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A ROBUST AND RISK-AVERSE MEDICAL WASTE CHAIN NETWORK DESIGN BY CONSIDERING VIABILITY REQUIREMENTS

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Abstract. This research suggests a Robust and Risk-Averse Medical Waste Chain Network Design by considering Viability requirements (RRMWCNDV). The aim is to locate a waste management facility that minimizes waste and promotes the recycling of materials like metal and plastic, contributing to environmental benefits. The proposed RRMWCNDV aims to be viable, robust and risk-averse. A two-stage robust stochastic programming model was utilized to develop this framework. It incorporates risk by employing the Weighted Value at Risk (WVaR) approach for the first time. The study reveals that incorporating risk and robustness scenarios results in a lower cost function. The degree of conservatism in decision-making can be adjusted between 0% and 100%, increasing the cost function. The confidence level in WVaR indicates risk aversion, with an increase in the cost function with a 4% increase. The agility coefficient, which indicates the percentage of waste demand production from HC transferred to another facility, also affects the cost function and population risk. A decrease in the sustainability coefficient results in a 53% rise in the cost function and a 12.82% increase in population risk. The model demonstrates NP-hard characteristics and becomes exponentially complex for larger scales.

Mathematics Subject Classification. 90B06, 90C17, 90C90.

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1. Introduction

A MWCN is a complex system that involves the generation, collection, transportation, treatment, and disposal of medical waste. Medical waste is any waste generated by healthcare facilities, such as hospitals, clinics, and laboratories. It can include various materials, such as sharps, infectious waste, pathological waste, pharmaceuticals, and hazardous waste [28].

Keywords. Viability, medical waste, network design, robustness, risk-averse.

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MWCNs are designed to ensure that medical waste is managed safely and environmentally sound. Protecting human health and the environment from the risks associated with medical waste, such as infection and hazardous exposure, is essential [31].

A MWCN comprises key components such as waste generators, waste collectors, waste transporters, waste treatment facilities, and waste disposal facilities. These networks are subject to complex regulations at both federal and state levels, making it difficult for operators to stay compliant. The high cost of managing medical waste is also challenging, as it involves collection, transportation, treatment, and disposal. Exposure to hazardous materials, such as sharps and infectious waste, also risks workers and the public [1,34].

To improve MWCN management, strategies include developing comprehensive waste management plans, investing in new technologies like automated waste sorting systems and waste-to-energy incinerators, providing proper training to workers handling medical waste, and educating the public on proper disposal of unused or expired medications and the use of reusable medical supplies [9]. These strategies aim to improve the efficiency and sustainability of MWCNs and reduce the amount of medical waste generated. MWCNs are essential for protecting human health and the environment from the risks associated with medical waste. By implementing effective waste management practices, healthcare facilities and MWCN operators can play a key role in ensuring the safe and sustainable disposal of medical waste [25,26].

Designing a robust and risk-averse MWCN ensures safe, efficient, and environmentally sound MW management (MWM). This subject involves considering various viability requirements to minimize potential disruptions and ensure the network's resilience in the face of uncertainties [28,33].

Strategies to achieve a robust and risk-averse MWCN include network diversification, maintaining excess capacity, integrating technology, continuous monitoring and adaptation, and fostering stakeholder collaboration [42,44]. Diversifying the network by utilizing multiple waste collectors, transporters, and treatment facilities can reduce reliance on a single provider and mitigate disruptions [22,43]. Maintaining excess capacity at collection and transportation stages can accommodate sudden increases in waste generation or disruptions in other network parts. Implementing advanced technologies, such as automated waste sorting and real-time tracking systems, can improve efficiency and reduce risks. Regular monitoring and implementing corrective measures can prevent disruptions and ensure the network's long-term viability [39, 46]. Fostering collaboration among healthcare facilities, waste management companies, and regulatory bodies can facilitate information sharing, problem-solving, and coordinated decision-making to address network-wide challenges [18].

By incorporating these viability requirements and strategies into the design and operation of MWCNs, healthcare providers and waste management professionals can create a resilient, risk-averse system that effectively manages medical waste while protecting human health and the environment (see Fig. 1).

The research introduces an innovative concept for the RRMWCNDV and focuses on achieving the following objectives:

- Designing a MWCN that is viable and efficient is a first-time endeavor.
- Considering the aspects of robustness and novel risk criteria in viable MWCND.

The structure of the paper is as follows: Section 2 provides a comprehensive overview of related work in the field of MWCND. Section 3 outlines the details and features of RRMWCNDV and introduces the concept of risk-averse RRMWCNDV. Section 4 presents the research findings and includes sensitivity analysis. Section 5 discusses the managerial insights and practical implications derived from the study. Section 6 summarizes the conclusion drawn from the research.

2. Survey on recent MWCND

Due to COVID-19, there has been an evident surge in the volume of waste generated. Consequently, researchers have been conducting studies to address managing, enhancing, and reducing losses associated with medical facilities. The following is an overview of the recent investigations conducted on MWCND.

2.1. Simple MWCND

Due to the COVID-19 pandemic, there has been a surge in the production of infectious medical waste (IMW). As a result, there is a need to establish an efficient reverse logistics network for IMW management. In their study, Kargar *et al.* [26] propose a linear programming model with three objective functions: cost minimization, risk reduction, and minimizing uncollected waste at medical waste generation centres (MWGCs). The model utilizes the Revised Multi-Choice Goal Programming (MCGP) method and draws insights from a real case study conducted in Iran. The model effectively balances these objectives by optimizing the flow between centres, implementing temporary treatment facilities, and controlling the amount of uncollected waste.

Reverse logistics (RL) is critical in supply chain management, encompassing collection, recovery, recycling, and disposal activities. In Shadkam [40], a sophisticated integer linear programming model is proposed for the integrated design of direct logistics and RL networks. The escalating medical waste caused by the COVID-19 pandemic necessitates implementing an inverse logistics system to manage waste effectively. The model comprises various components, including factories, consumer facilities, and recycling centres, each with subparts. The cuckoo optimization algorithm is employed to solve the model, and the computational findings are presented.

2.2. MWCND with a sustainability approach

Alizadeh *et al.* [3] discuss the significance of efficient design in medical supply chain networks to mitigate waste accumulation and its adverse environmental effects. The model aims to maximize profit by subtracting costs from supply chain revenues, reducing biological risks, and minimizing travel time between clinics and sterilization centres. The model is implemented in Tehran's 4th municipal district and employs the Bounded De Novo Programming (BDNP) approach to redesign sterilization centres, mitigate biological risks, enhance profitability, and increase recycling productivity. This approach addresses resource and policy constraints within the medical supply chain network.

Yu *et al.* [47] propose a novel multi-objective mixed integer program for designing an epidemic RL network to manage medical waste during disease outbreaks. The model targets identifying optimal locations for temporary facilities and transportation strategies to handle the exponential growth of medical waste. A case study based on the COVID-19 outbreak in Wuhan, China, is presented to illustrate the application of the model. The results indicate that installing temporary incinerators may be a practical solution, emphasizing the importance of careful site selection. However, further real-world data is needed to evaluate the effectiveness of the proposed solution comprehensively.

Balci *et al.* [6] propose a multi-purpose RL network for managing medical waste in Istanbul during and following the COVID-19 pandemic. The model integrates economic, environmental, and social objectives to maximize personnel and government earnings while minimizing fixed costs and carbon emissions. The existing facilities are deemed sufficient, but a sterilization facility near Komurcuoda is suggested as an optimal solution. The model results reveal a 42 000 € increase in total costs, with the quantity of medical waste having the most significant effect.

Govindan *et al.* [19] present a mixed-integer linear programming circular economy transition model for MWM, considering uncertainty in waste generation. The model employs queuing theory to manage waiting times for trucks transporting infectious waste to treatment centres. An improved augmented epsilon-constraint method (AUGMECON2) minimizes total costs and population risks. The model's efficacy is examined using data from a case study in Alborz province.

The COVID-19 pandemic has led to a surge in demand for medical products, resulting in increased medical waste generation. Mei *et al.* [35] aim to develop the RL recycling network to efficiently handle this waste, considering cost, safety, and time constraints. Based on New York City, the model proposes utilizing synergistic facilities and temporary waste disposal centres.

