



HAL
open science

Design of a robust waste recycling network integrating social and environmental pillars of sustainability

Arsalan Yousefloo, Reza Babazadeh, Mehrdad Mohammadi, Amir Pirayesh,
Alexandre Dolgui

► **To cite this version:**

Arsalan Yousefloo, Reza Babazadeh, Mehrdad Mohammadi, Amir Pirayesh, Alexandre Dolgui. Design of a robust waste recycling network integrating social and environmental pillars of sustainability. Computers & Industrial Engineering, 2023, 176, pp.108970. 10.1016/j.cie.2022.108970 . hal-03983519

HAL Id: hal-03983519

<https://hal.science/hal-03983519v1>

Submitted on 30 May 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Design of a robust waste recycling network integrating social and environmental pillars of sustainability

Arsalan Yousefloo¹, Reza Babazadeh¹, Mehrdad Mohammadi^{2*}, Amir Pirayesh³, Alexandre Dolgui⁴

¹ Faculty of Engineering, Urmia University, Urmia, West Azerbaijan Province, Iran

² IMT Atlantique, Lab-STICC, UMR CNRS 6285, F-29238 Brest, France

³ Centre of Excellence in Supply Chain and Transportation (CESIT), KEDGE Business School, Bordeaux, France

⁴ IMT Atlantique, LS2N-CNRS, La Chantrerie, 4, rue Alfred Kastler, Nantes cedex 3, F-44307, France

* Corresponding author: Mehrdad Mohammadi (mehrdad.mohammadi@imt-atlantique.fr), Tel: +33 2 29 00 10 30

Abstract

The design of an efficient Municipal Solid Waste (MSW) management network can reduce the network costs, such as investment, operational and recycling costs, and improve its sustainability, from economic to environmental and social perspectives. In this paper, a multi-objective scenario-based robust stochastic optimization model for designing a sustainable MSW management network under uncertainty is proposed. The proposed model has four objectives to seek sustainability from two quantitative and qualitative aspects. Considering the dynamicity of the factors affecting an MSW management network as well as the multiplicity of sustainability perspectives, the proposed model allows, on one hand, reaching a robust solution considering the potential scenarios, and on the other hand, integrating sustainability indicators while creating a balance between the quantitative and qualitative evaluation of such indicators. Moreover, the waste treatment technologies, as the highest added-value echelon of the MSW management network, which also distinguishes the network from a generic waste recycling network, has been investigated in the model. Finally, fuel consumption, have been particularly emphasized as critical factor, highly contributing to transportation costs and CO₂ emission that are decisive criteria from both economic and environmental points of view. The proposed model and solution approach are validated through a real case study.

Keywords: Municipal solid waste management, logistics network, multi-objective optimization, robust-stochastic optimization, sustainability.

1. Introduction

Along with urban development and population growth, the amount of solid waste as one of the main pollutants in the environment has increased more than ever in terms of diversity and quantity. According to the World Bank report, the world generates 2.01 billion tons of Municipal Solid Waste (MSW) annually, of which at least 33 percent is not environmentally safe (Hoornweg and Bhada-Tata, 2012). It is estimated that the global waste will reach more than 40 million tons by 2050, more than double the population growth over the same period (Slipa et al., 2018).

In general, there is a positive correlation between waste production and income level. Daily per capita waste production in high-income countries is predicted to increase up to 19% by 2050 and this amount in low- or middle-income countries is about 40% (Jiang et al., 2019). Total waste generated in low-income countries is

predicted to be more than triple by 2050. The East Asian and Pacific regions produce the most waste in the world at 23%, and the Middle East and North Africa produce at least 6% (Slipa et al., 2018, Mayer et al., 2019), wherein more than half of the waste is currently being dumped openly, and the waste growth path will have far-reaching consequences for the environment, health and prosperity; hence, immediate action is needed (Tsai et al. 2020). On the other hand, increasing the demand for energy and rising concerns about energy security and climate change due to CO₂ emission from fossil fuels have attracted many researchers to explore potential sources of renewable energy (Zandi Atashbar et al., 2018, Razm et al., 2021, Rathore and Sarmah, 2020). Energy recovery from MSW is one way to reach this goal that not only reduces the environmental threats imposed by traditional landfills, but also leads to renewable energy and reduces the use of fossil fuels. Therefore, MSW management has become one of the world's main concern due to the importance of sustainable development in urban communities, which can significantly reduce the effects and harms of high generation of wastes (Ba et al., 2016, Expósito-Márquez et al., 2019). MSW management is about the planning and decision making on waste collection, separation, storage, transferring, recycling, treatment, and disposal, wherein the principles of public health and the environment are considered (Haupt et al., 2018).

MSW management is a complex and multidimensional task which may require: facility location or handling and transportation management while considering the cost, time and environmental implications in different layers of the network, choosing the adapted waste treatment technology and its impact on sustainability indicators where expert opinion can be decisive, handling the uncertainty of the parameters, etc. Indeed, in MSW management, facility location decisions as well as the selection of the technologies should be made simultaneously while considering the impact of such decision on different sustainability pillars. The literature review, which is addressed in detail in the following section, indicated a gap around the lack of integration in the proposed solutions which may cause unsustainable or inefficient solutions in the long run (Mohammadi et al., 2019; Habibi et al., 2018). For the design of an integrated MSW management network, one of the most promising techniques is mathematical programming models which is able to consider the main concerns of decision makers and produces optimal solutions (Mavrotas et al., 2015, Ghiani et al., 2021). To avoid sub-optimality of the MSW management network, all of the echelons, from waste collection to landfills or energy production should be involved/integrated collectively and simultaneously in the problem modeling.

Some MSW management factors such as per capita production, waste quality, source separation rate, and waste reuse are not controllable, monitorable, or even predictable, but have a direct impact on the performance of the MSW management network (Engeland et al., 2020, Antmann et al., 2013). To enhance the robustness of the MSW management network against these factors, the uncertainty raised from factors such as the seasonal nature of the waste product, energy demand, cost changes, the amount of useful material in the waste, and the variation among the collected data, should be studied. The sustainability of the MSW management network and the improvement of environmental and social functions and the amount of CO₂ emissions, on the one hand, depend on the supervision and special attention of those in charge; by improving the quality of fuel used in transportation and processing, as well as monitoring the performance of waste processing facilities, it can help improve the stability of the waste management system. On the other hand, with the formation of a competitive environment between treatment centers for profit, it leads to the efforts of these centers to increase the demand for their products and as a result, increase the environmental and social standards. Social and environmental scores and the amount of CO₂ emissions in processing and transportation are considered as non-deterministic parameters that depend on the performance of the government in different sectors. One of the constructive approaches to manage uncertainty is the scenario planning method (Rezaei et al., 2020), which has been developed as a useful tool for dealing with dynamicity and complexity and is considered as a regular way to predict possible future variations (Abbaszadeh et al., 2013, Li et al., 2020).

This study presents a robust stochastic optimization model for designing an integrated sustainable MSW management network under uncertainty. The network includes the waste transfer from the waste generation points to waste treatment centers and final landfills. In addition, three products are produced by treatment centers including recycled materials, fertilizer, and electricity. The proposed model is a multi-objective mixed-integer linear programming (MILP) model that determines the location of different centers, technology type and capacity of the centers, waste flow in the network, waste allocation to the centers, transportation mode, the number of vehicles on the routes, and the amount of fuel consumed in the network. To cope with uncertainty, this paper uses a scenario-based method to investigate the impact of each of the uncertain factors on the economic, environmental, and social aspects of the waste management network.

Considering sustainable development paradigm, four objective functions are optimized in the proposed model. The first objective function minimizes the total network costs, the second objective function minimizes the amount of CO₂ emission in transportation and processing, the third and fourth objective functions maximize the environmental and social scores in the network, respectively, based on the adopted technology. The CO₂ emission in transportation and the transportation costs are calculated based on the type of the fuel used in transportation system, which yields a more realistic formulation of the problem. The amount of fuel consumed on the routes is itself calculated based on the speed, amount of load, route length, and technical characteristics of the vehicles and the road (Habibi et al., 2019). Certain parameters of the model such as the amount of generated waste, demand of final products, selling price of the recycled products, Co₂ emissions, sustainability parameters, and cost units are considered to be uncertain. To cope with these uncertainties, a set of discrete scenarios are first designed using cross-impact analysis (CIA) and visualization methods. Second, a robust stochastic programming method is applied.

The rest of this paper is organized as follows. Section 2 reviews the most relevant papers in the literature studying the MSW management. In Section 3, the proposed multi-objective MILP model for the MSW management network design problem is proposed. Section 4 presents the proposed stochastic robust solution approach to cope with the uncertainty of the input parameters as well as the case study. Afterwards, Section 5 provides the numerical results following by a sensitivity analysis. Finally, the paper is concluded in Section 6 and future research directions are highlighted.

The explanation of abbreviations and notations of the model presented in this paper can be seen in Table 1.

Table 1. Sets, variables and parameters defined for deterministic model

Sets and indices:	
<i>I</i>	Set of all points; $I = GP \cup TC \cup TS \cup HSC \cup RTW$; $i, j \in I$
<i>GP</i>	Set of waste generation points
<i>TC</i>	Set of TCs; TC' : Exciting TCs, TC'' : Potential TCs, $TC' \cup TC'' = TC$
<i>TS</i>	Set of TSs; TS' : Exciting TSs, TS'' : Potential TSs, $TS' \cup TS'' = TS$
<i>HSC</i>	Set of HSCs; HSC' : Exciting HSCs, HSC'' : Potential HSCs, $HSC' \cup HSC'' = HSC$
<i>RTW</i>	Set of RTWs; RTW' : Exciting RTWs, RTW'' : Potential RTWs, $RTW' \cup RTW'' = RTW$
<i>W</i>	Set of waste ($w \in W$); {1: Recyclable, 2: Organic, 3: Dry energetic, 4: Inert dry}
<i>T</i>	Set of vehicles ($t \in T$); {1: Compactor, 2: Truck}
<i>K</i>	Set of technologies ($k \in K$); {1: RCL, 2: COM, 3: ADS, 4: GFS, 5: PYR, 6: ICN, 7: WDS, 8: GRS}
<i>H</i>	Set of capacity levels ($h \in H$)
<i>R</i>	Set of residues ($r \in R$); {1: Effective, 2: Inert}
<i>P</i>	Set of products produced (from waste or residues processing) in the network ($p \in P$)
<i>E</i>	Set of environmental indicators of waste treatment technologies ($e \in E$)
<i>S</i>	Set of social indicators of waste treatment technologies ($s \in S$)
$L(i, j)$	Set of segments of the path $i-j$ ($l \in L(i, j)$)
Parameters:	
F_{jkh}^{TC}	Fixed cost of establishing technology k with capacity level h at TC j (USD)

F_{jwh}^{TS}	Fixed cost of establishing a TS with capacity level h for waste w at point j (USD)
F_{jh}^{HSC}	Fixed cost of establishing an HSC with capacity level h at point j (USD)
F_j^{RTW}	Fixed cost of establishing RTW at point j (USD)
F_t	Fixed cost of purchasing vehicle type t (USD)
DIS_{ij}	Distance of the shortest path between two points i and j (km)
$PC_{kw(r)}^{TC}$	Unit processing cost of waste (residue) w (r) by technology k (USD/ton)
PC_w^{TS}	Unit processing cost of waste w in TSs (USD/ton)
PC^{HSC}	Unit separation cost of wastes at HSCs (USD/ton)
TC_t	Unit transportation cost of vehicle type t (USD/km)
FL	Cost of fuel per liter for the vehicles (USD/ liter)
EL	CO ₂ emission from fuel consumption (Kg.CO ₂ /liter)
$\beta_{pkw(r)}$	Amount of product p produced from processing waste (residue) w (r) by technology k (ton/ton or kwh/ton)
PR_p	Sale price of product p (USD)
D_p	Demand of product p (ton or kwh)
φ_{iw}	Share of waste w from mixed waste at origin i (ton)
$\tau_{kw(r)}$	CO ₂ emission from processing waste (residue) w (r) by technology k (Kg. CO ₂ /ton)
$\omega_{e(s)}$	Weight of environmental (social) indicator e (s)
$\mu_{ke(s)}$	Advantage of waste treatment technology k based on environmental (social) indicator e (s)
POP_i	Population of generation point i
WS_{iw}	Amount of waste w generated and separated in source i (ton)
WM_i	Amount of mix waste generated in source i (ton)
δ_{kr}	Production rate of r -type residue by waste treatment technology k
Q_t	Capacity of vehicle t (ton)
ET_{ijt}	Expected number of trips for each vehicle t on route i - j
f_t	Failure probability of vehicle t
γ_{ijl}	Length of segment l in route i - j (Km)
PV_{ijl}	Permitted speed of vehicles on segment l of route i - j (KM/h)
UR_k^{TC}	Minimum utilization rate of waste treatment technology k in TCs
UR_w^{TS}	Minimum utilization rate at TSs for waste w
UR_j^{HSC}	Minimum utilization rate of HSCs at point j
Q_{jkh}^{TC}	Maximum capacity of waste treatment technology k with capacity level h at TC j (ton)
Q_{jwh}^{TS}	Maximum capacity of TSs with capacity level h to separate waste w at point j (ton)
Q_{jh}^{HSC}	Maximum capacity of HSCs with capacity level h at point j (ton)
Q_j^{RTW}	Maximum capacity of RTWs at point j
$\chi_{e(s)}$	Binary regulator parameter for environmental (social) score e (s) in the objective function
α_{jk}^{TC}	1 if TC j is suitable for establishing waste treatment technology k ; 0 otherwise
$\alpha_{kw(r)}^{TS}$	1 if waste treatment technology k is suitable for waste (residue) w (r); 0 otherwise
NS_w	Number of TSs required to be established for waste w

Decision variables:

Y_{jkh}^{TC}	1 if a TC waste treatment technology k is established with capacity level h at point j ; 0 otherwise
Y_{jwh}^{TS}	1 if a TS is established for waste w with capacity level h at point j ; 0 otherwise
Y_{jh}^{HSC}	1 if an HSC is established with capacity level h at point j ; 0 otherwise
Y_j^{RTW}	1 if an RTW is established at point j ; 0 otherwise
NR_t	Number of required vehicle t
MR_t	Number of vehicle t ready for possible replacement with damaged vehicles in the system
$X_{ijkw(r)}^{TC}$	Amount of waste (residue) w (r) transferred from waste generation point (TC) i to TC j and allocated to technology k (ton)
X_{ijw}^{TS}	Amount of waste w transferred from waste generation point i to TS j (ton)
X_{ij}^{HSC}	Amount of mix waste transferred from the waste generation point i to the HSC j (ton)
RT_{ij}	Number of trips required on the route i - j
FC_{ij}	Fuel consumed on route i - j
Z_{ijt}	Number of vehicle t required on route i - j

2. Literature review

The MSW management has been a concern of researchers of different fields. Table 1 classifies the most related and recent papers in the literature, adopting a mathematical programming model, from different points of view such as type of the objective function and main parameters, network echelon, sustainability pillar, decision variables, network geographical information, and uncertainty. In the reviewed articles, objective functions have been either quantitative or qualitative. In the former, the objectives have been simply quantified using mathematical expressions. However, in the latter providing a closed mathematical formulation has been impossible, and consequently, the objectives have been presented in terms of subjective scores based on decision-makers' preferences. Each of quantitative and qualitative objectives can be classified from a sustainability viewpoint into economic (EC), environmental (EN), and social (SO).

As it can be seen in Table 2, quantitative objectives have been more explored compared to qualitative ones. Among quantitative ones, economic objectives have gained the maximum attention due its simplicity of calculation. Quantitative environmental objectives possess the second place of popularity, while only two articles have studied quantitative social objectives in terms of minimizing the population exposed to risk (Yu and Solvang, 2017, Yousefloo and Babazadeh, 2020a).

Minimizing risks is one of the main goals in decision making. Minimizing or maximizing risk in optimization problems is expressed in various ways and with the aim of managing travel time or the cost of on-route transportation (Gurevsky et al., 2021(1), Gurevsky et al., 2021(2)). In the MSW management field, risk functions are often provided to manage the environmental and social aspects of the network in routes and treatment centers. The risk function is mostly used in hazardous waste management (Yu and Solvang, 2016, Zhao and Ke, 2017, Wang et al., 2021). Few articles have studied profit maximization as a single objective problem (Rizwan et al., 2018, Heidari et al., 2019, Munguía-López et al., 2020), while it has been also incorporated in the cost minimization objective function (Wang et al., 2012, Mavrotas et al., 2015, Mohsenizadeh et al., 2020, Liu and Liao, 2020). In terms of quantitative environmental objectives, minimizing emission from transportation or from processing have gained the same level of popularity in the literature. To the best of our knowledge, only two papers (Heidari et al., 2019; Mamashli and Javadian, 2020) have studied qualitative objective functions.

The number of studied echelons differs among different articles while transfer stations (TS) and treatment center (TCs) are the most considered echelons and other necessary echelons (hybrid separation center (HSC),

distribution center (DC), and replacement truck warehouse (RTW)) are left unstudied. In some papers, TS is used in networks (Rathore and Sarmah, 2019), and, in some papers, the SC is included in the network (Rizwan et al., 2018, Mohammadi et al., 2019). As far as we know, these two facilities have not been used together in any model. These two facilities have practical differences, and the use of them together would be appropriate for cities where separation from the source is not complete. Some authors focus only on waste collection at the waste generation points and do not provide an integrated network for waste management, and focus more on routing waste-collecting vehicles (Huang and Lin, 2015, Vecchi et al., 2016). However, involving all necessary echelons leads to a more efficient MSW management network and it provides the decision makers with more flexibility. In addition, a model with the highest number of echelons for a region/city can be easily generalized to other regions/cities. In designing an MSW management network and depending on the considered echelons, different decisions are made including location-allocation (LA), capacity planning (CP), inventory planning (IP), technology assignment (TA), etc. In this regard, LA, TA, and CP are among the most studied decisions when designing MSW management networks; however, other decisions including amount of fuel consumed (FC), number of vehicles (NV), and number of required trips (TRI) might be required to consider when designing an efficient MSW management network closed to reality.

Technologies to transform wastes into useful products or even to efficiently dump wastes are at the core of an MSW management network. These technologies include recycling (RCL) in material recovery facility (MRF), gasification (GFS), pyrolysis (PYR), compost (COM), incineration (ICN), gas recovery system (GRS), and waste disposal system (WDS) in landfills (LF). Each of these technologies has particular functionality and they impose different establishment cost, CO_2 emission, utilization rate etc. to the MSW management network. Accordingly, selecting among different technologies to establish in an MSW management network is a big challenge for a decision maker (Ooi et al., 2021; Paul et al., 2019; Rizwan et al., 2018; Yousefloo and Babazadeh, 2020a; Hosseinalizadeh et al., 2021). On the other hand, investigating the impact of assigning different technologies in an MSW management network helps decision-makers in choosing the right technologies to design an efficient network (Yousefloo and Babazadeh, 2020a; Hosseinalizadeh et al., 2021).

