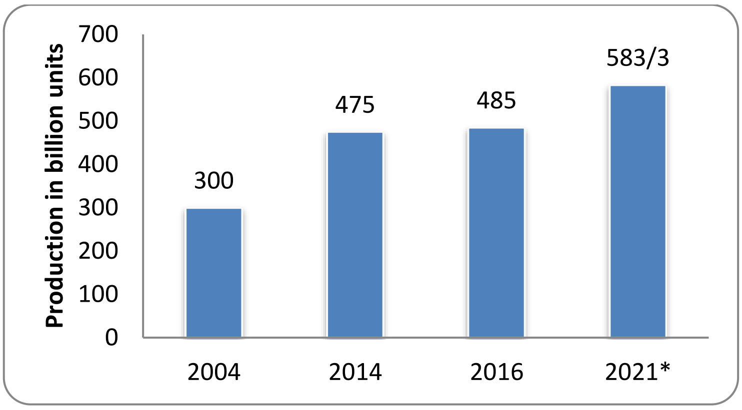

Figure 2. World production of PET bottles from 2004-2021
(Source: Statista, 2019)

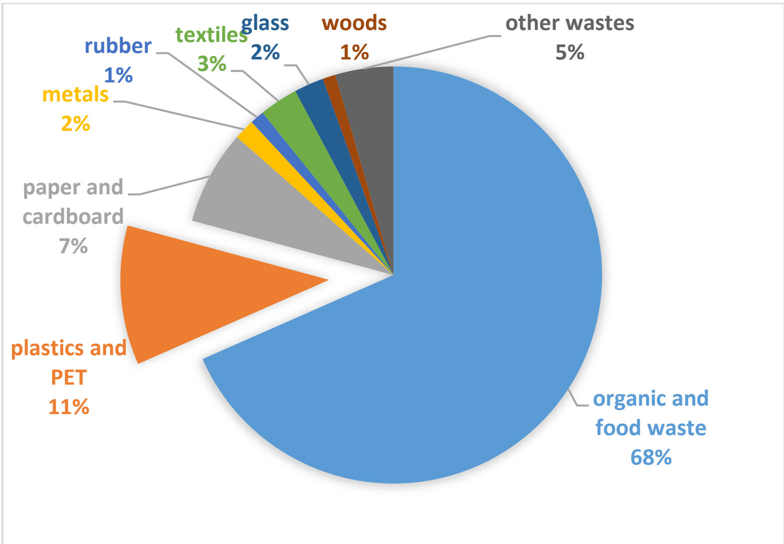

Figure 3. The average composition of MSW in Iran (2009-2019)

Considering the growing population and shortening the life cycle of manufactured products, solid waste has increased rapidly over the last 20 years (Wang and Nie, 2001); (Sanjeevi and Shahabudeen, 2015); (Bing et al., 2016). Economic and environmental challenges around the world have forced governments to implement various tools to collect and recycle solid waste. Some solid materials, such as electronic waste and household plastic, consist of valuable recyclable materials (Ayvaz et al., 2015); (Bing et al., 2015); (Xu et al., 2017). Therefore, governments and organizations need a more efficient reverse supply chain (RSC) design to recycle this waste at the lowest possible cost (Golroudbary and Zahraee, 2015).

Moreover, uncertainty is the main attribute in managing the (reverse) supply chains (Mahnam et al., 2009). Indeed, based on the amount of available information, there are three types of uncertainties: a) randomness b) epistemic and c) deep uncertainty (Bairamzadeh et al., 2018). Randomness uncertainty when occurred that the probability distribution can be estimated based on adequate and valid historical data. Epistemic is often related to the lack of knowledge in parameters. Finally, deep uncertainty is relevant to the lack of information about the related parameters (Bairamzadeh et al., 2018). Uncertainty of parameters is an important factor that could lower the quality of long-term plans of companies (Hamidieh and Fazli-Khalaf, 2017). Therefore, it is necessary to consider uncertainty in reverse supply chain design.

Meanwhile, few studies have been conducted on solid waste management through RSC design, but some research gaps still remain. The novel contributions of this study can be expressed as follows:

1. A mathematical optimization model is presented to design the Municipal Solid Waste (MSW) supply chain (PET bottles) under the uncertainties of the recycling market prices of recycled products, the supply of raw materials, and recycling costs.
2. In the proposed model, the concept of Conditional Value-at-Risk (CVaR) is used as a risk criterion to control shortages at each demand center.
3. In this study, two distinct objective functions (E(profit) and CVaR(Profit)) are employed, and their results are compared.
4. To validate the applicability and efficiency of the proposed mathematical model, real data from 6 different districts of Tehran city are implemented.

The remainder of the present study is organized as follows: In Section 2, some of the most relevant studies carried out in the field of RSC are reviewed. Section 3 presents the research methodology used in the study. Section 4 analyzes the findings of the study, and Section 5 is dedicated to the discussion and conclusion.

2. Literature Review

2.1 Designing the Supply Chain Network

The simulation-based optimization model improves the decisions made by the analytical model further under a stochastic (Chiadamrong and Piyathanavong, 2017). The RSC can be described as a business strategy that acts as a driving force for recycling process activities (specifically to improve the value of recycling) (Ayvaz et al. (2015) and Xu et al. (2017)). In recent years, closed-loop and reversed supply chain design issues have attracted the attention of many scholars, and a large number of papers have been published in this field. Fleischmann et al. (1997) were the first to study articles published in the field of logistic networks. They classify the published articles into three main categories, i.e., distribution planning, production planning, and inventory. Shih (2001) explored reverse logistics (RL) planning for the recycling of electronic appliances in Taiwan. In this study, a MILP is applied to optimize the infrastructure and the RL flow. The model proposed in this study aimed to minimize the total cost, which includes the cost of transport, operating cost, fixed cost, final discharge cost, and landfill cost, as well as to optimize the proceeds of the recycled material. The results are shown for different scenarios in terms of harvesting rate and operational conditions. Nagurney and Toyasaki (2005) worked on RL management and recycling of e-waste using a multi-objective balance framework for e-waste. This study describes the behavior of different decision-makers, including e-waste sources, processors, and consumers associated with demand markets for distinctive products. The proposed model is solved using the proposed algorithm.

Dat et al. (2012) presented a recycling network model for different types of returned e-products to minimize the total cost of processing such products. This study modeled a complete recycling network, including different recycling sites, by extending prior research. The proposed model consists of four different recycling stages, i.e., the collection site, the separation site, the recycling and repair site, and the final site, consisting of the landfill site, and the primary and secondary markets. The optimal location of the facilities and the flow of materials in the RL network are determined. It should be noted that the most critical way to reduce the total cost of the system is to reduce transportation costs (Mohsenizadeh et al., 2020).

Bing et al. (2014) investigated the RL network design for household plastic waste. In this study, a MILP model (a mixed integer linear programming model) is designed to simultaneously minimize transportation costs and environmental impacts. By comparing the selected scenarios, the results of this study show that the current baseline network settings are efficient under logistics conditions are. However, these settings have the requirements in terms of strategic changes according to the presented hypotheses regarding required processing facilities for dealing with plastic waste.

