Viable medical waste chain network design by considering risk and robustness

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Abstract

Medical waste management (MWM) is an important and necessary problem in the COVID-19 situation for treatment staff. When the number of infectious patients grows up, the amount of MWMs increases day by day. We present medical waste chain network design (MWCND) that contains health center (HC), waste segregation (WS), waste purchase contractor (WPC), and landfill. We propose to locate WS to decrease waste and recover them and send them to the WPC. Recovering medical waste like metal and plastic can help the environment and return to the production cycle. Therefore, we proposed a novel viable MWCND by a novel two-stage robust stochastic programming that considers resiliency (flexibility and network complexity) and sustainable (energy and environment) requirements. Therefore, we try to consider risks by conditional value at risk (CVaR) and improve robustness and agility to demand fluctuation and network. We utilize and solve it by GAMS CPLEX solver. The results show that by increasing the conservative coefficient, the confidence level of CVaR and waste recovery coefficient increases cost function and population risk. Moreover, increasing demand and scale of the problem makes to increase the cost function.

Keywords Viable · Medical waste chain · Network design · Resiliency · Sustainable · Robust optimization

Introduction

Medical waste management (MWM) is a critical problem in the COVID-19 situation. In the COVID-19 condition, amount of infectious patients grows up and amount of MWMs increases. As a result, we must pay more attention to MWMs and improve waste disposal. In many workers that do waste

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disposal, this subject threatens them very much. MWMs include infectious waste, hazardous waste, radioactive waste, and general waste (municipal solid waste). The WHO classifies medical waste into sharps, infectious, pathological, radioactive, pharmaceuticals, and other (including toilet waste produced at hospitals). About 85% of MWMs are general waste and 15% of MWMs are infectious waste, hazardous waste, and radioactive waste (Tsai 2021). Therefore, the importance of MWMs makes many researchers contribute to this subject and present mathematical approach and decision support system. Some researchers consider a location-routing problem for medical waste management (Suksee and Sindhuchao 2021; Tirkolaee et al. 2021). Others investigate reverse logistics by the mathematical model (Sepúlveda et al. 2017; Suksee and Sindhuchao 2021). Also, some scientists analyze the MWM systems by multi-criteria-decision approach (Aung et al. 2019; Narayanamoorthy et al. 2020). The objective of these tools is to improve waste management performance and decrease risks for workers that we can see in Figure 1.

One of the new discussions in the present age is the viability of network design in post-pandemic adaptation. The viability of networks that are proposed by Ivanov and Dolgui

Figure 1 MWM in the COVID-19 situation

(2020) is integrated agility, resilience, and sustainability in the network. Therefore, it is needed to suggest a systematic and mathematical model for setting up viable medical waste chain network design (VMWCND), because improving the performance of waste management in urban is needed and makes to prevent COVID-19 outbreak. Eventually, we should design a new mathematical model to consider agility, resilience, sustainability, risks, and robustness to cope with environmental requirements and disruption.

Eventually, the innovation of this research and the main objective is as follows:

- First time designing viable medical waste chain network design (VMWCND)
- Considering robustness and risk in VMWCND

The paper is organized as follows. In the "Survey on recent MWCND" section, we survey on related work in scope of MWCND. In the "Problem description" section, the VMWCND and risk-averse VMWCND are stated. In the "Results and discussion" section, the results of research and sensitivity analysis are presented. In the "Managerial insights and practical implications" section, the managerial insights and practical implications are discussed. In the "Conclusions and outlook" section, the conclusion is summarized.

Survey on recent MWCND

The amount of waste has increased because of the COVID-19 situation. Therefore, researchers research to manage, improve, and decrease losses from medical centers. We survey on the recent investigation on MWCND which is as follows.

Mantzaras and Voudrias (2017) considered an optimization model for medical waste in Greece. They tried to minimize total cost including location and transfer between locations. The genetic algorithm (GA) is applied to solve the model. Budak and Ustundag (2017) designed a reverse logistic for multi-period, multi-type waste products. The model's

objective was to minimize total cost and the model's decision included location, flow, and inventory. The case was in Turkey. They found that by increasing waste amounts, the numbers of facilities and strategies are changed. Wang et al. (2019) designed a two-stage reverse logistics network for urban healthcare waste with multi-objective and multi-period. In stage 1, they predicted the amount of medical waste, and in the second stage, they minimized total cost and environmental impact.

Kargar et al. (2020a) presented a reverse supply chain for medical waste. They used mix-integer programming (MIP) to model problem. The objectives included total costs, technology selection, and the total medical waste stored that are minimized. A robust possibilistic programming (RPP) approach is applied to cope with uncertainty. A fuzzy goal programming (FGP) method is embedded to solve the objectives. The real case study is investigated in Babol, Iran. Other works of Kargar et al. (2020b) studied a reverse logistics network design for MWM in the COVID-19 situation. They minimized the total costs, transportation, and treatment MW risks, and maximized the amount of uncollected waste. They employed the revised multi-choice goal programming (RMGP) method. Homayouni and Pishvaee (2020) surveyed hazardous hospital waste collection and disposal network design problem with a bi-objective robust optimization (RO) model. The objectives include total costs and total operational and transportation risk. An augmented ε-constraint (AUGEPS) method is embedded to solve the problem. The real case study is investigated in Tehran, Iran.

Yu et al. (2020b) considered a reverse logistics network design for MWM in epidemic outbreaks in Wuhan (China). The objectives included risk at health centers, risk related to the transportation of medical waste and total cost. They solved the model by fuzzy programming (FP) approach for multi-objective. They determine temporary transit centers and temporary treatment centers in their model. In addition, Yu et al. (2020a) studied a stochastic network design problem for hazardous WM. They minimized cost and transportation cost of hazardous waste and the population exposure risk. They applied stochastic programming with sample average approximation (SAA) for scenario reduction. They solved the model by goal programming (GP). Saeidi-Mobarakeh et al. (2020a) presented bi-level programming (BP) for a hazardous WM problem. They used an environmental approach for upper level and routing and cost for lower level. They solve mix-integer nonlinear programming (MINLP) by GA.