Effective waste management systems are necessary due to the elevated healthcare waste resulting from the COVID-19 pandemic. Aydemir-Karadag [5] proposes a bi-objective mixed-integer nonlinear programming model that integrates periodic inventory routing with location decisions for healthcare waste management. The model combines a mixed-integer linear model with a Bi-Objective Adaptive Large Neighborhood Search Algorithm (BOALNS) to optimize waste collection decisions. Performances of various algorithms are compared, demonstrating the superiority of the BOALNS algorithm in terms of performance and the delivery of high-quality Pareto-optimal solutions.

Bani *et al.* [7] present a mixed-integer mathematical programming model for designing a COVID-19 Vaccine Waste Reverse Supply Chain (CVWRSC) to minimize total costs and carbon emissions. The model incorporates vaccination tendency rate uncertainties and employs a Robust Optimization (RO) approach. A real-life case study is conducted to demonstrate the model's practicality, showing its superiority over disintegrated models. Autoclaving technology is identified as being crucial for the treatment of infectious wastes. The model's robustness is evaluated under various scenarios, with the average objective function being lower than that of deterministic models.

Tirkolaee *et al.* [45] present a mixed-integer mathematical programming model for designing a CVWRSC to minimize total costs and carbon emissions. The model considers uncertainties in vaccination tendency rates and employs the RO approach. A real-life case study is conducted to demonstrate the model's practicality, showcasing its improved performance compared to disintegrated models. Autoclaving technology is identified as being crucial for the treatment of infectious wastes. The model's robustness is evaluated under various scenarios, with the average objective function being lower than that of deterministic models.

The COVID-19 pandemic has significantly impacted supply chains, necessitating the development of solutions for managing COVID-19 Pandemic Wastes (CPWs). Mosallanezhad *et al.* [36] propose an IoT-enabled supply chain network for CPWs that incorporates sustainability aspects. The model employs optimization modeling tools and 15 experiments, utilizing metaheuristic algorithms and seven evaluation indicators. It is found that the MOGWO algorithm outperforms others for medium-sized experiments. At the same time, NSHHO excels in small-sized and large-sized experiments, as determined by the Entropy Weights method and Combined Compromise Solution approach.

2.3. MWCND with sustainability and resiliency approach

Hospital activity and patient volume are rising, making Hospital Waste Management (HWM) more difficult. To solve this problem, Negarandeh and Tajdin [37] created a brand-new multi-objective mixed integer linear programming model for HWM in Sari, Iran. The model uses an Improved Goal Programming (IGP) technique and a robust fuzzy programming approach to consider sustainability, resilience, and uncertainty. The findings indicate that goal programming performs better than the Lp-metric approach for every target, proving the effectiveness of the suggested methodology for long-term HWM networks.

2.4. MWCND with viability approach

Using a multi-stage stochastic method, Alizadeh *et al.* [4] suggest a flexible healthcare network design for the COVID-19 pandemic. The network's goals are to lower the rate of coronavirus deaths, maximize patient recovery, and minimize expenses. It consists of health centres, hospitals, and clinics. An Iranian case study demonstrates the applicability of the concept.

Lotfi *et al.* [28] proposed a unique MWCND to address waste reduction and recovery. Resiliency and sustainability were considered when designing health facilities, contractors, waste segregation, and landfills. The effect of waste recovery and conservative coefficients on the population risk and cost function was solved by using the GAMS CPLEX solver.

2.5. MWCND with antifragility approach

Lotfi *et al.* [31] examined the management of healthcare waste during the COVID-19 pandemic, explicitly investigating the Healthcare Waste Chain Network (HWCND) framework. A robust stochastic optimization method is introduced, incorporating risk criteria and principles of antifragility, sustainability, and agility. The

Figure 1. MWCN with viability approach.

findings indicate that implementing antifragility leads to a 5.85% reduction in the cost function, and adjusting conservatism and confidence levels affects the cost function. Furthermore, the magnitude of challenges impacts both solution time and costs.

2.6. Research gap

The literature classification is presented in Table 1. Previous researchers have not explicitly examined the RRMWCNDV problem. The current study investigates the RRMWCNDV problem and utilizes mathematical models to determine the optimal location for MWCND. This research introduces several innovations, which are as follows:

– The first-time design of RRMWCNDV.
– Incorporation of agility, resiliency, sustainability, robustness, and risk-averse factors in MWCND.

3. Problem description

This research focuses on the RRMWCNDV, which addresses the limitations of existing MWCNDs regarding their viability approach. It emphasizes sustainability, resiliency, and agility. The network consists of four key

TABLE 1. Survey of MWCND.

			Viability								
				Sustainability							
Research	HWCND type	Antifragility	Resiliency	Economic	Environmental	Social	Agility	Risk criteria	Uncertainty	Methodology	Case study
[26]	HWCND	–	–	✓	–	–	–	–	–	MILP+MCGP	Iran
[47]	GHWCND	–	–	✓	✓	–	–	–	–	MOMILP	Wuhan, China
[3]	GHWCND	–	–	✓	–	–	✓	–	–	BDNP	Tehran
[28]	VHWCND	–	✓	✓	✓	✓	✓	CVaR	RO	MILP	Tehran
[19]	GHWCND	–	–	✓	✓	–	–	–	–	MOMILP+ AUGMECON2	Alborz province
[6]	SHWCND	–	–	✓	✓	✓	–	–	–	MOMILP	Istanbul
[37]	RSHWCND	–	✓	✓	✓	✓	–	–	Fuzzy	MOMILP+IGP	Sari
[40]	HWCND	–	–	✓	–	–	–	–	–	MILP+Cuckoo	Numerical exmple
[35]	SHWCND	–	–	✓	✓	–	–	–	–	MILP	New York
[5]	SHWCND	–	–	✓	✓	–	–	–	–	MOMINLP+ BOALNS	Numerical exmple
[7]	SHWCND	–	–	✓	✓	–	–	–	–	MILP	Numerical exmple
[45]	SHWCND	–	–	✓	✓	–	–	–	–	MILP	Numerical exmple
[31]	ASAHWCND	✓	✓	✓	✓	✓	✓	EVaR	RO	MILP	Tehran
[36]	SHWCND	–	–	✓	✓	–	–	–	–	MILP+ MOGWO	Numerical exmple
[4]	VHWCND	–	–	✓	–	✓	✓	–	–	MILP	Iran
This research	RRMWCNDV	–	✓	✓	✓	✓	✓	WVaR	MILP	MILP	Iran

components: Health Center (HC), Waste Segregation (WS), Waste Purchase Contractor (WPC), and landfill. To achieve resiliency, RRMWCNDV incorporates flexible capacity, complex nodes, and scenario-based strategies to adapt to changing circumstances and manage disruptions effectively. The considerations also include sustainability constraints such as energy consumption and environmental pollution. Agility is achieved by balancing waste flow and meeting demand requirements [13, 16]. The strategic placement of WS facilities is crucial in enhancing waste collection and recovery while adhering to sustainability and environmental guidelines. Additionally, transportation modes are considered to enhance agility in responding to demand (see Fig. 2).

The following viability policies are being explored for VSSOARR:

- *Agility approach*: flow constraints and satisfying coefficient of demand [11, 12, 14, 23].
- *Sustainability approach*: pay attention to CO_2 emissions and energy consumption [15, 38].
- *Resiliency strategy*: flexible and scenario-based capacity and node complexity [27].

Assumptions

- To ensure efficient waste management (agility), it is recommended that all waste be directed to Health Centers (HCs) [31, 33].
- The limitations of existing MWCNDs, including constraints on flow and capacity, remain unchanged [28, 31].
- Sustainability guidelines, such as allowable emissions and energy consumption, are integrated into the approach [21].