Table 2. Review of recent research in MSW management

Reference	Method ^a	Objective Function ^b					Waste type	Echelons ^c	Decision Variable ^d	Technology ^e	Uncertainty method ^f	Uncertain parameter ^g	GIS		VE ⁱ		
		Quantitative			Qualitative								Scenario making ^h				
		EC	EN	SO	EC	EN							SO	Input		Output	
Wang et al. (2012)	MILP	✓	-	-	-	-	-	MSW	GP, TC	ALC, CP	ICN, WDS, COM	FS	WG, TRC, OC, ESC, SP	-	-	-	
Mavrotas et al. (2015)	MILP	✓	-	-	✓	-	-	MSW	GP, TS, TC	LA, CP, TA	RCL, ICN, ADS, WDS, COM	-	-	-	-	-	
Huang and Lin (2015)	MINLP	-	-	-	-	-	-	MSW	GP	ALC, NV, TT	-	-	-	-	-	-	
Vecchi et al. (2016)	MILP	✓	-	-	-	-	-	MSW	GP	LAR, TT	-	-	-	-	-	-	
Yadav et al. (2017)	NLP	✓	-	-	-	-	-	MSW	GP, TS, TC	LOC	-	IO	WG, TRC, OC, SP	-	✓	-	
Yu and Solvang (2016)	MILP	✓	-	-	-	✓	-	Hazardous	GP, TC	LA, TA	RCL, WDS	-	-	-	-	-	
Yu and Solvang (2017)	MILP	✓	-	-	✓	✓	-	MSW	GP, TS, TC	LA	RCL, WDS	-	-	-	-	EC	
Xu et al. (2017)	MILP	✓	-	-	✓	✓	-	MSW	GP, SC, TC	LA	RCL	RO	WG, TRC, CER	-	-	EC	
Zhao and Ke (2017)	MILP	✓	-	-	-	✓	-	Hazardous	GP, SC, TC	LAR, IP, TT, NV	RCL	-	-	-	-	-	
Rizwan et al. (2018)	MINLP	-	✓	-	-	-	-	MSW	GP, SC, TC, CO	ALC	RCL, GFI, ICN, PYR, ADS, GRS, COM	-	-	-	-	-	
Mohammadi et al. (2019)	MILP	-	✓	-	-	-	-	MSW	GP, SC, TC, DC, CO	LA, IP, NV, TA	-	-	-	-	-	-	
Rathore and Sarmah (2019)	MILP	✓	-	-	-	-	-	MSW	GP, TS, TC	LA	RCL, ICN, COM, WDS	-	-	-	✓	-	
Paul et al. (2019)	LP	✓	-	-	-	-	-	MSW	GP, TC, CO	ALC, TRI	RCL, ICN, COM, WDS	-	-	-	-	-	
Heidari et al. (2019)	MILP	-	✓	✓	✓	-	✓	MSW	GP, SC, TC, CO	LA, CP, TA, RL	RCL, ICN, ADS, COM, WDS	FP	WG, ESC, OC, TRC, SP	-	-	EC	
Mohsenizadeh et al. (2020)	MILP	✓	-	✓	-	-	-	MSW	GP, TS, TC, CO	LA, TRI, FC	WDS	-	-	✓	-	EM	
Yousefloo and Babazadeh (2020a)	MILP	✓	-	✓	✓	✓	-	MSW	GP, TS, TC, CO	LA, TA	RCL, GFI, ICN, PYR, ADS, LFGRS, COM	-	-	-	-	EC	
Mamashli and Javadian (2020)	MILP	✓	-	-	✓	-	-	MSW	GP, TC, CO	LA, NV	RCL, ICN, WDS, COM	RFP	PD, OC, Cap, TRC	-	-	-	
Munguía-López et al. (2020)	MILP	-	✓	-	-	-	-	MSW	GP, TC, CO	ALC, PRC	RCL, GF, ICN, PYR, WDS	-	-	-	-	-	
Liu and Liao (2020)	MILP	✓	-	✓	-	-	-	MSW	GP, TS, TC, CO	LR, FC	WDS, ICN	-	-	-	-	EM	
Hosseinalizadeh et al. (2021)	MILP	✓	-	-	✓	-	-	MSW	GP, TC, CO	LA, CP, TA	RCL, GFI, ICN, ADS, GRS, WDS, COM	-	-	-	-	-	
Ooi et al. (2021)	MILP	✓	-	✓	-	-	-	MSW	GP, TC, CO	ALC	WDS, ADS, GFI, COM, ICN, RCL	-	-	-	-	EC	
Wang et al. (2021)	MILP	✓	-	-	-	✓	-	Hazardous	GP, TS, TC, CO	LA	-	2SP	WG, PR	-	-	-	
This study	MILP	✓	-	✓	✓	-	✓	✓	GP, SC, TS, TC, RTW, CO	LA, CP, TA, TRI, RTRI, NV, FC	RCL, GF, ICN, PYR, ADS, GRS, WDS, COM	SRO	WG, OC, TRC, UFC, SP, PD, SO, EN, Co ₂ , SSR	CIA	✓	✓	EM

a. MILP: Mixed-integer linear programming, MINLP: Mixed-integer non-linear programming, NLP: Non-linear programming

b. EC: Economic, EN: Environmental, SO: Social

c. GP: Waste generation point, SC: Separation center, RTW: Replacement truck warehouses, TS: Transfer station, TC: Treatment center, CO: Customer, DC: Distribution center

d. DV: Decision variables, ALC: Allocation, CP: Capacity planning, LA: Location-Allocation, TA: Technology assignment, LAR: Location-Allocation-Routing, TT: Travel time, LOC: Location, IP: Inventory planning, RV: Residue's volume, NV: Number of required vehicles, RL: Required labor, TRI: Number of required trips, FC: Amount of fuel consumed, RTRI: Real number of trips in route segments, PRC: Sales price

e. RCL: Recycling, GFI: Gasification, ICN: Incineration, PYR: Pyrolysis, ADS: Anaerobic digestion, COM: Compost, GRS: Gas recovery system, WDS: Waste disposal system, SFI: Solidification

f. FS: Fuzzy-stochastic, IO: Interval optimization, RO: Robust optimization, FP: Fuzzy programming, RFP: Robust fuzzy programming, SRO: Stochastic robust optimization, 2SP: Two-stage stochastic programming

g. WG: Waste generated amount, TRC: Transportation cost, OC: Operational cost, FC: Unit fuel cost, ESC: Establishment cost, SP: Sale price, Cap: Facilities capacity, CER: Currency exchange rate, PD: Products demand, SO: Social indicators, EN: Environmental indicators, Co₂: Co₂ emission, SSR: Source separation rate, PR: Production rate

h. CIA: Cross Impact Analysis

i. VE: vehicle emissions, EC: emission coefficient, EM: emission model

Another aspect in designing an MSW management network in the literature is the uncertainty of input parameters. Different types of uncertainty have been considered for the parameters including fuzzy-stochastic (Wang et al., 2012), interval (Yadav et al., 2017) and robust-fuzzy (Mamashli and Javadian, 2020) parameters. To cope with these uncertainties, different methods have been used such as interval-valued fuzzy-stochastic programming (Wang et al., 2012) to handle fuzzy-stochastic parameters or interval optimization to handle interval parameters (Yadav et al., 2017). One of the main contributions of this paper is the presentation of a robust stochastic programming model for a sustainable transportation and processing waste management network. A scenario-making approach is presented in this paper, based on the effective indicators in the waste management problem, to deal with the complexity and uncertainty of the problem. With the help of this approach, a larger set of uncertain parameters can be considered and the defined scenarios will be more likely to happen. To the best of our knowledge, there is no paper in the field of MSW supply chain management that uses scenario-making methods to define scenarios. Some MSW management works have calculated the number of trips between two points on the network.

However, they have not paid attention to sharing different trips on the network. Some authors have used GIS software to obtain input data, such as the shortest paths between centers and the geographical location of the network's points. In this paper, in addition to generating inputs such as allowable speed on routes, geographical location and the shortest route between network points, GIS has been used to generate the output of the number of actual trips in the network. This output helps to better manage the transportation in high-traffic areas. The last issue that need to be discussed in Table 2 is the way of accounting for CO₂ emission from transportation when designing an MSW management network. The majority of articles in this field calculate the amount of emission in transportation in a simple way, either as given coefficients or as a function of the traveled distance (Xu et al., 2017, Heidari et al., 2019, Yousefloo and Babazadeh, 2020a). Few studies have tried to model the fuel consumption of vehicles to calculate the amount of emission in transportation, wherein various parameters such as vehicle speed, vehicle engine technical specifications, and road conditions are considered. As a result, it offers a more accurate and realistic calculation of the consumed fuel and consequently the amount of CO₂ emission (Mohsenizadeh et al., 2020, Liu and Liao, 2020).

Based on the reviewed papers in Table 2, the main contributions of this paper that differentiate it from the available works in the literature include:

- Developing an integrated multi-objective MILP model for designing an optimal MSW management network,
- Considering all echelons of an MSW management network from waste generation points to waste recycling/disposal facilities,
- Incorporating quantitative and qualitative aspects of sustainability in terms of economic, environmental, and social pillars,
- Incorporating vehicle's technical characteristics as well as road properties (e.g., speed limitation) for calculating fuel consumption,
- Considering the input parameters under uncertainty and developing a scenario-based robust-stochastic optimization method to cope with the uncertainties, and
- Verifying and validating the proposed model through a real case study.

3. Problem statement and formulation

The MSW management network designed in this paper is mainly a six-echelon network with various flows from waste generation to recycled energy and materials. As depicted in Figure 1, these echelons (Ech) include waste generation points, waste Hybrid Separation Centers (HSCs), Transfer Stations (TSs), Replacement Truck Warehouses (RTWs), Treatment Centers (TCs), and customers. The echelon of TCs encompasses different facilities to process the waste with particular technologies including Biochemical Treatment Facilities (BTFs), Material Recovery Facilities (MRFs), Landfills (LFs), and Thermal Treatment Facilities (TTFs). The customer echelon includes three recycled Materials' Customers (MCs), Fertilizer Customers (FCs) and power plants to produce electricity for Electricity Customers (ECs). In the following, the main elements of the network including different waste flows and technologies are explained in details.

3.1. Classification of flows in the network

The waste flow in the network is classified from two viewpoints: the *form* of the waste and the *type* of the waste. In terms of the *form* of waste at generation points, waste is distinguished into *separated*, *unseparated*, and *inert* wastes. Unseparated wastes are transported to HSCs, wherein the wastes are first separated and, then, if necessary, they are compressed and loaded into trucks to be transported to corresponding TCs. The wastes separated at the generation points are transported to TSs, to be compacted in larger volumes. The separated wastes can be also transported directly from the generation points to TCs. TCs

are indeed the ultimate destination of all usable wastes. Inert wastes, distinguished at a generation point or any other echelon, are transferred to LFs.

From the latter viewpoint, MSWs are mainly classified into *organic, recyclable, dry energetic* and *inert dry* types of waste (Defra, 2004; Korai et al., 2016; Arena and Gregorio, 2014; Singh et al., 2011; Singh, 2019). Organic waste, which is perishable and constitutes the major and sensitive part of the waste flow, is processed through different technologies including TTFs to convert the wastes to heat and energy, BTFs to recycle organic waste, and GRS in LFs (Rizwan et al., 2017). Non-perishable recyclable waste is processed in MRFs. MRFs are facilities where recyclable waste is classified into more and different groups according to market (i.e., FC and MC) needs and sold to producers for secondary processing (Defra, 2004). Dry waste, being also non-perishable but non-recyclable, can be used to produce energy (Korai et al., 2016) in power plants to produce electricity for ECs. Finally, inert dry waste, which is non-perishable, non-recyclable and non-energy-efficient, is transferred to LFs for disposal (Arena and Gregorio, 2014).

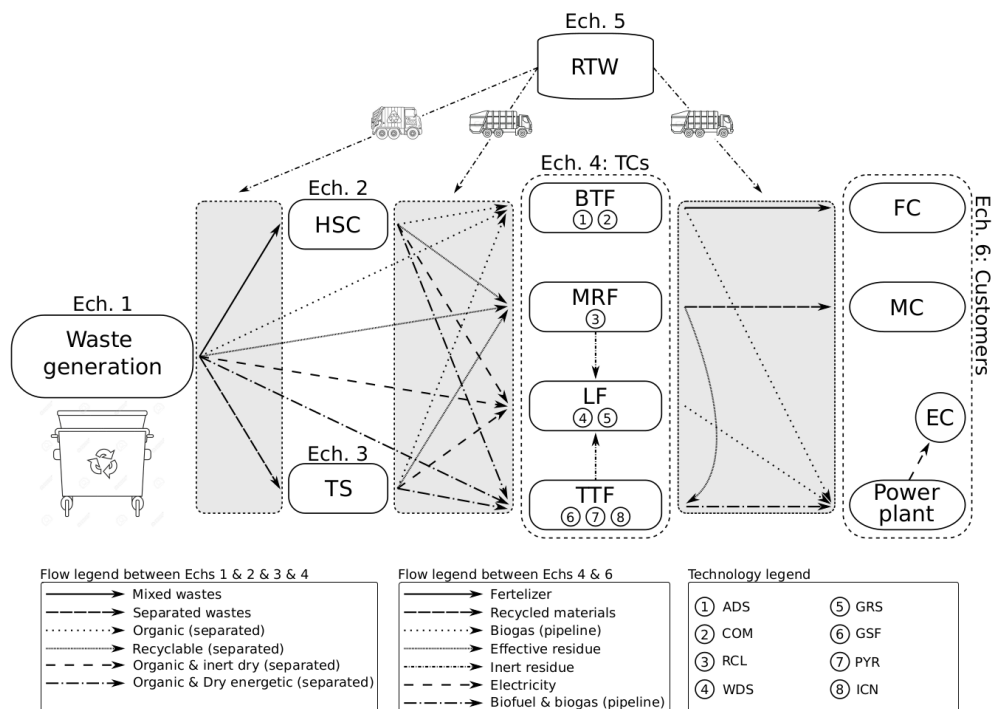


Figure 1. Structure of the designed MSW management network

The outputs of TCs are mainly recycled products or residues. The former includes fertilizer, recycled materials, biogas and biofuel. The fertilizer produced in BTFs is transferred directly to FCs; recycled materials from MRFs are sent to MCs to be sold; and biogas and biofuel generated from LFs and TTFs are transferred to power plants through pipelines or by trucks to produce electricity. Besides the recyclable output of TCs, there might be residues produced after waste processing that are divided into two *effective* and *inert* residues. The

effective residues produced in MRFs contain a percentage of recyclable waste but they are not totally recyclable like non-recyclable plastics and papers; however, they can be converted into energy in TTFs. Accordingly, effective residues are transferred from MRFs to TTFs for energy production. The inert residues such as ash and non-recyclable glass and metals remained in TTFs and MRFs are transferred to LFs.

3.2. Technologies to process wastes in the network

In general, five types of technologies are utilized to process MSWs in different facilities of TCs' echelon (MRF, LF, BTF, and TTF) of the network as: recycling, gas recovery, waste disposal, biochemical conversion, and thermal conversion technologies. Recycling (RCL) technology in MRFs is to recycle wastes into useable products. Gas recovery system (GRS) and waste disposal system (WDS) in LFs are to recover the gas from organic wastes and to efficiently dump inert wastes, respectively. Accordingly, if organic wastes are allocated to LFs, an GRS technology must be established there.

Non-recyclable and energy-efficient MSW are generally converted to energy using two thermal and biochemical conversion technologies (Ng et al., 2014). Thermal conversion, done at TTF locations, uses heat energy to reduce the volume of MSW and produce biofuels, such as combustible gas (syngas), coal, etc. The advantages of using high-temperature thermal conversion are energy recovery and a significant reduction of waste volume for final disposal. The output is usually about 10% of the input volume. Other advantages of this type of technology include reducing land use and having the potential to generate electricity (Tabasová et al., 2012). Thermal conversion technology can be categorized into ICN, PYR, and GFS. GFI and PYR technologies were first employed to extract biofuels from biomass. Afterwards, due to the proper performance of these technologies in various economic, environmental, and social aspects, they were also used in the treatment and production of energy from MSW (Razm et al., 2021). Biochemical conversion, done at BTF locations, uses enzymes and microorganisms to break down organic wastes to produce biogas and collect valuable products. Biochemical conversion is one of the most environmentally friendly methods used to obtain energy fuels from MSWs. The biochemical technology is itself categorized into ADS and COM generation (Ng et al., 2014; Singh et al., 2011). A complete scheme of the technologies for converting non-recyclable waste and the final products produced by each technology can be found in (Tan et al., 2015).

3.3. Vehicle types in the network

Two compactor and truck types of vehicles are used to transport the wastes between different locations of the network. Waste compactors collect the wastes from waste generation points and transports them to

various centers (i.e., HSCs, TSs, and TCs) in the network. For instance, the wastes separated at the generation points are transported by compactor vehicle to TSs, where they are loaded into larger compactors. Trucks transport compacted waste from TSs or HSCs to TCs. Waste compactors are smaller than trucks and could be easily used to collect the urban wastes. We consider a specific location called RTWs that contain backup vehicles to replace the failed ones in the network. In this way, the backup/reserved vehicles are directly transferred from the RTWs to the origin of the desired routes and are replaced with the failed ones.

Hereafter, important concepts and components of the problem, as key contributions of this paper to the MSW network design problem, are clarified. In the proposed model, the waste-processing echelon and its technology and sustainability implications, as the heart of the network, is more investigated. Then, to reinforce the model, the quantitative aspects of the model are combined with expert opinions, reflected as environmental and social scores. Before explaining the proposed mathematical model, the fuel consumption, as an important source of CO₂ emission, is detailed and linked to network characteristics via GIS.

3.4. Fuel consumption in the model

Transportation costs and CO₂ emission are among the most important factors that need to be minimized or at least controlled when designing the MSW management network (Yousefloo and Babazadeh, 2020a). The high level of fuel consumption in transportation imposes huge economic and environmental costs on the MSW management network. This paper tries to minimize the consumption of fossil fuels in the network. One of the main contributions of this paper is to better highlight and quantify these factors in the designed MSW management network. A parameter that directly contributes to these factors is the vehicles' fuel consumption (Franceschetti et al., 2013; Demir et al., 2014; Mohsenizadeh et al., 2020). Equation (1) calculates FC, the amount of fuel consumed by heavy vehicles, as a function of vehicles' and roads' properties. Please refer to Table A (Appendix A) for the notations. To have a more precise calculation of the fuel consumption, particularly by considering the network fleet and geographical characteristics, this paper incorporates additional parameters including fixed coefficients of shipping costs and CO₂ emission, waste flow, distance traveled by the vehicles, speed of the vehicles and a set of other parameters related to the property of the vehicles and the roads, obtained from GIS.

$$FC = (\xi/\kappa\psi) \left(eNV \frac{z}{v} + \gamma\alpha z\ell + \gamma\alpha\mu z + \beta\gamma v^2 z \right) \quad (1)$$

where, z is the distance (in meters) that the vehicle travels at speed v (meters per second); ℓ is the amount of cargo (in kg) that the vehicle carries for the whole traveled distance. In addition, let's consider $\gamma = 1/1000\delta\pi$, $\beta = 0.5C_dA\rho$, and $\alpha = g \sin(\Phi) + gC_r \cos(\Phi)$. For the sake of simplicity, we consider the coefficients $\lambda^1 = \xi eNV/\kappa\psi$, $\lambda^2 = \xi\gamma\alpha/\kappa\psi$, $\lambda^3 = \xi\gamma\alpha\mu/\kappa\psi$ and $\lambda^4 = \xi\beta\gamma/\kappa\psi$. Finally, Equation (1) can be summarized to (2).

The value of the fuel consumed per unit distance is a U-shaped convex curve (See Figure 2) as a function of velocity presented as Equation (1) (Bektaş & Laporte, 2011). The optimum transportation speed is the speed that minimizes fuel consumption based on Equation (1). Equation (1) as a function of speed shows that the optimum speeds of the compactor and the truck are 44 km/h and 46 km/h, respectively.

$$FC = \lambda^1 \frac{z}{v} + \lambda^2 z \ell + \lambda^3 z + \lambda^4 v^2 z \quad (2)$$

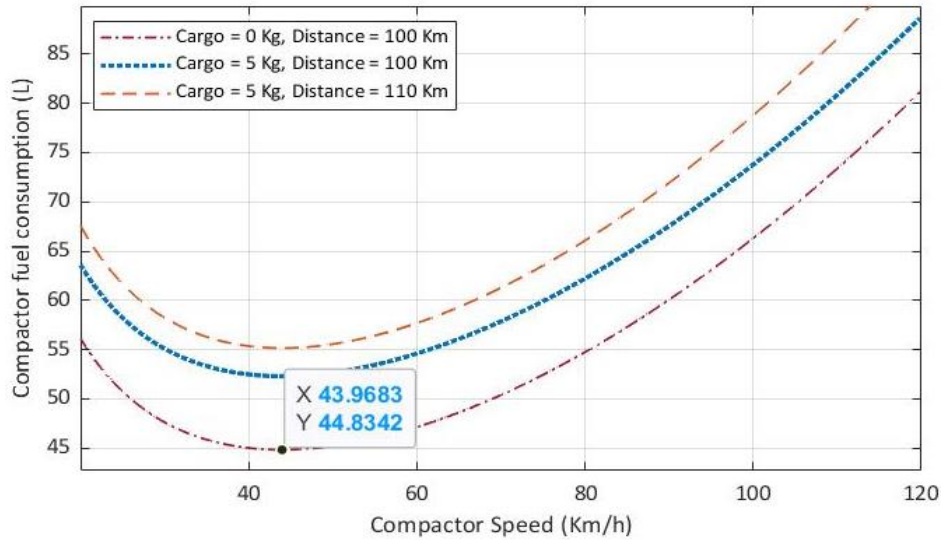


Figure 2a. Fuel consumption according to compactor vehicle speed

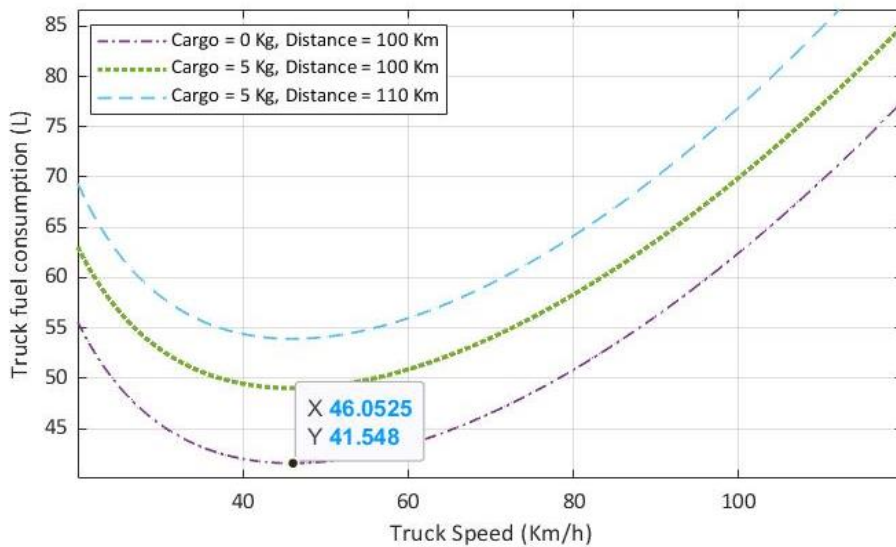


Figure 2b. Fuel consumption according to truck vehicle speed

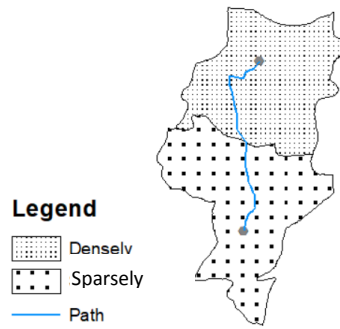


Figure 3. Example of road segments with different vehicle speed limits

The optimum speed of vehicles may be also limited due to traffic constraints (e.g., speed limit and traffic regulations) and population density in an area. In addition, a vehicle may go through different areas, with different speed limits, from one point to another. The shortest routes between points in the network were mapped on the Arc GIS software. Next, the areas under study were divided into three segments based on the areas' population density and regulated speed. For example, as illustrated in Figure 3, the map is divided into two areas based on the population density, where the transportation speed is different. Therefore, the speed of the vehicle traveling the route between the two points in these areas, drawn as a solid line in blue, will change when the vehicle crosses the areas' border.