In addition, Saeidi-Mobarakeh et al. (2020b) developed a robust bi-level optimization model to model hazardous WCND. They suggested a robust optimization approach to cope with the uncertainty. Also, the decisions of the model include location, determining capacity, and routing. Eventually, a commercial solver is utilized to solve the model. Tirkolaee et al. (2021) surveyed a sustainable fuzzy

multi-trip location-routing problem for MWM during the COVID-19 outbreak. They embedded fuzzy chance-constrained programming (FCCP) technique to tackle the uncertainty. Therefore, they implemented weighted GP (WGP) method to analyze and solve the problem. A case study is determined in Sari, Iran to show the performance of the proposed model. Tirkolaee and Aydın (2021) suggested a sustainable MWM for collection and transportation for pandemics. They minimized total cost and the total risk exposure imposed by the collection. Eventually, a commercial solver is utilized to solve the model with meta-goal programming (MGP) for multi-objective. Shadkam (2021) designed a reverse logistics network for COVID-19 and vaccine waste management. They utilized cuckoo optimization algorithm (COA). They tried to minimize total cost. Nikzamir et al. (2021) suggested a location-routing network design for MWM that tried to minimize the total cost and risks of population contact with infectious waste. They offered a mix-integer linear programming (MILP) and solved it by a hybrid meta-heuristic algorithm based on imperialist competitive algorithm (ICA) and GA. Li et al. (2021) surveyed a vehicle routing problem (VRP) for MWM by considering transportation risk. They suggested MILP for time window VRP and developed a particle swarm optimization (PSO) algorithm to solve large-scale problems.

The classification of the literature is addressed in Table 1. It can be seen that researchers do not survey the VMWCND problem. This study investigates the VMWCND problem and used mathematical problems to locate the best place for MWCND.

The main innovation of this research is as follows:

- First time designing VMWCND
- Considering agility, resilience, sustainability, robustness, and risk-averse in MWCND

Problem description

In this research, we try to design VMWCND. The previous section shows a lack of research in resilience, sustainability, and agility MWCND. In the present study, we have health center (HC), waste segregation (WS), waste purchase contractor (WPC), and landfill that wastes move through this network. Eventually, we present VMWCND through resilience strategy (flexible and scenario-based capacity and node complexity), sustainability constraints (energy and environmental pollution), and agility (balance flow and demand satisfaction). We need to locate WS to improve and recover waste and consider sustainability and environmental requirements in this situation (Fig. 2).

Assumptions:

- All wastes should be transferred to HC (agility).
- All forward MWCND constraints include flow and capacity constraint is active.
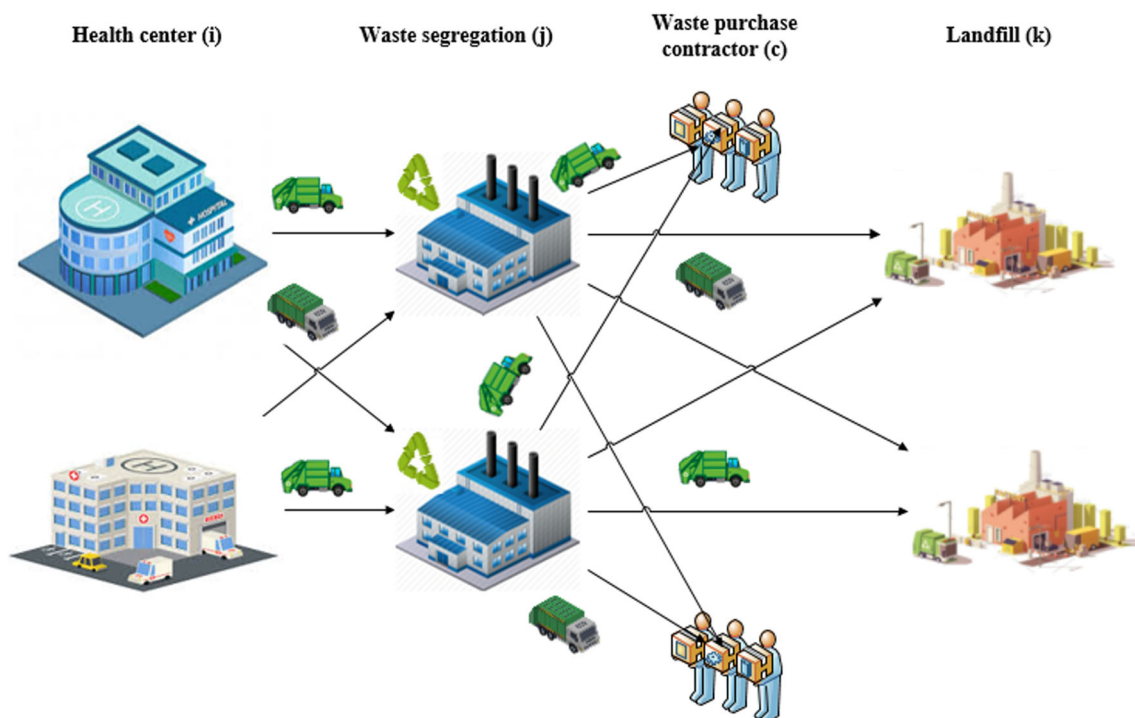
Figure 2 Viable medical waste chain network design (VMWCND)

Table 1 Survey of MWCND

Reference	Kind	Decisions	Objectives					Methodology	Uncertainty	Case study
			Economic	Environmental	Energy	Social	others			
Mantzaras and Voudrias (2017)	-	Location, capacity	✓	-	-	-	-	MILP + GA	-	Greece
Budak and Ustundag (2017)	-	Location, flow, inventory	✓	-	-	-	-	MILP	-	Turkey
Wang et al. (2019)	Green	Location, flow, inventory	✓	✓	-	-	-	MILP	-	Shanghai, China
Kargar et al. (2020a)	-	Location, flow, inventory	✓	-	-	-	✓	MILP + FGP	RPP	Babol, Iran
Kargar et al. (2020b)	-	Location, flow	✓	-	-	-	✓	MILP + RMGP	-	Iran
Homayouni and Pishvaee (2020)	-	Location, flow	✓	-	-	-	✓	MILP + AUGEPS	RO	Tehran, Iran
Yu et al. (2020b)	-	Location, flow	✓	-	-	-	✓	MILP + FP	-	Wuhan, China
Yu et al. (2020a)	-	Location, flow	✓	-	-	-	✓	MILP + GP	Stochastic	Numerical example (NE)
Saeidi-Mobarakeh et al. (2020b)	-	Routing, environmental	✓	✓	-	-	-	MINLP (BP) + GA	-	Isfahan, Iran
Saeidi-Mobarakeh et al. (2020b)	-	Location, capacity, routing	✓	-	-	-	✓	MILP (BP)	RO	Isfahan, Iran
Tirkolaee et al. (2021)	Sustainable	Location, routing	✓	-	-	-	-	MILP + WGP	FCCP	Sari, Iran
Tirkolaee and Aydın (2021)	Sustainable	Location, routing	✓	-	-	-	✓	MILP + MGP	-	NE
Shadkam (2021)	-	Location, flow	✓	-	-	-	-	MILP + COA	-	NE
Nikzamir et al. (2021)	Green	Location, routing	✓	-	-	-	✓	MILP + ICA, GA	-	NE
Li et al. (2021)	-	Routing	✓	-	-	-	-	MILP + PSO	-	NE
This research	Viable (resilience + sustainable + agile)	Location, flow	✓	-	-	-	-	MILP	RO stochastic	Tehran

Table 2 Number of indices, constraints, and variables for case study

Problem	$|i|. |j|. |c|. |k|. |t|. |s|$	Binary variable	Positive variable	Free variable	Constraint	Cost function	Time solution (second)	Population risk
P1-main	118.4.3.1.3.3	4396	4393	12	8818	1,520,407	9.422	54,026.33

- Sustainability constraints include allowed emission and energy consumption is added (sustainability).
- Flexible capacity for facilities and node complexity in WS is considered a resilience strategy (resiliency).
- Using scenario-based robust optimization against risks (robustness, risk, resiliency) (Ivanov 2020; Lotfi et al. 2021b).