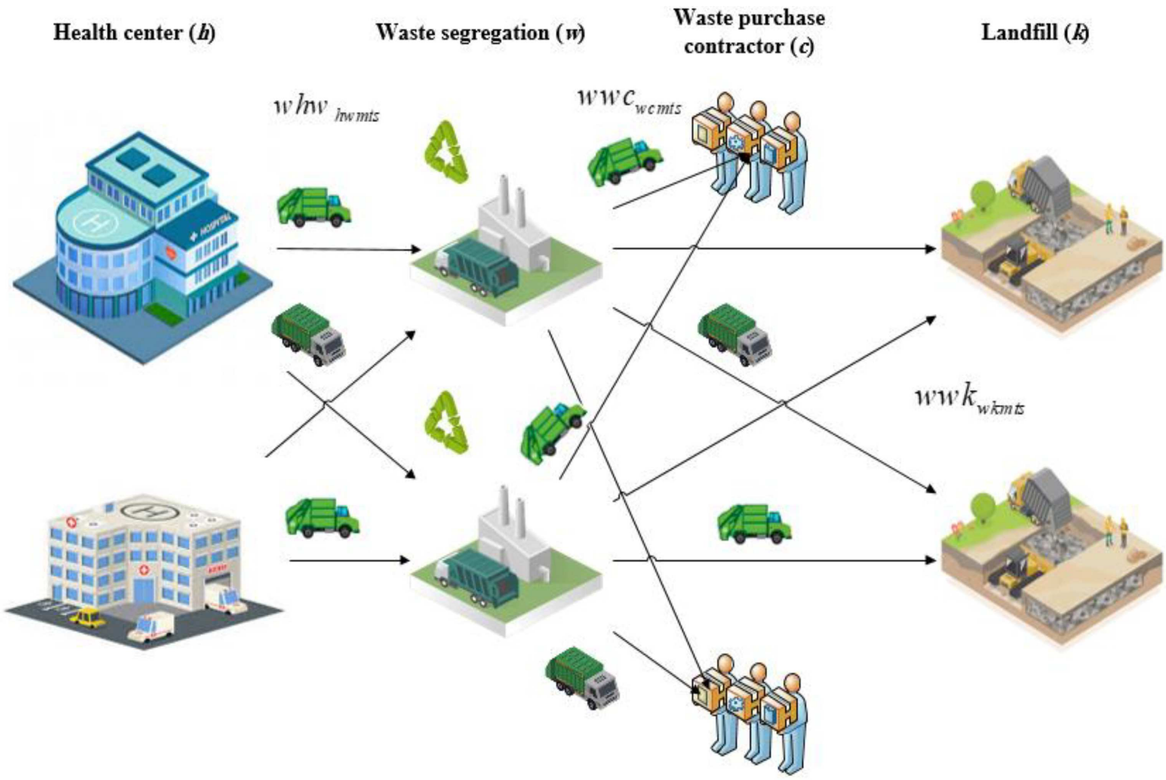

FIGURE 2. RRMWCNDV model.

- Resilience is enhanced through the use of flexible capacity adjustment and node complexity for Waste Segregation (WS) facilities [31].
- Scenario-based RO techniques are employed to mitigate risks and ensure system reliability [28].

Notation list

Sets (Indices)

h	Set (index) of Health Center (HC) $h \in H = \{1, 2, \ldots, \bar{h}\}$.
w	Set (index) of Waste Segregation (WS) $w \in W = \{1, 2, \ldots, \bar{w}\}$.
c	Set (index) of Waste Purchase Contractor (WPC) $c \in C = \{1, 2, \ldots, \bar{c}\}$.
k	Set (index) of landfill $k \in K = \{1, 2, \ldots, \bar{k}\}$.
m	Set (index) of transportation mode $m \in M = \{1, 2, \ldots, \bar{m}\}$.
t	Set (index) of time period $t \in T = \{1, 2, \ldots, \bar{t}\}$.
s	Set (index) of scenario $s \in S = \{1, 2, \ldots, \bar{s}\}$.

Parameters	Description	Value	Unit
ww_{hts}	Medical waste created in HC h for time period t under scenario s.	$U(1000, 1100)(0.8 + 0.4(s-1)/(\lvert S\rvert - 1))$	Ton
Costs			
vhw_{hwmts}	Variable cost from HC h to WS w with mode m for time period t under scenario s.	$U(0.5, 1)$	\$/Ton

vwc_{wcmts}	Variable cost from WS w to WPC c with mode m for time period t under scenario s.	$U(0.5, 1)$	\$/Ton
vwk_{wkmts}	Variable cost from WS w to the landfill k with mode m for time period t under scenario s,	$U(0.5, 1)$	\$/Ton
fw_w	Activation cost of WS w.	$1000U(500, 600)$	\$
CO_2 emission			
$emhw_{hwmts}$	CO_2 emission for flow from HC h to WS w with mode m for time period t under scenario s.	$U(2, 4)/1000$	Ton
$emwc_{wcmts}$	CO_2 emission for flow from WS w to WPC c with mode m for time period t under scenario s.	$U(2, 4)/1000$	Ton
$emwk_{wkmts}$	CO_2 emission for flow from WS w to landfill k with mode m for time period t under scenario s.	$U(2, 4)/1000$	Ton
EMSY_t	Maximum allowed emission for time period t.	$10\,000U(2, 4)(\lvert H\rvert\lvert J\rvert + \lvert J\rvert\lvert C\rvert + \lvert J\rvert\lvert K\rvert)$	Ton
Energy consumption			
$enhw_{hwmts}$	Energy consumption for flow from HC h to WS w with mode m for time period t under scenario s.	$U(4, 5)/1000$	MJ
$enwc_{wcmts}$	Energy consumption for flow from WS w to WPC c with mode m for time period t under scenario s.	$U(4, 5)/1000$	MJ
$enwk_{wkmts}$	Energy consumption for flow from WS w to landfill k with mode m for time period t under scenario s.	$U(4, 5)/1000$	MJ
ENSY_t	Maximum allowed energy consumption for time period t.	$10\,000U(4, 5)(\lvert H\rvert\lvert J\rvert + \lvert J\rvert\lvert C\rvert + \lvert J\rvert\lvert K\rvert)$	MJ
Population risk			
$pophw_{hwts}$	Population risk contact from HC h to WS w for time period t under scenario s.	$[U(100, 200)]$	Person
$popwc_{wcts}$	Population risk contact from WS w to WPC c for time period t under scenario s.	$[U(150, 200)]$	Person
$popwk_{wkts}$	Population risk contact from WS w to landfill k for time period t under scenario s.	$[U(100, 200)]$	Person
θ	Max population contact.	$200(\lvert H\rvert\lvert J\rvert + \lvert J\rvert\lvert C\rvert + \lvert J\rvert\lvert K\rvert)/\lvert S\rvert$	Person
Other parameters			
$Capw_{wts}$	The capacity of WS w for time period t under scenario s.	$U(20, 21)(0.8 + 0.4(s - 1)/(\lvert S\rvert - 1))$	Ton
Ω_s	Probably of scenario s.	$1/\lvert S\rvert$	%
β	Coefficient of conservative.	10	%
ρ_w	Availability coefficient of WS w.	90	%
$Mbig$	Big positive number.	100 000 000 000	
ε	Very little positive number.	0.00000000001	
α	The confidence level for Value at Risk.	5	%
π	Waste recovery coefficient.	90	%

TT	Threshold of node complexity for resiliency.	$3000(\|H\|\|J\|+\|J\|\|C\|+\|J\|\|K\|)$	Ton
φ	The ratio of HC to WS.	30	%
ψ	Sustainability coefficient.	95	%
λ	Coefficient of demand (agility coefficient).	100	%
$\varepsilon_1, \varepsilon_2, \varepsilon_3$	Coefficient of WVaR.	$(10, 20, 70)$	%

Decision variables

Binary variables

x_w If WS w is established, equal 1; otherwise, 0.

Continues variables

whw_{hwmts}	Medical waste flow from HC h to WS w with mode m for time period t under scenario s.
wwc_{wcmts}	Medical waste flow from WS w to WPC c with mode m for time period t under scenario s.
wwk_{wkmts}	Medical waste flow from WS w to landfill k with mode m for time period t under scenario s.

Auxiliary variables

FC	Fix cost of establishing WS.
VC_s	Variable cost for scenario s.
Γ_s	Fix cost and variable cost for scenario s.
mhw_{hwmts}	Auxiliary and binary variable for linearization sign function for whw_{hwmts}.
mwk_{wkmts}	Auxiliary and binary variable for linearization sign function for wwk_{wkmts}.
mwc_{wcmts}	Auxiliary and binary variable for linearization sign function for wwc_{wcmts}.
$\delta\delta_s^+, \delta\delta_s^-$	Auxiliary variable for linearization of absolute function in WVaR.