Govindan et al. (2015) examined the latest literature on the design of RL networks and closed loops. In this study, the authors showed that among a total of 328 articles published in the field of the supply chain during 2007-2013, 190 articles were in the field of the closed-loop supply chain, 152 were in the field of RL, 24 articles were related to sustainability, and only six articles were related to the green supply chain. Paydar and Olfati (2018) developed a MILP model for an RL network in Iran. Considering the process of collecting and remanufacturing PET bottles, and minimizing total costs, their results indicated the applicability and efficiency of the proposed model. In this study, two meta-heuristic algorithms were implemented, and in order to obtain reliable results, parameters were set using the Taguchi method. (Diabat and Jebali, 2021) address the closed loop supply chain (CLSC) network design problem for durable products with the consideration of take-back legislation. Results show that a higher reverse service level and CLSC profit can be achieved when a regulation based on a reward-penalty mechanism is implemented

2.2. Supply Chain Design with Uncertainties

In recent years, assessing supply chain coordination under uncertainties has become a trending topic in various studies (Hu and Feng, 2017). Uncertainty is one of the main characteristics of RL. These uncertainties arise from every individual activity in the RL ((Klibi et al., 2010), (Senthil et al., 2018)). Table 1 presents a summary of some significant features of the relevant studies, which have considered uncertainties in the MSW recycling system.

Table 1. Significant Features of the Relevant Studies

Author(s)	Object(s)	Model	Uncertainty	Application
Kara and Onut (2010)	revenue-maximization	two-stage stochastic programming	Demand and the amount of paper that can be collected from customers	paper recycling
Pishvaee et al. (2011)	Total cost minimization	MILP	Demand, type, and quantity of returned products	…
Komly et al. (2012)	Multi-objective optimization	A mathematical model based on life-cycle assessment (LCA)	Input parameters	PET bottles
Ramezani et al. (2013)	Profit maximization, and minimization of the number of defective raw material	MILP	The quantity of price, production, operating, and disposal costs, demands, and return rates	…
Liu and Nagurney (2013)	Profit maximization	two-stage stochastic programming	Demand and Cost	…
Ayvaz et al. (2015)	Profit maximization	Two-stage stochastic programming	return quantity, sorting quality, and transportation cost	electronic equipment
(Ene and Öztürk, 2015)	the total profit maximization, and environmental impact minimization	mathematical programming	the number of returned products	end-of-life vehicles' recovery network

Table 1. Continued

Author(s)	Object(s)	Model	Uncertainty	Application
Xu et al. (2017)	total emission and cost minimization	MILP	waste collection levels	recycling systems of solid waste
(Fazli-Khalaf and Hamidieh, 2017)	maximizes social responsibility while minimizing fixed establishing and variable processing costs of network	Robust Reliable Forward-reverse Supply Chain Network Design	demand, capacity of facilities and costs	applicable in most of industrial case
(Habibi et al., 2017)	minimizing the total cost, and pollution from the greenhouse gas emission	multi-objective robust optimization	non-recyclable and recyclable waste generation	MSW
(Hamidieh and Fazli-Khalaf, 2017)	Minimizing the total costs of network design along with maximization of total responsiveness of distribution network	Hybrid analytical–simulation modeling approach	demand of the customer zones and capacity of facilities	Warehouses
Babazadeh and Sabbaghnia (2018)	total costs minimizing	Robust stochastic programming and CVaR	demand parameter	medium-density fiberboard (MDF) industry
Senthil et al. (2018)	Prioritization of risks	hybrid MCDM	Business interruption value, Price and Business recovery time	plastic recycling firm
Diaz-Barriga-Fernandez et al. (2018)	multi-objective optimization	MILP	the availably of the residues and the product prices	MSW
Garibay-Rodriguez et al. (2018)	minimizing the overall cost	MILP	The selling price of recycled materials	MSW
Alizadeh et al. (2019)	Production optimization	robust three-stage stochastic programming model	Carbon Tax Rate	MSW
Asefi et al. (2019)	total costs (logistics and transportation) minimizing	MILP	MSW generation	MSW
Fan et al. (2019)	Profit maximization	two-stage supply chain model	raw material supply	solid biomass fuel
Gambella et al. (2019)	minimizing the total management cost	two-stage multi-period stochastic programming	waste generation rates	solid waste
Heidari et al. (2019)	Profit maximization	multi-objective mathematical programming	Economic, social, and Environmental Parameters	MSW
Singh (2019)	optimization of the efficiency	fuzzy, stochastic, and interval programming	the rate of produced waste, disposal facility, and treatment cost	MSW
(Fazli-Khalaf et al., 2019)	reliable supply chain network design	Robust possibilistic programming	input parameters	lead-acid battery
(Nayeri et al., 2020)	optimizing financial, environmental, and social impacts of the SCLSC	multi-objective mathematical model	demand, transportation costs, and carbon emission capacity	water tank
(Gumte et al., 2021)	1 Nationwide supply chain setup to optimally determine the operational and design decisions	mixed integer linear programming model	biomass feed supply, demand, and import product price	bio-waste

Although there have been extensive studies on the RSC, some research gaps remain, which can be addressed as follows:

1. In the objective function of the model, the profit from recycling PET bottles is maximized by designing the RSC model and considering the minimum cost of logistics under uncertainty.
2. In the second model with the objective function of CVaR(Profit), the total expected CVaR profit is maximized with and without shortage constraint and results compared with model with objective function of E(Profit).
3. In this study, the concept of CVaR is used as a criterion to control the shortage at each demand center.
4. Only a few studies have been carried out on the development of the RSC for PET bottles.

3. Methodology

3.1. Problem Statement

Figure 4 illustrates the schematic of the proposed model. The waste supply chain network consists of collection centers, separation centers, recycling plants, and retailers. To design the model, two optimization models are developed to maximize the profit from the waste recycling supply chain as well as to reduce the risk of demand for recycling in demand centers. In this model, the following assumptions are made:

1) Logistics costs, the initial amount of collected waste, the prices of recycled materials, and the demand for recycled materials are non-deterministic.
2) Each separation center is supplied by more than one collection center, each recycling center is supplied by more than one separation center, and each retail center is supplied by more than one recycling center.
3) Each collection center can supply more than one separation center, each separation center can supply more than one recycling center, and each recycling center can supply more than one retail center.

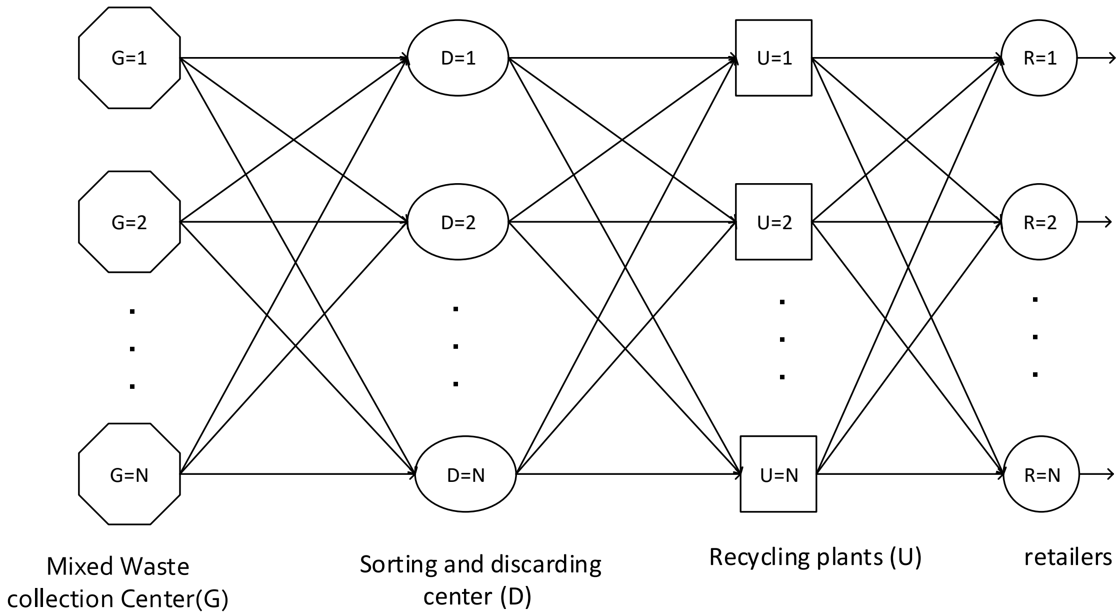

Figure 4. Schematic of the Proposed Model

To maximize profits from the RL network, the problem was modeled by using two stochastic programming methods. The uncertainties of the model are defined by a set of non-deterministic parameters described by discrete distribution. The model's scenarios are considered based on a combination of non-deterministic parameters.