3.5. Model framework, assumptions and notations

The conceptual framework of the proposed mathematical programming model to design a sustainable MSW management network is illustrated in Figure 4. In this model, the sustainability of the MSW management network is investigated through four objective functions including minimizing total costs, minimizing CO₂ emission, and maximizing environmental and social scores. As illustrated in Figure 3, input parameters include both deterministic and uncertain parameters. To cope with the uncertainty of input parameters, a robust stochastic programming method is going to be employed. The main outputs of the model are the optimal location for the establishment of TCs, the type of technology in the treatment facilities, the optimal capacity of the facilities, the optimal allocation of wastes to the treatment facilities, the amount of fuel required, and the number of different type of vehicles required in the MSW management network.

The main assumptions of the proposed model are:

- Waste is separated in domestic places (by people) or the mixed wastes are directly transported into separation centers (HSCs).

- A maximum of one TS can be established at each potential point for each waste type.
- A maximum of one HSC is established at each potential point.
- In each TC, more than one treatment facility can be set up and the facilities within a TC will not have the same technology.
- If a GRS is established in a LF, organic waste can be allocated to the landfill and electricity can be generated.
- RTWs stores both types of transportation vehicles.
- Vehicles may break down in the network.
- The speed of vehicles varies in different segments of a route.

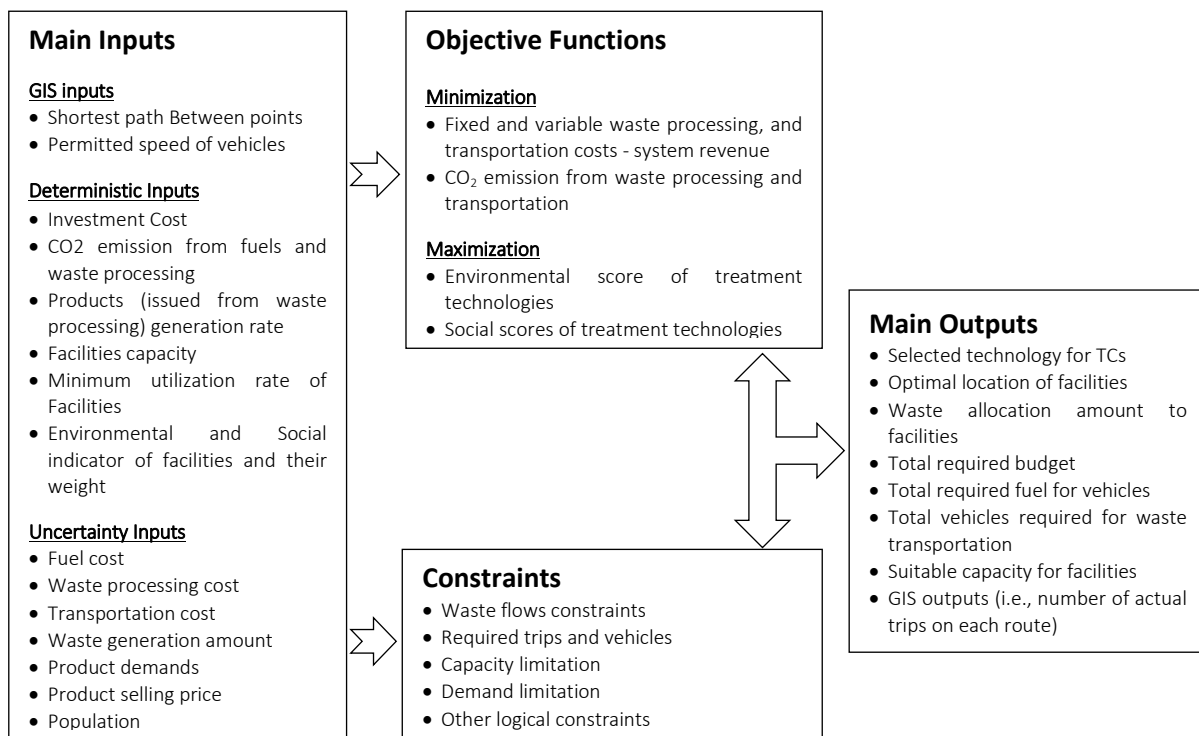


Figure 4. Structure of the presented model

3.6. Objective functions

The proposed MILP model has four objectives: minimizing the total costs, minimizing the total CO₂ emission, maximizing the total environmental scores, and maximizing the total social scores. The two maximization objectives, with qualitative foundations, have been integrated in the model to enhance the consideration of waste processing sustainability impact knowing that this echelon is a critical part of the network. The four objectives are presented in the following subsections.

3.6.1. Minimization the total cost

The first objective function minimizes the total costs, which include the fixed establishment costs and variable (per volume of wastes) processing and transportation costs. System revenue is finally deducted from the total cost. In the following, the costs and revenue components of the model are described.

Fixed establishment cost -- Expression (3) represents the fixed establishment cost of facilities (i.e., TCs, TSs, HSCs, and RTWs), and the cost of purchasing different vehicles.

$$\begin{aligned} & \sum_{j \in TC''} \sum_{k \in K} \sum_{h \in H} F_{jkh}^{TC} \cdot Y_{jkh}^{TC} + \sum_{j \in TS''} \sum_{w \in W} \sum_{h \in H} F_{jwh}^{TS} \cdot Y_{jwh}^{TS} + \sum_{j \in HSC''} \sum_{h \in H} F_{jh}^{HSC} \cdot Y_{jh}^{HSC} + \sum_{j \in RTW} F_j^{RTW} \cdot Y_j^{RTW} \\ & + \sum_{t \in T} F_t (NR_t + MR_t) \end{aligned} \quad (3)$$

Variable processing cost -- Expression (4) includes the cost of processing wastes in TCs, TSs, HSCs, and the cost of processing residues in corresponding TCs, respectively.

$$\begin{aligned} & \sum_{i \in I \setminus \{TC, RT\}} \sum_{j \in TC} \sum_{k \in K} \sum_{w \in W} PC_{kw}^{TC} \cdot X_{ijkw}^{TC} + \sum_{i \in GP} \sum_{j \in TS} \sum_{w \in W} PC_w^{TS} \cdot X_{ijw}^{TS} \\ & + \sum_{i \in GP} \sum_{j \in HSC} \sum_{w \in W} (PC^{HSC} + PC_w^{TS} \cdot \varphi_{iw}) X_{ij}^{HSC} + \sum_{i \in TC} \sum_{j \in TC} \sum_{k \in K} \sum_{r \in R} PC_{kr}^{TC} \cdot X_{ijk}^{TC} \end{aligned} \quad (4)$$

Variable transportation cost -- Expression (5) includes the transportation cost of different vehicles throughout the network. The transportation cost is obtained by multiplying the shipping unit cost by the traveled distance. Expression (6) shows the total fuel cost in the network, which is obtained by multiplying the unit fuel cost by its total consumption.

$$\begin{aligned} & 2 \left(TC_1 \sum_{i \in GP} \sum_{j \in I \setminus \{GP, RTW\}} DIS_{ij} \cdot RT_{ij} + TC_2 \sum_{i \in I \setminus \{GP, RTW\}} \sum_{j \in TC} DIS_{ij} \cdot RT_{ij} \right) + TC_1 \sum_{i \in RTW} \sum_{j \in GP} DIS_{ij} \cdot RT_{ij} \\ & + TC_2 \sum_{i \in RTW} \sum_{j \in I \setminus \{GP, RTW\}} DIS_{ij} \cdot RT_{ij} \end{aligned} \quad (5)$$

$$FL \left(\sum_{i \in GP} \sum_{j \in I \setminus \{GP, RTW\}} FC_{ij} + \sum_{j \in I \setminus \{GP, RTW\}} \sum_{j \in TC} FC_{ij} + \sum_{i \in RTW} \sum_{j \in GP} FC_{ij} + \sum_{i \in RTW} \sum_{j \in I \setminus \{GP, RTW\}} FC_{ij} \right) \quad (6)$$

Revenue -- Expression (7) shows the revenue from the sales of final products resulted from the wastes or residues, respectively.

$$\sum_{i \in I \setminus \{TC, RTW\}} \sum_{j \in TC} \sum_{k \in K} \sum_{p \in P} PR_p \left(\sum_{w \in W} X_{ijkw}^{TC} \cdot \beta_{pkw} + \sum_{r \in R} X_{ijk}^{TC} \cdot \beta_{pkr} \right) \quad (7)$$

The sum of Expressions (3) to (6) minus Expression (7) constitutes the cost objective function.

3.6.2. Minimization total CO₂ emission

The second objective function maximizes the total CO₂ emission in transportation and waste processing.

CO₂ emission in transportation -- Expression (8) allows calculating the amount of CO₂ emission in transportation by multiplying the coefficient of emission by the fuel consumption on different routes.

$$EL \left(\sum_{i \in GP} \sum_{j \in I \setminus \{GP, RTW\}} FC_{ij} + \sum_{i \in I \setminus \{GP, RTW\}} \sum_{j \in TC} FC_{ij} + \sum_{i \in RTW} \sum_{j \in GP} FC_{ij} + \sum_{i \in RTW} \sum_{j \in I \setminus \{GP, RTW\}} FC_{ij} \right) \quad (8)$$

CO₂ emission in processing -- Expression (9) shows the sum of total CO₂ emission of waste and residue processing in TCs, wherein the amount of CO₂ emission is obtained by multiplying the emission coefficient by the amount of waste allocated to each treatment facility.

$$\sum_{i \in I \setminus \{TC, RTW\}} \sum_{j \in TC} \left(\sum_{k \in K} \sum_{w \in W} \tau_{kw} \cdot X_{ijkw}^{TC} + \sum_{k \in K} \sum_{r \in R} \tau_{kr} \cdot X_{ijkr}^{TC} \right) \quad (9)$$

Finally, the sum of Expressions (8) and (9) is to be minimized in the CO₂ emission objective function.

3.6.3. Maximization of environmental and social scores

The calculation of CO₂ emission, as well as other common quantitative sustainability indicators, may be sometimes inaccurate or biased, vary from one calculator to another, or even lacks the consideration of other sustainability indicators. This issue could be less observed in the transportation, where this field has been subject to extensive studies on the CO₂ emission, but when it comes to waste processing technologies, a more holistic and long-term approach is required. Therefore, on one hand, additional indicators could be integrated in the evaluation of the technologies' sustainability, and on the other hand, expert could be helpful. Khan and Kabir (2019) proposed a set of environmental and social indicators, with minimum overlap, for the sustainability of waste processing technologies. In their study, common technologies are compared using a multicriteria decision making (MCDM) technique and environmental and social weight are calculated for each indicator. Finally, each technology is given a score according to its relative performance (Khan and Kabir, 2019). In other words, higher score means higher sustainability. Besides to the work of Khan and Kabir (2019), in this paper, we have also integrated compost and LFGR technologies into the technology comparison and updated the weights to cover more waste types, particularly those who can be processed in landfills. Accordingly, to reinforce the network design decisions, made based on the sustainability of such waste processing facilities, two additional objectives are included in the model for maximizing the environmental and social scores. We have also proposed to relate these indicators to the population of the area, where the waste generation points are situated, affected by the facilities, the amount of wastes transferred to the facilities, and inversely to the distance of the facilities from the areas. Accordingly, facilities that have low environmental scores are likely to be located further to densely populated areas and less waste is allocated to them, and vice-versa.

Environmental score maximization -- As the quantitative-qualitative objective function, Expression (10) maximizes the environmental score of waste processing facilities based on a set of indicators as: land use, water use, pollutant production, total emission, CO₂ emission, SO_x emission, NO_x emission, dust, ash, noise (i.e., from construction, operations, and traffic), and odor. The weight (relative importance) of an environmental indicator e is determined by parameters ω_e and χ_e (i.e., $\chi_e \in \{0,1\}$), where the latter is a binary regulator. For χ_e , the values equal to one belong to the indicators that affect the populated areas (e.g., noise) and 0, otherwise.

$$\sum_{i \in CC} \sum_{j \in C2UC1} \sum_{k \in K} \sum_{e \in E} \frac{\omega_e \cdot \mu_{ke} \cdot (Pop_i)^{\chi_e} \cdot \left(\sum_{i' \in I \setminus \{TC, RTW\}} \sum_{w \in W} X_{i'jkw}^{TC} + \sum_{i' \in TC} \sum_{r \in R} X_{i'jkr}^{TC} \right)}{(DIS_{ij})^{\chi_e}} \quad (10)$$

Social score maximization -- As the second quantitative-qualitative objective function, Expression (11) maximizes the social score of waste processing facilities based on a set of indicators as: people displacement, disturbance to existing social infrastructure and services, visual disturbance due to the infrastructures, heatwave, public health risk, job creation, impact on land value, community acceptance, and local economy development (Khan and Kabir, 2019). Similar to environmental indicators, the weight (relative importance) of a social indicator s is determined by parameters ω_s .

$$\sum_{i \in CC} \sum_{j \in C2UC1} \sum_{k \in K} \sum_{s \in S} \frac{\omega_s \cdot \mu_{ks} \cdot (Pop_i)^{\chi_s} \cdot \left(\sum_{i' \in I \setminus \{TC, RTW\}} \sum_{w \in W} X_{i'jkw}^{TC} + \sum_{i' \in TC} \sum_{r \in R} X_{i'jkr}^{TC} \right)}{(DIS_{ij})^{\chi_s}} \quad (11)$$

3.7. Constraints

In this section, the constraints of the proposed model are described in detail. These constraints are mainly about the mass flow equations in different centers, the limitation of the number of trips and the number of transportation vehicles required on the routes, the capacity limitations of the centers, the demand limitation, and other logical constraints.

3.7.1. Waste flow conservation

The following constraints are the flow conservation constraints that define the balance of input and output flow of waste and residues at different nodes of the network. The amount of isolated and separated waste, from a waste generation point, should be equal to the amount of waste transported to TCs and to TSs (see Equation (12)). The amount of mixed wastes, from a waste generation point, should be equal to the amount of waste transferred to HSCs (see Equation (13)). The amount of separated wastes entering TSs should be equal to the amount of waste transported from TSs to TCs (see Equation (14)). The amount of mixed wastes

being separated and compacted at HSCs should be equal to the amount of waste transported from HSCs to TCs (see Equation (15)). The amount of residues generated at a TC should be equal to the amount of residues transported from that TC to another TC, having the suitable technology for the treatment of the residues (see Equation (16)). The suitability condition is further guaranteed in the capacity constraints.

$$\sum_{j \in TC} \sum_{k \in K} X_{ijkw}^{TC} + \sum_{j \in TS} X_{ijw}^{TS} = WS_{iw} \quad \forall i \in GP, w \in W \quad (12)$$

$$\sum_{j \in HSC} X_{ij}^{HSC} = WM_i \quad \forall i \in GP \quad (13)$$

$$\sum_{i \in GP} X_{ijw}^{TS} = \sum_{i \in TC} \sum_{k \in K} X_{jikw}^{TC} \quad \forall j \in TS, w \in W \quad (14)$$

$$\sum_{i \in GP} \varphi_{iw} \cdot X_{ij}^{HSC} = \sum_{i \in TC} \sum_{k \in K} X_{jikw}^{TC} \quad \forall j \in HSC, w \in W \quad (15)$$

$$\sum_{i \in I \setminus \{TC, RTW\}} \sum_{k \in K} \sum_{w \in W} \delta_{kr} \cdot X_{ijkw}^{TC} = \sum_{i \in TC} \sum_{k \in K} X_{jikr}^{TC} \quad \forall j \in TC, r \in R \quad (16)$$

3.7.2. Transportation capacity constraints

The constraints included in this section are about the transportation capacity, in terms of required vehicles, which is mainly calculated based on the number of trips required on the network's routes. The constraints concerning the part of network where we have the waste transportation are first mentioned and then, the transportation between RTWs and other locations is addressed.

The number of trips required on a route i - j of the network, should be greater or equal to the total amount of waste (or residue) transported between points i and j divided by the capacity of the vehicles required on that route. Constraints (17) to (21) ensure this condition, knowing that, depending on the nature of the origin and destination points, the transported entities (i.e. waste or residues) and accordingly, the vehicle type varies.

$$RT_{ij} \geq \sum_{k \in K} \sum_{w \in W} \frac{X_{ijkw}^{TC}}{Q_t} \quad i \in GP, j \in TC, t = 1 \quad (17)$$

$$RT_{ij} \geq \sum_{w \in W} \frac{X_{ijw}^{TS}}{Q_t} \quad i \in GP, j \in TS, t = 1 \quad (18)$$

$$RT_{ij} \geq \frac{X_{ij}^{HSC}}{Q_t} \quad i \in GP, j \in HSC, t = 1 \quad (19)$$

$$RT_{ij} \geq \sum_{k \in K} \sum_{w \in W} \frac{X_{ijkw}^{TC}}{Q_t} \quad i \in I \setminus \{GP, TC, RTW\}, j \in TC, t = 2 \quad (20)$$

$$RT_{ij} \geq \sum_{k \in K} \sum_{r \in R} \frac{X_{ijk}^{TC}}{Q_t} \quad i, j \in TC, t = 2 \quad (21)$$

Number of trips required on the network's routes actually affects the number of vehicles required in the network. This number should be therefore greater than or equal to the number of trips required on the route

divided by the expected number of trips from the vehicles on that route (see Constraints (22) and (23), for compactors and trucks).

$$Z_{ijt} \geq \frac{RT_{ij}}{ET_{ijt}} \quad \forall i \in GP, j \in I \setminus \{GP, RTW\}, t = 1 \quad (22)$$

$$Z_{ijt} \geq \frac{RT_{ij}}{ET_{ijt}} \quad \forall i \in I \setminus \{GP, RTW\}, j \in TC, t = 2 \quad (23)$$

Since no waste is transported on routes of the network, that originated at RTW, the capacity of vehicles has no effect on the number of trips on these routes. In addition, given the assumption that, when each replacement vehicle is replaced by a broken-down vehicle, it will work on other routes defined in the network and will not travel back to RTW until it is broken down. As a result, in this route of the network, the value of the parameter of the number of required trips is equal to the number of possible replacement cars needed in the route (See respectively Equations (24) or (25) for routes from RTW to GP or to other locations).

$$Z_{ijt} = RT_{ij} \quad \forall i \in RTW, j \in GP, t = 1 \quad (24)$$

$$Z_{ijt} = RT_{ij} \quad \forall i \in RTW, j \in I \setminus \{GP, RTW\}, t = 2 \quad (25)$$

The number of required vehicles on routes from an RTW depends itself on the vehicles required on other parts of the network and their failure probability. In fact, the number of reserved compactors and trucks required for possible transfers from RTWs is at least equal to the probability of compactor or truck failure multiplied by the total number of compactors required for the transportations between other points of the network (see Constraints (26) and (27) respectively for routes from an RTW to GPs or to other points)

$$\sum_{i \in RTW} Z_{ijt} \geq \sum_{i \in I \setminus \{GP, RTW\}} f_t \cdot Z_{jit} \quad \forall j \in GP, t = 1 \quad (26)$$

$$\sum_{i \in RTW} Z_{ijt} \geq \sum_{i \in TC} f_t \cdot Z_{jit} \quad \forall j \in I \setminus \{GP, RTW\}, t = 2 \quad (27)$$

Finally, Constraints (28) and (29) guarantee that the number of replacement vehicles should not exceed the total number of busy vehicles in the network.

$$\sum_{i \in RTW} \sum_{j \in GP} Z_{ijt} \leq NR_t \quad \forall t = 1 \quad (28)$$

$$\sum_{i \in RTW} \sum_{j \in I \setminus \{GP, RTW\}} Z_{ijt} \leq NR_t \quad \forall t = 2 \quad (29)$$

3.7.3. Fuel consumption calculation

Among the various parameters of the initial fuel consumption equation (see Equation (2)), vehicle type (capacity) and vehicle load and vehicle speed vary different routes of the network. Accordingly, there will be three situations: I) vehicles with full load on routes from origins to destinations, II) vehicles with partial load

(less than the capacity of the vehicle) on routes from origins to destinations, and III) vehicles with no load in case of a replacement vehicle from RTWs to any point.

