# Viable Medical Waste Chain Network Design by Considering Risk and Robustness

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# 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 and amount of MWMs increases day by day. We present Medical Waste Chain Network Design (MWMCND) 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 make to increase the cost function.

**Keywords:** Viable; Medical waste; Network design; Resiliency; Sustainable; Robust optimization.

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## 1. Introduction

Medical Waste Management (MWM) is a critical problem in the COVID-19 situation. In the COVID-19 condition, amount of infectious patients grow up and amount of MWMs increase. As a result, we must pay more attention to MWMs and improve waste disposal. Many workers that do waste 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, other (including toilet waste produced at hospitals). About 85% of MWMs are general waste and 15% of MWMs are infectious waste, hazardous waste, radioactive waste (Tsai, 2021). Therefore, the importance of MWMs, make many researchers contribute this subject and present mathematical approach and decision support system. Some researchers consider a location-routing problem for medical waste management (Suksee & Sindhuchao, 2021; Tirkolaee, Abbasian, & Weber, 2021). Others investigate reverse logistics by the mathematical model (Sepúlveda, Banguera, Fuertes, Carrasco, & Vargas, 2017; Suksee & Sindhuchao, 2021). Also, some scientists analysis of MWM systems by multi-criteria-decision approach (Aung, Luan, & Xu, 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.

**Figure 1**. MWM in the COVID-19 situation.

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 (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 is urban need and make 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 Section 2, we survey on related work in scope of MWCND. In Section 3, the VMWCND and risk-averase VMWCND is stated. In Section 4, the results of research and sensitivity analysis are presented. In Section 5, the managerial insights and practical implications is discussed. In Section 6, the conclusion is summarized.

## 2. 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 is as follows.

Mantzaras and Voudrias (2017) considered an optimization model for medical waste in Greece. They tried to minimize total cost include location and transfer between location. The Genetic Algorithm (GA) is applied to solve the model. Budak and Ustundag (2017) designed a reverse logistic for multiperiod, multitype waste products. The model's objective was to minimize total cost and the model's decision included location, flow, inventory. The case was in Turkey. They found that by increasing waste amounts, the numbers of facilities and strategies are changed. Wang, Huang, and He (2019) designed a two-stage reverse logistics network for urban healthcare waste with multi-objective and multi-period. In stage one, they predicted the amount of medical waste, and in the second stage, they minimized total cost and environmental impact.

Kargar, Paydar, and Safaei (2020) 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 are 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, Pourmehdi, and Paydar (2020) 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, the 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, Sun, Solvang, and Zhao (2020) 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, Sun, Solvang, Laporte, and Lee (2020) 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). Z Saeidi-Mobarakeh, R Tavakkoli-Moghaddam, M Navabakhsh, and H Amoozad-Khalili (2020) presented bi-level programming (BP) for a hazardous WM problem. They used an enviormental approach for upper-level and routing and cost for lower-level. They solve Mix-Integer Non-Linear Programming (MINLP) by GA.

In addition, Zahra Saeidi-Mobarakeh, Reza Tavakkoli-Moghaddam, Mehrzad Navabakhsh, and Hossein Amoozad-Khalili (2020) 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, Baradaran, and Panahi (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 Optimisation (PSO) algorithm to solve large-scale problems.

**Table 1.** Survey of MWCND.

| **Reference** | **Kind** | **Decsion** | **Objectives** | | | | | **Methodology** | **Uncertainty** | **Case study** |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Economic | Environmental | Energy | Social | others | | | |
| (Mantzaras & Voudrias, 2017) | - | Location, capacity | ✓ | - | - | - | - | MILP+ GA | - | Greece |
| (Budak & Ustundag, 2017) | - | Location, flow, inventory | ✓ | - | - | - | - | MILP | - | Turkey |
| (Wang et al., 2019) | Green | Location, flow, inventory | ✓ | ✓ | - | - | - | MILP | - | Shanghai, China |
| (Kargar, Paydar, et al., 2020) | - | Location, flow, inventory | ✓ | - | - | - | ✓ | MILP+ FGP | RPP | Babol, Iran |
| (Kargar, Pourmehdi, et al., 2020) | - | Location, flow | ✓ | - | - | - | ✓ | MILP+RMGP | - | Iran |
| (Homayouni & Pishvaee, 2020) | - | Location, flow | ✓ | - | - | - | ✓ | MILP+ AUGEPS | RO | Tehran, Iran |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| (Yu, Sun, Solvang, & Zhao, 2020) | - | Location, flow | ✓ | - | - | - | ✓ | MILP+FP | - | Wuhan, China |
| (Yu, Sun, Solvang, Laporte, et al., 2020) | - | Location, flow | ✓ | - | - | - | ✓ | MILP+GP | Stocastic | Numerical example (NE) |
| (Z Saeidi-Mobarakeh et al., 2020) | - | Routing, environmental | ✓ | ✓ | - | - | - | MINLP (BP)+GA | - | Isfahan, Iran |
| (Zahra Saeidi-Mobarakeh et al., 2020) | - | Location, capacity, routing | ✓ | - | - | - | ✓ | MILP (BP) | RO | Isfahan, Iran |
| (Tirkolaee et al., 2021) | Sustainable | Location, routing | ✓ | - | - | - | - | MILP+WGP | FCCP | Sari, Iran |
| (Tirkolaee & 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 +sutainable +agile) | Location, flow | ✓ | - | - | - | - | MILP | RO Stochastic | Tehran |