A two-stage stochastic programming method is employed to examine decision making in terms of uncertainty. The fundamental idea in the programming method is the returning concept, i.e., the corrective action can be carried out after implementing a scenario. The decision in the first stage includes variables that must be derived before determining the actual value of uncertainty. After the primary stage, uncertainty is established and the decision-maker must choose an action that advances his/her goals by considering the realization of the optimal scenario. The second stage variables are characterized by the realization of the unknown parameters. When the uncertainty of the existing raw materials is resolved, the decisions of the second stage are taken, including waste flows from collection centers to demand centers.

3.2. VaR and CVaR Concepts

Using VaR is a common method to incorporate the concept of risk into the model ((Rockafellar and Uryasev, 2000); (Pflug, 2000); (Zhu and Fukushima, 2009); (Kazemzadeh and Hu, 2013); (Uryasev, 2013). With a specified probability level, the VaR for a certain asset is the lowest value of α such that the loss will not exceed α with a certain confidence level (Rockafellar and Uryasev, 2000). However, due to conceptual and computational constraints, it is preferable to use CVaR constraints. The CVaR (a.k.a. Mean Excess Loss) is a useful approach for considering uncertainty and optimizing the performance of mathematical models (Babazadeh and Sabbaghnia, 2018). Although the VaR is one of the most prevailing risk measures, some of its main weaknesses cannot be ignored. The VaR is continuous only for the normal distribution, and it is very difficult to calculate for scenario-based models. In contrast, the CVaR is always continuous and convex, and it can be used properly in stochastic scenario-based models. The CVaR is also optimized using stochastic and mathematical programming approaches (Babazadeh et al., 2012).

To define VaR and CVaR for a loss function, the right tail is usually considered as a Probability Density Function (PDF) (Di Bernardino et al., 2015), (Kleinow et al., 2017). In this study, the CVaR is used for the right tail of a PDF for the shortage of the demand centers.

According to (Kazemzadeh and Hu, 2013) and Babazadeh and Sabbaghnia (2018), $VaR_{\ 1-\alpha}$ is a stochastic variable x for the minimum value of t so that with the probability of α, the loss does not exceed t, while $CVaR_{\ 1-\alpha}$ is the conditional expectation of loss higher than t, mathematically can be represented as:

$$VaR_{\ 1-\alpha}(x) = inf\{t: pr(x \le t) \ge 1-\alpha\} \tag{1}$$

$$CVaR_{\ 1-\alpha}(x) = E[x|x \ge VaR_{\ 1-\alpha}] \tag{2}$$

Since in this problem it is assumed that the stochastic variables are discrete and because the shortage of demand is defined as a discrete distribution, the discrete-state definition of CVaR for the stochastic variable X with a probability of α is:

$$CVaR_{\ 1-\alpha}(x) = inf_t\left\{t + \frac{1}{\alpha}E[(x-t)_+]\right\} \tag{3}$$

Where

$$\alpha_+ = max\{0, \alpha\} \tag{4}$$

In the RL design of waste recycling, CVaR loss (the shortage of demand for recycled material in this study) is considered as a criterion to control the risk of recycling in the demand centers. The constraint that limits the upper boundary of $CVaR(shortage)$ of demand is introduced in the model. Figure 5 presents the VaR and CVaR for the continuous distribution associated with loss or shortage with α %.

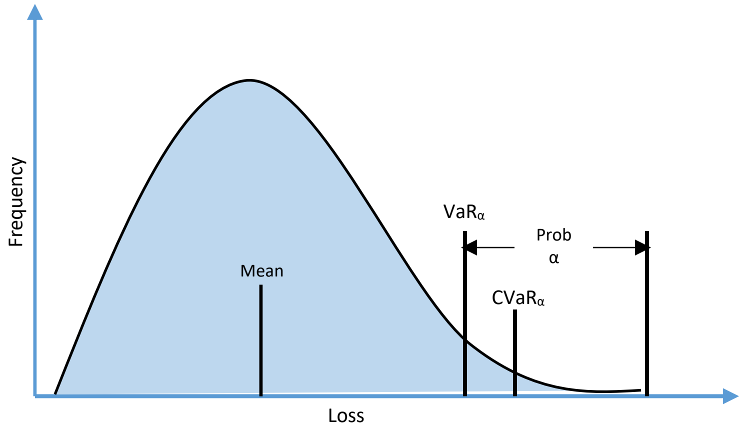

Figure 5. VaR and CVaR(shortage)

While CVaR has usually been utilized for adverse distribution in financial literature, it can also be used for optimal distribution, such as profit distribution. In this study, CVaR has been used to calculate the uncertainty of the profit. To distribute the profit, the VaR and CVaR are considered, while the probability density function is considered for the left tail (Figure 6). Moreover, $CVaR_{\ 1-\beta}$ is a stochastic variable with the maximum value of t so that the profit will not be lower than t with the probability of β, while the expected conditional profit $CVaR_{\ 1-\beta}$ is more moderate than t.

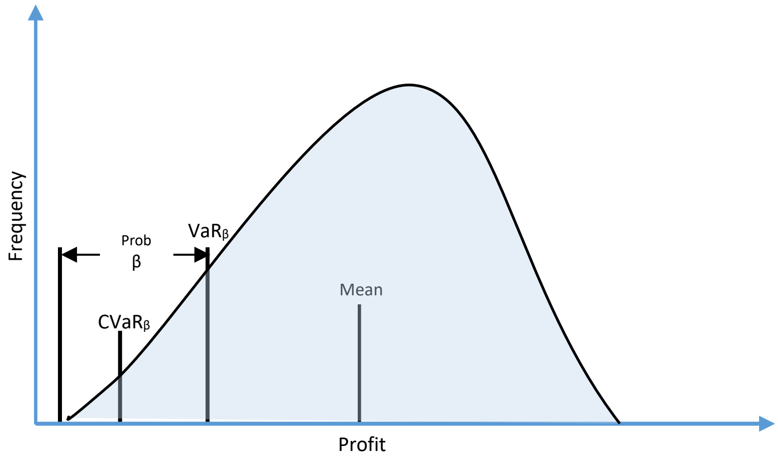

Figure 6. VaR and CVaR(Profit)

The mathematical terms of this definition can be expressed as:

$$VaR_{\ 1-\beta}(x) = sup\{t: pr(x \geq t) \geq 1-\beta\}, \tag{6}$$

$$CVaR_{\ 1-\beta}(x) = E\left[x | x \leq VaR_{\ 1-\beta}\right] \tag{7}$$

The discrete definition of CVaR is as follows:

$$VaR_{\ 1-\beta}(x) = sup_t \left\{t - \frac{1}{\beta} E[(t-x)_+]\right\} \tag{8}$$

3.2. Objective Function and Constraints

In this section, the indices and parameters of the designed model are presented.