In this regard, a set of intermediate variables are defined as follows:

- θ_{ijt}^I to calculate the fuel consumed on the trip of type I between any points in the network to TCs,
- θ_{ijt}^{TC} , θ_{ijt}^{TS} , and θ_{ijt}^{HSC} to calculate the fuel consumed on the trip of type II for transferring wastes to destinations of TCs, TSs, and HSCs, respectively,
- $\bar{\theta}_{ijt}^{TC}$ to calculate the fuel consumed on the trip of type II for transferring residues to destinations of TCs, and
- $\bar{\theta}_{ijt}^I$ to calculate the fuel consumed on the trip of type III.

The above three types of trips can happen in any route of the network. The routes of the network are categorized in seven classes including 1) from generation points to TCs by compactor vehicles, 2) from generation points to TSs by compactor vehicles, 3) from generation points to HSCs by compactor vehicles, 4) from TSs and HSCs to TCs by trucks, 5) from TCs to TCs for transferring of residues by trucks, 6) from RTWs to generation points by compactor vehicles, 7) from RTWs to TCs, TSs, and HSCs by trucks.

Equation (30) calculates the fuel consumed on the first class of the routes, for which we have three types of trips on the route. The number of trips of type I on the first class of routes is equal to $RT_{ij} - 1$. In addition, the number of trips of type II on the first class of routes is equal to one. Finally, the number of trips of type III on the first class of routes is equal to RT_{ij} . To calculate the fuel consumed for the trips of type I (θ_{ijt}^I), we first calculate the fuel consumption for a trip using Equation (2), then multiply the resulting expression by $RT_{ij} - 1$. The amount of truckload on the trips of type I is equal to the capacity of the vehicles. The amount of truckload on the trips of type II is equal to the total waste transported on the route deducted by $(RT_{ij} - 1)Q_t$. The amount of truckload on the trips of type III is equal to 0. It should be noted that due to the variability of the vehicle's speed on a route, the speed and the distance of the segments of each route are considered instead of the whole route. The calculation of the fuel consumed in other routes is done in the same way as Equations (31) to (36).

$$FC_{ij} = \theta_{ijt}^I + \theta_{ijt}^{TC} + \bar{\theta}_{ijt}^I \quad \forall i \in GP, j \in TC, t = 1 \quad (30)$$

$$FC_{ij} = \theta_{ijt}^I + \theta_{ijt}^{TS} + \bar{\theta}_{ijt}^I \quad \forall i \in GP, j \in TS, t = 1 \quad (31)$$

$$FC_{ij} = \theta_{ijt}^I + \theta_{ijt}^{HSC} + \bar{\theta}_{ijt}^I \quad \forall i \in GP, j \in HSC, t = 1 \quad (32)$$

$$FC_{ij} = \theta_{ijt}^I + \theta_{ijt}^{TC} + \bar{\theta}_{ijt}^I \quad \forall i \in \{TS, HSC\}, j \in TC, t = 2 \quad (33)$$

$$FC_{ij} = \theta_{ijt}^I + \bar{\theta}_{ijt}^{TC} + \bar{\theta}_{ijt}^I \quad \forall i \in TC, j \in TC, t = 2 \quad (34)$$

$$FC_{ij} = \bar{\theta}_{ijt}^I \quad \forall i \in RTW, j \in GP, t = 1 \quad (35)$$

$$FC_{ij} = \bar{\theta}_{ijt}^I \quad \forall i \in RTW, j \in I \setminus \{GP, RTW\}, t = 2 \quad (36)$$

$$\theta_{ijt}^I = (RT_{ij} - 1) \left(\lambda_t^1 \sum_{l \in L(i,j)} \frac{\gamma_{ijl}}{PV_{ijl}} + \lambda_t^2 \cdot Q_t \cdot DIS_{ij} + \lambda_t^3 \cdot DIS_{ij} + \lambda_t^4 \sum_{l \in L(i,j)} (PV_{ijl})^2 \cdot \gamma_{ijl} \right) \quad \forall i \in I, j \in I \setminus \{GP, RTW\}, t \in T \quad (37)$$

$$\theta_{ijt}^{TC} = \lambda_t^1 \sum_{l \in L(i,j)} \frac{\gamma_{ijl}}{PV_{ijl}} + \lambda_t^2 \left(\sum_{k \in K} \sum_{w \in W} X_{ijkw}^{TC} - (RT_{ij} - 1)Q_t \right) DIS_{ij} + \lambda_t^3 \cdot DIS_{ij} + \lambda_t^4 \sum_{l \in L(i,j)} (PV_{ijl})^2 \cdot \gamma_{ijl} \quad \forall i \in I \setminus \{TC, RTW\}, j \in TC, t \in T \quad (38)$$

$$\theta_{ijt}^{TS} = \lambda_t^1 \sum_{l \in L(i,j)} \frac{\gamma_{ijl}}{PV_{ijl}} + \lambda_t^2 \left(\sum_{w \in W} X_{ijw}^{TS} - (RT_{ij} - 1)Q_t \right) DIS_{ij} + \lambda_t^3 \cdot DIS_{ij} + \lambda_t^4 \sum_{l \in L(i,j)} (PV_{ijl})^2 \cdot \gamma_{ijl} \quad \forall i \in GP, j \in TS, t = 1 \quad (39)$$

$$\theta_{ijt}^{HSC} = \lambda_t^1 \sum_{l \in L(i,j)} \frac{\gamma_{ijl}}{PV_{ijl}} + \lambda_t^2 (X_{ij}^{HSC} - (RT_{ij} - 1)Q_t) DIS_{ij} + \lambda_t^3 \cdot DIS_{ij} + \lambda_t^4 \sum_{l \in L(i,j)} (PV_{ijl})^2 \cdot \gamma_{ijl} \quad \forall i \in GP, j \in HSC, t = 1 \quad (40)$$

$$\bar{\theta}_{ijt}^{TC} = \lambda_t^1 \sum_{l \in L(i,j)} \frac{\gamma_{ijl}}{PV_{ijl}} + \lambda_t^2 \left(\sum_{k \in K} \sum_{r \in R} X_{ijk_r}^{TC} - (RT_{ij} - 1)Q_t \right) DIS_{ij} + \lambda_t^3 \cdot DIS_{ij} + \lambda_t^4 \sum_{l \in L(i,j)} (PV_{ijl})^2 \cdot \gamma_{ijl} \quad \forall i, j \in TC, t = 2 \quad (41)$$

$$\bar{\theta}_{ijt}^I = RT_{ij} \left(\lambda_t^1 \sum_{l \in L(i,j)} \frac{\gamma_{ijl}}{PV_{ijl}} + \lambda_t^3 \cdot DIS_{ij} + \lambda_t^4 \sum_{l \in L(i,j)} (PV_{ijl})^2 \cdot \gamma_{ijl} \right) \quad \forall i \in I, j \in I \setminus \{RTW\}, t \in T \quad (42)$$

3.7.4. Demand constraints

The number of products produced from the processing of wastes and residues in TCs including recycled material (e.g., paper, glass, metal and plastic), electricity, and fertilizer, should be less than or equal to the demand of such products as Constraint (43).

$$\sum_{i \in I \setminus \{TC, RTW\}} \sum_{j \in TC} \sum_{k \in K} \sum_{w \in W} X_{ijkw}^{TC} \cdot \beta_{pkw} + \sum_{i \in TC} \sum_{j \in TC} \sum_{k \in K} \sum_{\gamma \in \Upsilon} X_{ijk\gamma}^{TC} \cdot \beta_{pk\gamma} \leq D_p \quad \forall p \in P \quad (43)$$

3.7.5. Processing Capacity constraints

Constraints (44) to (46) apply the capacity limitation on the waste treatment facilities and the minimum utilization rate of the treatment facilities, respectively. Each technology is established with a suitable capacity and utilization rate. The appropriate capacity and utilization rate for each technology were obtained by reviewing the past literature in the MSW management area (Mirdar Harijani et al., 2017, Mohsenizadeh et al., 2020, Yousefloo and Babazadeh, 2020a). Constraint (45) also ensures that waste transferred to GRS technology occupies landfill capacity. In other words, by building a GRS technology in a landfill, the capacity of the landfill

is reduced. Constraint (46) guarantees that if the GRS is established in a landfill, the organic waste must occupy at least 50% of the landfill capacity, and if no GRS is established, the organic waste allocation should be 0. GRS is a system established in landfills to recover gases produced in landfills. Since the gases emitted from the landfill originate from wet or organic waste, then the establishment of the GRS in the landfill requires the allocation of organic waste in the landfill. (Tan et al., 2015, Yousefloo and Babazadeh, 2020a, DEFRA, 2004, ERM, 2011). Constraints (47) and (48) guarantee that allocating a waste type or residue to a processing technology is based on their consistency. Any municipal solid waste treatment technology can process and treat a range of waste types. But some technologies may not be effective for treating one type of waste. (Yousefloo and Babazadeh, 2020b, Arena and Gregorio, 2014). Constraints (49) and (50) apply capacity limits and minimum utilization rates at TSs and HSCs, respectively (EPA, 2002). Finally, Equation (51) corresponds to the storage capacity of RTWs, wherein it is assumed that a truck occupies the storage capacity of two compactor vehicles.

$$\sum_{i \in I \setminus \{TC, RTW\}} \sum_{w \in W} X_{ijkw}^{TC} + \sum_{i \in TC} \sum_{r \in R} X_{ijkr}^{TC} \leq \sum_{h \in H} Q_{jkh}^{TC} \cdot Y_{jkh}^{TC} \quad \forall j \in TC, k \in K \setminus \{7,8\} \quad (44)$$

$$\sum_{i \in I \setminus \{TC, RTW\}} \sum_{w \in \{2,4\}} \sum_{k \in \{7,8\}} X_{ijkw}^{TC} + \sum_{i \in TC} \sum_{r \in R} \sum_{k=7} X_{ijkr}^{TC} \leq \sum_{h \in H} Q_{jkh}^{TC} \cdot Y_{jkh}^{TC} \quad \forall j \in TC \quad (45)$$

$$UR_k^{TC} \sum_{h \in H} Q_{jkh}^{TC} \cdot Y_{jkh}^{TC} \leq \sum_{i \in I \setminus \{TC, RTW\}} \sum_{w \in W} X_{ijkw}^{TC} + \sum_{i \in TC} \sum_{r \in R} X_{ijkr}^{TC} \quad \forall j \in TC, k \in K \quad (46)$$

$$\sum_{i \in I \setminus \{TC, RTW\}} X_{ijkw}^{TC} \leq \sum_{h \in H} Q_{jkh}^{TC} \cdot Y_{jkh}^{TC} \cdot \alpha_{kw}^{TC} \quad \forall j \in TC, k \in K, w \in W \quad (47)$$

$$\sum_{i \in TC} X_{ijkr}^{TC} \leq \sum_{h \in H} Q_{jkh}^{TC} \cdot Y_{jkh}^{TC} \cdot \alpha_{kr}^{TC} \quad \forall j \in TC, k \in K, r \in R \quad (48)$$

$$UR_w^{TS} \sum_{h \in H} Q_{jwh}^{TS} \cdot Y_{jwh}^{TS} \leq \sum_{i \in CC} X_{ijw}^{TS} \leq \sum_{h \in H} Q_{jwh}^{TS} \cdot Y_{jwh}^{TS} \quad \forall j \in TS, w \in W \quad (49)$$

$$UR_j^{HSC} \sum_{h \in H} Q_{jh}^{HSC} \cdot Y_{jh}^{HSC} \leq \sum_{i \in CC} X_{ij}^{HSC} \leq \sum_{h \in H} Q_{jh}^{HSC} \cdot Y_{jh}^{HSC} \quad \forall j \in HSC \quad (50)$$

$$2 \sum_{j \in I \setminus \{TC, RTW\}} \sum_{t=2} Z_{ijt} + \sum_{j \in GP} \sum_{t=1} Z_{ijt} \leq Q_i^{RTW} \cdot Y_i^{RTW} \quad \forall i \in RTW \quad (51)$$

3.7.6. Other logical constraints

Constraint (52) sets the minimum number of TSs for each type of the wastes. Equations (53) to (56) ensure that existing facilities including TSs, TCs, and RTWs with their corresponding properties (i.e., technology and capacity level) should be used. Constraint (57) guarantees that facilities within a TC do not have the same technology, and a technology will not be established if the location is not suitable for launching that technology. Constraint (58) forces that a maximum of one TS should be established in each point for each type of the

wastes. Constraint (59) ensures that a maximum of one HSC should be established at each point. Finally, Constraint (60) guarantees that a gas recovery system will be installed where the landfill is located or established.

$$\sum_{j \in TS} \sum_{h \in H} Y_{jwh}^{TS} \geq NS_w \quad \forall w \in W \quad (52)$$

$$Y_{jkh}^{TC} = 1 \quad \forall j \in TC', k \in K, h \in H \quad (53)$$

$$Y_{jwh}^{TS} = 1 \quad \forall j \in TS', w \in W, h \in H \quad (54)$$

$$Y_{jh}^{HSC} = 1 \quad \forall j \in HSC', h \in H \quad (55)$$

$$Y_j^{RTW} = 1 \quad \forall j \in RTW' \quad (56)$$

$$\sum_{h \in H} Y_{jkh}^{TC} \leq \alpha_{jk}^{TC} \quad \forall j \in TC'', k \in K \quad (57)$$

$$\sum_{h \in H} Y_{jwh}^{TS} \leq 1 \quad \forall j \in TS'', w \in W \quad (58)$$

$$\sum_{h \in H} Y_{jh}^{HSC} \leq 1 \quad \forall j \in HSC'' \quad (59)$$

$$Y_{jkh}^{TC} \leq Y_{jk'h}^{TC} \quad \forall j \in TC, k' = 7, k = 8, h \in H \quad (60)$$

Equations (62) and (63) calculate the total number of main compactor and trucks required in the network, respectively. Equation (64) and (65) calculates the number of replacement compactors and trucks required in the network, respectively.

$$NR_t = \sum_{i \in CC} \sum_{j \in I \setminus \{GP, RTW\}} Z_{ijt} \quad \forall t = 1 \quad (62)$$

$$NR_t = \sum_{i \in I \setminus \{GP, RTW\}} \sum_{j \in TC} Z_{ijt} \quad \forall t = 2 \quad (63)$$

$$MR_t = \sum_{i \in RTW} \sum_{j \in GP} Z_{ijt} \quad \forall t = 1 \quad (64)$$

$$MR_t = \sum_{i \in RTW} \sum_{j \in I \setminus \{GP, RTW\}} Z_{ijt} \quad \forall t = 2 \quad (65)$$

Equations (66) to (68) apply the non-negative, binary and integrity properties of the decision variables.

$$X_{ijkw(r)}^{TC}, X_{ijw}^{TS}, X_{ij}^{HSC}, FC_{ij} \geq 0 \quad \forall i, j \in I, k \in K, w \in W, r \in R \quad (66)$$

$$Y_{jkh}^{TC}, Y_{jwh}^{TS}, Y_{jh}^{HSC}, Y_j^{RTW} \in \{0, 1\} \quad \forall i, j \in I, k \in K, w \in W, h \in H \quad (67)$$

$$NR_t, MR_t, RT_{ij}, Z_{ijt} \in Z_+ \quad \forall i, j \in I, t \in T \quad (68)$$

4. Experimental design

Robust stochastic programming (RSP) method is applied to cope with the uncertainty of the input parameters of the proposed model. To consider space limitation this method is explained in Appendix B.

4.1. Case study

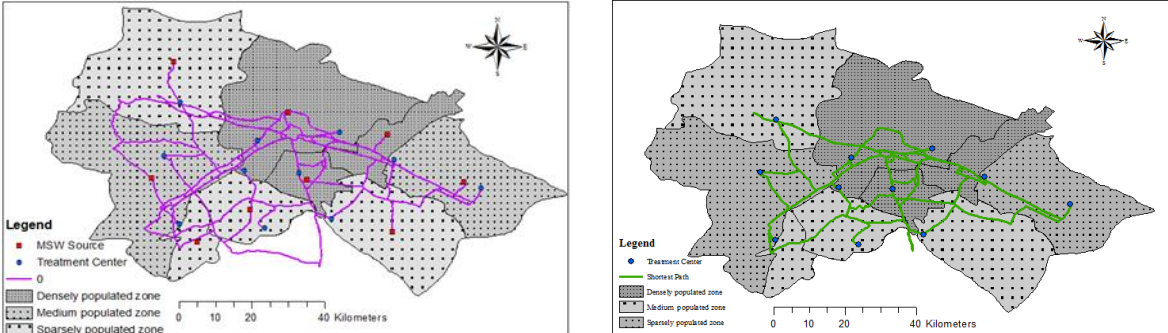
The proposed multi-objective MILP model and the robust stochastic approach are validated on a real case study of Qazvin province in Iran. In this province, about 750 to 850 tons of wastes is buried daily, which is

transferred from 21 cities and some villages to an LF located 28km away from the center of the province. Due to the huge volume of generated wastes, the wastes are dumped in LFs without any separation and this causes LF saturation. Considering this issue and the benefits of waste recycling, MSW management organization of the province has decided to establish a set of facilities for recycling, processing, disposal, and conversion of the generated wastes through private sector participation and the state investment. In the following, more details of the case study, the logical scenarios and their related probability are provided.

4.1.1. Identifying the routes of the network

The province of the case study consists of eight main regions from which a large amount of wastes is generated daily and transferred to the LF. Following the approach explained in section 3.4, the optimum vehicles’ speed is first calculated based on the fuel consumption on a route, and are then adjusted based on the different areas of the route, their population and specific traffic restrictions. In the case study, the minimum and maximum speeds in low-density areas are 40 and 70 km, respectively. These values for the medium and densely populated areas are 30 and 55 km, and 20 and 30 km, respectively. The delimitation of these areas is defined as polygon in the ArcGIS software (See Figure 5).

The centers of the eight regions have been considered as MSW generation sources and eleven candidate points were considered for locating TCs. The shortest routes between these locations, obtained from Google Earth, were mapped on the segmented areas on ArcGIS software (see the routes on parts “a” and “b” of Figure 5, respectively, for the network of the shortest routes, between TCs and the waste generation points and between potential TCs themselves). The shortest route between other locations (i.e., between generation points and twelve candidate points for TS and HSC, between potential TSs and TCs, and between potential RTWs and other locations of the network) were also mapped accordingly.



a) Shortest routes between generation points and potential TCs
 b) Shortest routes between potential TCs
 Figure 5. Areas segmentation and shortest routes in the ArcGIS software

4.1.2. Environmental and social scores

As discussed in Section 3.6.3, two objectives have been dedicated to maximize environmental and social scores of establishing waste processing technologies. In this paper, certain social and environmental indicators are used to identify and evaluate the sustainability of the waste treatment technologies. These indicators are important for the local government, the community, as well as the government in accounting and monitoring the relevant sustainable development goals and objectives. For this aim, 22 indicators have been selected including 13 and 9 environmental and social indicators, respectively (Khan and Kabir, 2019). The environmental and social indicators used in this study have been presented in Table B and C (Appendix A). It is worth mentioning that RCL technology in MRFs and the WDS in LFs are two unique and essential technologies that have their own waste and must be established in a number that have sufficient capacity to receive and process all recyclable and inert dry waste, respectively. In other words, these two technologies have no alternative in the network for processing recyclable and inert dry waste. As a result, comparing environmental and social indicators for these two technologies has no effect on the final results. Accordingly, this section only compares technologies that are not essential and can replace each other in the network.

4.1.3. Case Scenarios

To elaborate effective scenarios in the MSW management network under study, we first identified the key factors affecting waste management networks in the case study and their dominant trends for each factor were selected according to expert opinions (see Table 3). For this aim, we employed the CIA method that allows detecting trends of mutual impacts and determining their probability (see Tables D and E in Appendix A, respectively). The CIA is a method of detecting interactions and is used to determine the likelihood of events occurring, where the impact of each trend on other trends is graded. The information that the CIA method provides is a picture of the interaction of related trends and factors (Chaharsooghi et al., 2015, Rezaei et al., 2019).

The cross-impact matrix related to the trends presented in Table 3 can be seen in Table D (Appendix A). The values of matrix range from -2 to +2. For example, mutual impact X52-X43 has the highest degree (2), which shows that the quality of waste factor has a direct effect on the demand of the products. The probability matrix is then calculated using the following equation (Abbaszadeh et al., 2013). Where CI is the value of the CIA matrix and SENS is the sensitivity coefficient, which is 0.75.