3.1. RRMWCNDV mathematical model

$$\text{minimize } Z = (1-\beta)\sum_s p_s\Gamma_s + \beta(\mathrm{WVaR}_{(1-\alpha)}(\Gamma_s)), \tag{1}$$

subject to:

Economic constraints (Cost)

$$\mathrm{WVaR}_{(1-\alpha)}(\varepsilon) = \bar{\mu} + \left(\varepsilon_1 z_{1-\alpha} + \varepsilon_2 \frac{\phi(z_{1-\alpha})}{\alpha} + \varepsilon_3\sqrt{-2\alpha\ln(\alpha)}\right)\bar{\sigma}, \tag{2}$$

$$\bar{\sigma} = \sum_s \Omega_s|\bar{\mu} - \Gamma_s|, \tag{3}$$

$$\bar{\mu} = \sum_s \Omega_s\Gamma_s, \tag{4}$$

$$\Gamma_s = \mathrm{FC} + \mathrm{VC}_s, \qquad \forall s \tag{5}$$

$$\mathrm{FC} = \sum_w fw_w x_w, \tag{6}$$

$$\begin{aligned}\mathrm{VC}_s = \sum_t\sum_m\Bigg(&\sum_h\sum_w vhw_{hwmts}whw_{hwmts} + \sum_w\sum_k vwk_{wkmts}wwk_{wkmts}\\ &+ \sum_w\sum_c vwc_{wcmts}wwc_{wcmts}\Bigg), \qquad \forall s.\end{aligned} \tag{7}$$

Agility constraints (flow constraints)

$$\sum_m \sum_w whw_{hwmts} = \lambda ww_{hts}, \qquad \forall h,t,s \tag{8}$$

$$\sum_w whw_{hwmts} \leq \sum_w wwk_{wkmts} + \sum_w wwc_{wcmts}, \qquad \forall h,k,c,t,s,m \tag{9}$$

$$\sum_h whw_{hwmts} = \sum_k wwk_{wkmts} + \sum_c wwc_{wcmts}, \qquad \forall w,m,t,s \tag{10}$$

$$\sum_k wwk_{wkmts} \geq (1-\pi) \sum_h whw_{hwmts}, \qquad \forall w,m,t,s. \tag{11}$$

Resiliency constraints (flexible and scenario-based capacity and node complexity)

$$\sum_m \left(\sum_k wwk_{wkmts} + \sum_c wwc_{wcmts} \right) \leq \rho_w Capw_{wts} x_w, \qquad \forall w,t,s \tag{12}$$

$$\sum_w x_w \geq \min(|H|\varphi, |W|), \tag{13}$$

$$\frac{\sum_m (\sum_h whw_{hwmts} + \sum_k wwk_{wkmts} + \sum_c wwc_{wcmts})}{\mathrm{TT}} \leq 1, \qquad \forall w,t,s. \tag{14}$$

Sustainability constraints (allowed emission and energy consumption)

$$\min\left(\frac{\mathrm{EM}_t}{\mathrm{EMSY}_t}, \frac{\mathrm{EN}_t}{\mathrm{ENSY}_t} \right) \leq \psi, \qquad \forall t \tag{15}$$

$$\begin{aligned} \mathrm{EM}_t = \sum_s \Omega_s \sum_m \Bigg(&\sum_h \sum_w emhw_{hwmts} whw_{hwmts} \\ &+ \sum_w \sum_k emwk_{wkmts} wwk_{wkmts} + \sum_w \sum_c emwc_{wcmts} wwc_{wcmts} \Bigg), \qquad \forall t \end{aligned} \tag{16}$$

$$\begin{aligned} \mathrm{EN}_t = \sum_s \Omega_s \sum_m \Bigg(&\sum_h \sum_w enhw_{hwmts} whw_{hwmts} \\ &+ \sum_w \sum_k enwk_{wkmts} wwk_{wkmts} + \sum_w \sum_c enwc_{wcmts} wwc_{wcmts} \Bigg), \qquad \forall t \end{aligned} \tag{17}$$

$$\begin{aligned} Pop_s = \sum_t \sum_m \Bigg(&\sum_h \sum_w pophw_{hwmts}[whw_{hwmts}] + \sum_w \sum_k popwk_{wkmts}[wwk_{wkmts}] \qquad \forall s \\ &+ \sum_w \sum_c popwc_{wcmts}[wwc_{wcmts}] \Bigg), \end{aligned} \tag{18}$$

$$\sum_s \Omega_s Pop_s \leq \theta. \tag{19}$$

Decision variables

$$x_w \in \{0,1\}, \qquad \forall w \tag{20}$$

$$whw_{hwmts}, wwk_{wkmts}, wwc_{wcmts} \geq 0 \qquad \forall h, w, c, k, t, s. \tag{21}$$

This objective (1) aims to reduce the cost function's expected value and WVaR across all scenarios. This cost function formulation is designed to enhance resilience and address disruption risks under challenging conditions. Constraints (2) show the formulation of WVaR. WVaR is a new risk coherent criteria containing three risk criteria: VaR, CVaR and EVaR by normal distribution assumption [2]. Constraints (3) and (4) show the mean and Mean Absolute Deviation (MAD) of the total cost.

Constraint (5) presents the total cost for all scenarios, including fixed and variable costs. Constraint (6) reflects the fixed costs incurred when landfills (WS) are activated throughout the planning horizon. Constraints (7) define the variable costs associated with waste flow between HC, WS, WPC, and landfills. Constraint (8) determine the satisfying coefficient of demand as an agility approach.

Constraints (9)–(11) establish flow constraints in the RRMWCNDV network for all transportation modes. Constraint (11) determine the proportion of waste sent to landfills. Constraints (12)–(14) present flexible and scenario-based capacity for WS and node complexity in the network as resiliency constraints. Constraint (15) ensures that a portion of the total emissions and energy is below the specified threshold.

Constraints (16) and (17) calculate the total amount of emissions and the total amount of energy for every period. Constraints (18) address the risks involved in transporting medical waste. Constraint (19) specifies that the total risk of transporting medical waste that could come into contact with people must remain below the designated threshold. The decision variables are represented by constraints (20) and (21), where constraint (20) concerns the location of sanitation facilities (waste collection) and binary variables. In contrast, constraint (21) is related to the inter-facility flow variables, which must be positive.

3.2. Linearization of Sign, Absolute and WVaR (Preliminary)

The constraints (3), (15), and (18) are MINLP form. It is necessary to convert them into MILP format using operational research methods to optimize them within the shortest possible time and achieve a seamless improvement in the solution [17, 41]. Linearization methods have been employed to quickly solve the model using these equations [10, 20, 29] (see Tab. 2).

TABLE 2. Linearization methods.

Function	Nonlinear function	Linearization method
Absolute	$k = \lvert\Omega_s\rvert,$	$k = \alpha_s + \beta_s, \quad \Omega_s = \alpha_s - \beta_s, \quad \alpha_s, \quad \beta_s \geq 0, \quad \forall s$
Sign	$\beta_s = [\Omega_s],$	$\beta_s \leq 1 + \dfrac{\Omega_s}{Mbig} - \varepsilon, \quad \beta_s \geq \dfrac{\Omega_s}{Mbig}, \quad \forall s$

3.3. Linearization of RRMWCNDV

To enhance the solution approach for model (1), we incorporated operational research techniques to linearize it. By applying a MIP solver, we discovered that solving the model became simpler than using MINLP. This issue led to a decrease in solution time and overall model complexity. Specifically, we linearized constraints (3), (15), and (18) associated with the absolute, minimum, and sign functions. As a result of these transformations, constraints (22)–(34) were created as follows.