Table 2. sets, parameters, and decision variables

Sets
S = Set of scenarios
= Set of the mixed waste collection center$G$
D = Set of sorting and discarding centers
U= Set of recycling factories
R = Set of retailers
L= level of recycling plan
Parameters
Z_g= the sustainability factor in the collection center g
C_{gs}^{sc}=cost of collecting waste in center g under scenario s
e_d = Reduction factor
DI_{gd}= the direct distance between the d and g nodes under scenario s
T = Factor of the meandering of the path
C_s^{gT}= the cost of transportation per unit of unseparated waste under scenario s
W_d = the capacity of separation center d
Y= factor of the amount of waste that is sent to the separation centers
C^{DC}= cost of per unit waste in sorting and discarding centers
C^{DT}= the cost of transportation per unit of separated waste
DI_{du}= the direct distance between u and d nodes under scenario s
T= Factor of the meandering of the path
C^{UC}= the cost of separated recycled waste per unit
U_{Lu}= Capacity of recycling plants
λ= factor of the separated waste sent to recycling factories
B= Budget
C_L^B= cost of construction of waste plants in level L
C^{UT} = Transportation cost per unit of recycled waste
Q_{gs}=amount of mixed waste collection center g under scenario s
DI_{ur} = the direct distance between the r and u nodes
K_r = The total demand value of retailer r
P_{rs} = the price of recycled materials sold to the retailer r under scenario s
sh_{rs}= the shortage of demand in retailer r under scenario s
H= the maximum amount of shortage in retailer
δ_{lu} = A set of binary variables to determine whether a waste recycling factory with l capacity is located in the location u or not.
W_s= the probability of occurrence of scenario s
Decision (Optimization) Variables
h_{dus}= The amount of separated waste flows from the separation center d to the recycling plant u under scenario s
q_{urs}= The amount of recycled waste flows from the recycling plant u to the retailer r under scenario s
f_{gds}= The amount of unseparated waste flows from the collecting center g to the separation center s under scenario s
γ_s, η= the variables used to the formulation of the shortage of CVaR

3.3. Model Constraints

The model's constraints in the first stage involved the selection of locations for the recycling plants. A set of binary variables δ_{lu} is considered to determine whether a waste recycling plant with capacity l is located in location u or not. To ensure that the cost of construction of waste recycling plants does not exceed the existing budget B, the constraint can be considered as:

$$\sum_u \sum_l C_l^B \, \delta_{lu} \leq B. \tag{9}$$

At any desired location, only one waste recycling plant can be constructed, which is characterized by the following constraints:

$$\sum_l \delta_{lu} \leq 1 \qquad \forall u \in U. \tag{10}$$

The remaining constraints relate to the decisions of the second stage, which determine the amount of initial waste and recycling waste among supply chain nodes.

With regards to the total waste collection centers, it is assumed that each of these centers $g \in G$ can collect Q_{gs} tons of waste per year. Also, $Z_g$is the sustainability factor for the collection centers, which remains for different reasons (e.g., seasonal reasons). Therefore, any collection center can provide $(1 - Z_g)Q_{gs}$ tons of waste. Assuming that the amount of waste flow from the $g - th$ recycling center to the $d - th$ separation center in scenario s is equal to f_{gds}:

$$\sum_d f_{gds} \leq (1 - Z_g)Q_{gs} \qquad \forall g \in G, \quad \forall s \in S. \tag{11}$$

The reduction factor ed ϵ [0,1) is considered to possible losses during transport and loading, which depends on the amount of waste collected. Therefore, the amount of initial waste sent to the separation centers is less than or equal to the capacity of the $d - th$ separation center (W_d).

$$(1 - e_d) \sum_g f_{gds} \leq W_d \qquad \forall d \in D, \quad \forall s \in S. \tag{12}$$

The amount of waste sent to the separation centers is separated using the $Y \in [\,0, 1)$ factor, and then it is sent to the recycling plants. The amount of waste sent from the $d - th$ separation center to recycling plants should not exceed the capacity of the separation center, hence:

$$(1 - e_d) \sum_g f_{gds} Y \leq \sum_d h_{dus} \qquad \forall u \in U, \quad \forall s \in S. \tag{13 }$$

On the other hand, the amount of waste sent to the $u - th$ plant should be less than or equal to its capacity (V_{lu}).

$$\sum_d h_{dus} \leq \sum_l V_{lu} \, \delta_{lu} \qquad \forall u \in U, \quad \forall s \in S. \tag{14}$$

It is assumed that the separated waste sent to recycling plants is recycled with the λ factor and is sent to the retail centers. That amount should be equal to the amount of recycled material sent from the $u - th$ recycling plant to retail centers.

$$(1 - e_d) \sum_g f_{gds} \, Y\lambda = \sum_r q_{urs} \quad \forall d \in D, \quad \forall s \in S. \tag{15}$$

The decision variable q_{urs} represents the amount of recycled materials sent from the $u-th$ factory to the $r-th$ demand center under the s scenario. In the s scenario, the total demand value of the $r-th$ retailer (K_r) is not met; sh_{rs} denotes the shortage in the following constraint:

$$\sum_{u} q_{urs} + sh_{rs} = K_r \qquad \forall r \in R, \quad \forall s \in S. \tag{16}$$

As discussed earlier, the amount of recycled material may not be enough to supply the entire retail demand, so demand centers encounter with a shortage. To manage this shortage, the conditional value-at-risk is used as a risk criterion measurement. Recycling plants have to determine the maximum amount of their shortage, which is denoted by$H$. Based on the definition of the conditional value-at-risk for the discrete distribution, the maximum amount of the conditional value-at-risk with the probability of α % ($CVaR_{1-\alpha}(sh) \leq H$) is applied.

By linearizing this constraint using auxiliary variables η and γ and the CVaR for the discrete distribution, it can be represented as:

$$\eta + \frac{1}{\alpha}\sum_{s} w_s \gamma_s \leq H. \tag{17}$$

$$\gamma_s \geq sh_{rs} - \eta \qquad \forall s \in S, \quad \forall r \in R \tag{18}$$

$$\gamma_s \geq 0 \qquad \forall s \in S. \tag{19}$$

3.4. Objective Function

The purpose of the model is to maximize profit, which is defined as the total revenue from the sale of recycled waste minus total costs. There are many costs in the RL of recycling. The first cost is the cost of collecting each unit of waste, denoted by C_{gs}^{SC}. Another cost is the cost of transportation per unit of unseparated waste, denoted by C_s^{ST}. Assuming that the direct distance between the $g-th$ collection center and the $d-th$ separation center is equal to DI_{gd}, the total cost of collection and transportation of non-recycled waste is equivalent to:

$$\sum_{g,d,s} (C_{gs}^{SC} + \tau DI_{gd} C_s^{ST}) w_s f_{gds} \tag{20}$$

Which, DI_{gd} denotes the direct distance between the nodes, in this problem, the actual distance between the nodes is considered by multiplying this distance by the meandering of the path denoted by τ. Costs for the recycling centers and recycling plants were calculated according to the above conditions. The total costs of separation and transportation of the separated waste:

$$\sum_{d,u,s} \left(C_s{}^{DC} + \tau D_{du} C_s{}^{DT}\right) w_s h_{dus}. \tag{21}$$