The classification of the literature is addressed in Table 1. It can be seen; 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.

## 3. 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), landfill that waste 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.

Assumptions:

- All wastes should be transferred to HC (agility),
- All forward MWCND constraints include flow and capacity constraint is active,
- Sustainability constraints include allowed emission and energy consumption are added (sustainability),
- Flexible capacity for facilities and node complexity in WS is considered as a resilience strategy (resiliency),
- Using scenario-based robust optimization against risks (robustness, risk, resiliency) (Ivanov, 2020; Lotfi, Mehrjerdi, Pishvaee, Sadeghieh, & Weber, 2021).

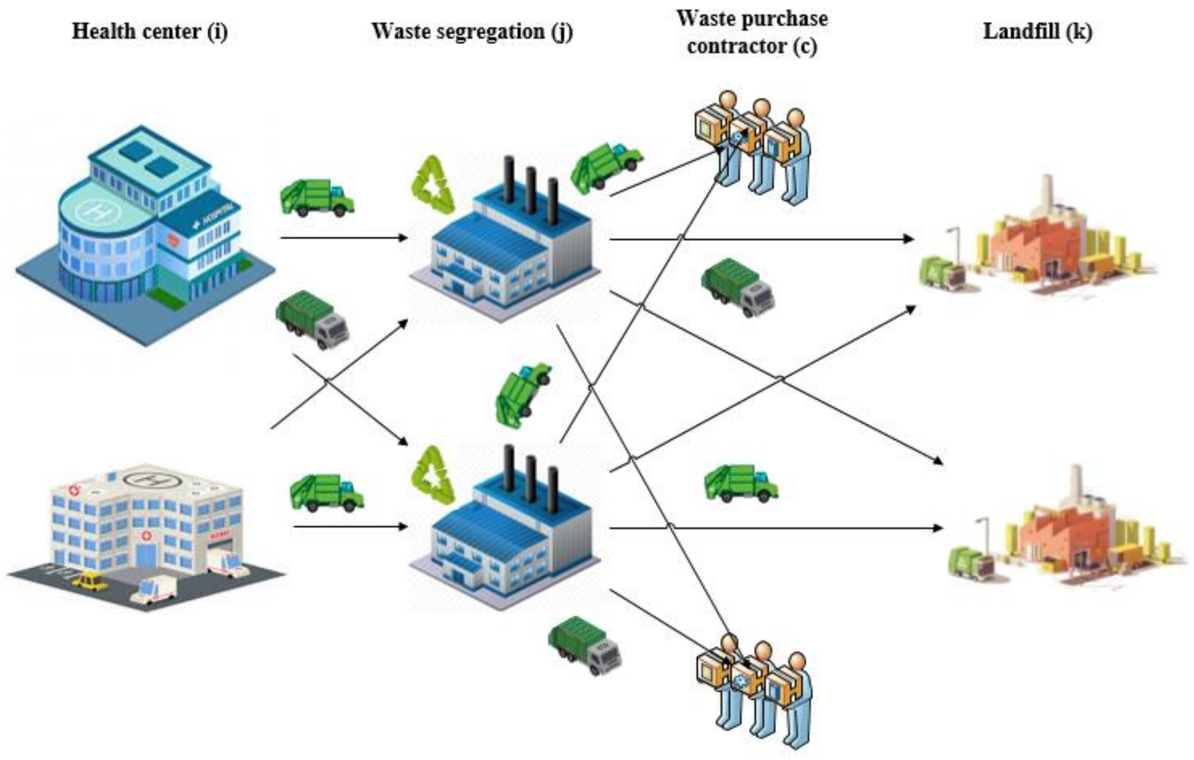

**Figure 2**. Viable medical waste chain network design (VMWCND).

Notations:

*Indices:*

| | |
|---|---|
| $i$ | Index of Health Center (HC) $i$, |
| $j$ | Index of Waste Segregation (WS) $j$, |
| $c$ | Index of Waste Purchase Contractor (WPC) $c$, |
| $k$ | Index of landfill $k$, |
| $t$ | Index of time period, |
| $s$ | Index of scenario; |

*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 $s$, |
| $fj_{j}$ | Cost of activation WS $j$, |
| $Emij_{ijts}$ | Emission $CO_2$ for transfering from HC $i$ to WS $j$ for time period $t$ under scenario $s$, |
| $Emjc_{jcts}$ | Emission $CO_2$ for transfering from WS $j$ to WPC $c$ for time period $t$ under scenario $s$, |
| $Emjk_{jkts}$ | Emission $CO_2$ for transfering from WS $j$ to landfill $k$ for time period $t$ under scenario $s$, |
| $Enij_{ijts}$ | Energy consumption for transfering from HC $i$ to WS $j$ for time period $t$ under scenario $s$, |

| | |
|---|---|
| $Enjc_{jcts}$ | Energy consumption for transfering from WS $j$ to WPC $c$ for time period $t$ under scenario $s$, |
| $Enjk_{jkts}$ | Energy consumption for transfering from WS $j$ to landfill $k$ for time period $t$ under scenario $s$, |
| $Capj_{jts}$ | Capacity WS $j$ for time period $t$ under scenario $s$ , |
| $p_s$ | Probably of scenario $s$ , |
| $\lambda$ | 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 $s$, |
| $\rho_j$ | Coefficient of availability of WS $j$, |
| $Mbig$ | Big positive number, |
| $eps$ | Very little positive number, |
| $\alpha$ | The confidence level for conditional value at risk, |
| $\pi$ | Waste recovery coefficient, |
| $TT$ | Threshold of node complexity for resiliency, |
| $\varphi$ | The ratio of HC to WS. |
| $popij_{ijts}$ | 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, equal 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 $s$ , |
| $\Gamma_s$ | Fix cost and variable cost for scenario $s$. |
| $VaR$ | Value at Risk |
| $\Delta$ | 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 $wjc_{jcts}$. |

## 3.1. VMWCND mathematical model

$$\text{minimize } Z = (1-\lambda)\sum_{s} p_s \Gamma_s + \lambda\left(\frac{\max(\Gamma_s) + CVaR_{(1-\alpha)}(\Gamma_s)}{2}\right) \tag{1}$$

subject to:

$$\Gamma_s = FC + VC_s, \tag{2}$$

$$FC = \sum_{j} fj_j x_j, \tag{3}$$

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

Agility constraints (flow constraints):

$$\sum_j wij_{ijts} = ww_{its}, \qquad \forall i, t, s \tag{5}$$

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

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

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

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

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

$$\frac{\sum_j x_j}{|i|} \geq \varphi, \tag{10}$$

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

Sustainability constraints (allowed emission and energy consumption):

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

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

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

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

Decision variables:

$$x_j \in \{0,1\}, \qquad \forall j \qquad (16)$$

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

The 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. Constraints (2) include fix and variable costs. Constraints (3) show fix-costs that include fix-cost activating WS for all periods. Constraints (4) indicate the variable costs of HC, WS, WPC and landfill. Constraints (5) show waste transshipment from HC to WS. Constraints (6) to (7) are flow constraints in forwarding VMWCND. Constraints (8) determine the ratio of waste that goes to the landfill. Constraints (9) are flexible capacity constraints for WS that less than the capacity of WS system. Constraints (10) are resilience constraints and the number of WS is greater than the coefficient of HC. Constraints (11) are resilience constraints and show node complexity in WS that summation of input and output of every WS is less than the threshold. Constraints (12) guarantee the network's total environmental emissions are less than allowed emission. Constraints (13) guarantee that the network's total energy consumption is less than the allowed energy consumption. Constraints (14) risks related to the transportation of medical waste. Constraints (15) show summation risks related to medical waste transport that contact with population is less than threshold. Constraints (16) to (17) are decision variables, and constraints (16) are facilities location for WC and binary variables and constraints (17) are flow variables that are positive between facilities.

## 3.2. Linearization of VMWCND

The objective function (1) is nonlinear and makes the model mixed-integer nonlinear programming (MINLP). We trnsform them to mixed-integer programming (MIP) by mathematical method to improve time solution and solve smoothly (Gondal & Sahir, 2013; Sherali & 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 $\beta_s = sign(\Omega_s)$, 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 & Govindan, 2014). CVaR (also known as the expected shortfall) is considered as a measure for assessing the risk. CVaR is embedded in portfolio optimization to better risk management (Goli, Zare, Tavakkoli-Moghaddam, & Sadeghieh, 2019; Kara, Özmen, & Weber, 2019). This measure is the average of losses are beyond the VaR point in confidence level. CVaR has a higher consistency, coherence, and conservation than other risk-related criteria.