Notations:

Indices:

i	Index of health center (HC) $i \in I = \{1,2,…,I\}$,
j	Index of waste segregation (WS) $j \in J = \{1,2,…,J\}$,
c	Index of waste purchase contractor (WPC) $c \in C = \{1,2,…,C\}$,
k	Index of landfill $k \in K = \{1,2,…,K\}$,
t	Index of time period $t \in T = \{1,2,…,T\}$,
S	Index of scenario $s \in S = \{1,2,…,S\}$,

Parameters:

ww_{its}	Waste generated in HC i for time period t under scenario s,
vij_{ijts}	Variable cost from HC i to WS j for time period t under scenario s,
vjc_{jcts}	Variable cost from WS j to WPC c for time period t under scenario s,
vjk_{jkts}	Variable cost from WS j to the landfill k for time period t under scenario s,
ff_j	Cost of activation WS j
$Emij_{ijts}$	CO_2 emission for transferring from HC i to WS j for time period t under scenario s
$Emjc_{jcts}$	CO_2 emission for transferring from WS j to WPC c for time period t under scenario s
$Emjk_{jkts}$	CO_2 emission for transferring from WS j to landfill k for time period t under scenario s,
$Enij_{ijts}$	Energy consumption for transferring from HC i to WS j for time period t under scenario s,
$Enjc_{jcts}$	Energy consumption for transferring from WS j to WPC c for time period t under scenario s,
$Enjk_{jkts}$	Energy consumption for transferring from WS j to landfill k for time period t under scenario s,
$Capj_{jts}$	Capacity of WS j for time period t under scenario s,
p_s	Probably of scenario s,
λ	Coefficient of conservative,
$EMSC_{ts}$	Maximum allowed emission for time period t under scenario s,
$ENSC_{ts}$	Maximum allowed energy consumption for time period t under scenario s
ρ_j	Coefficient of availability of WS j,
$Mbig$	Big positive number,
eps	Very little positive number,
α	The confidence level for conditional value at risk,
π	Waste recovery coefficient,
TT	Threshold of node complexity for resiliency,
φ	The ratio of HC to WS.

Table 3 Parameters of case study

Parameters	Value	Unit	Parameters	Value	Unit
ww_{its}	$U(1000, 1100)(0.8 + 0.4$ $(S-1)/(|s|-1))$	Ton	λ	50	%
vij_{ijts}	$U(0.5, 1)$	$/Ton	$EMSC_{ts}$	$U(20,000, 40,000)(|i||j| +$ $|j||c| + |j||k|)$	Ton
vjc_{jcts}	$U(0.5, 1)$	$/Ton	$ENSC_{ts}$	$U(40,000, 50,000)(|i||j| +$ $|j||c| + |j||k|)$	MJ
vjk_{jkts}	$U(0.5, 1)$	$/Ton	ρ_j	90	%
ff_j	$U(500,000, 600,000)$	$	α	5	%
$Emij_{ijts}$	$U(2, 4)/1000$	Ton	π	90	%
$Emjc_{jcts}$	$U(2, 4)/1000$	Ton	TT	$3000(|i||j| + |j||c| + |j||k|)$	Ton
$Emjk_{jkts}$	$U(2, 4)/1000$	Ton	φ	1	%
$Enij_{ijts}$	$U(4, 5)/1000$	MJ	θ	$200 \ (|i||j| + |j||c| +$ $|j||k| \ )/|s|$	Person
$Enjc_{jcts}$	$U(4, 5)/1000$	MJ	$popij_{ijts}$	$[U(100, 200)]$	Person
$Enjk_{jkts}$	$U(4, 5)/1000$	MJ	$popjc_{jcts}$	$[U(150, 200)]$	Person
$Capj_{jts}$	$U(222,222, 233,333)(0.8 + 0.4$ $(S-1)/(|s|-1))$	Ton	$popjk_{jkts}$	$[U(100, 200)]$	Person
p_s	$100/|s|$	%	[]: Sign function		

Table 4 Assigning location for the VMWCND facility

Problem: P1	Binary variable	Place			
		Robat Karim	Shurabad	Parand	Nasim Shahr
WPC	xj_j	1	0	1	0

$popij_{ijts}$ Population risk contact from HC i to WS j for time period t under scenario s,

$popjc_{jcts}$ Population risk contact from WS j to WPC c for time period t under scenario s,

$popjk_{jkts}$ Population risk contact from WS j to landfill k for time period t under scenario s;

Decision variables:

  Binary variables:

x_j If WS j is established, it is equal to 1; otherwise 0;

  Continues variables:

wij_{ijts} Waste transshipment from HC i to WS j for time period t under scenario s,

wjk_{jkts} Waste transshipment from WS j to landfill k for time period t under scenario s,

wjc_{jcts} Waste transshipment from WS j to WPC c 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.

VaR Value at risk

Δ Auxiliary variable for linearization max function,

yij_{ijts} Auxiliary and binary variable for linearization sign function for wij_{ijts},

yjk_{jkts} Auxiliary and binary variable for linearization sign function for wjk_{jkts},

yjc_{jcts} Auxiliary and binary variable for linearization sign function for wjc_{jcts}.