The total costs of recycling and transportation of the recycled waste:

$$\sum_{u,r,s} (C_s{}^{UC} + \tau D_{ur} C_s{}^{UT})\, w_s q_{urs}. \tag{22}$$

In order to calculate the profit, it is need to calculated revenue first. To this end, it is assumed the prices of recycled materials sold to retailer r are equal to P_r, so total revenue from recycled material is equal to $\sum_{u,r,s} p_{rs}\, w_s q_{urs}$. To maximize the total profit (the total revenue minus the total cost), the problem is estimated based on two methods, i.e., the E(profit) and the CVaR. The first method (E(profit)), can be formulated as follows:

$$max \sum_{u,r,s} p_{rs}\, w_s q_{urs} - \sum_{g,d,s} (C_{gs}^{SC} + \tau DI_{gd} C_s^{ST}) w_s f_{gds} - \sum_{d,u,s} (C^{DC} + \tau DI_{du} C^{DT})\, w_s h_{dus}$$
$$- \sum_{u,r,s} (C^{UC} + \tau DI_{ur} C^{UT})\, w_s q_{urs} - PMT \left(\sum_{l,u} C_l^B \delta_{lu} \right) \tag{23}$$

$s.t. Constraints\ (9) - (19),$

$$W_d \geq 0 \qquad \forall d \in D. \tag{24}$$

$$V_{lu} \geq 0 \qquad \forall l \in L, \quad \forall u \in U. \tag{25}$$

$$K_r \geq 0 \qquad \forall r \in R. \tag{26}$$

$$\gamma_s \geq 0 \qquad \forall s \in S. \tag{27}$$

$$f_{gds} \geq 0 \qquad \forall g \in G, \quad \forall u \in U, \quad \forall s \in S. \tag{28}$$

$$h_{dus} \geq 0 \qquad \forall d \in D, \quad \forall u \in U, \quad \forall s \in S. \tag{29}$$

$$q_{urs} \geq 0 \qquad \forall u \in U, \quad \forall r \in R, \quad \forall s \in S. \tag{30}$$

$$sh_{rs} \geq 0 \qquad \forall r \in R, \quad \forall s \in S. \tag{31}$$

$$\delta_{lu} \in \{0,1\} \qquad \forall l \in L, \quad \forall u \in U. \tag{32}$$

Since E(Profit) does not explicitly include risk in its objective function, in the second method, the CVaR(profit) is utilized for the objective function. The purpose of the second method is to maximize the total CVaR(profit). Indeed, the objective function can be considered as the maximization of the expected value of β percent of the worst scenario (Kazemzadeh and Hu, 2013). Variables ζ and φ_s are used to formulate and linearize CVaR(profit) for a discrete distribution. The objective function used in this linearization model is to define the discrete CVaR for the left side tail by implementing auxiliary variables ζ and φ_s .

Table 3. Parameters of Stochastic Programming (CVaR(profit) Objective Function)

$Profit_s$	Total profit under scenario s
$Cost_s$	Total costs under scenario s
$Revenue_s$	Total revenue under scenario s
φ_s, ζ	Variables for formulating CVaR(profit)

The model with the CVaR(profit) objective function is as follows:

$$Max\ \zeta - \frac{1}{\beta} \sum_{s} w_s \varphi_s \tag{33}$$

$$s.t \quad \varphi_s \geq \zeta - profit_s \qquad \forall s \in S. \tag{34}$$

$$\varphi_s \geq 0 \qquad \forall s \in S. \tag{35}$$

$$profit_s = Revenue_s - Cost_s \qquad \forall s \in S. \tag{36}$$

$$Revenue = \sum_{u,r} p_{rs} q_{urs} \qquad \forall s \in S. \tag{37}$$

$$cost_s = \sum_{g,d} (C_{gs}^{SC} + \tau D_{gd} C_s^{ST}) f_{gds} + \sum_{d,u} (C^{DC} + \tau D_{du} C^{DT})\, h_{dus} + \sum_{u,r} (C^{UC} + \tau D_{ur} C^{UT})\, q_{urs} + PMT(\sum_{l,u} C_l^B \delta_{lu}). \tag{38}$$

Subject to constraints (9) – (19), and (24) – (32).

4. Empirical Results

4.1. Case Study

In this study, a problem is investigated with real data for the RL network of PET bottles recycling from 6 districts of Tehran City. To this end, it be assumed that in each of these districts, there are centers for collection and separation of waste. The desired amount of waste can be collected from each of the six districts. Then, the waste is transferred from these centers to the separation centers to be completely separated. Afterward, the waste is transferred to recycling centers, whose optimal locations are determined by the model. Finally, the waste is transferred from the recycling centers to the sales centers (in this study, 5 districts are considered in Tehran City).

4.2. Data

The model has been implemented in 6 districts (District 15 to District 20) as collection centers and separation centers, while six districts around Tehran are considered as candidates for recycling plants, and five districts (Districts 3, 5, 8, 12 and 18) are considered as retail centers according to the data released by the Waste Organization of Tehran. In this study, it be assumed that each of these districts is a candidate for the construction of recycling plants with three levels of capacity, i.e., 500, 600, and 700 tons per day for recycling separated PET. According to the statistics of the Waste Organization, about 30% of the total waste is dry waste, while about 5% of the dry waste is PET (disposed bottles). According to the statistics published by the abovementioned organization, the budget allocated for recycling the municipal waste in Tehran is about two billion dollars a year. Therefore, given that six different districts among the total 22 districts of Tehran City were considered as candidates for the recycling plant, the budget with these proportions is about 34.5 billion dollars.

In this study, five districts as demand areas in Tehran were considered. The demand for each of these areas were determined relatively based on the size of the population in each district according to the Census Report of 2011. It was also assumed that the percentage of recyclable bottles is 30% of the total amount of used bottles, which equals 130 tons per day.

Both confidence levels α and β are assumed as 20%, and they are used to calculate the CVaR of shortage and CVaR of profit. Moreover, the maximum value of recycled materials demand is set at 18 tons per day.

The sustainability factor in all waste collection centers and the reduction factor, for possible losses during transportation and loading, are both set to 5%. The separation factor and the recycling factor for all separation centers and recycling plants are set equal to 80%. The meandering factor (the indirectness of the path) which is used to transform the direct distance between a pair of nodes to the actual distance between the two nodes is equal to 1.26 based on Kheyrollahi et al. (2016).

The scenarios of our study are estimated based on the average parameter value. Three scenarios are considered for the mixed collected waste, three scenarios for recycling materials prices, and eight scenarios for the cost of transport between collection and separation centers. By combining these scenarios, there will be 72 states for the selected problem. These states are shown in the Table 4.