We used linearization for model (1) by operational research method. Solving the model by MIP is more straightforward than MINLP in the solver in equations (18) to (30), and this methods decrease time solution and the complexity of the model.

Linearization of VMWCND

$$\text{minimize } Z = (1-\lambda)\sum_{s} p_s \Gamma_s + 0.5(\lambda\Delta + CVaR_{(1-\alpha)}(\Gamma_s)), \tag{18}$$

subject to:

$$\Delta \geq \Gamma_s \qquad \forall s \tag{19}$$

$$CVaR_{(1-\alpha)}(\Gamma_s) = VaR + \frac{1}{1-\alpha}\sum_{s} p_s v_s, \qquad \forall s \tag{20}$$

$$v_s \geq \Gamma_s - VaR, \qquad \forall s \tag{21}$$

$$v_s \geq 0, \qquad \forall s \tag{22}$$

$$Pop_s = \sum_t \Big(\sum_i \sum_j popij_{ijts}\, yij_{ijts} + \sum_j \sum_k popjk_{jkts}\, yjk_{jkts} + \sum_j \sum_c popjc_{jcts}\, yjc_{jcts}\Big), \qquad \forall s \tag{23}$$

$$yij_{ijts} \le 1 + \frac{wij_{ijts}}{Mbig} - eps, \qquad \forall i, j, t, s \tag{24}$$

$$yij_{ijts} \ge \frac{wij_{ijts}}{Mbig}, \qquad \forall i, j, t, s \tag{25}$$

$$yjk_{jkts} \le 1 + \frac{wjk_{jkts}}{Mbig} - eps, \qquad \forall j, k, t, s \tag{26}$$

$$yjk_{jkts} \ge \frac{wjk_{jkts}}{Mbig}, \qquad \forall j, k, t, s \tag{27}$$

$$yjc_{jcts} \le 1 + \frac{wjc_{jcts}}{Mbig} - eps, \qquad \forall j, c, t, s \tag{28}$$

$$yjc_{jcts} \ge \frac{wjc_{jcts}}{Mbig}, \qquad \forall j, c, t, s \tag{29}$$

$$yij_{ijts}, yjk_{jkts}, yjc_{jcts} \in \{0,1\}, \qquad \forall i, j, c, k, t, s \tag{30}$$

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

The complexity of linearization of VMWCND includes numbers of binary, positive, free variables and constraints is indicated in equations (31) to (34). As can be seen, one of the essential factors for constraints, positive and free variables, is scenario sets. Relation between scenario and constraints, positive and free variables is completely linear.

$$\text{Binary variables} = |j| + |t|.|s|(|i|.|j| + |j|.|c| + |j|.|k|), \tag{31}$$

$$\text{Positive variables} = |t|.|s|(|i|.|j| + |j|.|c| + |j|.|k|) + 1, \tag{32}$$

$$\text{Free variables} = 6 + 2|s|, \tag{33}$$

$$\text{Constraints} = 6 + 4|s| + |t|.|s|(|i| + |i|\cdot|k|\cdot|c| + 4|j| + 2 + |i|.|j| + |j|.|c| + |j|.|k|). \tag{34}$$

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

## 4. 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 are 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 has happened.

**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** | **Population risk** |
|---|---|---|---|---|---|---|---|---|
| P1-main | 118.4.3.1.3.3 | 4396 | 4393 | 12 | 8818 | 1520407 | 9.422 | 54026.33 |

**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 | $\lambda$ | 50 | % |
| $vij_{ijts}$ | U(0.5,1) | \$/Ton | $EMSC_{ts}$ | U(20000,40000) ($\|i\|\,\|j\|+\|j\|\,\|c\|+\|j\|\,\|k\|$); | Ton |
| $vjc_{jcts}$ | U(0.5,1) | \$/Ton | $ENSC_{ts}$ | U(40000,50000) ($\|i\|\,\|j\|+\|j\|\,\|c\|+\|j\|\,\|k\|$); | MJ |
| $vjk_{jkts}$ | U(0.5,1) | \$/Ton | $\rho_j$ | 90 | % |
| $fj_j$ | U(500000,600000). | \$ | $\alpha$ | 5 | % |
| $Emij_{ijts}$ | U(2,4)/1000 | Ton | $\pi$ | 90 | % |
| $Emjc_{jcts}$ | U(2,4)/1000 | Ton | $TT$ | 3000($\|i\|\,\|j\|+\|j\|\,\|c\|+\|j\|\,\|k\|$) | Ton |
| $Emjk_{jkts}$ | U(2,4)/1000 | Ton | $\varphi$ | 1 | % |
| $Enij_{ijts}$ | U(4,5)/1000; | MJ | $\theta$ | 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(222222,233333)(0.8+0.4($s$ -1)/(\|$s$\|-1)) | Ton | $popjk_{jkts}$ | [U(100,200)] | Person |
| $p_s$ | 100/\|$s$\| | % | | []: Sign function | |

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.