VMWCND mathematical model

Minimize $Z = (1-\lambda)\sum_s p_s \Gamma_s$

$$+ \lambda\left(\frac{\max(\Gamma_s) + CVaR_{(1-\alpha)}(\Gamma_s)}{2}\right) \quad (1)$$

subject to:

$$\Gamma_s = FC + VC_s \quad (2)$$

$$FC = \sum_j fj_j x_j \quad (3)$$

$$VC_s = \sum_t\left(\sum_i\sum_j vij_{ijts} wij_{ijts} + \sum_j\sum_k vjk_{jkts} wjk_{jkts} + \sum_j\sum_c vjc_{jcts} wjc_{jcts}\right), \quad \forall s \quad (4)$$

Agility constraints (flow constraints):

$$\sum_j wij_{ijts} = ww_{its}, \forall i, t, s \quad (5)$$

$$\sum_j wij_{ijts} \leq \sum_j wjk_{jkts} + \sum_j wjc_{jcts}, \forall i, k, c, t, s \quad (6)$$

$$\sum_i wij_{ijts} = \sum_k wjk_{jkts} + \sum_c wjc_{jcts}, \forall j, t, s \quad (7)$$

$$\sum_k wjk_{jkts} \geq (1-\pi)\sum_i wij_{ijts}, \forall j, t, s \quad (8)$$

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

$$\sum_k wjk_{jkts} + \sum_c wjc_{jcts} \leq \rho_j Capj_{jts} x_j, \forall j, t, s \quad (9)$$

$$\frac{\sum_j x_j}{|i|} \geq \varphi, \quad (10)$$

$$\sum_i wij_{ijts} + \sum_k wjk_{jkts} + \sum_c wjc_{jcts} \leq TT, \forall j, t, s \quad (11)$$

Table 5 Comparing P1-VMWCND with risk and worst case and without risk and worst case

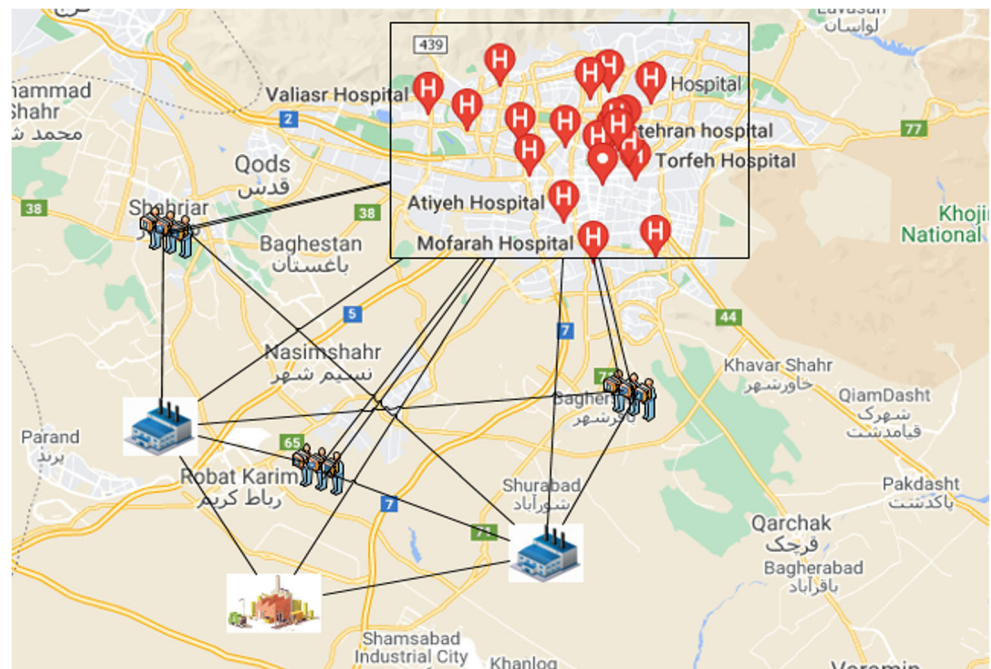| Model	P1-VMWCND	P1-VMWCND without risk and worst case	Gap
P1-main	1,520,407	1,495,346.97	1.65%

Figure 3 Potential location for the facilities

Sustainability constraints (allowed emission and energy consumption):

$$\sum_i\sum_j Emij_{ijts}wij_{ijts} + \sum_j\sum_k Emjk_{jkts}wjk_{jkts} + \sum_j\sum_c Emjc_{jcts}wjc_{jcts} \leq EMSC_{ts}, \quad \forall t,s \tag{12}$$

$$\sum_i\sum_j Enij_{ijts}wij_{ijts} + \sum_j\sum_k Enjk_{jkts}wjk_{jkts} + \sum_j\sum_c Enjc_{jcts}wjc_{jcts} \leq ENSC_{ts}, \quad \forall t,s \tag{13}$$

Figure 4 Final location for VMWCND facility

Table 6 Effects of variation of conservative coefficient

Problem	Conservative coefficient (λ)	Cost function	Time solution	Cost variation	Population risk
P1	0.00	1,495,346.97	6.289	−1.65%	54,026.33
P1	0.25	1,507,877.11	5.52	−0.82%	54,026.33
P1-main model	0.5	1,520,407.25	9.422	0.00%	54,026.33
P1	0.75	1,532,937.39	5.526	0.82%	54,026.33
P1	1.00	1,545,467.53	6.4	1.65%	54,026.33

$$Pop_s = \sum_t \left(\sum_i \sum_j popij_{ijts} \left[wij_{ijts} \right] + \sum_j \sum_k popjk_{jkts} \left[wjk_{jkts} \right] + \sum_j \sum_c popjc_{jcts} \left[wjc_{jcts} \right] \right), \quad \forall s \qquad (14)$$

$$\sum_s p_s Pop_s \leq \theta, \qquad (15)$$

Decision variables:

$$x_j \in \left\{ 0, 1, \quad \forall j \right. \qquad (16)$$

$$wij_{ijts}, wjk_{jkts}, wjc_{jcts} \geq 0, \quad \begin{matrix} \forall i, j, c, \\ k, t, s \end{matrix} \qquad (17)$$

Objective (1) considered minimizing the weighted expected value, minimax, and conditional value at risk of the cost function and for all scenarios. This form of the cost function is proposed for robustness and risk-averse against disruption with worst condition. Constraint (2) includes the fix and variable costs. Constraint (3) shows the fix costs that include fix

cost activating WS for all periods. Constraint (4) indicates the variable costs of HC, WS, WPC, and landfill. Constraint (5) shows the waste transshipment from HC to WS. Constraints (6)-(7) are the flow constraints in forwarding VMWCND. Constraint (8) determines the ratio of waste that goes to the landfill. Constraint (9) is the flexible capacity constraints for WS that is less than the capacity of the WS system. Constraint (10) is the resilience constraints and the number of WS is greater than the coefficient of HC. Constraint (11) is the resilience constraints and shows node complexity in WS that summation of input and output of every WS is less than the threshold. Constraint (12) guarantees that the network's total environmental emissions are less than the allowed emission. Constraint (13) guarantees that the network's total energy consumption is less than the allowed energy consumption. Constraint (14) is the risks related to the transportation of medical waste. Constraint (15) shows the summation risks related to medical waste transport that contact with population