Table 4. Scenarios assumptions

Scenarios	Amount of collected waste	probability of the occurrence
Scenario 1	$\Delta Q = -5\%$	1/3
Scenario 2	Q	$1/3$
Scenario 3	$\Delta Q = +5\%$	$1/3$
	Price of recycled waste	
Scenario 1	$\Delta P_{rs} = -10\%$	$1/3$
Scenario 2	P_{rs}	$1/3$
Scenario 3	$\Delta P_{rs} = +10\%$	$1/3$
	Transportation cost for unseparated wastes	
Scenario 1	$\Delta C^{gt} = -10\%$	$1/2$
Scenario 2	$\Delta C^{gt} = +10\%$	$1/2$
	Transportation cost for separated wastes	
Scenario 1	$\Delta C^{dt} = -10\%$	$1/2$
Scenario 2	$\Delta C^{dt} = +10\%$	$1/2$
	Transportation cost for recycled wastes	
Scenario 1	$\Delta C^{ut} = -10\%$	$1/2$
Scenario 2	$\Delta C^{ut} = +10\%$	$1/2$

Source: Research Assumptions

The proposed models are intended to determine investment decisions for the location and the capacity of recycling plants, as well as decisions related to waste transport and waste delivery. The decisions of the first stage must be made before the uncertainty evaluation, and the decisions of the second stage will be made after the system parameters are estimated. In this study, decisions of the first stage involve investment decisions (for location and capacity of the recycling plants). When uncertainty is perceived, the decisions of the second stage are taken, including collection flows from collection sites to the separation and recycling centers, and recycled material flows into demand areas. The uncertainty considered in this model includes initial waste supply, recycling market price, and logistics transportation costs. Since the expected value of risk ignores the risk of decision-making in adverse conditions, to manage the risk management system, The CVaR was used in the second objective function.

4.3. Results

One of the main challenges in the RSC network design involves controlling the shortage of estimated demand. In our case study, the two proposed models have been implemented and compared with models with the same data as default, but without considering the CVaR of shortage. The first model, with the E(profit) objective function, is named model (A), while the second model is the model with the CVaR objective function, which is named model (B)[*]. Model A can be represented as follows:

$$Max \sum_{u,r,s} p_{rs}\, w_s q_{urs} - \sum_{g,d,s} (C_{gs}^{SC} + \tau DI_{gd} C_s^{ST}) w_s f_{gds} - \sum_{d,u,s} (C^{DC} + \tau DI_{du} C^{DT})\, w_s h_{dus}$$

$$- \sum_{u,r,s} (C^{UC} + \tau DI_{ur} C^{UT})\, w_s q_{urs} - PMT\left(\sum_{l,u} C_l^B \delta_{lu}\right) \quad (39)$$

[*] The models are run in *GAMS V. 24.8.3* software application with the *Baron* solver.

Subjected to the constraints (9) - (19), (24) - (26), and (28) - (32).

Figure 7 depicts the results obtained from model A. As shown in the figure, there is a shortage of demand which is not estimated in districts 3, 5, and 8. In particular, district 8 is facing a shortage of 7550100.4 kilograms per year, triggering the risk criterion to be used to control shortages.

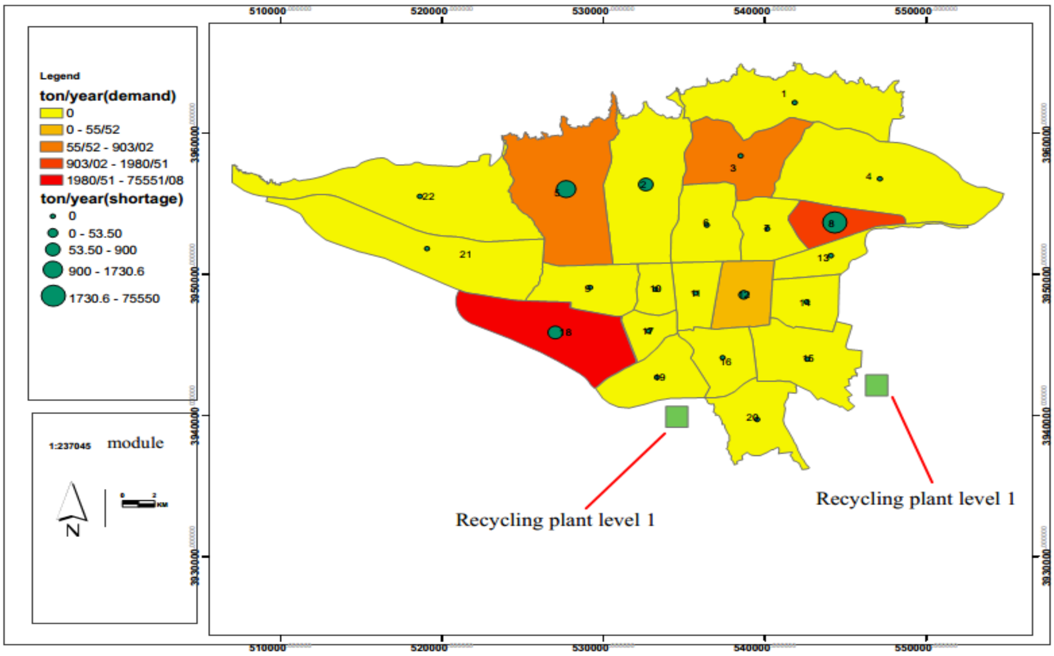

Figure 7. The location of recycling plants for model A without the constraint of shortage

Model A with the constraint of value-at-risk of shortage is formulated as follows:

$$Max \sum_{u,r,s} p_{rs}\, w_s q_{urs} - \sum_{g,d,s} (C_{gs}^{SC} + \tau DI_{gd} C_s^{ST}) w_s f_{gds} - \sum_{d,u,s} (C^{DC} + \tau DI_{du} C^{DT})\, w_s h_{dus}$$
$$- \sum_{u,r,s} (C^{UC} + \tau DI_{ur} C^{UT})\, w_s q_{urs} - PMT \left(\sum_{l,u} C_l^B \delta_{lu} \right) \qquad (40)$$

Subject to constraints (9) – (19), and (24) – (32).

In Figure 8, when the constraint of CVaR of shortage is added to the model with the objective function of E(Profit), there is not much shortage in a specific node. Moreover, after adding the constraint of VaR of shortage, the total shortage of a system is reduced due to restricting the upper limit of the shortage. In addition, the total profit of the model is reduced due to the addition of constraints to the model.

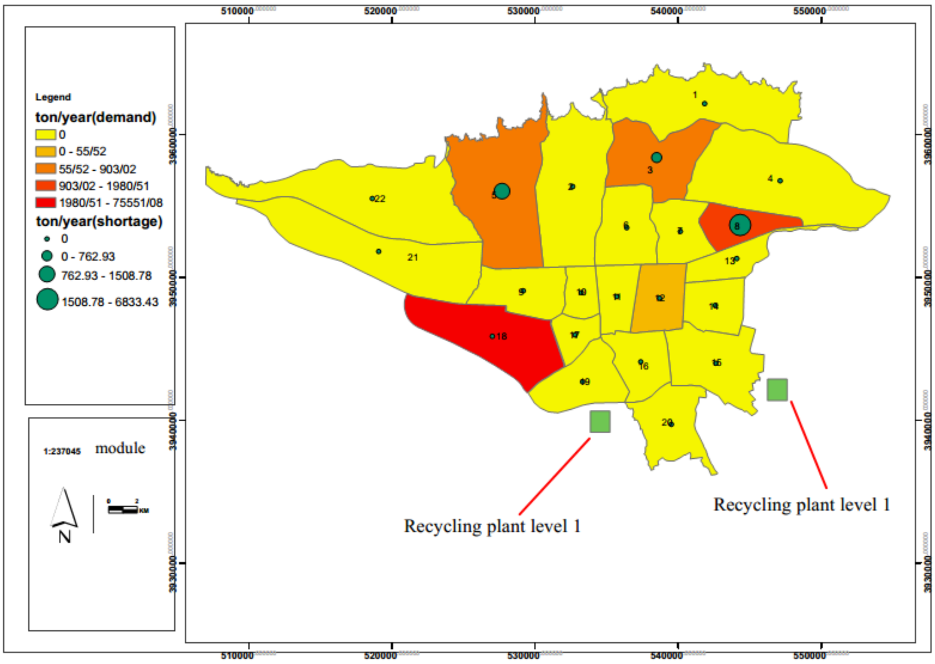

Figure 8. The location of recycling plants for model A with the constraint of shortage