Finally, the scenarios were designed according to the assumptions in each trend and the result of the combination of trends. Accordingly, to form the initial structure of the scenarios in each row of the probability matrix, a trend with a probability above 0.6 is selected from the trends related to each factor. Considering different combinations and removing the repetitions, four scenarios were elaborated (see Table 4).

$$p = 0.5 + \frac{(0.5 \times SENS \times CI)}{2} \quad (69)$$

Table 3. Effective key factors, trends and assumptions in MSW management network

Key factors	Trends	Assumptions
X1 Bearable (Environmental impacts and social responsibility)	Increase X11	<ul style="list-style-type: none"> The participation of non-governmental companies in the waste management system and the creation of a competitive environment in the market and government supervision to comply with environmental and social standards. Increase fuel quality.
	Decrease X12	<ul style="list-style-type: none"> Lack of outsourcing in the waste management sector, lack of insistence of the government on compliance with environmental and social standards. Decreased fuel quality
X2 Culture of material production from waste (reduction of waste production and reuse, separation of origin, use of waste industry as raw materials)	Increase X21	<ul style="list-style-type: none"> Informing the public, pricing separate waste, changing consumption patterns, government laws and regulations to combat extravagance
	Constant X22	<ul style="list-style-type: none"> Lack of cultural infrastructure and culture-building by the government
X3 Fuel prices	Increase X31	<ul style="list-style-type: none"> Realize fuel prices, enforce targeted subsidies
	Constant X32	<ul style="list-style-type: none"> Price stabilization plan to prevent inflation
X4 Demand for waste products	Increase X41	<ul style="list-style-type: none"> Guaranteed government purchase
	Constant X42	<ul style="list-style-type: none"> Lack of government support
	Decrease X43	<ul style="list-style-type: none"> High price of products and people's reluctance to use waste products
X5 Waste quality (quality of products produced in various industries)	Increase X51	<ul style="list-style-type: none"> Legislation, government oversight and industry support
	Decrease X52	<ul style="list-style-type: none"> Non-compliance with the required standards by the industry

The variation of uncertain parameters among different scenarios is estimated based on the conditions in the scenarios (See Table F in Appendix A). The variation of all parameters take place around their current deterministic values (i.e., baseline value) and these variations differ among parameters. The amount of variation of the cost-related parameters in different scenarios is estimated based on expert's opinions and according to future economic inflation, fuel prices, and waste quality. Furthermore, the amount of variation of the parameters related to the waste productions is estimated according to population factors, the amount of waste separated from the source, and waste quality.

Table 4. The scenarios framework

Scenario	X1	X2	X3	X4	X5	Mix of trends
1	Increase	Increase	Increase	Increase	Increase	X11, X21, X31, X41, X51
2	Decrease	Constant	Increase	Constant	Decrease	X12, X22, X31, X42, X52
3	Decrease	Increase	Constant	Decrease	Decrease	X12, X21, X32, X43, X52
4	Increase	Constant	Constant	Constant	Increase	X11, X22, X32, X42, X51

5. Results and discussion

In this section, the results of the application of the proposed multi-objective mathematical model and the adopted robust stochastic approach on the case study are presented and discussed for validation purposes.

As explained in Appendix, Model F in Table A (Appendix B) was employed to cope with the uncertainty of the parameters as well as to aggregate the four objective functions. For this aim and based on the opinion of the decision makers through pairwise comparison method, the weights w_j ($j=1,2,3,4$) are considered as 0.5, 0.3, 0.1 and 0.1, respectively. Indeed, these weights might be different from one project to another or according to the characteristics of the region under study. In addition, the sensitivity of the results respect to the changes in the weight of the functions are analyzed through further experiments. The final aggregated model was run by GAMS 25 software using Cplex solver.

To solve the aggregated model, it is first needed to obtain optimal objective function values Z_j^* ($j=1,2,3,4$). These values are obtained by solving the model with each objective function in isolation with the whole body of constraints. Theoretically, the aggregated model has 56,301 constraints, 104,419 continuous variables and 454 binary variables. The execution time taken by Cplex solver to find the optimal solution is 16302 seconds. In the following, the most important results obtained from solving the proposed scenario-based robust stochastic optimization model, in terms of objective values and decision variables, are presented.

5.1. Optimal establishment costs

This section presents the optimal establishment costs including the costs of facilities and required vehicles. Figure 6 shows the share of established facilities and vehicles required in the total initial cost to design the optimal waste management network. The total initial cost for setting up an optimally designed network is a maximum of \$ 515,881,124. The TC echelon in the designed network consumes 62% of the initial budget. 5% of the initial budget was allocated to establish a new TS in the network. 3% of the budget is spent on building an RTW and purchasing the required vehicles. The number of different vehicles varies by one or two in each scenario, which changes the total initial cost. On the other hand, the cost of existing vehicles in the case study can be deducted from the total initial cost.

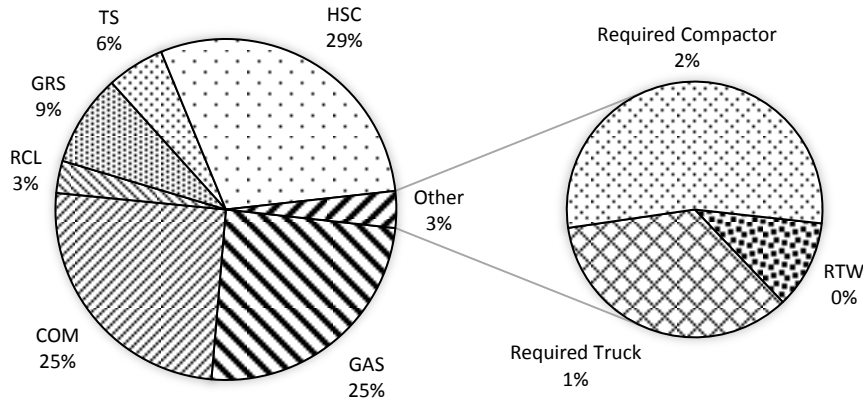


Figure 6. Optimal establishment cost of facilities and required vehicles

Finally, 29% of the initial budget should be spent on the construction of waste separation centers. This shows the high importance of waste separation from the source. By increasing the rate of source separation and reducing the number of separation centers, it is possible to reduce the cost of initial setup of the network. At the TC echelon, GFI technology accounts for a large share of the budget (25% of the initial investment cost), and is an expensive technology in our case study. Details of the centers mentioned in this section (Technology type, capacity, optimal location, coverage areas and shortest route between points) as well as the required number of each type of vehicles can be found in the Appendix C.

5.2. Optimal allocated amount of wastes to TCs

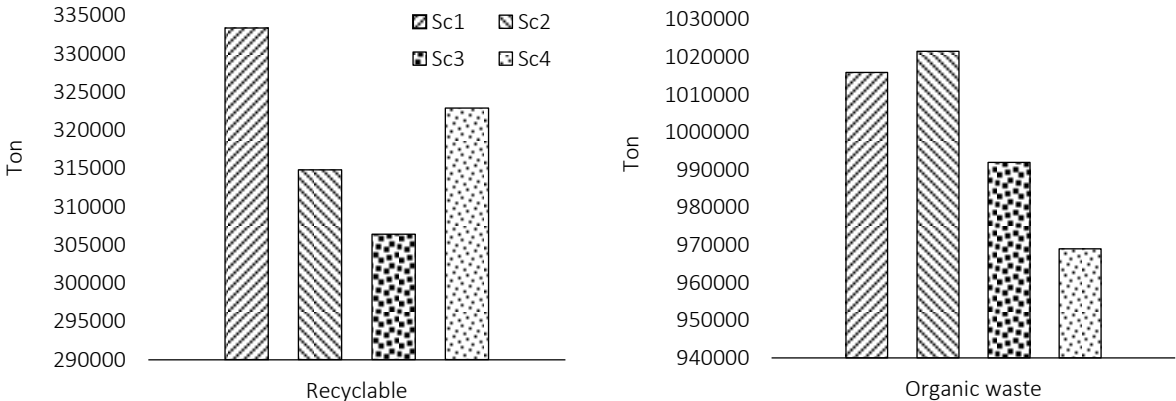
The allocated amount of waste and residue to the technologies in all scenarios can be seen in Figure 7. The difference between the scenarios indicates that the three main factors of the source separation rate, the waste quality (i.e., quality of products produced in manufacturing industries), and the per capita waste generation significantly affect the amount of waste production. As the quality of waste increases, the amount of recyclable waste increases, and the other types decrease. Due to the high quality of separation at sources compared to HSCs, recyclable waste will increase. As the per capita waste generation rate increases, the total waste increases.

The difference between the scenarios in terms of parameters related to waste separation and waste quality has a positive correlation with the potential amount of each waste type. In Sc 1, high quality of waste, high intention of waste generation and separation (low per capita production and high source separation) mean increased production of recyclable waste (See Figure 7a). The two factors of waste quality and waste production and the intention of separation, reduce the production of organic and inert dry wastes. Reduction of waste quality and culture of waste production and separation factors in the Sc2 compared to the Sc1, leads

to a decrease of 5.8% in the production and allocation of recyclable waste to RCL technologies. Decreasing source separation, compensates for the increase in waste quality, so the dry energetic waste does not change much. As a result, the two factors of waste quality and culture has a positive correlation with amount of organic and dry inert waste.

Waste allocated to the facilities can be affected by the operational costs or emissions, the capacity of facilities, generation rate, and or the demand for the productions. For instance, reduction of waste generation per capita in Sc3 has a negative correlation with the amount of waste in all groups. Generation of organic waste in Sc3 decreases by 10% compared to Sc2, but the allocation of this waste to GFI technology increases (See Figure 7c), and to COM technology it decreases even more (27%) (See Figure 7b). The reason for this is the decrease in demand for products in Sc3. Due to the high necessity for electricity, the demand for this product is unlimited and the remaining capacity of GFI technology in all scenarios is filled with organic waste. The use of recycled materials helps to reduce the use of fossil fuels, and its demand is much higher than the volume of production. As a result, changes in the demand affect fertilizer production and allocations to COM. Therefore, cost and demand parameters related to organic waste can not only reverse the correlation but also amplifies it.

The demand in Sc4 is lower than in the first two scenarios. Increasing the waste quality in this scenario leads to a 5% increase in recyclable waste and a decrease in organic, dry, and energetic waste by 2%, 5% and 6%, respectively. Organic waste compared to others, can be allocated to more technologies, so demand, generation rate, and costs have the greatest impact on the allocation of organic waste to technologies. Depending on the cost and production rates of technologies, the amount of allocated organic waste to GRS is constant in the first three scenarios, But in Sc4, the opposite is true (See Figure 7d); By filling the GFI capacity in Sc4, with increasing effective residue, the excess organic waste is transferred to GRS.



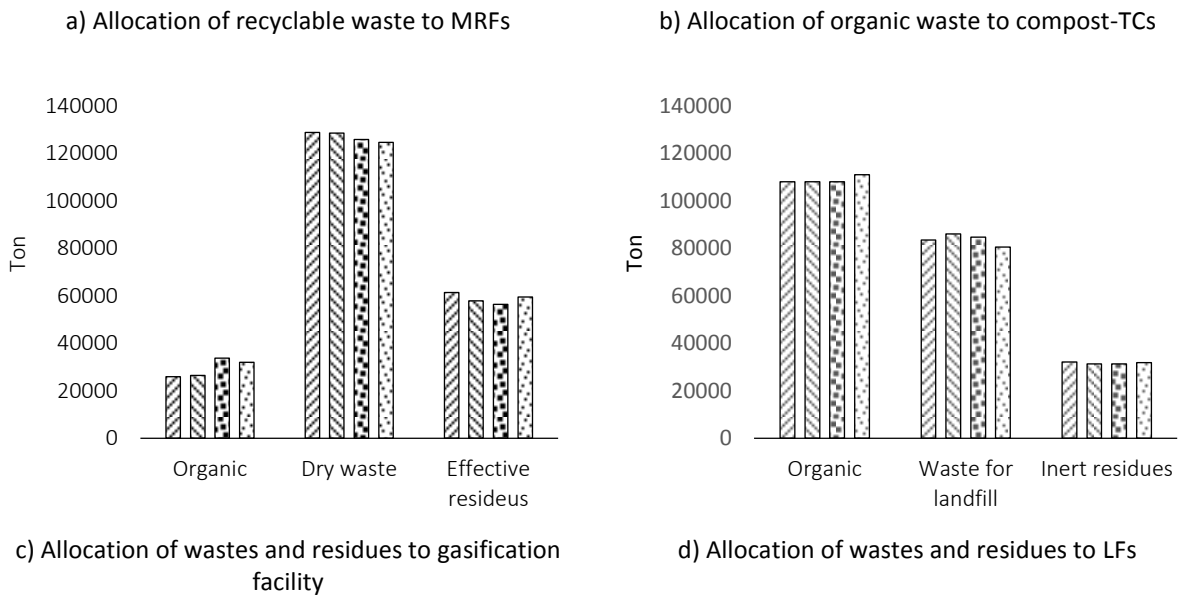


Figure 7. Optimal allocation of wastes to facilities in the network for different scenarios

5.3. Optimal processing and transportation CO₂ emission and costs

CO₂ emission and the variable (processing, transportation, and fuel) costs have been shown in Figure 8 for scenarios. Figure 8c and 8d help to better compare technologies and other facilities. GFI accounts for about 26-28% of the total annual operating cost; however, about 43-44% of the total annual revenue is generated by this technology. On the other hand, the total annual operating cost of the four COM facilities is less than the GFI.

Revenues from COMs are lower than GFI. As a result, the establishment cost of GFI and COMs balances the costs and revenues in the network. Although RCLs receive about 15% of the total waste, the revenue from those is approximately equal to the revenue of COMs. It is possible to increase the revenue by strengthening the waste quality of the network. Waste separation centers account for 16-17% of the annual operating costs. The total operational cost can be effectively reduced by increasing the source separation rate. 48-50% of the waste allocated to landfills is organic and the rest is inert waste and residues. the annual revenue of this facility is about 5-9%, which is much lower than other technologies.

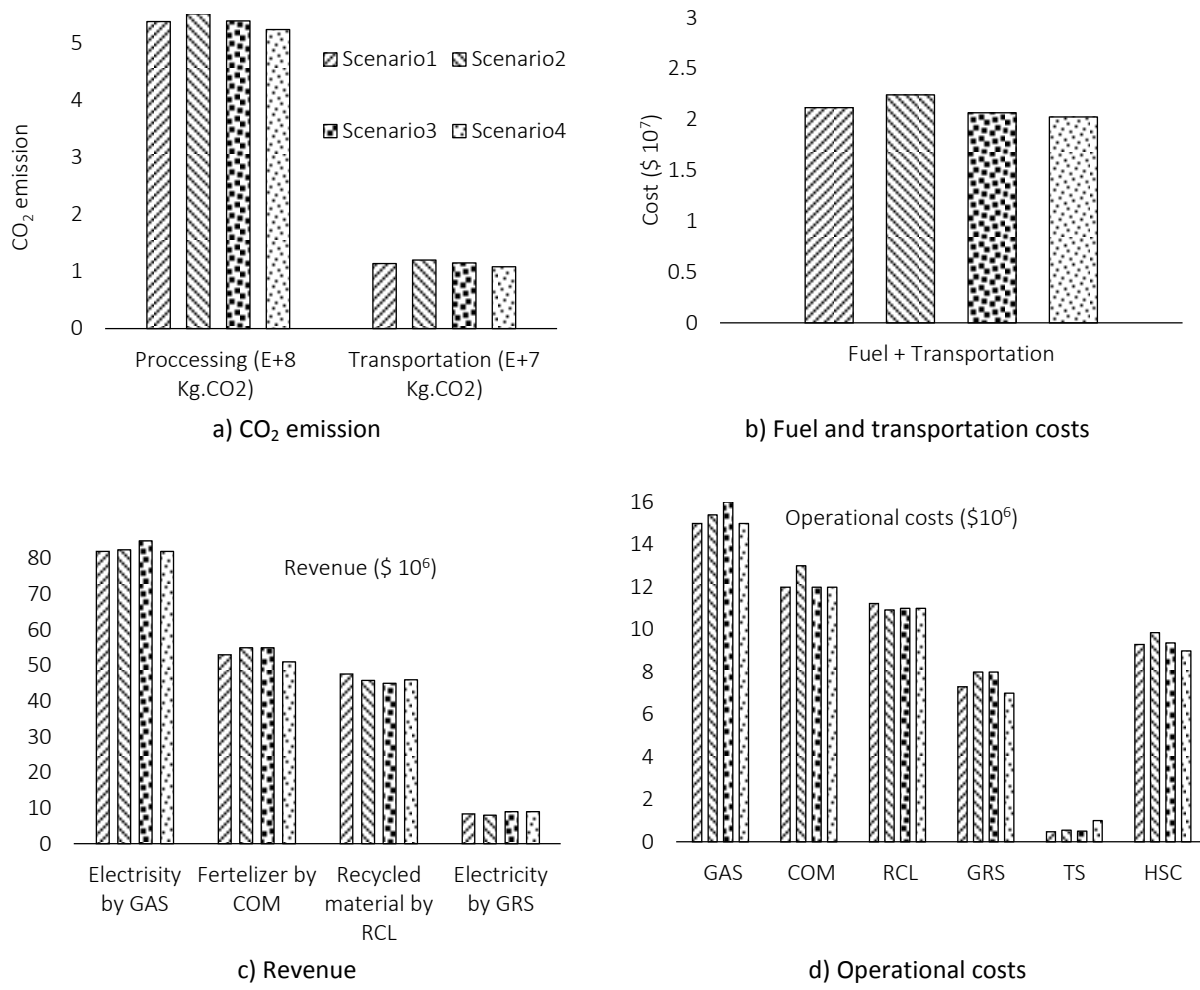


Figure 8. CO₂ emission and costs in different sectors of the network in each scenario

The amount of CO₂ emission in processing potentially depends on the waste quality, the waste allocation to facilities, environmental impacts and social responsibility factors, and in transportation depends on the amount of fuel consumed and fuel quality. Emissions in processing in Sc2 have the highest amount of emissions with a difference of 5% from Sc4, and Sc4 has the lowest amount among the scenarios. Emissions in transportation in Sc4 have the lowest amount between scenarios with a difference of 10% compared to Sc2. In Sc3, due to the negativity of the mentioned factors, the amount of emissions is high. In general, since the total generated waste is higher in Sc1 and Sc2, their emission is higher.

Processing and transportation costs, and revenues in different scenarios depend not only on the amount of waste but also on the variable (per unit) costs, product prices, the production rate of facilities, and finally the products' demand. Sc1 indicates lower variable costs thanks to the reduced processing and transportation unit costs, while the total amounts of waste are almost the same or higher than other scenarios.

In Sc1, although the price of fuel increases, the unit transportation cost decreases, and the total transportation cost in the network is lower. In Sc2, compared to Sc1, on one hand, some of the operating unit costs increase and the product demand decreases which are not in favor of the costs or revenue; on the other hand, product price increases, and the ratio of recyclable waste is higher. This resulted in an increase in both costs and revenues. In other terms, Sc2 can be considered as efficient as Sc1 to the eyes of the deciders. Therefore, it can be concluded that impact of variable costs on the processing and transportation costs is somehow compensated by the impact of waste amount, product demand and price parameters within the scenarios and they are almost the same in terms of operational costs.

5.4. Optimal environmental and social scores

Figure 9 illustrates the optimal value of environmental and social scores for COM, GRS, and GFI technologies. The overall values of the social and environmental scores depend on the allocation, the technology scores parameter, the population of the affected areas, and the distance of the technologies from the affected areas. The location of the technologies and the distance of the facilities from the affected areas are equal in all four scenarios.

As a result, the scores parameters, waste allocation rate, and the population of the affected areas become the most important parameters affecting the optimal value of scores. In Sc4, despite the reduction in total generated waste (Figure 7b), the value of social and environmental scores are higher than other scenarios (maximally 9% difference). The reason can be found in the amount of waste allocated to the four COM technologies (i.e. points 24, 25, 26, and 31 in Figure Aa) and the high sustainability factor in this scenario. In Sc4, a greater share of the produced waste has been allocated to more sustainable technologies and closer to densely populated areas, and on the other hand, according to the predicted scenarios, the provision of more favorable conditions to make the network more sustainable from the social and environmental point of view, the scores functions in this scenario are higher than other scenarios.

In general, due to the high allocation rate in the four established COMs, the scores values of COMs are higher than other technologies. In order to better show the impact of the amount of waste allocation on the scores, Figure 9c depicts the environmental score without considering the impact of the allocated wastes on the COM at point 25. In this regard, GFI technology becomes more environmentally and socially sustainable. In this situation, decision-makers can set up a more sustainable and higher-profit network with a more initial investment to establish more GFI technologies.