Figure 5 Cost function for different lambda
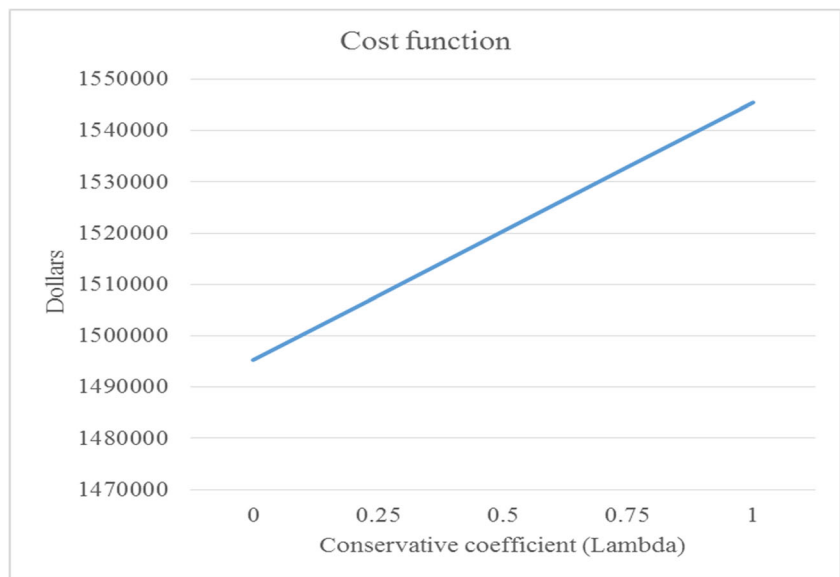
Figure 6 Time solution for different lambda
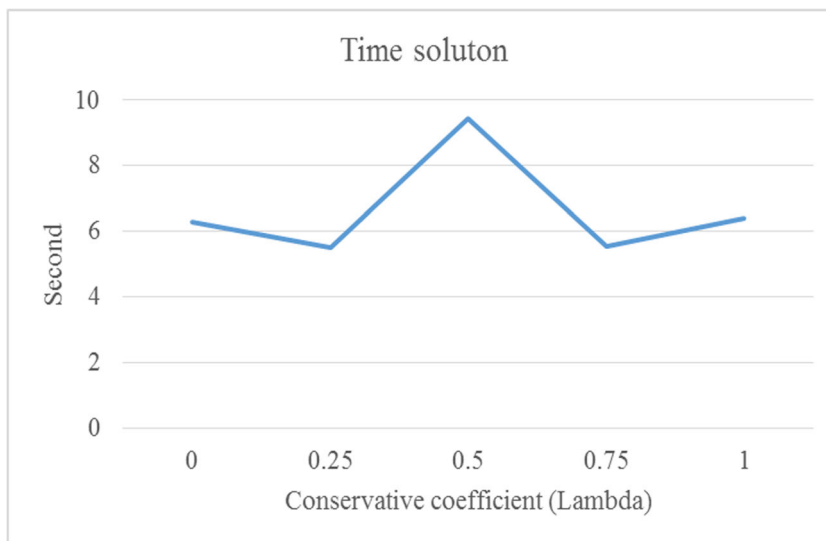
is less than the threshold. Constraints (16)-(17) are the decision variables, and Constraint (16) is the facility location for WC and binary variables and Constraint (17) is the flow variables that are positive between facilities.

Linearization of max, sign, and CVaR (preliminary)

The objective function (1) is nonlinear and makes the model mixed-integer nonlinear programming (MINLP). We transform them to mixed-integer programming (MIP) by mathematical method to improve time solution and solve smoothly (Gondal and Sahir 2013; Sherali and Adams 2013).

Linearizing max and sign function:

Suppose If, $\beta = \max(\Omega_s)$, then we can change $\beta \geq \Omega_s$, $\forall$ s.

Suppose If $\beta_s = [\Omega_s]$, then we can change $\beta_s \leq 1 + \frac{\Omega_s}{Mbig} - eps, \beta_s \geq \frac{\Omega_s}{Mbig}, \forall s$.

We used conditional value at risk (CVaR), which is a coherent risk measure. Uryasev and Rockfeller designed the CVaR criterion applied to a novel embed risk measure (Soleimani and Govindan 2014). CVaR (also known as the expected shortfall) is considered a measure for assessing the risk. CVaR is embedded in portfolio optimization to better risk management (Goli et al. 2019; Kara et al. 2019). This measure is the average of losses which are beyond the VaR point in confidence level. CVaR has a higher consistency, coherence, and conservation than other risk-related criteria. This measure is the average of losses which are beyond the VaR point in confidence levelα. CVaR has a higher consistency, coherence, and conservation than other risk-related criteria.

$$\min \ CVaR_{(1-\alpha)}(\Gamma\Gamma_s) = VaR + \frac{1}{1-\alpha}\sum_s pr_s v_s \qquad (18)$$

$$v_s \geq \Gamma\Gamma_s - VaR, \quad \forall s \qquad (19)$$

$$v_s \geq 0 \qquad (20)$$

Linearizing CVaR:

Table 7 Effects of the confidence level of CVaR

Problem	Confidence level	Cost function	Time solution	Cost variation
P1	1%	1,519,419.405	5.92	−0.06%
P1	2%	1,519,658.805	5.666	−0.05%
P1	3%	1,519,903.141	5.751	−0.03%
P1-main model	5%	1,520,407.25	5.45	0.00%
P1	6%	1,520,667.342	5.544	0.02%
P1	7%	1,520,933.032	5.728	0.03%

Figure 7 Effects of the confidence level of CVaR

Linearization of VMWCND

We used linearization for model (1) by operational research method. Solving the model by MIP is more straightforward than MINLP in the solver and this method decreases time solution and the complexity of the model. We linearized objective (1) for max and CVaR, and linearized Eq. (14) for sign function; as a result, we change to Eqs. (21)-(33):

Linearization of VMWCND

Minimize $Z = (1-\lambda)\sum_s p_s \Gamma_s$

$$+ 0.5\big(\lambda\Delta + CVaR_{(1-\alpha)}(\Gamma_s)\big) \qquad (21)$$

subject to:

$$\Delta \geq \Gamma_s, \quad \forall s \qquad (22)$$

$$CVaR_{(1-\alpha)}(\Gamma_s) = VaR + \frac{1}{1-\alpha}\sum_s p_s v_s, \quad \forall s \qquad (23)$$