The following formula shows model B without the constraint of CVaR of shortage:

$$max\ \zeta - \frac{1}{\beta}\sum_{s} w_s\varphi_s \tag{41}$$

$$s.t \quad \varphi_s \geq \zeta - profit_s \qquad \forall s \in S. \tag{42}$$

$$\varphi_s \geq 0 \qquad \forall s \in S. \tag{43}$$

$$profit_s = Revenue_s - Cost_s \qquad \forall s \in S. \tag{44}$$

$$Revenue = \sum_{u,r} p_{rs}q_{urs} \qquad \forall s \in S. \tag{45}$$

$$cost_s = \sum_{g,d}(C_{gs}^{SC} + \tau D_{gd}C_s^{ST})f_{gds} + \sum_{d,u}(C^{DC} + \tau D_{du}C^{DT})\,h_{dus} + \textstyle\sum_{u,r}(C^{UC} + \tau D_{ur}C^{UT})\,q_{urs} + PMT\left(\sum_{l,u} C_l^B\delta_{lu}\right) \tag{46}$$

Subjected to the constraints (9) - (19), (24) - (26), and (28) - (32).

As shown in Figure 9, there is a significant amount of shortage in district 8. The total amount of shortage is significantly higher compared to model A. The reason for this difference is that model A seeks to maximize E(Profit) regardless of the risk of decisions, while model B maximizes the total profit by considering the risk of undesirable decisions.

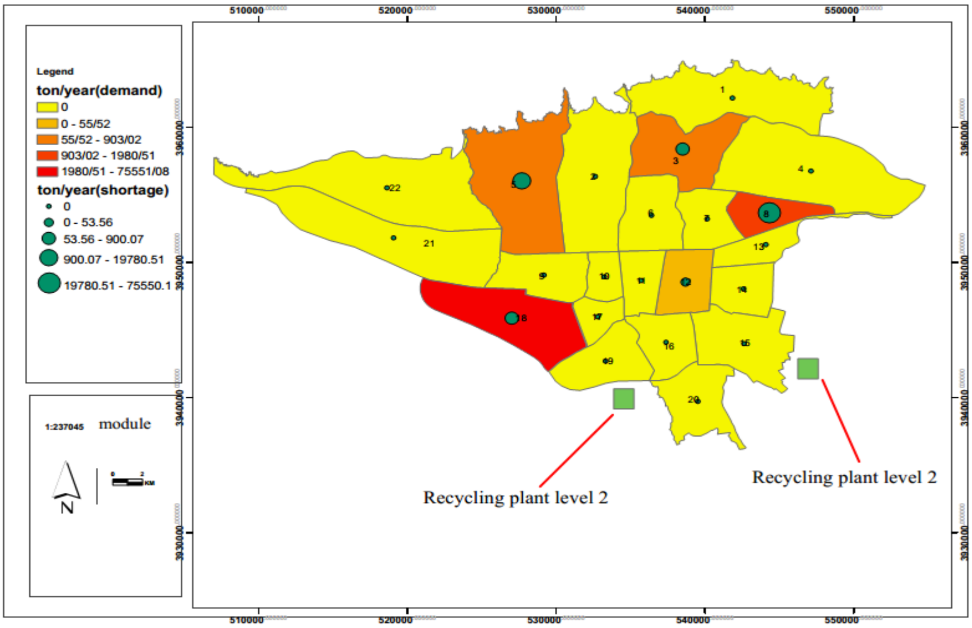

Figure 9. The location of recycling plants for model B without the constraint of shortage

In this case, Model B considers an upper limit for the CVaR of shortage to reduce shortages in demand areas. The model is formulated as follows:

$$\max \zeta - \frac{1}{\beta}\sum_{s} w_s \varphi_s \tag{47}$$

$$s.t \quad \varphi_s \geq \zeta - profit_s \qquad \forall s \in S. \tag{48}$$

$$\varphi_s \geq 0 \qquad \forall \in S. \tag{49}$$

$$profit_s = Revenue_s - Cost_s \qquad \forall s \in S. \tag{50}$$

$$Revenue = \sum_{u,r} p_{rs} q_{urs} \qquad \forall s \in S. \tag{51}$$

$$\begin{aligned} cost_s = &\sum_{g,d} (C_{gs}^{SC} + \tau D_{gd} C_s^{ST}) f_{gds} + \sum_{d,u} (C^{DC} + \tau D_{du} C^{DT})\, h_{dus} \\ &+ \sum_{u,r} (C^{UC} + \tau D_{ur} C^{UT})\, q_{urs} + PMT\left(\sum_{l,u} C_l^B \delta_{lu}\right) \end{aligned} \tag{52}$$

Subjected to the constraints (9) - (19), and (24) - (26).

The result of implementing the model with the objective function and the constraint of the value-at-risk of shortage is shown in Figure 10. As can be observed from this figure, the sum of the total shortage is reduced compared to model B without constraints.

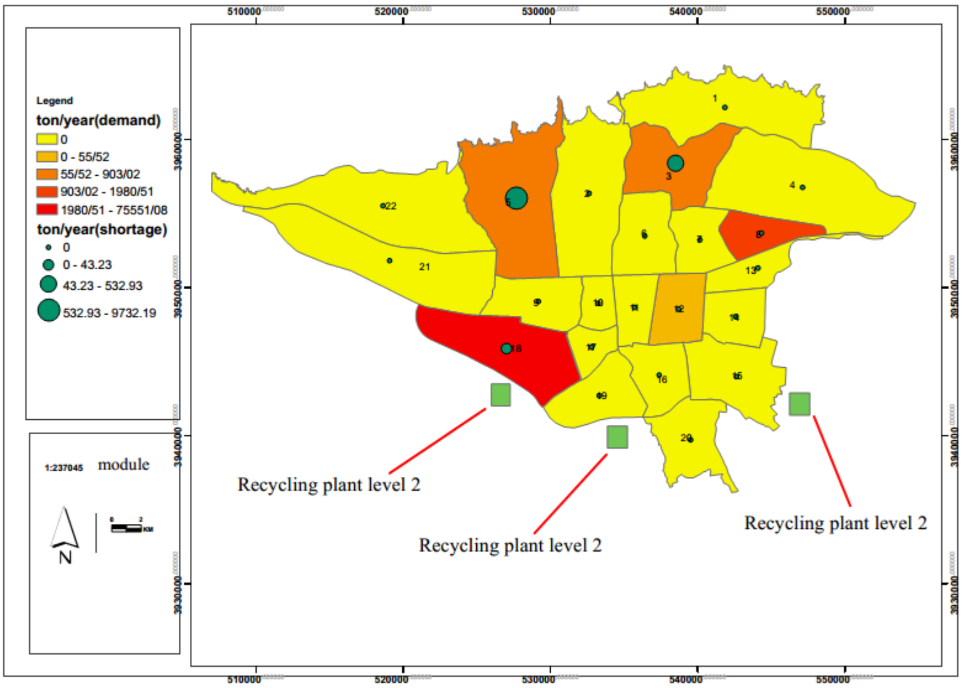

Figure 10. The location of recycling plants for model B with shortage constraints

E(Profit) is increased after the constraints of shortage are applied in these models. Moreover, CVaR(Profit) is reduced due to the addition of constraints. This is because Model B maximizes profits in the worst condition, while the objective of Model A is maximizing E(Profit). The results of the two models show that the constraint of CVaR of shortage is a reasonable and appropriate method to deal with the risk of a shortage, which can be applied in systems where there is a tremendous shortage in some demand areas with high shortage cost. Since the constraints of the model can divide a significant shortage in the district by the parameter α of the CVaR in total demand centers, there will be no extreme shortage in a particular district. Moreover, by comparing Models A and B, regardless of the CVaR constraint, it is found that Model B is more efficient for conservative decisions due to the risk-taking feature embedded in the objective function.