**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 |

We show the potential location for assigning HC, WS, WPC, 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. The objective function is 1520407 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 54026.33 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.

**Figure 3**. Potential location for the facilities.

**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 | 1520407 | 1495346.97 | 1.65% |

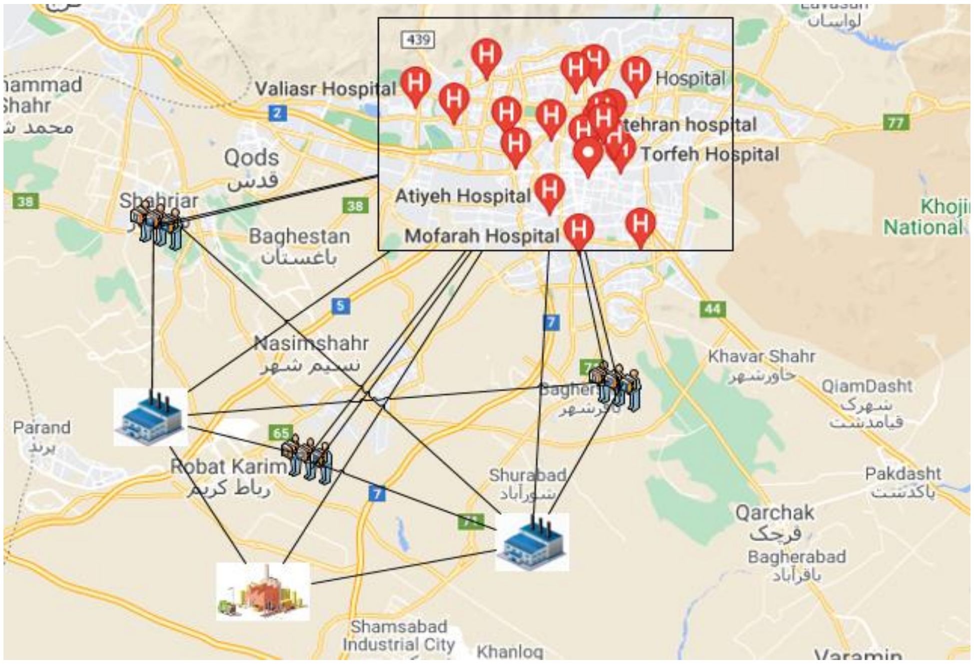

**Figure 4**. Final location for VMWCND facility.

## 4.1. Variation on the conservative coefficient

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

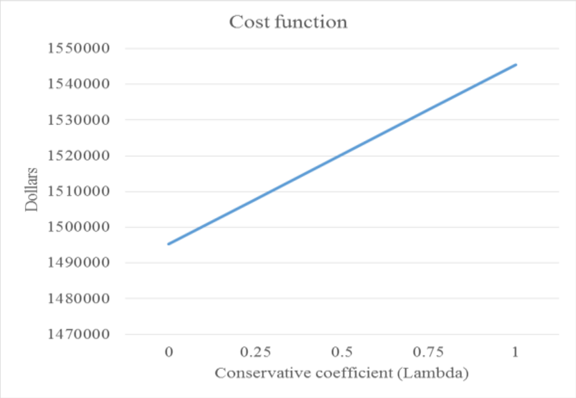

**Figure 5**. Cost function for different Lambda.

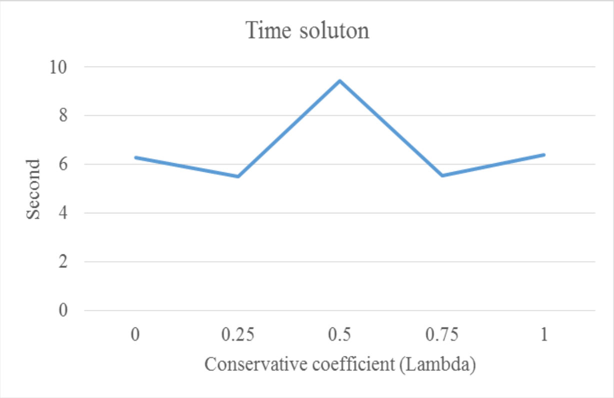

**Figure 6**. Time solution for different Lambda.

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

**Table 6**. Effects of variation of conservative coefficient.

| Problem | Conservative coefficient ( $\lambda$ ) | Cost function | Time solution | Cost variation | Population risk |
|---|---|---|---|---|---|