$$v_s \geq \Gamma_s - VaR, \quad \forall s \qquad (24)$$

$$v_s \geq 0, \quad \forall s \qquad (25)$$

$$Pop_s = \sum_t \left(\sum_i \sum_j popij_{ijts} yij_{ijts} + \sum_j \sum_k popjk_{jkts} yjk_{jkts} + \sum_j \sum_c popjc_{jcts} yjc_{jcts}\right), \quad \forall s \qquad (26)$$
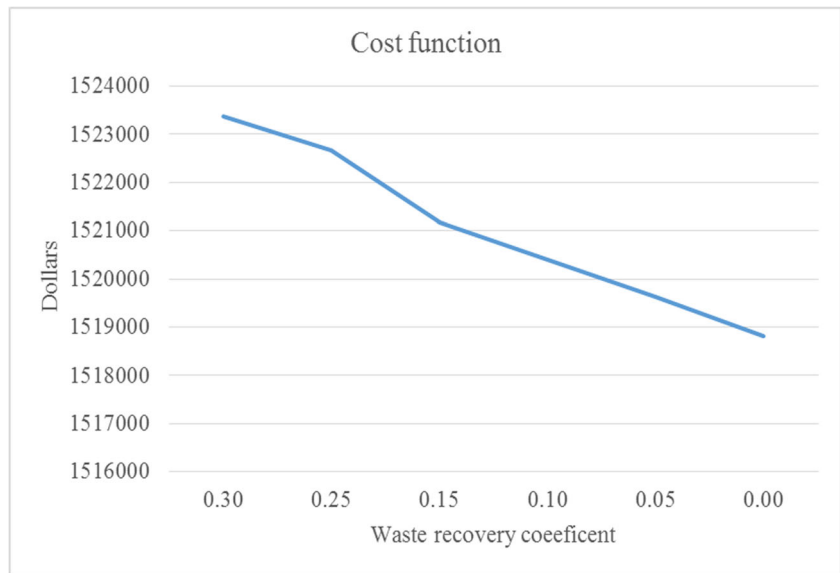
$$yij_{ijts} \leq 1 + \frac{wij_{ijts}}{Mbig} - eps, \quad \forall i,j,t,s \qquad (27)$$

$$yij_{ijts} \geq \frac{wij_{ijts}}{Mbig}, \forall i,j,t,s \qquad (28)$$

Table 8 Effects of changing waste recovery coefficient

Problem	Waste recovery coefficient	Cost function	Time solution	Cost variation	Population risk
P1	30%	1,523,371	6.004	0.19%	54,196
P1	25%	1,522,667	5.436	0.15%	54,142.3
P1	15%	1,521,177	5.676	0.05%	54,112.7
P1-main model	10%	1,520,407	5.45	0.00%	54,026.3
P1	5%	1,519,622	5.967	−0.05%	53,897.7
P1	0%	1,518,823	6.07	−0.10%	53,662.3

Figure 8 Effects of variation waste recovery coefficient on the cost function

$$yjk_{jkts} \le 1 + \frac{wjk_{jkts}}{Mbig} - eps, \quad \forall j, k, t, s \tag{29}$$

$$yjk_{jkts} \ge \frac{wjk_{jkts}}{Mbig}, \quad \forall j, k, t, s \tag{30}$$

$$yjc_{jcts} \le 1 + \frac{wjc_{jcts}}{Mbig} - eps, \quad \forall j, c, t, s \tag{31}$$

$$yjc_{jcts} \ge \frac{wjc_{jcts}}{Mbig}, \quad \forall j, c, t, s \tag{32}$$

$$yij_{ijts}, yjk_{jkts}, yjc_{jcts} \in \{0, 1\}, \quad \begin{array}{l} \forall i, j, c, \\ k, t, s \end{array} \tag{33}$$

Constraints (2)-(13) and (15)-(17).

The complexity of linearization of VMWCND includes numbers of binary, positive, free variables, and constraints which is indicated in Eqs. (34)-(37). As can be seen, one of the essential factors for constraints and positive and free variables is scenario sets. Relation between scenario and constraints and positive and free variables is completely linear.

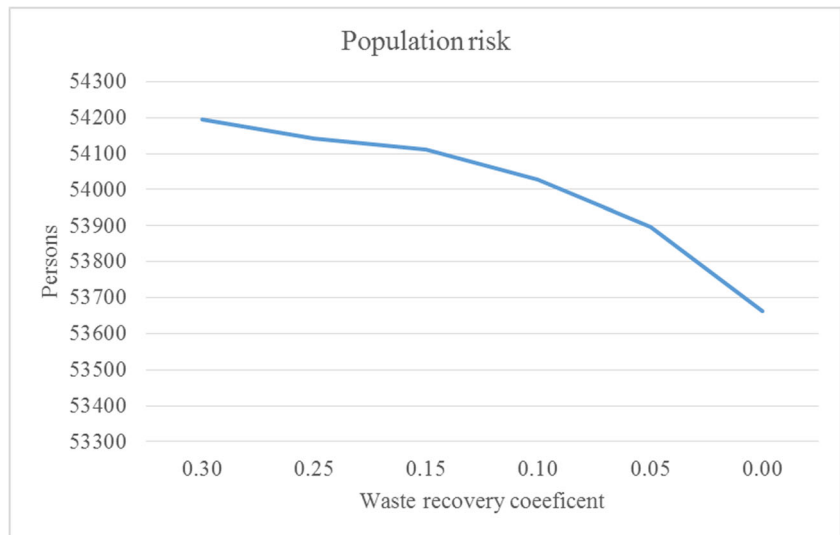$$\text{Binary variables} = |j| + |t|.|s|(|i|.|j| + |j|.|c| + |j|.|k|), \tag{34}$$

$$\text{Positive variables} = |t|.|s|(|i|.|j| + |j|.|c| + |j|.|k|) + 1 \tag{35}$$

$$\text{Free variables} = 6 + 2|s| \tag{36}$$

$$\text{Constraints} = 6 + 4|s| + |t|.|s|(|i| + |i|.|k|.|c| + 4|j| + 2 + |i|.|j| + |j|.|c| + |j|.|k|) \tag{37}$$

We suggested scenario reduction and new algorithms to remove constraints and binary variables. This subject can help solve minimum time.

Figure 9 Effects of variation waste recovery coefficient on population risk

Table 9 Effects of changing demand

Problem	Changing demand	Cost function	Time solution	Cost variation	Population risk
P1	−50%	1,277,474.078	5.941	−15.98%	53,843.001
P1	−40%	1,326,060.712	5.888	−12.78%	53,906.334
P1	−20%	1,423,233.979	6.528	−6.39%	53,965.334
P1-main model	0%	1,520,407	5.45	0.00%	54,026.334
P1	+20%	1,617,580.513	6.295	6.39%	54,026.334
P1	+40%	1,714,753.780	5.963	12.78%	54,026.334

Results and discussion

We surveyed hospitals in Tehran, Iran, and estimated parameters from data of MWCND by managers of health centers. The performance of the mathematical model is presented. The number of indices is defined in Table 2 and the values of the parameters are determined in Table 3. The probability of occurrence is the same and optimistic, pessimistic, and possible scenarios have happened.

We applied a computer with this configuration: CPU 3.2 GHz, processor core i3-3210, 6.00 GB RAM, 64-bit operating system. Finally, we solve the mathematical models by GAMS CPLEX solver.

We show the potential location for assigning HC, WS, WPC, and landfill in Tehran, Iran (cf. Figure 3). After solving the model, it suggests that we activate WS and determine the location and the flow of VMWCND components (Table 4). The objective function is 1,520,407 in Table 2 and the final location-allocation is drawn in Figure 4. Finally, we calculate population risk (left-hand side of Constraint (15)) that are 54,026.33 persons. Eventually, we compare VMWCND with risk and worst case and without risk and worst case in Table 5. We can see that by embedding risk and worst case, the cost

function is almost 1.65% greater than without risk and worst case.