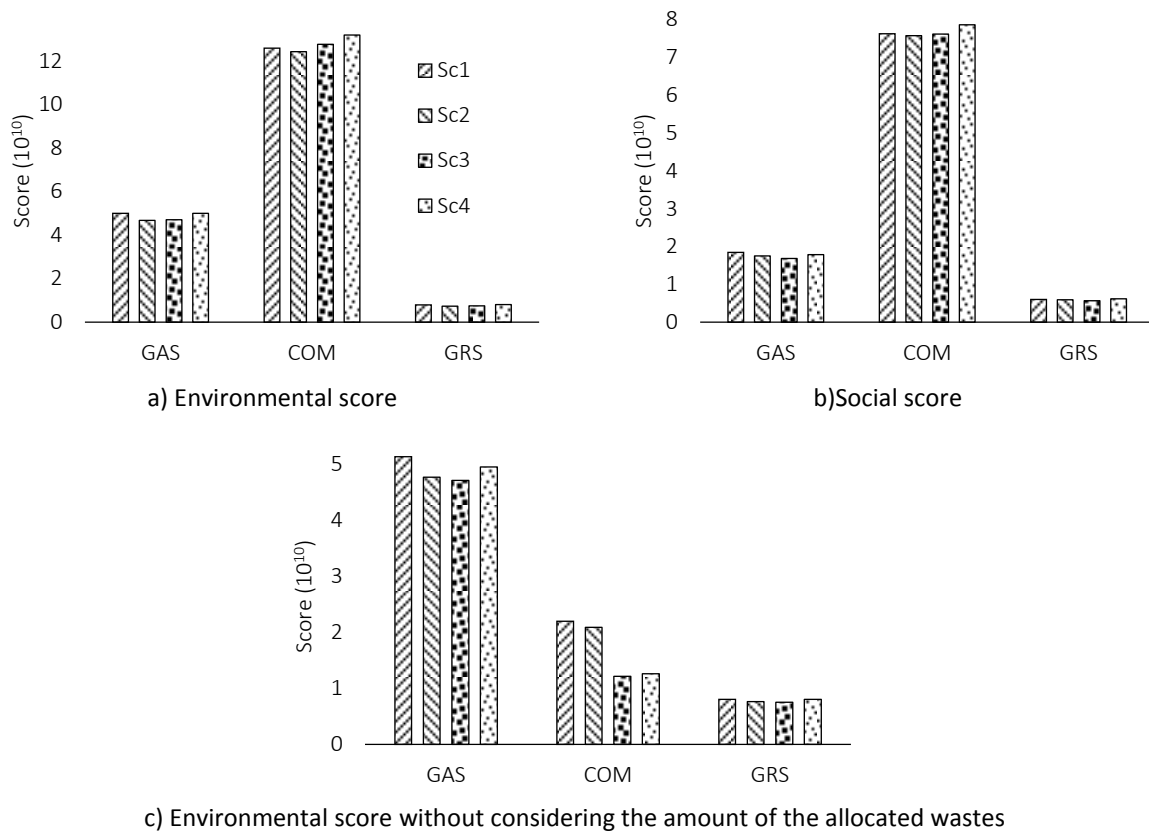


Figure 9. Optimal Environmental and Social score of facilities in different scenarios

As mentioned, sustainable technologies are more likely to be closer to densely populated areas. For instance, the GFI technology at point 29 is closer to Zone 2 (the most populous area) (20 km) compared to three COM technologies at points 24, 25, and 31 (See Figure Aa). It is also further away from Zone 2 compared to the GRS technology at point 23 and the COM technology at point 26. The reason goes back to the high importance weight of the transportation cost, relative to the score objective functions.

5.5. Optimal routes and number of trips

Resembling Figures Aa to Ae (Appendix C) with the number of trips in Table E (Appendix C) results in Figure 10 that illustrates the density of the trips on different segments of the whole routes in Sc2. Based on Figure 10, the busiest segments of the network are at the center of the network. Indeed, these segments are shared between numerous routes and a high number of trips are performed by both compactor and trucks on these segments.

Another information that can be extracted from the result of the case study is the frequency of trips on different routes for each type of the vehicles. For this aim, the frequency of trips performed by each vehicle is

calculated on each segment of routes (i.e., colored routes with different density of trips in Figure 10). This frequency is calculated as:

$$\left(\sum_i \sum_t ANT_{it} \cdot SD_i \right) / \sum_i SD_i \quad \forall t \quad (70)$$

where ANT_{it} is the number of actual trips of vehicle type t in a route of segment i , and SD_i is the length of the routes in segment i .

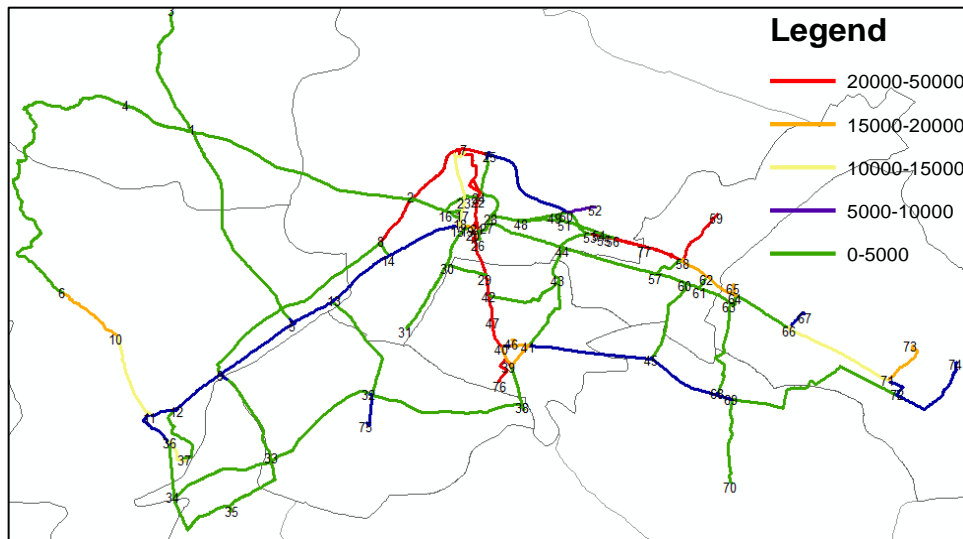


Figure 10. Trips density in different segments of the routes

According to Table 5, in Sc2, most trips of compactor vehicles are performed on the red segment of the routes (high density routes). Although the red segment account only for 11% of the total routes of the network in terms of travelled distance, it includes 48% of compactor's annual trips. In other terms, compactor frequency is 48% in the red segment. Considering that the origin of compactor vehicles is waste generation points and urban areas, it can be concluded that these areas are exposed to a high number of trips by compactors. Accordingly, the transportation of all types vehicles on these busy segments requires an efficient transportation scheduling to minimize environmental issues. Regarding the trucks, they have higher frequency on the purple segment rather than the red one. The segments with green color, accounting for 70% of the total routes in terms of travelled distanced, include the minimum frequency for both types of vehicles.

Finally, by considering that the vehicles always travel with their full capacity, an analysis could be done on the transportation of wastes on the routes. Considering the capacity of vehicles, it is figured out that the largest amount of wastes (i.e., 58% of annual wastes) is transported through the segments with blue and

orange colors. Furthermore, 37% of the annual wastes is transferred through the segments with yellow and blue colors. Finally, the segments with green color transfer only 5% of the annual wastes

Table 5. The average number (frequency) of actual trips in each routes' segment

Routes Segment	Sc1		Sc2		Sc3		Sc4	
	Compactor	Truck	Compactor	Truck	Compactor	Truck	Compactor	Truck
Red	26557	1685	26040	1673	27668	1136	24210	2185
Orange	14087	2913	13217	3056	14054	3224	10729	5202
Yellow	10345	1996	10696	1708	10538	1615	11366	1465
Blue	3620	3376	3133	3653	3945	2824	2987	4550
Green	1159	611	1085	582	1229	711	1156	677

5.6. Verification and Validation

In the current system of waste management in Qazvin, waste from two densely populated areas is transported to the landfill located at point 23 through the TS located at point 3, and the waste from the other centers is transported directly to the landfill. In the current system, separation is not done and the waste is buried in the landfill immediately after it arrives. One of the main drawbacks of the current system is the huge costs for sanitary disposal and the depletion of landfill capacity. The only way to earn money in this system is the fee received from people for collecting garbage and selling recyclable garbage to contractors.

The annual shipping cost of the current system is about \$21 million. The proposition of the model presented in this paper, in addition to using the existing landfill to bury inert waste, is to establish a new landfill equipped with a gas recovery system, an MRF center, and a GAS center in the vicinity of three densely populated zones. In addition, in other points and at different distances, it proposes the establishment of other treatment centers with new technologies to produce good materials. The presented model proposes the establishment of HSC's and TS's and transportation of waste by vehicles with a high capacity to improve the quality of the sent materials and reduce the number and distance of trips by vehicles. Finally, reducing the distance and the number of trips between origins and destinations in the presented model brings a 32% reduction in annual transportation costs compared to the current system.

Moreover, the use of fossil fuels and emissions in transportation is reduced by 14% compared to the current system. About 80% of the waste generated in the current system is buried in the existing landfill and has no revenue for the Qazvin Municipality. Collecting, transporting and burying this amount of waste cost the municipality about \$26 million a year. The revenue generated by the network proposed in this paper, in addition to covering annual expenses, generates a net profit of about \$104 million per year for the municipality. It should be noted, however, that launching the proposed network would require approximately

\$470 million as the initial capital. These results were validated by the decision-makers of the Qazvin Municipality.

It is also important to mention that all the limitations and goals considered in the design of MSW management network, by reviewing the past literature in this field and evaluating the importance of each of these cases, are included in the modeling of this network. Finally, the considered limitations and goals in the proposed model have been approved by experts of the field.

5.6.1 Model's sensitivity to capacity and demand

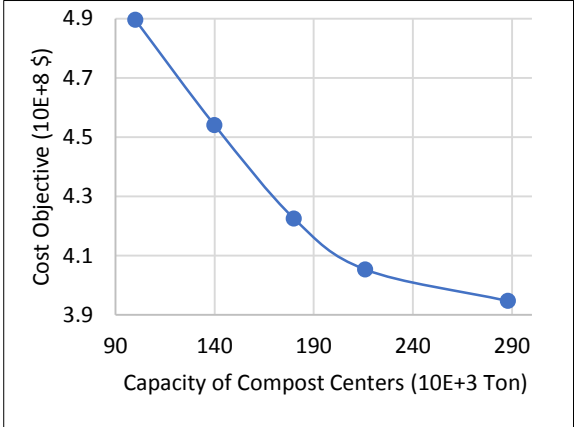
In order to validate the presented model, some influential parameters were subjected to sensitivity analysis. The parameters whose changes are analyzed on the model include the capacity of compost technology, as the most used technology in the optimal network, and the capacity of thermal conversion technologies, as well as the demand for fertilizer, as the most produced product in the network.

According to Figure 11a, with the reduction of the capacity of compost centers, the cost function goes through a logical and upward trend. One of the reasons for this upward trend is the increase in the number of compost centers to compensate for the reduced capacity. On the other hand, according to the assumption that only one compost can be established in each center, as a result, new composts are located far from densely populated centers, which increases transportation costs. Finally, with the further reduction of compost capacity, alternative technologies such as AD, INC, and PYR are suggested by the model, which have a higher establishment cost than compost.

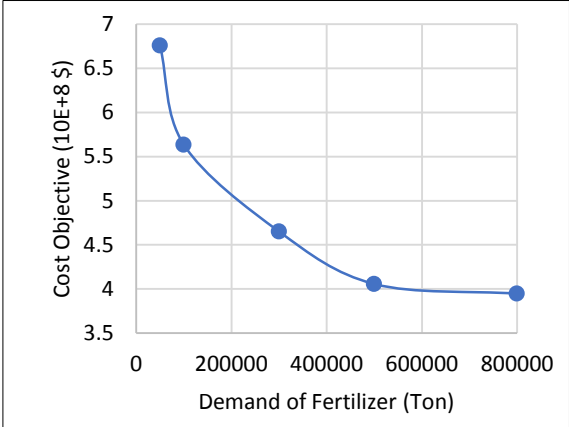
In Figure 11b, by reducing the fertilizer demand parameter, the amount of fertilizer producing technologies such as compost and AD in the network decreases, and alternative treatment technologies such as GAS, INC and PYR are proposed by the model to process this type of waste. Alternative technologies are more expensive and have higher processing costs, and the cost function increases steeper as fertilizer demand decreases further.

In Figure 11c, the cost objective increases with the decrease in TTFs capacity. According to the assumption of the model, these types of technologies are the only ones available for the treatment of energetic dry waste, and with the further reduction of the capacity, the number of these centers in the optimal network will increase to compensate for the lack of capacity. On the other hand, organic waste in these centers is reduced and allocated to compost and LFG technologies. Finally, with the increase in the number of TTFs and compost or LFG, the establishment cost increases. Furthermore, with the dispersion of technologies to distant

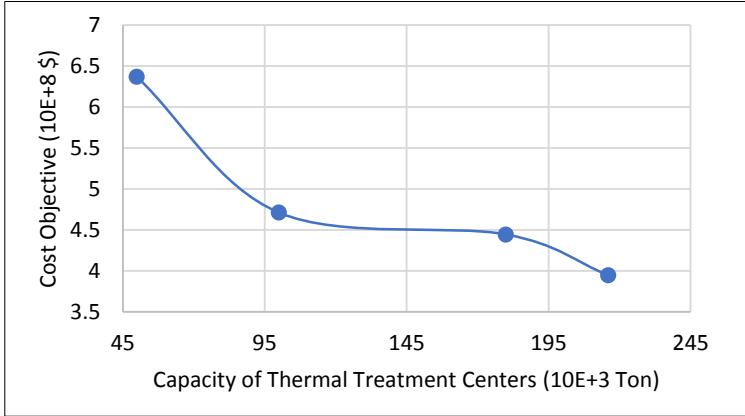
places, the cost of transportation also increases. By reducing the capacity of TTFs to less than 5000 tons, increasing the number of these technologies does not provide enough capacity to cover dry energetic waste and the model becomes infeasible.



a) Sensitivity analysis on the capacity parameter of compost centers



b) Sensitivity analysis on the demand parameter of fertilizer



c) Sensitivity analysis on the capacity parameter of thermal treatment centers
 Figure 11. Sensitivity analysis of the model on some parameters

5.6.2 Model sensitivity to the weight of objective functions

In this section, the optimal Pareto set of the proposed model is plotted using a parallel coordinate diagram (See Figure 12). In is diagram, each colored line represents a Pareto point and plots each coordinate variable into a related vertical line. The values of the objective functions in the Pareto set are obtained by varying the weight of the objective functions. According to the definition of a Pareto set and according to the type of functions considered in this model, in order to recognize the optimality of this Pareto front, both lines in the second space should not intersect each other, and if they intersect, they should be at least in one of the two Other space also have an intersection point. The results show that considering the environmental and

social aspects with economic objectives helps to provide a variety of solutions that provide managers with alternative options. Based on the cost function, Pareto points are divided into three parts: low cost, medium cost and high cost. The value of the other objective functions in the Pareto optimal set are then affected based on the cost values and their corresponding weight coefficients.

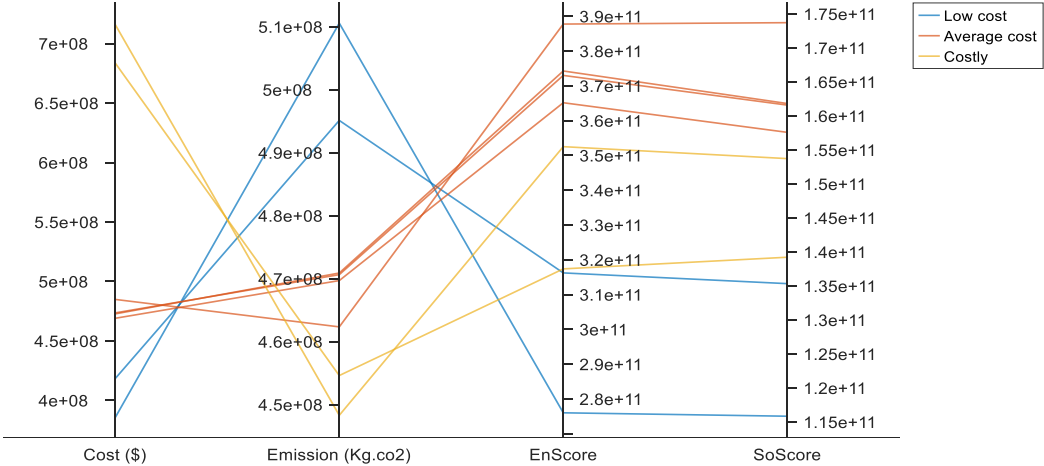


Figure 12. Visualization of Pareto front of the proposed model, using the parallel coordinates plot method

In general, it can be said that by reducing the costs of the entire network, the average network sustainability decreases with respect to emissions, and environmental and social benefits. The slope of the lines between two vertical lines related to the score functions is less than the other two parts, which indicates that these two functions of the environmental and social scores are less contradictory. As a result, the selected treatment technologies that have high environmental benefits are also socially sustainable. The lines of the average cost category also intersect the vertical line for the emission function in the middle of the line, and the lines for the score functions intersect at the top of the lines. As a result, it can be interpreted that with a medium cost, a network with appropriate social and environmental sustainability can be set up. The options provided by these lines can be attractive options for decision makers.

The line in the high cost category intersects the vertical line of the emission at the bottom of the line and the score functions at the top. As a result, the ideal network in terms of social and environmental sustainability can be achieved with high investment. The low cost lines intersect the emission function at the top of the line and the score functions at the bottom of the line. This option is suitable for decision makers who want to allocate the minimum budget to set up the network. From each category introduced in Figure 12, the

details of some Pareto points have been provided in Table D (Appendix C). According to Table D, with the increase in cost, expensive technologies but appropriate in terms of environment and social aspects are suggested by the model. The remarkable thing about these technologies is the increase in annual income. It can be said that the type of technologies plays an important role in the amount of emission and scores objectives; and the establishment of more TS and WTR are also effective in reducing the cost of transportation and emission in transportation.

6. Conclusion

This paper proposes a four-objective scenario-based robust stochastic optimization model for the design of a sustainable municipal solid waste management network under uncertainty. The objective functions of the proposed model include minimizing the total cost, minimizing CO₂ emission, maximizing environmental impacts, and maximizing social impacts. A set of input parameters of the proposed model, including the unit processing cost in different centers, the unit fuel cost, CO₂ emission, environmental and social indicators scores, product demand, product price, and annual production of various types of waste are uncertain. A scenario planning method is used to design different scenarios for the proposed robust stochastic optimization model. The scenario planning approach presented in this paper is based on cross-impact analysis and visualization methods. In this method, uncertain parameters in each scenario are given a certain value and the probability of each scenario is estimated. The two objective functions of environmental and social impacts have a special structure. According to these two objective functions, higher-rated technologies will be closer to densely populated areas. The amount of fuel consumed in transportation is calculated and optimized in terms of certain parameters such as vehicle speed, the amount of wastes carried by the vehicle, the length of the route traveled by the vehicle, and other technical parameters related to the road and the vehicle engine. In order to accurately calculate the amount of fuel consumed, the shortest routes drawn between network points in GIS software are divided into three parts based on speed limits, and the optimal speed of vehicles in each part of the routes is determined. Four scenarios were generated to cope with the uncertainty of the parameters. Finally, the proposed model and solution approach was validated on a real case study and the results were provided in details.

The case study was solved to optimality and based on the results, four recycling, four compost, one gasification, and one waste dumping technologies along with a treatment center, seven hybrid separation centers, and a replacement truck warehouse have been established in the network. Gasification and recycling

technologies are among the most sustainable technologies with a high initial investment cost. There was no significant difference in the annual net profit in all four scenarios. Due to the overall reduction in waste generation, high quality of fuel and waste in the fourth scenario, this scenario is more sustainable in terms of CO₂ emission, environmental and social scores, than other scenarios. The proposed RSP model enables the decision-makers to create a stable and robust MSW network in an Unstable environment. In the transportation sector, considering the number of actual trips on network routes, 11% of the total network routes, in addition to being in high-traffic and densely populated areas, comprise 48% of the compactor's annual trips. For transferring the wastes on these routes, a travel schedule is accordingly needed. As network sustainability increases, more sustainable technologies such as anaerobic digestion and pyrolysis are replacing compost technologies. These technologies require more capital to set up, but the high production rate of these technologies leads to greater profitability in the network.

According to the results, the proposed model is able to optimize strategic and tactical decisions in an MSW network including waste collection layer to waste recycling/disposal layer under uncertainty. Furthermore, the number of required vehicles, routings, and consumed fuel are optimized by the model. The proposed solution approach provides robust solution immunizing the established MSW network for all realizations of scenarios.