| P1 | 0.00 | 1495346.97 | 6.289 | -1.65% | 54026.33 |
| P1 | 0.25 | 1507877.11 | 5.52 | -0.82% | 54026.33 |
| P1-main model | 0.5 | 1520407.25 | 9.422 | 0.00% | 54026.33 |
| P1 | 0.75 | 1532937.39 | 5.526 | 0.82% | 54026.33 |
| P1 | 1.00 | 1545467.53 | 6.4 | 1.65% | 54026.33 |

## 4.2. Variation on confidence level of CVaR

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

**Table 7**. Effects of the confidence level of CVaR.

| Problem | Confidence level | Cost function | Time solution | Cost variation |
|---|---|---|---|---|
| P1 | 1% | 1519419.405 | 5.92 | -0.06% |
| P1 | 2% | 1519658.805 | 5.666 | -0.05% |
| P1 | 3% | 1519903.141 | 5.751 | -0.03% |
| P1-main model | 5% | 1520407.25 | 5.45 | 0.00% |
| P1 | 6% | 1520667.342 | 5.544 | 0.02% |
| P1 | 7% | 1520933.032 | 5.728 | 0.03% |

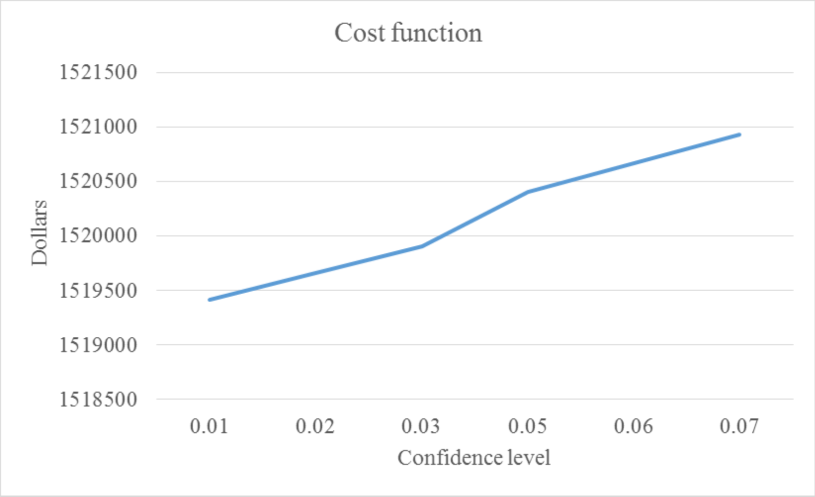

**Figure 7**. Effects of the confidence level of CVaR.

## 4.3. Variation on waste recovery coefficient

The waste recovery coefficient ($\pi$) 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 increase. But this issue helps systems to use and recover waste.