Variation on the conservative coefficient

The conservative coefficient (λ) is the amount of conservative decision-makers. We change it by varying between 0 and 1 that the conservation of decision-maker has been changed.

If the conservative coefficient increases to 1, the cost function grows as shown in Table 6, Figure 5, and Figure 6. If the conservative coefficient increases by 50%, the cost function will increase by 1.65%, but time solution and population risk do not change significantly.

Variation on confidence level of CVaR

The confidence level of CVaR (α) is the amount of risk-averse decision-makers. If the confidence level grows up, we can see that the cost function will increase (cf. Table 7 and Figure 7). By increasing 2% for confidence level, the cost function increases by 0.03%.

Figure 10 Effects of variation demand on cost function
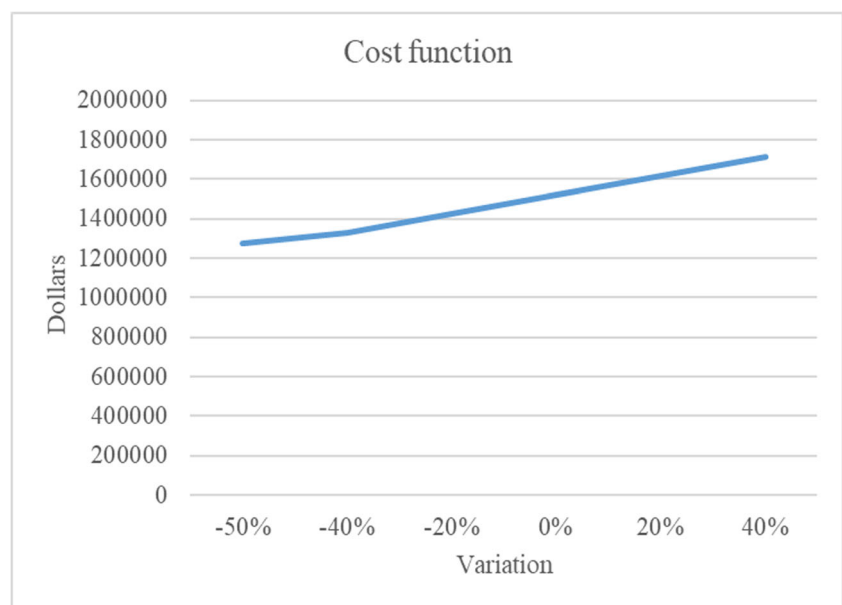
Figure 11 Effects of variation demand on population risk
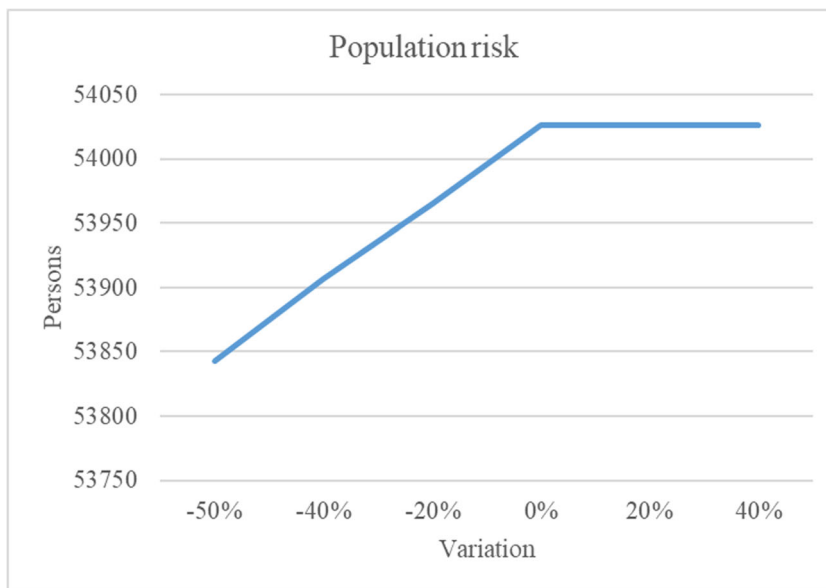
Variation on waste recovery coefficient

The waste recovery coefficient (π) is the ratio of waste that goes to landfills. If the waste recovery coefficient grows, we can see that the cost function and population risk will decrease (cf. Figure 8, Figure 9, and Table 8). Increasing waste recovery coefficient, transportation to WPC increases and then the cost function increases. But this issue helps systems to use and recover waste.

Variation on demand

We test the effects of changing demand. By increasing the demand, the cost function increases, too (cf. Table 9). As can be seen, when the demand increases by 40%, the cost function grows by 12% and when demand decreases by 50%, it grows down by 16% (cf. Figure 10 and Figure 11).

Variation on scale of the main model

The several large-scale problems are defined in Table 10. When the scale of problems is increased, the time solution

and cost function increase as shown in Figure 12 and Figure 13. As can be seen, the proposed model shows the NP hard and the behavior of this model is exponential for large scale. Therefore, we need to solve the model by heuristic, meta-heuristic, and new exact solution in minimum time on large scale.

## Managerial insights and practical implications

We surveyed viable waste medical chain network design (VWMCND). We try to pay more attention to five concepts in medical waste network design. We design VWMCND that considers agility, resilience, sustainability, risks, and robustness to cope with disruption and requirements of the government. As managers of the VWMCND, we should move forward to applying the novel concept to decrease cost and population risk, and increase the resiliency of facility, robustness, risk-averse, and agility of WMCND. In this research, we have health center (HC), waste segregation (WS), waste purchase contractor (WPC), and landfill. We propose to locate WS to decrease waste and recover them and send to the WPC. Recovering medical waste like metal and plastic can help the

Table 10 Cost and time solution for several problems

Problem	$|i|\cdot|j|\cdot|c|\cdot|k|\cdot|t|\cdot|s|$	Binary var.	Positive var.	Free var.	Constraint	Cost function	Time solution	Population risk
P1	118.4.3.1.3.3	4396	4393	12	8818	1,520,407	9.422	54,026.33
P2	10.8.4.2.7.7	6280	6273	20	12,380	609,257	6.796	9201.68
P3	118.4.3.1.3.5	7324	7321	16	14,694	1,591,272	13.49	54,408.4
P4	120.5.4.1.5.3	9380	9376	12	18,721	1,906,117	21.548	91,725.33
P5	120.5.4.2.7.3	13,235	13,231	12	36,388	2,160,152	72.426	128,016.7
P6	120.8.4.2.7.3	21,176	21,169	12	44,578	2,152,882	249.904	127,924