Linearization of RRMWCNDV

$$\text{minimize } Z = (1-\beta)\sum_s p_s \Gamma_s + \beta\big(\mathrm{WVaR}_{(1-\alpha)}(\Gamma_s)\big),$$

subject to:

$$\bar{\sigma} = \sum_s \Omega_s\big(\delta\delta_s^+ + \delta\delta_s^-\big), \tag{22}$$

$$\bar{\mu} - \Gamma_s = \delta\delta_s^+ - \delta\delta_s^-, \qquad \forall s \tag{23}$$

$$\delta\delta_s^+, \delta\delta_s^- \geq 0, \qquad \forall s \tag{24}$$

$$\frac{\mathrm{EM}_t}{\mathrm{EMSY}_t} \leq \psi, \qquad \forall t \tag{25}$$

$$\frac{\mathrm{EN}_t}{\mathrm{ENSY}_t} \leq \psi, \qquad \forall t \tag{26}$$

$$\begin{aligned} Pop_s = \sum_t \sum_m \Bigg(& \sum_h \sum_w pophw_{hwmts} mhw_{hwmts} \\ & + \sum_w \sum_k popwk_{wkmts} mwk_{wkmts} \\ & + \sum_w \sum_c popwc_{wcmts} mwc_{wcmts} \Bigg), \qquad \forall s \end{aligned} \tag{27}$$

$$mhw_{hwmts} \leq 1 + \frac{whw_{hwmts}}{Mbig} - \varepsilon, \qquad \forall h, w, m, t, s \tag{28}$$

$$mhw_{hwmts} \geq \frac{whw_{hwmts}}{Mbig}, \qquad \forall h, w, m, t, s \tag{29}$$

$$mwk_{wkmts} \leq 1 + \frac{wwk_{wkmts}}{Mbig} - \varepsilon, \qquad \forall w, k, m, t, s \tag{30}$$

$$mwk_{wkmts} \geq \frac{wwk_{wkmts}}{Mbig}, \qquad \forall w, k, m, t, s \tag{31}$$

$$mwc_{wcmts} \leq 1 + \frac{wwc_{wcmts}}{Mbig} - \varepsilon, \qquad \forall w, c, m, t, s \tag{32}$$

$$mwc_{wcmts} \geq \frac{wwc_{wcmts}}{Mbig}, \qquad \forall w, c, m, t, s \tag{33}$$

$$mhw_{hwmts}, mwk_{wkmts}, mwc_{wcmts} \in \{0, 1\}, \qquad \forall h, w, c, k, t, s. \tag{34}$$

Constraints (2),(4)–(14), (16)–(17), (19)–(21).

3.4. Scale of RRMWCNDV

The complexity involved in linearizing RRMWCNDV can be evaluated by considering the number of binary, positive, and free variables and the constraints outlined in equations (35)–(38). It becomes evident that scenario sets are crucial in defining these constraints, positive variables, and free variables. The relationship between scenarios and these variables and constraints is entirely linear. To tackle this, we proposed techniques and algorithms for scenario reduction, aiming to eliminate constraints and binary variables. These efforts have the potential to simplify the resolution of time-related problems with minimal requirements, particularly when dealing with large-scale scenarios.

$$\text{Binary variables} = |W|(1 + |M||T||S|(|H| + |C| + |K|)), \tag{35}$$

$$\text{Positive variables} = |S|(2 + |W||M||T|(|H| + |C| + |K|)), \tag{36}$$

$$\text{Free variables} = 3|S| + 2|T| + 5, \tag{37}$$

$$\begin{aligned} \text{Constraints} = {} & 7 + 4|T| + 4|S| + |T||S|(2|W||M|(|H| + |C| + |K| + 1) \\ & + |H|(1 + |K||C||M|) + 2|W|). \end{aligned} \tag{38}$$

TABLE 3. The number of indices, constraints, and variables for case study.

Problem	$\lvert H\rvert \cdot \lvert W\rvert \cdot \lvert C\rvert \cdot \lvert K\rvert \cdot \lvert M\rvert \cdot \lvert T\rvert \cdot \lvert S\rvert$	Variables			Constraint	Cost function (Dollar)	Time solution (s)	Population risk
		Binary	Positive	Free				
$P1$	$6 \cdot 4 \cdot 3 \cdot 3 \cdot 3 \cdot 3 \cdot 3$	1300	1302	20	4423	1 074 444.5	1.2	10 267.3

FIGURE 3. Potential location for the facilities.

4. RESULTS AND DISCUSSION

To gather data on RRMWCNDV, we conducted surveys among health centre managers in Tehran. This data was utilized to estimate various parameters and assess the effectiveness of our mathematical model, as shown in Table 3. The parameter values were derived from the managers' data and are included in the notation list. Throughout our analysis, we maintained a constant probability for event occurrences and considered optimistic, pessimistic, and plausible scenarios.

For the computational aspect, we utilized a computer with the following specifications: a 1.7 GHz CPU, an Intel Core i5-4210U processor, 16.00 GB RAM, and a 64-bit operating system. With the help of the GAMS-CPLEX solver, we successfully solved the mathematical models.

We present the potential sites in Tehran for allocating HC, WS, WPC, and landfills. These sites are depicted in Figure 3 and summarized in Table 4.

The model was solved to determine the best recommendation for implementing WS. The location and flow of various components related to RRMWCNDV were also identified. The objective function, as shown in Table 3,

Table 4. Assigning location for the RRMWCNDV facility.

Problem: $P1$	Binary variable	Place			
		Andisheh	Shahriar	Nasimshahr	Baghershahr
WPC	xw_w	0	0	1	1

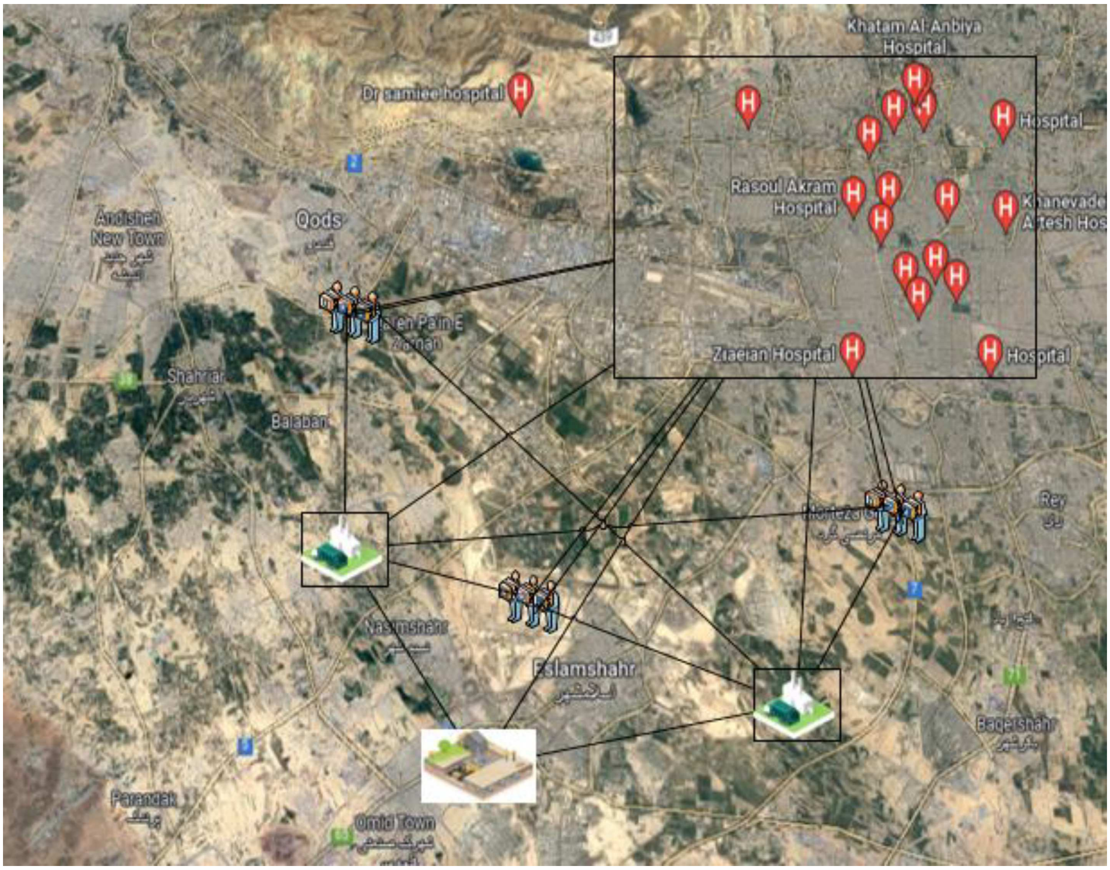

Figure 4. Final location for RRMWCNDV facility.

is 1 074 444.5 dollars. The finalized location allocation is shown in Figure 4. In addition, the population risk was calculated to be 10 267.3 persons. This issue is represented on the left-hand side of the constraint in equation (19).

4.1. Compare models

When comparing the different scenarios of RRMWCNDV, as shown in Table 5, it becomes clear that incorporating risk and robustness scenarios results in a notably lower cost function. Specifically, the cost function is approximately 0.23% less when these scenarios are considered than when they are not (Fig. 5).

Table 5. Comparing $P1$-RRMWCNDV.