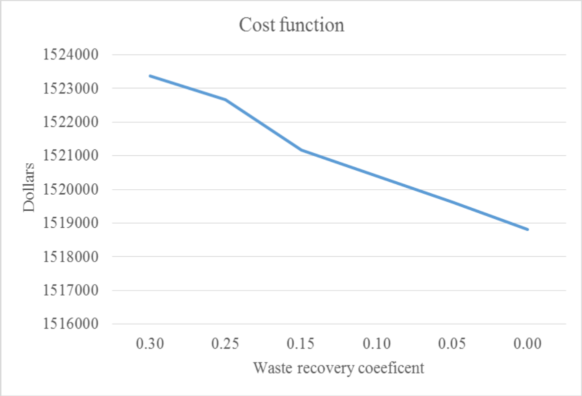

**Figure 8**. Effects of variation waste recovery coefficient on the cost function.

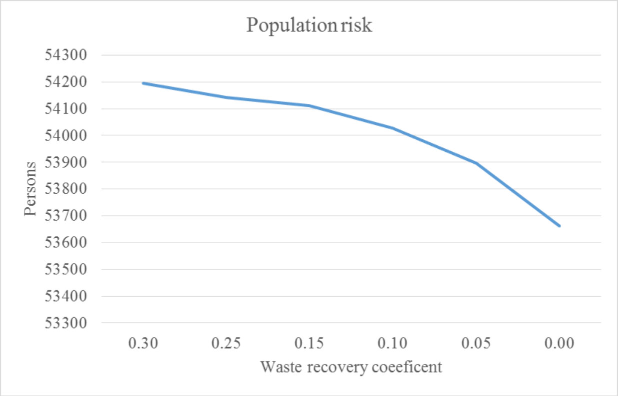

**Figure 9**. Effects of variation waste recovery coefficient on population risk.

**Table 8**. Effects of changing waste recovery coefficient.

| **Problem** | Waste recovery coefficent | Cost function | Time solution | Cost variation | Population risk |
|---|---|---|---|---|---|
| P1 | 30% | 1523371 | 6.004 | 0.19% | 54196 |
| P1 | 25% | 1522667 | 5.436 | 0.15% | 54142.3 |
| P1 | 15% | 1521177 | 5.676 | 0.05% | 54112.7 |
| P1-main model | 10% | 1520407 | 5.45 | 0.00% | 54026.3 |
| P1 | 5% | 1519622 | 5.967 | -0.05% | 53897.7 |
| P1 | 0% | 1518823 | 6.07 | -0.10% | 53662.3 |

## 4.4. Variation on demand

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

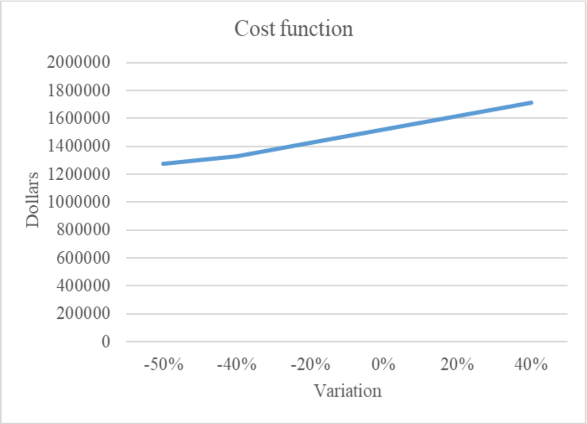

**Figure 10**. Effects of variation demnad on cost function.

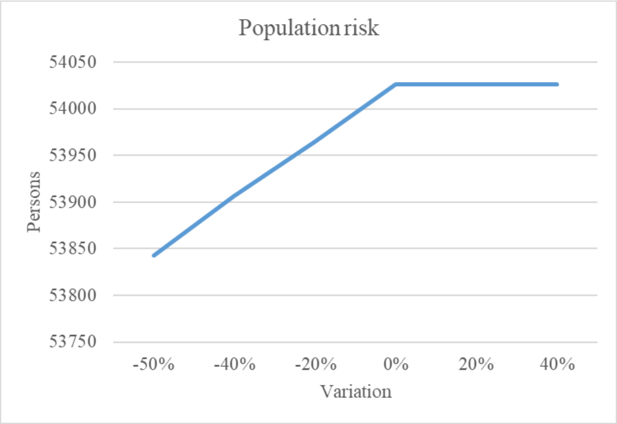

**Figure 11**. Effects of variation demand on population risk.

**Table 9**. Effects of changing demand.

| **Problem** | **Changing demand** | **Cost function** | **Time solution** | **Cost variation** | **Population risk** |
|---|---|---|---|---|---|
| P1 | -50% | 1277474.078 | 5.941 | -15.98% | 53843.001 |
| P1 | -40% | 1326060.712 | 5.888 | -12.78% | 53906.334 |
| P1 | -20% | 1423233.979 | 6.528 | -6.39% | 53965.334 |
| P1-main model | 0% | 1520407 | 5.45 | 0.00% | 54026.334 |
| P1 | +20% | 1617580.513 | 6.295 | 6.39% | 54026.334 |
| P1 | +40% | 1714753.780 | 5.963 | 12.78% | 54026.334 |

## 4.5. Variation on scale of the main model

The several large-scale problems is defined in Table 10. When the scale of problems is increased, the time solution and cost function increase in Figure 12 and Figure 13. As can be seen, the proposed model show NP-hard and the behavior of this model is exponential for large scale. Therefore, we need to solve the model by heuristic, metaheuristic and new exact solution in minimum time on large scale.

**Table 10**. Cost and time solution for several problems.

| **Problem** | $|i|.|j|.|c|.|k|.|t|.|s|$ | **Binary var.** | **Positive var.** | **Free var.** | **Constraint** | **Cost function** | **Time solution** | **Population risk** |
|---|---|---|---|---|---|---|---|---|
| P1 | 118.4.3.1.3.3 | 4396 | 4393 | 12 | 8818 | 1520407 | 9.422 | 54026.33 |
| P2 | 10.8.4.2.7.7 | 6280 | 6273 | 20 | 12380 | 609257 | 6.796 | 9201.68 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| P3 | 118.4.3.1.3.5 | 7324 | 7321 | 16 | 14694 | 1591272 | 13.49 | 54408.4 |
| P4 | 120.5.4.1.5.3 | 9380 | 9376 | 12 | 18721 | 1906117 | 21.548 | 91725.33 |
| P5 | 120.5.4.2.7.3 | 13235 | 13231 | 12 | 36388 | 2160152 | 72.426 | 128016.7 |
| P6 | 120.8.4.2.7.3 | 21176 | 21169 | 12 | 44578 | 2152882 | 249.904 | 127924 |