4.4. Sensitivity Analysis

In this section, Model B with the total CVaR(Profit) and the constraints of CVaR(Shortage) was examined through a sensitivity analysis; the results are presented in Figure 11 ,12 , and 13. First, the sensitivity of the objective function to the price of recycled materials was analyzed. By controlling other parameters of the recycled materials at each stage (base price of 28,000 Rials), the results show that the overall profit of the supply chain is increased. Moreover, by reducing the price of the total supply chain, the total revenue is reduced to zero at the price of 3900 Rials (Figure 11).

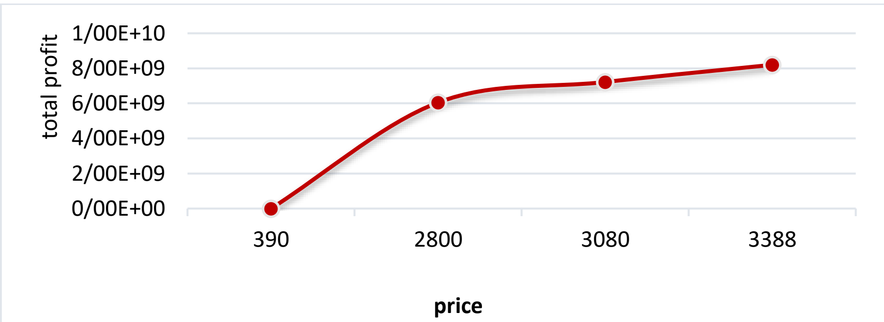

Figure 11. Sensitivity analysis of total profit to the price

In this section, the cost of transportation can be increased by 10% at each stage to analyze the sensitivity of the objective function to the cost of transportation by keeping other parameters constant. As shown in the diagram below, the overall profits of the supply chain are significantly reduced by increasing the transportation cost. Therefore, transportation cost plays a vital role in the cost structure of recycling. Therefore, the most effective way to reduce the total cost of the system is to reduce transportation costs (Figure 12). This result is in the line with the findings of (Dat et al., 2012).

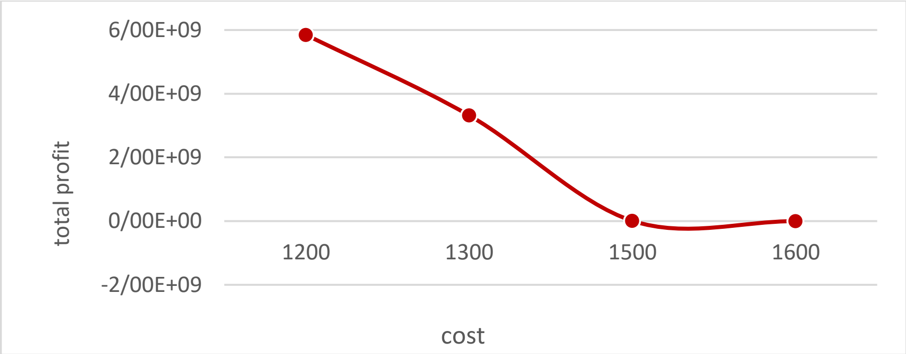

Figure 12. Sensitivity analysis of total profit to the transportation cost

In this section, the goal of the objective function is to analyze the initial amount of the collected waste. In this section, by keeping other parameters constant, the initial amount of waste collected can be increased by 5, 10, and 20 %, respectively. The results show that by increasing the initial amount of the collected waste, the total revenue increases, while the total profit is almost constant since the capacity of waste collection centers is assumed to be limited (Figure 13).

Figure 13. Sensitivity analysis of total profit to the collected waste

5. Discussion and Conclusions

Waste management in Tehran City with a population of 8.43 million people and a 790-gram per capita annual production of wastes (about 2.5 times the global average) is highly important in pursuit of achieving circular economy goals. In this regard, the main purpose of this study is to investigate the design of an RSC network for recycling PET bottles under uncertainty. To realize this objective, a mathematical programming framework is presented with a systematic planning approach for investment decisions for the location and capacity of recycling plants, transportation, and delivery of recycling materials. Uncertainty in this problem involves the supply of raw materials, market prices of recycling materials, and logistics costs. Also, one of the main challenges in this study is incurring a large amount of shortage in a single demand area.

Two approaches, i.e., E(Profit) and CVaR(Profit), have been modeled and used in the objective function formulation with and without shortage constraint (CVaR(shortage). The first approach tries to maximize E(Profit), while the second method is more focused on reducing the risk of the system under demand shortage conditions. Furthermore, by introducing CVaR(shortage) as a constraint, the effects of the integration of the model with stochastic shortage control have been investigated. To evaluate the effectiveness of the proposed models, real data from different districts of Tehran City were applied.

Comparing the results of the two models indicates that the constraint of value-at-risk of shortage is a reasonable and appropriate way to deal with the risk of a shortage, which can be applied in systems where there is a significant and costly shortage in some demand areas. Accordingly, in a particular district, there will be no extreme shortage. In summary, the comparison between the proposed models shows that models with E(Profit) objective function represent a lower overall shortage, whereas models with CVaR(Profit) objective function represent more shortage.

In summary, comparing the proposed models suggests that models with the objective function of E(Profit) represent a lower shortage, whereas models with the objective function of CVaR(Profit) represent more shortage in demand centers. Therefore, Model B is more conservative in the face of the risk of shortage due to the risk-taking feature embedded in the objective function, which can be adjusted in accordance with the decision maker's preference by altering the β coefficient.

Moreover, the results of the sensitivity show that the total profit of the supply chain is significantly reduced by increasing the cost of transportation. Therefore, transportation cost plays an essential role in the cost structure of recycling stages. Moreover, by increasing the initial amount of the collected waste, the total revenue increases, while from one of the stages onwards, the total profit remains almost constant because the capacity of the waste collection centers is limited.

As can be seen from the literature review, few studies have modeled the profit of waste recycling (PET bottles) using the CVaR approach. Therefore, future studies are suggested to include environmental impacts, and especially the social aspects of sustainable development in the model, and can also be performed at inter-city and even international levels (between countries). In addition, investigating the separation of waste at the source as a scenario and the impact of this parameter on the objective function; and carrying out a comparative study of efficient problem solving algorithms could be other directions for future work in this area.

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Abbreviations/Nomenclature

CE	Circular Economy
CVaR	Conditional Value at Risk
GDP	Gross Domestic Product
LCA	Life-Cycle Assessment
MILP	Mixed-Integer Linear Programming
MSW	Municipal Solid Waste
PET	Polyethylene Terephthalate
PDF	Probability Density Function
RL	Reverse Logistic
RSC	Reverse Supply Chain
SWM	Solid Waste Management
VaR	Value at Risk
WHO	World Health Organization