Model	Kind	$P1$-RRMWCNDV	$P1$-RRMWCNDV without risk and worst-case	Gap
P1-main	Cost (Dollar)	1 074 444.5	1 076 942.115	0.23%
	Population risk (Person)	10 267.335	10 328.5	0.60%

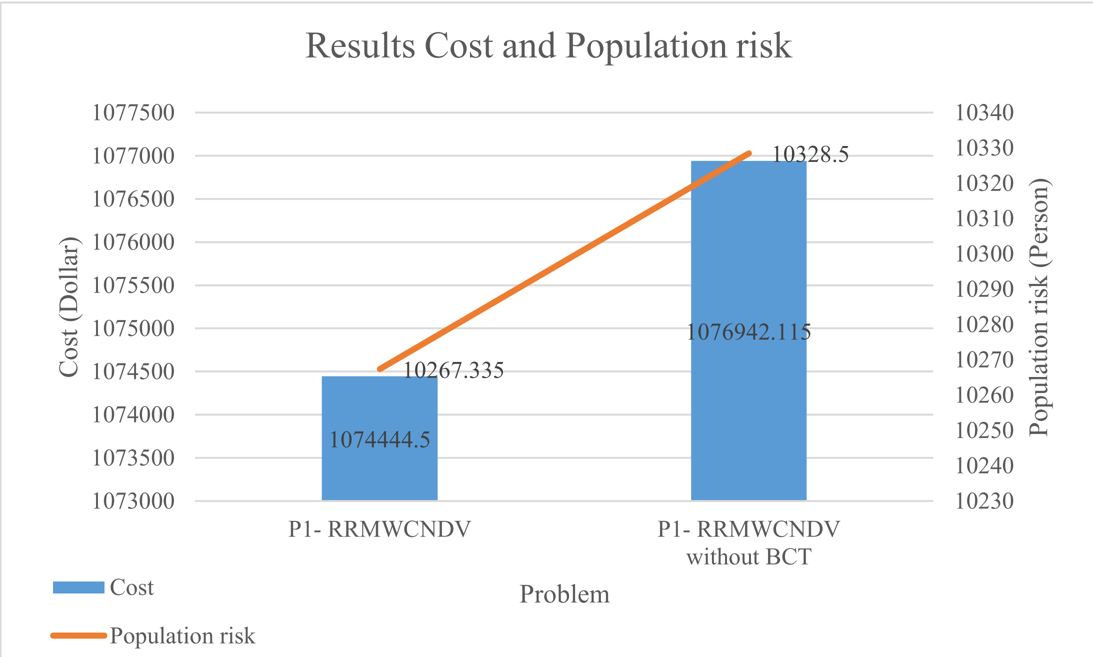

Figure 5. Comparing $P1$-RRMWCNDV.

4.2. Analysis of the conservatism coefficient

The existence of conservative decision-makers is indicated by the conservatism coefficient (β). We can change the degree of conservatism in our decision-making by varying it between 0% and 100%. Table 6, Figures 6 and 7 demonstrate an increase in the cost function when the conservative coefficient exceeds 100%. The population risk decreases with a 90% increase in the conservative coefficient, but the cost function increases by 0.31%.

4.3. Variation on confidence level of WVaR

Decision-makers' level of risk aversion is indicated by the confidence level $(1-\alpha)$ in WVaR. We note an increase in the cost function with increasing confidence levels (see Tab. 7 and Fig. 8). The cost function increases by 0.02% when the confidence level is raised by 4%.

4.4. Variation on agility coefficient

The agility coefficient (λ) indicates the percentage of waste demand production from HC transferred to another facility. A higher agility coefficient leads to higher values in both the cost function and population risk, as shown in Figures 9 and 10. Additionally, increasing the agility coefficient results in more waste being

TABLE 6. Effects of variation of conservatism coefficient.

Problem	Conservatism coefficient (β)	Cost function	Time solution	Cost variation	Population risk
$P1$	0%	1 073 753.1	0.919	−0.06%	9522.667
$P1$-main model	10%	1 074 444.5	0.725	0.00%	10 267.34
$P1$	50%	1 076 924.2	1.193	0.23%	8794.335
$P1$	75%	1 077 738.4	0.904	0.31%	7910.668
$P1$	100%	1 077 738.4	0.981	0.31%	7910.668

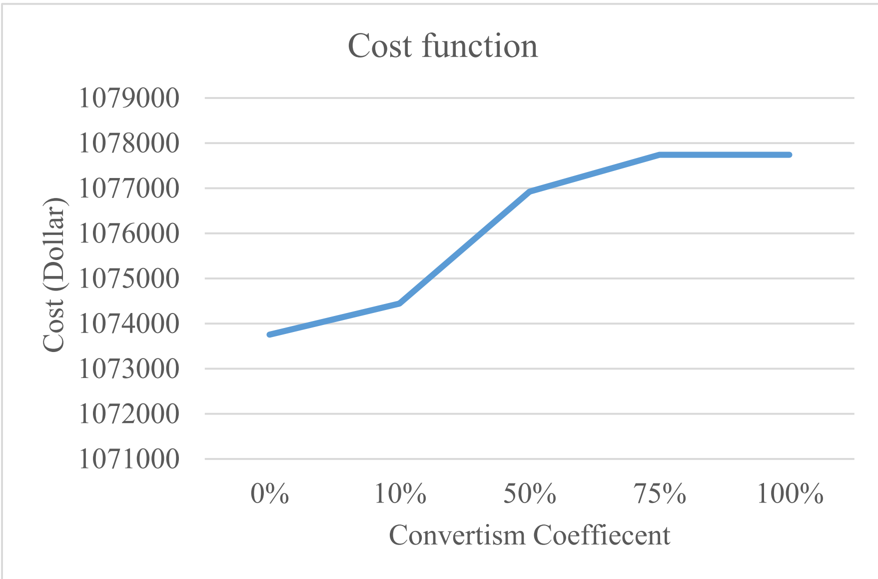

FIGURE 6. Cost function for variation of conservatism coefficient.

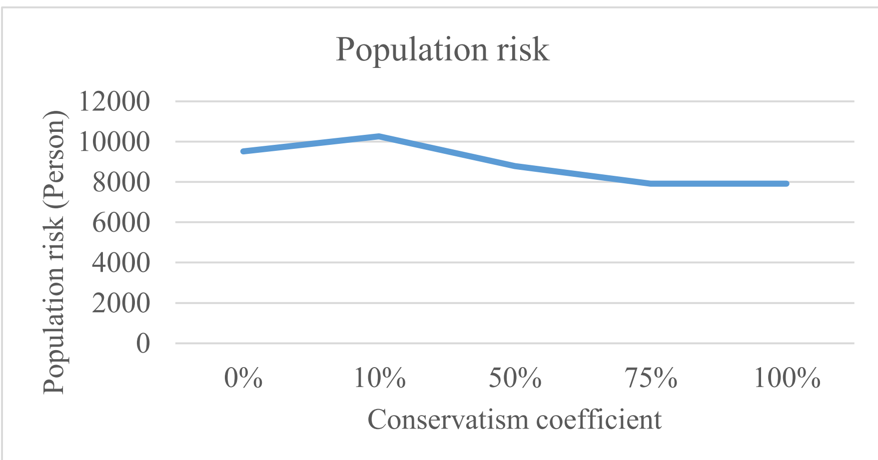

FIGURE 7. Population risk for variation of conservatism coefficient.

Table 7. Effects of the confidence level of WVaR.

Problem	Confidence level $(1-\alpha)$	Cost function	Time solution	Cost variation	Population risk
$P1$	90%	1 074 351.2	1.104	−0.01%	10 202
$P1$	93%	1 074 400.8	1.197	0.00%	10 202
$P1$-main model	95%	1 074 444.5	0.725	0.00%	10 267.34
$P1$	98%	1 074 552.3	1.171	0.01%	10 267.34
$P1$	99%	1 074 625.5	1.224	0.02%	10 202

Figure 8. Effects of the confidence level of WVaR.

Table 8. Effects of sustainability coefficient.

Problem	Agility coefficient (λ)	Cost function	Time solution	Cost variation	Population risk
$P1$	80%	1 069 795.4	1.114	−0.43%	10 162.34
$P1$	85%	1 070 957.7	1.116	−0.32%	10 162.34
$P1$	90%	1 072 119.9	1.214	−0.22%	10 227.67
$P1$	95%	1 073 282.2	1.586	−0.11%	10 202
$P1$-main model	100%	1 074 444.5	0.725	0.00%	10 267.34

transported to WPC, increasing the cost function. However, this increase in transportation also contributes to the utilization and recovery of waste within the systems.