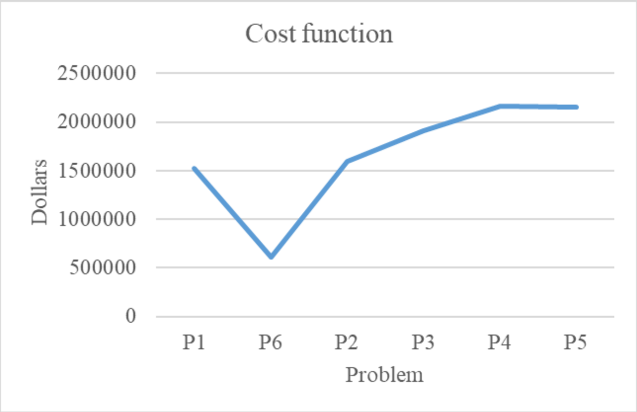

**Figure 12**. Cost function for several problems.

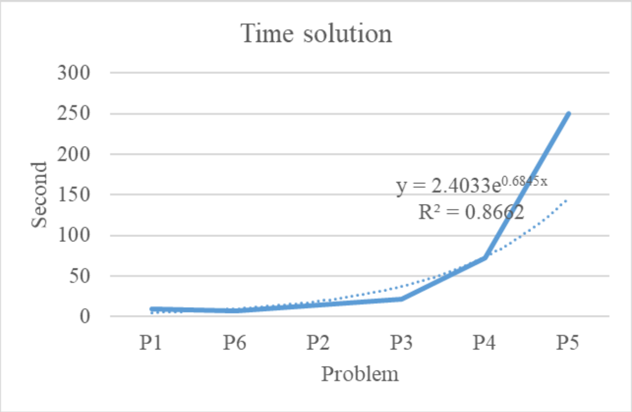

**Figure 13**. Time solution for several problems.

## 5. 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 government. As managers of the VWMCND, we should move forward to applying the novel concept in MCND to decrease cost and population risk, increase the resiliency of facility, robustness, risk-averse and agility of network. 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 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 Sustainable Development Goal (SDG12-Ensure sustainable consumption and production patterns) and the circular economy pillars.

## 6. 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 amount of MWMs increases day by day. We should think about this issue and find a solution for this issue. We suggest to recovery MWM by waste segregation. Therefore, we proposed a novel Viable Medical Waste Chain Network Design (VMWCND) that consider 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 in If the conservative coefficient increases to 1, the cost function grows in Table 6, Figure 5 and Figure 6. If the conservative coefficient increases 50%, the cost function will increase by 1.65%, but time solution and population risk do not change significantly.
2. If the conservative coefficient increases up to 50%, the cost function will increase 1.65%, but time solution and population risk do not change significantly.
3. If the confidence level of CVaR grows up, we can see, the cost function will increase (cf. Figure 7 and Table 7). Increasing for confidence level by 2%, the cost function increase 0.03%.
4. 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). By increasing the waste recovery coefficient, transportation to WPC increases and then the cost function increase. But it helps systems to use waste and recover them.
5. When demand increases 40%, the cost function grows 12% and when demand decreases 50%, it grows down 16% (cf. Figure 10 and Figure 11).
6. When the scale of problems is increased, the cost function and time solution grow up in Figure 12 and Figure 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, metaheuristic 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 benders decomposition, branch and price, branch and cut, column generation, heuristic and meta-heuristic algorithms to solve models in minimum time (Fakhrzad & Lotfi, 2018;

Lotfi, Mehrjerdi, & Mardani, 2017). 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.

Further, 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, Mardani, & Weber, 2021). Using new and novel uncertainty methods like data-driven robust optimization is advantageous for a conservative decision-maker in the recent decade. Eventually, we suggest equipping VMWCND with novel technology like blockchain for the viability of MWCND.

# 7. Ethical Approval

Not applicable

# 8. Consent to Participate

Not applicable

# 9. Consent to Publish

Not applicable

# 10. Authors Contributions

Reza Lotfi: conceptualization, supervision, software, methodology; software; 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;

# 11. Funding

There is not funding.

# 12. Competing Interests

The authors declare no competing interests.

# 13. Availability of data and materials

Not applicable

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