Some managerial insights could be extracted from the achieved results as follows:

- The proposed model is a comprehensive model in the literature that could be utilized to design a sustainable MSW network under uncertainty.
- The robust stochastic programming method provides robust solutions in designing MSW networks.
- The strategic decisions (location and capacity of established facilities) are immunized for all realizations of scenarios. However, the optimal values of tactical decisions could be updated when different scenarios are realized.
- Increasing the separation rate of wastes leads to significant savings in investment and annual operating costs and fuel consumption. Increasing waste quality in addition to saving fossil fuels contributes to high profitability in the network.
- To achieve a more sustainable MSW network, trends in the fourth scenario could be followed and supported to be occurred more likely.

In the proposed model, the budget is unlimited, for future studies, it is possible to limit the budget to several periods by expanding the multi-period model, wherein the demand or even other parameters change among different periods. In addition, in order to cope with uncertainty of the demand and the amount of generated wastes, machine learning techniques can be used to predict these parameters. Developing efficient heuristics or meta-heuristics to solve large-sized problem instances is another promising future research direction.

Acknowledgments

This work is based upon research funded by Iran National Science Foundation (INSF) under project No. 4001957. Also, the authors thank the editor and anonymous referees for their valuable comments.

Appendix A

Notations and Parameters

Table A. Parameters contributing to the fuel consumption (Barth et al., 2005)

Notation	Description	Notation	Description
ξ	Fuel-to-air mass ratio	ϕ	Road angel
κ	Heating value of a typical diesel fuel (kJ/g)	C_r	Coefficient of rolling resistance
ψ	Conversion factor (g/s to L/s)	C_d	Coefficient of aerodynamic drag
δ	Vehicle drive train efficiency	N	Engine Speed (rev/s)
π	Efficiency parameter for diesel engines	V	Engine displacement (L)
ρ	Air density (kg/m ³)	A	Frontal surface area (m ²)
e	Engine friction factor (kJ/rev/L)	μ	Curb weight (kg)
g	Gravitational constant (m/s ²)		

Table B. Environmental indicators and weights for waste treatment technologies

No.	Indicators	COM	GRS	ICN	GFS	PYR	ADS
1	Land use (m ²)	0.2708	0.0625	0.0625	0.1458	0.2708	0.5208
2	Water use*	0.1458	0.5208	0.1458	0.2708	0.5208	0.0625
3	Pollutants generation (types)	0.2708	0.2708	0.0625	0.1458	0.2708	0.5208
4	Life cycle CO ₂ /kWh	0.1458	0.1458	0.0625	0.2708	0.5208	0.1458
5	Overall emission (kgCO ₂ -e/kWh)	0.2708	0.5208	0.0625	0.1458	0.2708	0.5208
6	SO _x emission (mg/m ³)	0.5208	0.0625	0.0625	0.5208	0.1458	0.2708
7	NO _x emission (mg/m ³)	0.5208	0.0625	0.1458	0.5208	0.0625	0.2708
8	Particulate matters (mg/m ³)	0.1458	0.2708	0.0625	0.5208	0.1458	0.2708
9	Ash (% of fuel mass) RDF/Mass	0.2708	0.5208	0.0625	0.1458	0.2708	0.5208
10	Noise [Construction + Operation + Traffic]*	0.2708	0.1458	0.0625	0.1458	0.5208	0.2708
11	Dust* (comparative measure)	0.0625	0.1458	0.0625	0.1458	0.2708	0.5208
12	Odor* (comparative measure)	0.0625	0.0625	0.0625	0.1458	0.5208	0.2708
13	Litter* (comparative measure)	0.2708	0.1458	0.0625	0.1458	0.5208	0.2708

* Comparative measure

Table C. Social indicators score for waste treatment technologies

No.	Indicators (Comparative measure)	COM	GRS	ICN	GFS	PYR	ADS
1	People displacement	0.2708	0.0625	0.0625	0.1458	0.5208	0.2708
2	Disturbance to existing social infrastructure and services	0.1458	0.5208	0.0625	0.1458	0.5208	0.2708
3	Visual disturbance due to infrastructure	0.2708	0.2708	0.0625	0.1458	0.2708	0.5208
4	Heat wave	0.1458	0.1458	0.0625	0.1458	0.2708	0.5208
5	Public health risk	0.2708	0.5208	0.0625	0.1458	0.2708	0.5208
6	New job creation	0.5208	0.0625	0.5208	0.2708	0.1458	0.0625
7	Impact on land value	0.5208	0.0625	0.5208	0.2708	0.0625	0.1458
8	Community acceptance	0.1458	0.2708	0.0625	0.1458	0.2708	0.5208

9	Local economy development	0.2708	0.5208	0.5208	0.2708	0.1458	0.0625
---	---------------------------	--------	--------	--------	--------	--------	--------

Table D. Cross-impact matrix

	X11	X12	X21	X22	X31	X32	X41	X42	X43	X51	X52
X11	-	-	0.7	-0.5	1.2	0.9	2	1	-1.5	1	0.2
X12	-	-	-1	1.5	0.7	1	-0.5	0.7	2	-0.2	1.5
X21	0.7	-1	-	-	0.9	1	1.5	-1	1	1	1.5
X22	-0.5	1.5	-	-	0.7	0.9	-0.9	1.7	0.5	0.9	0.7
X31	1.2	0.7	0.9	0.7	-	-	0.9	1	-0.7	1	0.7
X32	0.9	1	1	0.9	-	-	-0.2	0.9	0.7	0.7	1
X41	2	-0.5	1.5	-0.9	0.9	-0.2	-	-	-	1	-1
X42	1	0.7	-1	1.7	1	0.9	-	-	-	1	1.5
X43	-1.5	2	1	0.5	-0.7	0.7	-	-	-	-2	2
X51	1	-0.2	1	0.9	1	0.7	1	1	-2	-	-
X52	0.2	1.5	1.5	0.7	0.7	1	-1	1.5	2	-	-

Table E. Probability matrix

	X11	X12	X21	X22	X31	X32	X41	X42	X43	X51	X52
X11	-	-	0.63125	0.40625	0.725	0.66875	0.875	0.6875	0.21875	0.6875	0.5375
X12	-	-	0.3125	0.78125	0.63125	0.6875	0.40625	0.63125	0.875	0.4625	0.78125
X21	0.63125	0.3125	-	-	0.66875	0.6875	0.78125	0.3125	0.6875	0.6875	0.78125
X22	0.40625	0.78125	-	-	0.63125	0.66875	0.33125	0.81875	0.59375	0.66875	0.63125
X31	0.725	0.63125	0.66875	0.63125	-	-	0.66875	0.6875	0.36875	0.6875	0.63125
X32	0.66875	0.6875	0.6875	0.66875	-	-	0.4625	0.66875	0.63125	0.63125	0.6875
X41	0.875	0.40625	0.78125	0.33125	0.66875	0.4625	-	-	-	0.6875	0.3125
X42	0.6875	0.63125	0.3125	0.81875	0.6875	0.66875	-	-	-	0.6875	0.78125
X43	0.21875	0.875	0.6875	0.59375	0.36875	0.63125	-	-	-	0.125	0.875
X51	0.6875	0.4625	0.6875	0.66875	0.6875	0.63125	0.6875	0.6875	0.125	-	-
X52	0.5375	0.78125	0.78125	0.63125	0.63125	0.6875	0.3125	0.78125	0.875	-	-

Table F. Variations of uncertain parameters in different scenarios (%)

Uncertain parameter	Effective factors	Notation	Scenarios			
			Sc1	Sc2	Sc3	Sc4
CO ₂ emission from processing waste (residue) w (r) by technology k (Kg. CO ₂ /ton)		$\tau_{kw(r)}$	-3.0	+2.0	+1.0	-2.0
Advantage of waste treatment technology k based on environmental (social) indicator e (s)	X1	$\mu_{ke(s)}$	+3.0	-2.0	-1.0	+2.0
CO ₂ emission from fuel consumption (Kg.CO ₂ /liter)		EL	-3.0	+3.0	+3.0	-3.0
Unit processing cost of waste (residue) w (r) by technology k (USD/ton)		$PC_{kw(r)}^{TC}$	-1.0	+2.0	+3.0	+0.1
Unit processing cost of waste w in TSS (USD/ton)		PC_w^{TS}	-1.0	+2.0	+3.0	+0.1
Unit separation cost of wastes at HSCs (USD/ton)	X3, X4	PC^{HSC}	-2.0	+1.0	+2.0	+0.1
Unit transportation cost of vehicle type t (USD/km)		TC_t	-2.0	+2.0	+2.0	+0.1
Cost of fuel per liter for the vehicles (USD/ liter)		FL	+2.0	+2.0	+0.1	+0.1
Sale price of product p (USD)		PR_p	+0.1	+2.0	+4.0	+1.0
Demand of product p (ton or kwh)	X4	D_p	+4.0	+0.1	-4.0	+0.1
Amount of waste type $w=1$ (recyclable) generated and separated in source i		WS_{iw}	+5.0	+1.0	-1.0	+2.0
Amount of waste type $w=2$ (organic) generated and separated in source i			+0.1	+3.0	+3.0	-2.0
Amount of waste type $w=3$ (dry) generated and separated in source i			+2.0	+2.0	+2.0	-1.0
Amount of waste type $w=4$ (for landfill) generated and separated in source i	X1, X2, X3		+0.1	+3.0	+4.0	-3.0
Share of type $w=1$ (recyclable) waste from mixed waste at origin i		φ_{iw}	+2.0	-2.0	-2.0	+2.0
Share of type $w=1$ (organic) waste from mixed waste at origin i			-1.0	+1.0	+1.0	-1.0
Share of type $w=1$ (dry) waste from mixed waste at origin i			+1.0	+1.0	+1.0	-1.0
Share of type $w=1$ (for landfill) waste from mixed waste at origin i			-3.0	+3.0	+3.0	-3.0
The amount of mixed waste at origin i		WM_i	+0.1	+3.0	-3.0	+0.1

Appendix B

Solution approach (Robust stochastic programming)

This section describes the robust stochastic programming (RSP) approach adopted to cope with the uncertain parameters of the proposed MSW network design model. In this regard, the approach introduced by Mulvey et al. (1995) is one of the most popular approaches to deal with uncertainty and is able to produce a

set of stable and insensitive solutions facing changing scenarios. RSP models are looking for a solution that fits all scenarios (Wang and Chen, 2020). The optimal solution in the scenarios is optimal until the uncertain parameters change slightly (Razm et al., 2021). Classified as a realistic approach to deal with uncertainty, this approach is used when uncertain parameters of the problem follow certain probabilistic distributions or can be expressed as different scenarios with relevant probabilities. This method also allows achieving a balance between the solution robustness (i.e., optimality robustness) and the model robustness (i.e., feasibility robustness) (Mulvey et al., 1995).

Consider the general form of a MILP problem under definite terms as described in Model A of Table A, where f and c represent the cost parameters, and T and A are the technological coefficients, and b is the right-hand side value. In Model A, to develop the form of an RSP, without loss of generality, assume that parameters c and b have scenario-based uncertainties. Assume that Ω represents the set of scenarios for uncertain parameters, θ represents a specific scenario, and π_θ indicates the probability of occurrence of scenario θ . Furthermore, consider that the decision variables y and x are the design and control variables, respectively, where design variables are determined before the scenarios occur and are therefore modeled independently from the scenario while the control variables are determined by the occurrence of the scenarios and are thus modelled depending on the scenarios.

Table A. Robust stochastic MILP models

Model A	Model D	Model F
$\min fy + cx$ $s. t. : Ax + Ty \geq b$ $x \geq 0, y \in \mathbb{Z}$	$\min \sum_{\theta \in \Omega} \pi_\theta \xi_\theta + \gamma \sum_{\theta \in \Omega} \pi_\theta \left \xi_\theta - \sum_{\theta' \in \Omega} \pi_{\theta'} \xi_{\theta'} \right $ $s. t. : \xi_\theta = fy + c_\theta x_\theta \quad \forall \theta$ $Ax_\theta + Ty \geq b \quad \forall \theta$ $x_\theta \geq 0, y \in \mathbb{Z}$	$\min z = \sum_{j=1}^J w_j \left(\frac{z_j^* - z_j}{z_j^*} \right)^\rho$ $s. t. : z_j = \sum_{\theta \in \Omega} \pi_\theta \xi_{j,\theta} + \gamma_j \sum_{\theta \in \Omega} \pi_\theta (G_{j,\theta}^+ + G_{j,\theta}^-) \quad \forall j, \theta$ $\xi_{j,\theta} = f_j y + c_{j,\theta} x_\theta \quad \forall j, \theta$ $Ax_\theta + Ty \geq b \quad \forall \theta$ $\xi_{j,\theta} - \sum_{\theta' \in \Omega} \pi_{\theta'} \xi_{j,\theta} = G_{j,\theta}^+ + G_{j,\theta}^- \quad \forall j, \theta$ $x_\theta, G_{j,\theta}^+, G_{j,\theta}^- \geq 0, y \in \mathbb{Z}$
Model B $\min fy + cx_\theta$ $s. t. : Ax_\theta + Ty \geq b \quad \forall \theta$ $x_\theta \geq 0, y \in \mathbb{Z}$		
Model C $\min \sum_{\theta \in \Omega} \pi_\theta \xi_\theta + \gamma \sum_{\theta \in \Omega} \pi_\theta \left(\xi_\theta - \sum_{\theta' \in \Omega} \pi_{\theta'} \xi_{\theta'} \right)^2$ $s. t. : \xi_\theta = fy + c_\theta x_\theta \quad \forall \theta$ $Ax_\theta + Ty \geq b \quad \forall \theta$ $x_\theta \geq 0, y \in \mathbb{Z}$	Model E $\min \sum_{\theta \in \Omega} \pi_\theta \xi_\theta + \gamma \sum_{\theta \in \Omega} \pi_\theta (G_\theta^+ + G_\theta^-)$ $s. t. : \xi_\theta = fy + c_\theta x_\theta \quad \forall \theta$ $Ax_\theta + Ty \geq b \quad \forall \theta$ $\xi_\theta - \sum_{\theta' \in \Omega} \pi_{\theta'} \xi_{\theta'} = G_\theta^+ + G_\theta^- \quad \forall \theta$ $x_\theta, G_\theta^+, G_\theta^- \geq 0, y \in \mathbb{Z}$	

For a specific scenario θ , the general form of an RSP model is written as Model B. The decisions made from Model B is specific to each scenario and are indeed similar to the definitive Model A for each scenario. The RSP model proposed by Mulvey et al. (1995) is written as Model C with the expected value over all scenarios as the objective function. In Model C, parameter ξ_θ represents the value of the objective function per scenario θ and γ ($0 < \gamma < 1$) is the coefficient of importance that decision makers place on decisions' risk.

Risk-sensitive decision makers choose high values for parameter γ to minimize the variance of cost changes. Model C guarantees the satisfaction of all constraints for all defined scenarios while minimizing the average and variance of costs. To linearize Model C, Yu and Li (2000) first presented the modified absolute value of Model C as Model D. The linear form of Model D is obtained by introducing two non-negative variables G_{θ}^{+} and G_{θ}^{-} as Model E where at most, one of these variables will always take a non-negative value.

Finally, according to the above descriptions, the RSP model for a multi-objective problem can be presented as Model F, wherein the LP metric method is used to handle multiple objective functions. LP-Metric method is one of the multi-criteria decision-making methods and is used to make decisions with different objectives. The difference between this method and other multi-objective optimization methods is that there is no need to prioritize objective functions, or turn functions into constraints. Also, this method produces only efficient solutions in the optimal Pareto set (Klinkowski and Walkowiak, 2011). Considering model F, w_j conveys the importance of the j th objective function and ρ indicates the degree of emphasis on deviations. In this paper, different scenarios and their probability are defined using the cross-impact analysis (CIA) and visualization method (Abbaszadeh et al., 2013).

Appendix C

Model results

Table A. Established treatment technologies and their details

Facility	Location point	Capacity (10^3 ton/year)	Covered MSW sources	Covered TSs	Covered HSCs	Covered RTWs
MRF	23	90	-	15 [*]	11,15	39
GRS	23	216	2,3,4	-	11	39
MRF	24	90	3,4,7	-	12,13	39
Compost	24	288	3,7	15	11,12,15,18	39
Compost	25	288	4	-	11,12,13,18	39
Compost	26	288	1,2,8	15	15	39
MRF	28	90	1,5,8,9	15 [*]	15,16,17,21	39
MRF	29	90	6	15 [*]	15,18	39
Gasification	29	216	1,2,3,4,5,6,7,8,9	-	11,12,13,15,16,18,21	39
Landfill	29 [*]	90	1,5,6,7,8,9	-	11,15,16,18,21	39
Compost	31	288	5,9	15	15,16,18,21	39

^{*} Existing

Table B. Optimal location of TSs and HSCs with their details

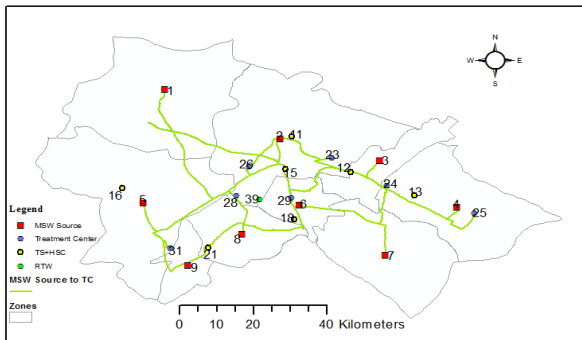
Location point	Type	Waste type	Capacity (10^3 ton)	Covered MSW sources	Covered RTWs
15	TS	Recyclable	144	1,2,6	39
15 [*]		Organic	72	2,6	39
11	HSC	NA ^{**}	216	2,3,4	39
12			144	2,3,4	39
13			72	4	39
15			216	2	39
16			144	1,2,5	39
18			216	2,3,4,6,7	39
21			72	2,8,9	39

^{*} Existing, ^{**} Not applicable

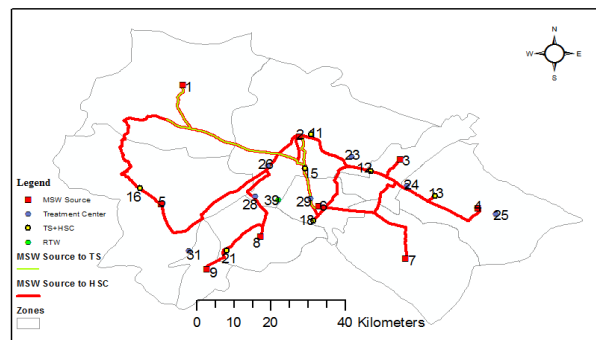
Table C. Optimal number of vehicles in the network in different scenarios

Origin point	Sc1		Sc2		Sc3		Sc4	
	Co*	Tr*	Co	Tr	Co	Tr	Co	Tr
1	6	-	6	-	7	-	6	-
2	46	-	46	-	45	-	44	-
3	15	-	14	-	14	-	14	-
4	10	-	11	-	10	-	11	-
5	11	-	11	-	11	-	11	-
6	10	-	10	-	11	-	11	-
7	4	-	4	-	4	-	4	-
8	5	-	5	-	5	-	5	-
9	5	-	5	-	5	-	5	-
11	-	5	-	4	-	4	-	4
12	-	4	-	5	-	4	-	4
13	-	4	-	4	-	4	-	4
15	-	8	-	9	-	8	-	10
16	-	4	-	4	-	4	-	4
18	-	5	-	5	-	6	-	5
21	-	3	-	3	-	3	-	3
23	-	1	-	1	-	1	-	1
24	-	2	-	2	-	2	-	2
28	-	1	-	1	-	1	-	1
39	46	13	47	14	47	14	47	14
Total	158	50	159	52	159	51	158	52