4.5. Variation on sustainability coefficient

We analyze the effects of the sustainability coefficient. The cost function increases as the sustainability coefficient decreases (see Tab. 9). Figures 11 and 12 demonstrate that a decrease of 11% in the sustainability coefficient results in a 53% rise in the cost function and a 12.82% increase in population risk.

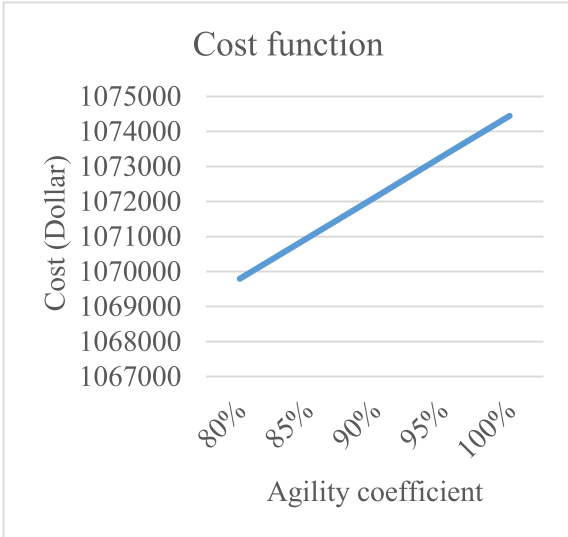

Figure 9. Effects of agility coefficient on the cost function.

Figure 10. Effects of agility coefficient on population risk.

4.6. Variation on scale of the main model

In Table 10, you can find the definition of a range of extensive problems as these problems become larger, both the time needed to find a solution and the associated cost increase, as shown in Figures 13 and 14. It is clear that the proposed model demonstrates NP-hard characteristics and becomes exponentially complex for larger scales. Therefore, to solve such a model efficiently within limited time constraints when dealing with large scales, we must utilize heuristic, metaheuristic, and new exact solution methods.

Table 9. Effects of sustainability coefficient.

Problem	Sustainability coefficient	Cost function	Time solution	Cost variation	Population risk	Population risk variation
$P1$	84%	1 648 665.4	2.982	53.44%	11 583.33	12.82%
$P1$	85%	1 077 274	3.017	0.26%	9756	−4.98%
$P1$	90%	1 074 505.8	1.975	0.01%	10 539.33	2.65%
$P1$-main model	95%	1 074 444.5	1.233	0.00%	10 267.34	0.00%
$P1$	100%	1 074 444.5	1.233	0.00%	10 267.34	0.00%

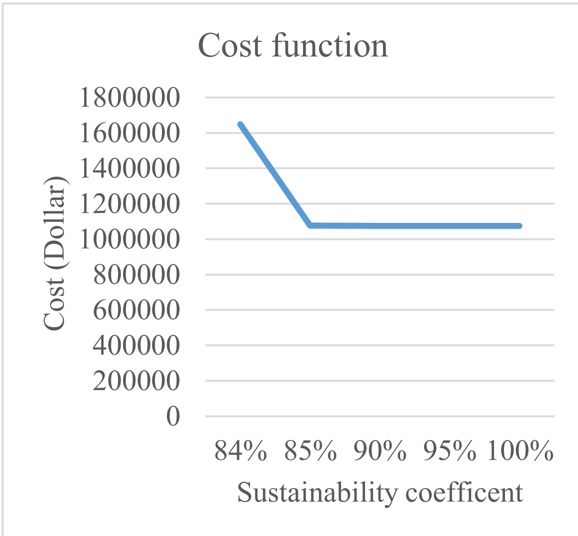

Figure 11. Effects of sustainability coefficient on the cost function.

4.7. Discussion

This research suggests the RRMWCND by considering Viability requirements. The aim is to locate a waste management facility that minimizes waste and promotes the recycling of materials like metal and plastic, contributing to environmental benefits. The proposed RRMWCNDV aims to be viable, robust and risk-averse. A two-stage robust stochastic programming model was utilized to develop this framework. It incorporates risk by employing the WVaR approach for the first time.

In comparison with this research, we can see [28,31]. These papers defined the complex and crucial area of MWCND, addressing various factors such as viability, risk, robustness, sustainability, and agility. Both papers aim to optimize the handling and management of medical waste, albeit with different focuses and approaches.

In the Lotfi *et al.* [28], the primary emphasis lies on the viability of the MWCN. The authors analyze the network's design by integrating risk and robustness considerations. This approach aims to ensure the effectiveness and sustainability of the waste management system by accounting for potential risks and ensuring resilience against uncertainties.

On the other hand, Lotfi *et al.* [31] take a more comprehensive and futuristic approach. In addition to addressing risk, robustness, and sustainability, this paper introduces new elements, such as blockchain technology and the concept of antifragility. It seems to expand the horizon by incorporating agile methodologies, blockchain

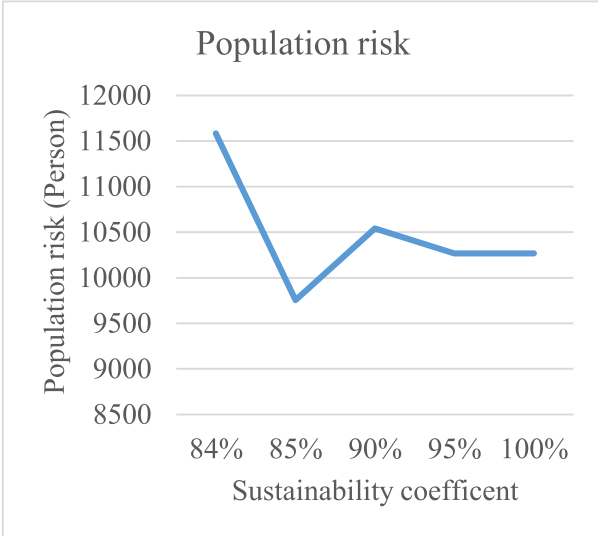

FIGURE 12. Effects of sustainability coefficient on population risk.

TABLE 10. Cost, time solution and population risk for different problems.

Problem	$\lvert H\rvert \cdot \lvert W\rvert \cdot \lvert C\rvert \cdot \lvert K\rvert \cdot \lvert M\rvert \cdot \lvert T\rvert \cdot \lvert S\rvert$	Variables			Constraint	Cost function (Dollar)	Time solution (s)	Cost variation	Population risk	Population risk variation
		Binary	Positive	Free						
$P1$	$6 \cdot 4 \cdot 3 \cdot 3 \cdot 3 \cdot 3 \cdot 3$	1300	1302	20	4423	1 074 445	1.2	0%	10 267	0%
$P2$	$10 \cdot 4 \cdot 3 \cdot 3 \cdot 3 \cdot 5 \cdot 3$	2884	2886	24	10 479	1 675 646	2.7	56%	21 672	111%
$P3$	$20 \cdot 5 \cdot 3 \cdot 3 \cdot 4 \cdot 5 \cdot 3$	7805	7806	24	27 489	2 784 799	1.9	159%	38 947	279%
$P4$	$50 \cdot 5 \cdot 3 \cdot 3 \cdot 4 \cdot 5 \cdot 5$	28 005	28 010	30	103 547	2 994 617	7.4	179%	63 080	514%
$P5$	$50 \cdot 10 \cdot 3 \cdot 3 \cdot 4 \cdot 5 \cdot 5$	56 010	56 010	30	160 797	5 774 587	14.3	437%	66 121	544%
$P6$	$200 \cdot 10 \cdot 3 \cdot 3 \cdot 4 \cdot 5 \cdot 5$	206 010	206 010	30	599 547	6 580 429	135.2	512%	181 219	1665%
$P7$	$200 \cdot 10 \cdot 4 \cdot 4 \cdot 4 \cdot 7 \cdot 5$	291 210	291 210	34	1 040 955	7 001 274	288.5	552%	260 101	2433%

technology, and the notion of antifragility to enhance the resilience and adaptability of the medical waste chain network.

Comparatively, while Lotfi *et al.* [28] concentrate on risk and robustness within the context of viability, Lotfi *et al.* [31] seem to push the boundaries by incorporating emerging technologies like blockchain and exploring the concept of antifragility in designing the waste chain network.