Figure 12 Cost function for several problems
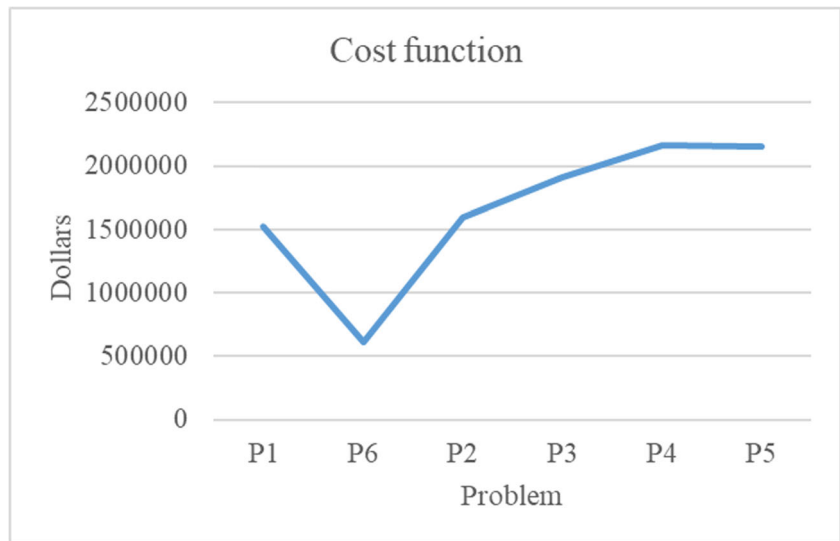
environment and return to production cycle. In this situation of COVID-19 and because of economic problem, we should use all power to utilize waste and move to circular economy and sustainable development. This issue is compatible with sustainable development goal (SDG12—Ensure sustainable consumption and production patterns) and the circular economy pillars. The maximum benefit from the proposed paper is people and service providers of the medical waste chain.

Conclusions and outlook

Medical waste management (MWM) is an important and necessary problem in the COVID-19 situation for treatment staff. The number of infectious patients grows up and the amount of MWMs increases day by day. We should think about this issue and find a solution for this issue. We suggest to recover

MWM by waste segregation. Therefore, we proposed a novel viable medical waste chain network design (VMWCND) that considers resiliency (flexibility and network complexity) and sustainable (energy and environment) requirement. Finally, we try to tackle decrease risks and increase robustness and agility to demand fluctuation and network. We utilize a novel two-stage robust stochastic programming and solve with a GAMS CPLEX solver.

Therefore, the results are as follows:

1. If the conservative coefficient increases up to 1, the cost function grows up. If the conservative coefficient increases to 1, the cost function grows as shown in Table 6, Figure 5 and 6. If the conservative coefficient increases by 50%, the cost function will increase by 1.65%, but time solution and population risk do not change significantly.

Figure 13 Time solution for several problems
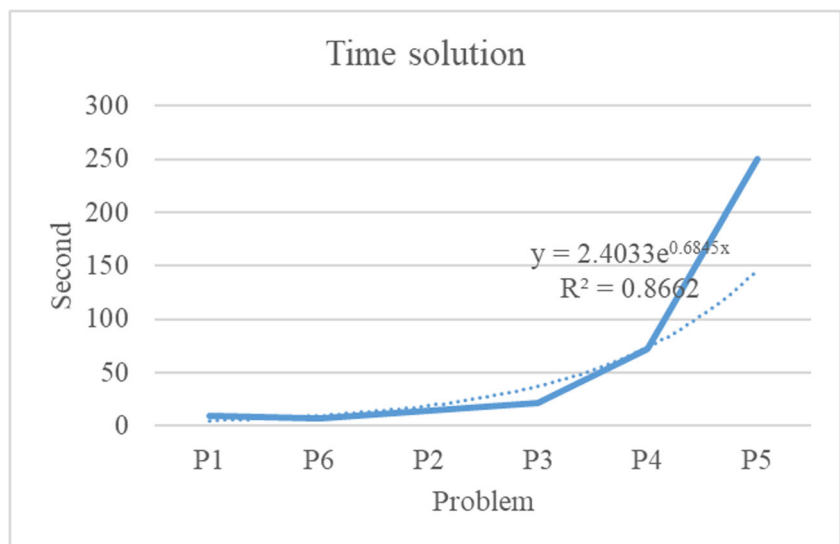
2. If the conservative coefficient increases up to 50%, the cost function will increase by 1.65%, but time solution and population risk do not change significantly.

3. If the confidence level of CVaR grows up, we can see that the cost function will increase (cf. Figure 7 and Table 7). Increasing for confidence level by 2%, the cost function increases by 0.03%.

4. If the waste recovery coefficient grows, we can see that the cost function and population risk will decrease (cf. Figure 8 and 9, and Table 8). By increasing the waste recovery coefficient, transportation to WPC increases and then the cost function increases. But it helps systems to use waste and recover them.

5. When demand increases by 40%, the cost function grows by 12% and when demand decreases by 50%, it grows down by 16% (cf. Figure 10 and 11).

6. When the scale of problems is increased, the cost function and time solution grow up as shown in Figure 12 and 13. As can be seen, the behavior of the proposed model is NP hard and exponential on large scale. Therefore, we need to solve the model by heuristic, meta-heuristic, and new exact solution in minimum time on large scale.

Finally, solving the main model on a large scale is the research constraint. We propose to apply exact algorithms like bender decomposition, branch and price, branch and cut, column generation, and heuristic and meta-heuristic algorithms to solve models in minimum time (Fakhrzad and Lotfi 2018; Lotfi et al. 2017; Maadanpour Safari et al. 2021). We can add other resilience and sustainable tools to the model until increasing the resiliency and sustainability of the model like backup facility and redundancy. Also, we suggest to apply multi-objective for environmental, energy, and occupational objective (Das et al. 2021; Ghosh et al. 2021; Mondal and Roy 2021; Pourghader Chobar et al. 2021).

Furthermore, we suggest adding coherent risk criteria like entropic value at risk (EVaR) (Ahmadi-Javid 2012) for considering risks. Researchers intend to investigate method uncertainty like robust convex (Lotfi et al. 2021a). Using new and novel uncertainty methods like data-driven robust optimization and fuzzy programming (Midya et al. 2021) is advantageous for a conservative decision-maker in the recent decade. Eventually, we suggest equipping VMWCND with novel technology like blockchain and neural learning (Khalilpourazari et al. 2020) for the viability of MWCND.

Author contribution Reza Lotfi: conceptualization, supervision, software, methodology, formal analysis, data curation, writing original draft, visualization.

Bahareh Kargar: methodology, software, formal analysis, data curation, writing original draft, writing review and edit, visualization.

Alireza Gharehbaghi: methodology, validation.

Gerhard-Wilhelm Weber: validation, writing review and edit.

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