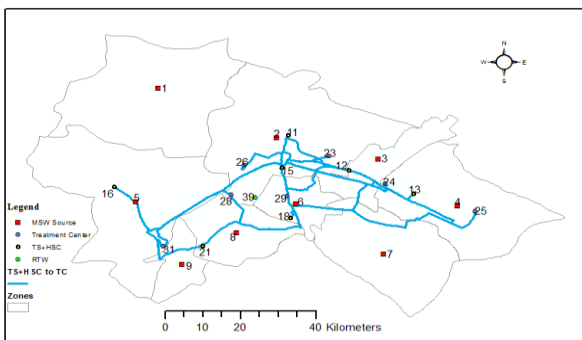
*Co: Compactor; Tr: Truck



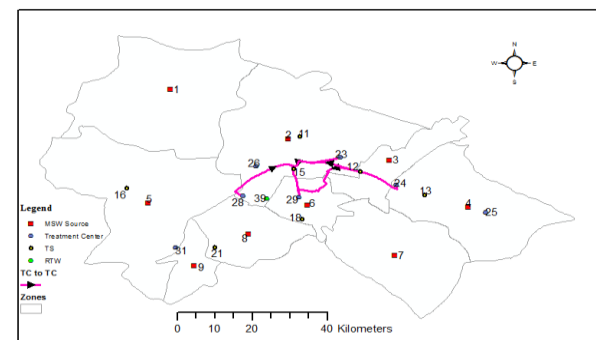
a) Between source points and TCs



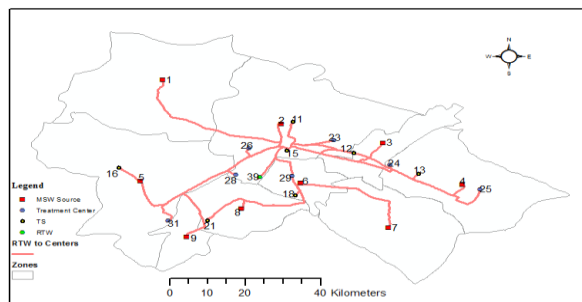
b) Between source points and HSCs or TSs



c) Between HSCs or TSs and TCs



d) Between TCs



e) Between RTW and other centers

Figure A. Shortest route between different points of the network in Sc2

Table D. Details of model results for Pareto Front points

Case	Cost/revenue (\$ 10 ⁸)				CO ₂ (10 ⁸ kg.co ₂)				Scores (10 ¹¹)		Established technology type {number}	Established TS {location}	Number of established truck warehouse
	Establishment	Transportation	Fuel	Processing	Revenue	Transportation	Processing	Social	Environmental				
Low cost	5.100	0.164	0.062	0.748	2.275	0.119	4.919	1.160	2.755	RCL {4} GRS {1} COM {3} ADS {1} GFI {1}	15	1	
Medium cost	6.581	0.150	0.056	0.939	2.958	0.107	4.430	1.778	3.966	RCL {4} INC {1} GRS {1} GFI {1} ADS {5}	15	1	
High cost	8.935	0.126	0.048	0.999	3.080	0.092	4.226	1.534	3.527	RCL {5} GRS {1} ADS {6} GFI {2}	11 {3}, 15, 16	10	

Table E. Annual number of trips and annual fuel consumption in the network (Part I)

Route	Number of trips				Fuel consumption (L)			
	Sc1	Sc2	Sc3	Sc4	Sc1	Sc2	Sc3	Sc4
1-15	-	-	129	-	-	-	7425	-
1-16	2550	2478	2401	2451	180709	175621	170182	173691
2-11	27000	27000	27000	27000	83394	83394	83394	83394
2-12	-	-	483	-	-	-	6306	-
2-15	37243	36857	37623	37967	317344	312639	321982	326178
2-16	1123	-	-	-	36686	-	-	-
2-18	10153	11203	8701	10487	162826	179661	139537	168170
2-21	1816	-	-	-	49611	-	-	-
3-12	18000	17568	17024	17375	213831	208694	202231	206401
3-18	77	-	-	-	1590	-	-	-
4-12	-	433	494	626	-	10531	12027	15232
4-13	9000	9000	9000	9000	90878	90878	90878	90878
4-18	1082	365	-	65	34034	11485	-	2018
5-16	13558	13176	12768	13031	70146	68171	66060	67422
6-15	3258	3644	2749	2534	47198	52787	39819	36703
6-18	13558	13176	12768	13031	112235	10075	105637	107876
7-18	2133	2073	2008	2050	63983	62182	60256	61498
8-21	3361	3266	3165	3230	52160	50691	49122	50134
9-21	3824	3717	3602	3676	35613	34610	33538	34230
1-26	987	1016	1016	966	40833	42016	42016	39976
1-28	291	280	145	286	16538	15908	8252	16223
1-29	171	174	175	167	11113	11313	11360	10840
2-23	1953	2010	2029	1893	34351	35346	35690	33287
2-26	24337	25199	24283	22902	377759	391133	376922	355489
2-29	2646	2672	2672	2593	54745	55287	55287	53661
3-23	521	536	541	505	11844	12187	12305	11477
3-24	9335	9464	9424	9143	125576	127315	126775	122996
3-29	737	744	744	722	25143	25392	25392	24645
4-23	291	299	302	282	12928	13302	13431	12527
4-24	1177	1132	1110	1155	26784	25764	25254	26274
4-25	4055	4172	4172	3969	58732	60434	60434	57500
4-29	417	421	421	409	23276	23507	23507	22815
5-28	1567	1507	1477	1537	53488	51451	50432	52469
5-29	938	955	958	915	54315	55286	55513	52986

5-31	5338	5493	5493	5226	88378	90939	90939	86524
6-29	4584	4310	5179	5144	52174	49055	58949	58545
7-24	1162	1177	1172	1139	21641	21914	21814	21198
7-29	204	208	208	200	7174	7290	7314	7005
8-26	1291	1328	1328	1264	33386	34354	34354	32686
8-28	379	365	357	372	5091	4897	4800	4994
8-29	238	242	243	232	8363	8514	8549	8157
9-28	447	430	421	438	12937	12444	12198	12691
9-29	340	346	347	332	17574	17881	17951	17148
9-31	1507	1551	1551	1476	26506	27274	27274	25950
11-23	4009	3984	3982	4055	81606	81100	81050	82535
11-24	518	1009	1009	863	23330	45473	45473	38878
11-25	418	-	-	-	32804	-	-	-
11-29	428	437	439	455	13060	13324	13399	13891
12-23	175	186	186	175	4570	4852	4852	4570

Table E. Annual number of trips and annual fuel consumption in the network (Part II)

Route	Number of trips				Fuel consumption (L)			
	Sc1	Sc2	Sc3	Sc4	Sc1	Sc2	Sc3	Sc4
12-24	3122	2830	3143	3122	54465	49367	54842	54465
12-25	-	314	-	-	-	15970	-	-
12-29	286	291	291	286	12023	12266	12266	12023
13-23	88	93	93	88	3681	3909	3909	3681
13-24	349	336	336	349	5072	4873	4873	5072
13-25	1212	1237	1237	1212	38766	39550	39550	38766
13-29	143	146	146	143	8499	8671	8671	8499
15-23	1204	1245	1245	1204	22751	23506	23527	22750
15-24	2236	1927	1834	2327	91033	78394	74670	94727
15-26	-	-	1875	2156	-	-	35443	41093
15-28	522	320	186	433	15161	9295	5386	12574
15-29	1812	1956	2091	1901	26339	28440	30394	27632
15-31	2300	2683	900	36	137102	159921	53659	2091
16-28	668	583	565	6001	38845	33907	32857	34903
16-29	441	415	402	396	39674	37342	36186	35648
16-31	2320	2151	2084	2085	80962	75040	72716	72746
18-24	-	-	217	-	-	-	11325	-
18-25	3636	3684	1530	1595	290752	294595	122327	127524
18-29	1737	1709	1496	1649	40394	39743	34794	38345
18-31	-	-	1479	1857	-	-	105380	132281
21-28	349	260	252	268	11160	8318	8060	8562
21-29	230	185	180	177	14038	11283	10933	10771
21-31	1212	960	930	930	35242	27892	27028	27039
23-23	113	113	113	113	0	0	0	0
23-29	414	414	414	414	13244	13244	13244	13244
24-23	88	85	84	88	2942	2828	2805	2919
24-29	324	312	309	322	16007	15386	15263	15883
28-29	486	393	347	428	19058	15421	13615	16778
29-29	914	914	926	918	0	0	0	0
39-1	2	2	2	2	37	36	36	36
39-2	17	17	17	17	169	167	164	163
39-3	5	5	5	5	81	80	79	78
39-4	3	3	3	3	70	69	68	68
39-5	4	4	4	4	96	95	93	93
39-6	4	4	4	4	40	40	39	39
39-7	1	1	1	1	17	17	7	17
39-8	2	2	2	2	19	19	19	19
39-9	2	2	2	2	29	29	28	28
39-11	2	2	2	2	10	10	10	10
39-12	1	1	1	1	8	8	8	8
39-13	1	1	1	1	8	8	8	8
39-15	2	2	2	2	10	10	9	9
39-16	1	1	1	1	22	20	20	20
39-18	2	2	2	2	14	14	12	13
39-21	1	1	1	1	8	6	6	6
39-23	1	1	1	1	1	1	1	1
39-24	1	1	1	1	1	1	1	1
39-28	1	1	1	1	1	1	1	1
39-29	1	1	1	1	1	1	1	1
Total	244457	241213	236058	241890	3926109	3726164	3594213	3592397

References

- Abbaszadeh P., Maleki A., Alipour M., Maman Y.K. (2013) Iran's oil development scenarios by 2025. *Energy Policy*, 56, 612–622.
- Antmann, E. D., Shi, X., Celik, N., & Dai, Y. (2013). Continuous-discrete simulation-based decision making framework for solid waste management and recycling programs. *Computers & Industrial Engineering*, 65(3), 438-454.
- Arena U., Di Gregorio F. (2014). A waste management planning based on substance flow analysis. *Resources, Conservation and Recycling*, 85, 54-66.
- Arena, U., & Di Gregorio, F. (2014). A waste management planning based on substance flow analysis. *Resources, Conservation and Recycling*, 85, 54-66.
- Ba, B. H., Prins, C., & Prodhon, C. (2016). Models for optimization and performance evaluation of biomass supply chains: An Operations Research perspective. *Renewable Energy*, 87, 977-989.
- Barth, M., Younglove, T., & Scora, G. (2005). Development of a heavy-duty diesel modal emission and fuel consumption model.
- Bektaş, T., & Laporte, G. (2011). The pollution-routing problem. *Transportation Research Part B: Methodological*, 45(8), 1232-1250.
- Chaharsooghi, S. K., Rezaei, M., & Alipour, M. (2015). Iran's energy scenarios on a 20-year vision. *International journal of environmental science and technology*, 12(11), 3701-3718.
- Del Carmen Munguía-López, A., Zavala, V. M., Santibañez-Aguilar, J. E., & Ponce-Ortega, J. M. (2020). Optimization of municipal solid waste management using a coordinated framework. *Waste Management*, 115, 15-24.
- DEFRA, 2004. Review of Environmental and Health Effects of Waste Management: Municipal Solid Waste and Similar Wastes. Defra, London.
- Demir, E., Bektaş, T., & Laporte, G. (2014). The bi-objective pollution-routing problem. *European Journal of Operational Research*, 232(3), 464-478.
- Stations, W. T. (2002). a Manual for decision-Making. United States Environmental Protection Agency (EPA).
- Exposito-Marquez, A., Exposito-Izquierdo, C., Brito-Santana, J., & Moreno-Pérez, J. A. (2019). Greedy randomized adaptive search procedure to design waste collection routes in La Palma. *Computers & Industrial Engineering*, 137, 106047.
- WR 0608 Emissions from Waste Management Facilities Final Report July 2011, <http://randd.defra.gov.uk/Document.aspx?Document=WR0608FinalReport.pdf>.
- Franceschetti, A., Honhon, D., Van Woensel, T., Bektaş, T., & Laporte, G. (2013). The time-dependent pollution-routing problem. *Transportation Research Part B: Methodological*, 56, 265-293.
- Ghiani, G., Manni, A., Manni, E., & Moretto, V. (2021). Optimizing a waste collection system with solid waste transfer stations. *Computers & Industrial Engineering*, 161, 107618.
- Gurevsky, E., Kopelevich, D., Kovalev, S., & Kovalyov, M. Y. (2021). Min-sum controllable risk problems with concave risk functions of the same value range. *Networks*.
- Gurevsky, E., Kovalev, S., & Kovalyov, M. Y. (2021). Min-max controllable risk problems. *4OR*, 19(1), 93-101.
- Huang, S. H., & Lin, P. C. (2015). Vehicle routing–scheduling for municipal waste collection system under the “Keep Trash off the Ground” policy. *Omega*, 55, 24-37.
- Haupt M., Kägi T., Hellweg S. (2018) Modular life cycle assessment of municipal solid waste management. *Waste Management*, 79, 815-827.
- Heidari R., Yazdanparast R., Jabbarzadeh A. (2019) Sustainable design of a municipal solid waste management system considering waste separators: A real-world application. *Sustainable Cities and Society*, 47, 101457.
- Habibi, M. K. K., Battaia, O., Cung, V. D., Dolgui, A., & Tiwari, M. K. (2019). Sample average approximation for multi-vehicle collection–disassembly problem under uncertainty. *International Journal of Production Research*, 57(8), 2409-2428.
- Hoorweg D., Bhada-Tata P. (2012) What a Waste: A Global Review of Solid Waste Management (Urban Development Series Knowledge Papers, World Bank), 1-116.
- Hosseinalizadeh, R., Izadbakhsh, H., & Shakouri, H. (2021). A planning model for using municipal solid waste management technologies-considering Energy, Economic, and Environmental Impacts in Tehran-Iran. *Sustainable Cities and Society*, 65, 102566.
- Jiang Y., May H. D., Lu L., Liang P., Huang X., Ren Z. J. (2019) Carbon dioxide and organic waste valorization by microbial electro synthesis and electro-fermentation. *Water Research*, 149, 42-55.
- Khan, I., & Kabir, Z. (2020). Waste-to-energy generation technologies and the developing economies: A multi-criteria analysis for sustainability assessment. *Renewable Energy*, 150, 320-333.
- Korai, M. S., Mahar, R. B., & Uqaili, M. A. (2016). Optimization of waste to energy routes through biochemical and thermochemical treatment options of municipal solid waste in Hyderabad, Pakistan. *Energy Conversion and Management*, 124, 333-343.
- Klinkowski, M., & Walkowiak, K. (2011). Routing and spectrum assignment in spectrum sliced elastic optical path network. *IEEE Communications Letters*, 15(8), 884-886.
- Liu, L., & Liao, W. (2021). Optimization and profit distribution in a two-echelon collaborative waste collection routing problem from economic and environmental perspective. *Waste Management*, 120, 400-414.
- Li, Y., Zhang, J., & Yu, G. (2020). A scenario-based hybrid robust and stochastic approach for joint planning of relief logistics and casualty distribution considering secondary disasters. *Transportation Research Part E: Logistics and Transportation Review*, 141, 102029.
- Mamashli, Z., & Javadian, N. (2021). Sustainable design modifications municipal solid waste management network and better optimization for risk reduction analyses. *Journal of Cleaner Production*, 279, 123824.
- Mavrotas G., Gakis N., Skoulaxinou S., Katsouros V., Georgopoulou E. (2015). Municipal solid waste management and energy production: Consideration of external cost through multi-objective optimization and its effect on waste-to-energy solutions. *Renewable and Sustainable Energy Reviews*, 51, 1205–1222.
- Mayer F., Bhandari R., Gäth S. (2019) Critical review on life cycle assessment of conventional and innovative waste-to-energy technologies. *Science of The Total Environment*, 672, 708-721.
- Mohammadi M., Jämsä-Jounela S.-L., Harjunkoski I. (2019) Optimal planning of municipal solid waste management systems in an integrated supply chain network. *Computers & Chemical Engineering*, 123, 155-169.
- Mohsenizadeh, M., Tural, M. K., & Kentel, E. (2020). Municipal solid waste management with cost minimization and emission control objectives: A case study of Ankara. *Sustainable Cities and Society*, 52, 101807.
- Mirdar Harijani, A., Mansour, S., & Karimi, B. (2017). A multi-objective model for sustainable recycling of municipal solid waste. *Waste Management & Research*, 35(4), 387-399.
- Mulvey, J. M., Vanderbei, R. J., & Zenios, S. A. (1995). Robust optimization of large-scale systems. *Operations research*, 43(2), 264-281.

- Ng W., Lam H., Varbanov P., Klemeš J. (2014). Waste-to-Energy (WTE) network synthesis for Municipal Solid Waste (MSW). *Energy Conversion and Management*, 85, 866-874.
- Panigrahi S., Dubey B. K. (2019) A critical review on operating parameters and strategies to improve the biogas yield from anaerobic digestion of organic fraction of municipal solid waste. *Renewable Energy*, 143, 779-797.
- Razm, S., Dolgui, A., Hammami, R., Brahimi, N., Nickel, S., & Sahebi, H. (2021). A two-phase sequential approach to design bioenergy supply chains under uncertainty and social concerns. *Computers & Chemical Engineering*, 145, 107131
- Rezaei M., Chaharsooghi S. K., Kashan A. H., Babazadeh R. (2020) A new approach based on scenario planning and prediction methods for the estimation of gasoil consumption. *International Journal of Environmental Science and Technology*, 17, 3241–3250.
- Rizwan M., Saif Y., Almansoori A., Elkamel A. (2018) Optimal processing route for the utilization and conversion of municipal solid waste into energy and valuable products *Journal of Cleaner Production*, 174, 857-867.
- Rathore, P., & Sarmah, S. P. (2020). Economic, environmental and social optimization of solid waste management in the context of circular economy. *Computers & Industrial Engineering*, 145, 106510.
- Rezaei, M., Chaharsooghi, S. K., Husseinzadeh Kashan, A., & Babazadeh, R. (2020). Optimal design and planning of biodiesel supply chain network: a scenario-based robust optimization approach. *International Journal of Energy and Environmental Engineering*, 11(1), 111-128.
- Singh, R. P., Tyagi, V. V., Allen, T., Ibrahim, M. H., & Kothari, R. (2011). An overview for exploring the possibilities of energy generation from municipal solid waste (MSW) in Indian scenario. *Renewable and Sustainable Energy Reviews*, 15(9), 4797-4808.
- Singh, A. (2019). Managing the uncertainty problems of municipal solid waste disposal. *Journal of environmental management*, 240, 259-265.
- Tan, S. T., Ho, W. S., Hashim, H., Lee, C. T., Taib, M. R., & Ho, C. S. (2015). Energy, economic and environmental (3E) analysis of waste-to-energy (WTE) strategies for municipal solid waste (MSW) management in Malaysia. *Energy Conversion and Management*, 102, 111-120.
- Tabasová, A., Kropáč, J., Kermes, V., Nemet, A., & Stehlík, P. (2012). Waste-to-energy technologies: Impact on environment. *Energy*, 44(1), 146-155.
- Tsai, F. M., Bui, T. D., Tseng, M. L., & Wu, K. J. (2020). A causal municipal solid waste management model for sustainable cities in Vietnam under uncertainty: A comparison. *Resources, Conservation and Recycling*, 154, 104599.
- Vecchi T.P.B., Surco D.F., Constantino A.A., Steiner M.T.A., Jorge L.M.M., Ravagnani M.A.S.S., Paraíso P.R. (2016) A sequential approach for the optimization of truck routes for solid waste collection. *Process Safety and Environmental Protection*, 102, 238-250.
- Van Engeland, J., Beliën, J., De Boeck, L., & De Jaeger, S. (2020). Literature review: Strategic network optimization models in waste reverse supply chains. *Omega*, 91, 102012.
- Wang S., Huang G.H., Yang B.T. (2012) An interval-valued fuzzy-stochastic programming approach and its application to municipal solid waste management. *Environmental Modelling & Software*, 29(1), 24-36.
- Wang, C., & Chen, S. (2020). A distributionally robust optimization for blood supply network considering disasters. *Transportation Research Part E: Logistics and Transportation Review*, 134, 101840.
- Wang, J., Cevik, M., Amin, S. H., & Parsaee, A. A. (2021). Mixed-integer linear programming models for the paint waste management problem. *Transportation Research Part E: Logistics and Transportation Review*, 151, 102343.
- Ooi, J. K., Woon, K. S., & Hashim, H. (2021). A multi-objective model to optimize country-scale municipal solid waste management with economic and environmental objectives: A case study in Malaysia. *Journal of Cleaner Production*, 316, 128366.
- Xu Z., Elomri A., Pokharel S., Zhang Q., Ming X.G., Liu W. (2017) Global reverse supply chain design for solid waste recycling under uncertainties and carbon emission constraint. *Waste Management*, 64, 358-370.
- Yadav V., Bhurjee A.K., Karmakar S., Dikshit A.K. (2017) A facility location model for municipal solid waste management system under uncertain environment. *Science of The Total Environment*, 603, 760-771.
- Yousefloo, A., & Babazadeh, R. (2020). Designing an integrated municipal solid waste management network: A case study. *Journal of Cleaner Production*, 244, 118824.
- Yousefloo, A., & Babazadeh, R. (2020). Mathematical model for optimizing green waste recycling networks considering outsourcing. *Industrial & Engineering Chemistry Research*, 59(17), 8259-8280.
- Yu, H., & Solvang, W. D. (2016). An improved multi-objective programming with augmented ϵ -constraint method for hazardous waste location-routing problems. *International journal of environmental research and public health*, 13(6), 548.
- Yu, H., & Solvang, W. D. (2017). A multi-objective location-allocation optimization for sustainable management of municipal solid waste. *Environment Systems and Decisions*, 37(3), 289-308.
- Yu, C. S., & Li, H. L. (2000). A robust optimization model for stochastic logistic problems. *International Journal of Production Economics*, 64 (1-3), 385-397.
- Zhao, J., & Ke, G. Y. (2017). Incorporating inventory risks in location-routing models for explosive waste management. *International Journal of Production Economics*, 193, 123-136.
- Zandi Atashbar, N., Labadie, N., & Prins, C. (2018). Modelling and optimisation of biomass supply chains: a review. *International Journal of Production Research*, 56(10), 3482-3506.