However, a detailed comparison between the methodologies, empirical findings, and the practical implications of these two papers would offer more insight into their specific contributions, strengths, and limitations. Evaluating the models, data sources, case studies (if any), and the extent of practical applicability in real-world scenarios could further enrich the discussion on these research works.

Therefore, this research suggested a novel risk criterion in the MWCND area that is not considered in recent research.

5. Managerial insights and practical implications

We conducted a survey exploring the design of an innovative and practical approach to the RRMWCNDV. Our focus was on five crucial concepts in medical waste network design: agility, resilience, sustainability, risk management, and robustness. Our VWMCND aims to effectively handle disruptions and comply with govern-

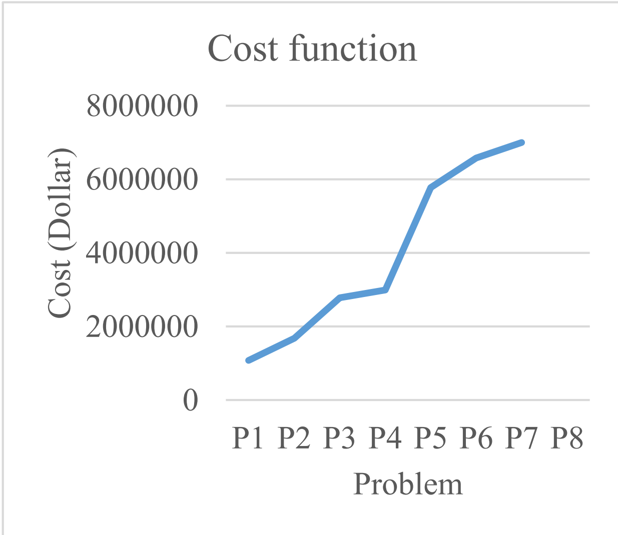

FIGURE 13. Cost function for several problems.

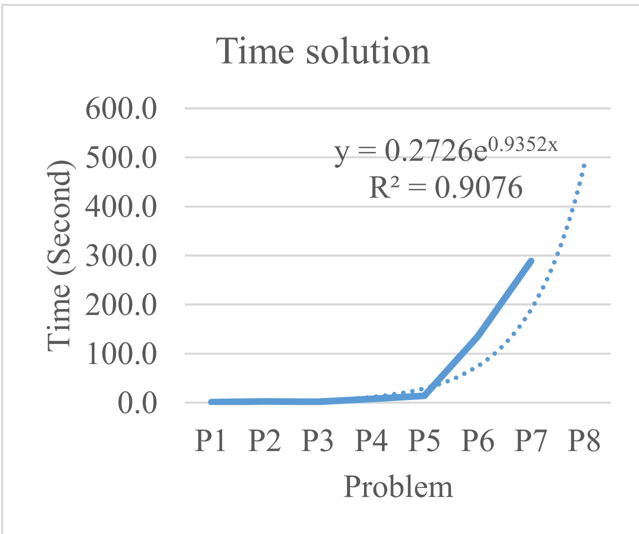

FIGURE 14. Time solution for several problems.

ment regulations by integrating these concepts. As managers of the VWMCND, we aim to implement innovative ideas that reduce costs and population risks while enhancing the network's resilience, robustness, risk mitigation, and agility.

In our research, the main components of the network are the HC, WS, WPC and landfill. Our proposal involves strategically placing the WS to minimize waste generation and promote its recovery, thereby contributing to environmental preservation and the circular production cycle.

Additionally, we introduce the WVaR concept, a risk-coherent criterion encompassing weighted VaR, CVaR, and EVaR through normal distribution approximation.

Considering the challenges brought by COVID-19 and the economy, it becomes crucial to fully leverage waste utilization and transition towards a circular economy and sustainable development. This approach aligns with Sustainable Development Goals (SDG7, SDG12, and SDG13) that promote sustainable consumption, production, and climate change, as well as the principles of the circular economy. Ultimately, the proposed research benefits individuals and service providers involved in the MWC.

6. Conclusions and outlook

MWM is crucial for optimizing environmental effects and public health risks while improving costs and efficiency. To design a robust and risk-averse MWCN, strategies such as network optimization, diversification of treatment options, redundancy, real-time monitoring, and continuous improvement and risk assessment can be employed. Network optimization identifies the most efficient and cost-effective network configuration, while diversification reduces reliance on a single source. Redundancy ensures continuity of operations in case of unexpected events. Real-time monitoring systems track waste movement, treatment status, and environmental parameters, enabling rapid detection and response to potential issues. Regular evaluation and risk assessment help healthcare providers design and implement robust MWCNs that manage medical waste while minimizing risks. The research aims to define the RRMWCNDV network that adheres to regulations, minimizes risks like leaks, spills, accidents, and exposure to hazardous materials, and optimizes costs while maintaining safety and environmental protection. The network should facilitate efficient collection, transportation, treatment, and disposal of medical waste, preventing stockpiling and hazards. The objective is to minimize risks and enhance system robustness and agility in dealing with fluctuations in demand and network disruptions.

To achieve this goal, we have devised a novel two-stage robust stochastic programming model, which was subsequently solved using the GAMS CPLEX solver.

Therefore, the results are as follows:

(1) When comparing the different scenarios of RRMWCNDV, as shown in Table 5, it becomes clear that incorporating risk and robustness scenarios results in a notably lower cost function. Specifically, the cost function is approximately 0.23% less when these scenarios are considered than when they are not.

(2) We can change the degree of conservatism in our decision-making by varying it between 0% and 100%. Table 6, Figures 6 and 7 demonstrate an increase in the cost function when the conservative coefficient exceeds 100%. The population risk decreases with a 90% increase in the conservative coefficient, but the cost function increases by 0.31%.

(3) Decision-makers' level of risk aversion is indicated by the confidence level $(1-\alpha)$ in WVaR. We note an increase in the cost function with increasing confidence levels (see Tab. 7 and Fig. 8). The cost function increases by 0.02% when the confidence level is raised by 4%.

(4) The agility coefficient (λ) indicates the percentage of waste demand production from HC that is transferred to another facility. A higher agility coefficient leads to higher values in both the cost function and population risk, as shown in Table 8, Figures 9 and 10. Additionally, increasing the agility coefficient results in more waste being transported to WPC, increasing the cost function. However, this increase in transportation also contributes to the utilization and recovery of waste within the systems.

(5) We analyze the effects of the sustainability coefficient. The cost function increases as the sustainability coefficient decreases (see Tab. 9). Figures 11 and 12 demonstrate that a decrease of 11% in the sustainability coefficient results in a 53% rise in the cost function and a 12.82% increase in population risk.

(6) In Table 10, you can find the definition of a range of extensive problems as these problems become larger, both the time needed to find a solution and the associated cost increase, as shown in Figures 13 and 14. It is clear that the proposed model demonstrates NP-hard characteristics and becomes exponentially complex for larger scales. Therefore, to efficiently solve such a model within limited time constraints when dealing with large scales, we must utilize heuristic, metaheuristic, and new exact solution methods.

This research aims to efficiently solve a large-scale model using multiple exact algorithms, including benders decomposition, branch and price, branch and cut, column generation, heuristic and meta-heuristic algorithms, and backup facilities and redundancy [5, 40]. A multi-objective approach considering environmental, energy, and occupational objectives is suggested for overall improvements. Risk criteria like Robust Conditional VaR (RCVaR) are also included to account for risks [8, 24]. Method uncertainty is examined using robust convex approaches and contemporary uncertainty techniques like data-driven RO and fuzzy methods [32]. To enhance viability, this research also recommends integrating cutting-edge technologies like blockchain and neural learning into the RRMWCNDV. By continuing research in these areas, the field can be advanced to optimize large-scale models efficiently and sustainably [30, 31].

Author contribution statement

Reza Lotfi: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Project Administration, Resources, Software, Supervision, Validation, Visualization, Writing – Original Draft, Writing – Review & Editing; *Nooshin Mardani*: Methodology, Software, Writing – Original Draft, Writing – Review & Editing; *Sadia Samar Ali*: Methodology, Software, Writing – Original Draft, Writing – Review & Editing; *Seyedeh Maryam Pahlevan*: Methodology, Validation; *Sayyed Mohammad Reza Davoodi*: Methodology, Validation.

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