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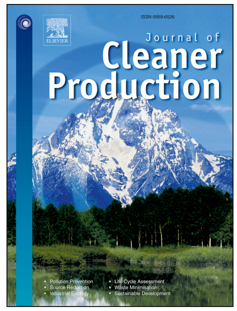

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Abstract

Carbon emission has been widely studied in transportation research in general, yet research on carbon emission specifically in hazardous material transportation remains surprisingly limited. This study presents a multi-objective model for locating transfer points and routing in a multi-modal network of hazardous materials, accounting for multiple different uncertainties, while minimizing carbon emission alongside risk and cost of transportation. This study models uncertainties in accident probabilities, emission factors, and costs of establishing transfer points with polyhedral uncertainty sets, and utilizes robust counterpart optimization to tackle these uncertainties. The application of the proposed approach is examined in a case study of petroleum product transportation. The results of our analyses confirm the effectiveness and robustness of the developed model. Specifically, it is found that the proposed model can reduce carbon emissions by 873 grams, and individuals at risk by 0.28, for every additional dollar spent.

Keywords: Hazardous materials transportation; Carbon emissions; Risk; Multi-modal transportation network; Bounded objective function; Robust counterpart optimization

1. Introduction

Decision making for hazardous materials (Hazmat) transportation, including the sub-domain of location and routing decisions, aims to minimize risk. Many factors impact Hazmat transportation, though, such as: traffic flow, driver behavior, condition of container, weather changes, and so on. As a result, it is difficult to precisely estimate some parameters of Hazmat transportation, such as the probability of accidents, consequences of accidents, traveling time, etc. Hence, it is essential to address uncertainties of Hazmat transportation in a decision-making model, with a coherent and effective strategy to cope with these uncertainties. To that end, we present a new optimization model for minimizing CO_2 emissions, alongside cost and risk, in multi-modal Hazmat transportation, employing a robust counterpart optimization.

Most extant studies in Hazmat transportation have presumed that parameters are deterministic and have not considered uncertainty (e.g., Asgari et al., 2017; Aydemir-Karadag, 2018; Beneventti et al., 2019; Bula et al., 2019; Fan et al., 2015; Kumar et al., 2018; Yousefloo and Babazadeh, 2020). Some studies have considered uncertainties in Hazmat transportation modeling (e.g., Berglund and Kwon, 2014; Jabbarzadeh et al., 2020; Jia et al., 2011; Mohammadi et al., 2017; Taslimi et al., 2017; Zero et al. 2019); however, the overwhelming majority have applied uncertainty only to risk parameters.

Only a few prior studies in Hazmat location-routing have considered uncertainty in parameters other than risk, Saeidi-Mobarakeh et al. (2020), for instance, in a study on hazardous waste management, considered waste generation rates as uncertain and utilized a scenario-based approach to tackle this uncertainty. They developed a bi-level optimization model to minimize risk in the upper level and minimize cost in the lower level. In another study in Hazardous waste management, Rabbani et al. (2019) considered both transportation risk and also amount of wastage accumulated at source node as uncertain and developed a model for optimizing locations of disposal facilities and transportation routes in a capacitated heterogeneous road network. Mohammadi et al. (2017), in addition to transportation risk uncertainty, also considered transportation time uncertainty. They presented a mixed fuzzy-stochastic programming approach to determine hub locations and routes in a way to minimize transportation risk. Finally, Ardjmand et al. (2016), in contrast with other studies, considered risk as deterministic and only considered cost as an uncertain parameter. They presented a stochastic model for routing, location and allocation of Hazmat so as to minimize the weighted sum of total cost and risk.

In order to cope with uncertainties of Hazmat transportation, prior studies in location-routing have either applied either stochastic programming (Ardjmand et al., 2016; Ghaderi and Burdett, 2019; Jabbarzadeh et al., 2020; Rabbani et al., 2019), fuzzy programming (Delfani et al., 2020; Mahmoudsoltani et al., 2018; Men et al., 2019, Pamučar et al., 2016; Sun et al, 2019; Zero et al., 2019), or scenario-based optimization (Saeidi-Mobarakeh et al., 2020; Ke, 2020). We believe there is an important gap between these stochastic, fuzzy, and/or scenario-based optimizations, on the one hand, and practical applications, on the other.

Due to the nature of Hazmat accidents (low probability and high consequence), it is logically infeasible to obtain probability distribution functions or fuzzy membership functions of Hazmat transportation risk. Hence, in this paper, we instead utilize robust counterpart programming to tackle uncertain parameters. In the robust counterpart approach, we only need to know the interval in which uncertain parameters vary. Moreover, robust counterpart optimization is a substantially more flexible method, allowing for optimization according to different levels of conservatism and risk aversion. Furthermore, robust counterpart programing provides solutions which remain feasible for realization of (almost) all uncertain parameters (feasibility robustness) and their optimal value remains close to an optimal value for any realization of uncertain parameters (optimality robustness, Pishvaee et al., 2012), which is particularly important for cases like Hazmat transportation in which deviation from optimal conditions can lead to catastrophic results.

Over the last decade there has been growing concern regarding the concentration of greenhouse gases (GHG) in the atmosphere, especially due to the effects on global warming. According to the International Energy Agency, in 2017, transportation was the second largest source of CO_2 emission (IEA, 2017). Relatedly, in recent years, multiple transportation studies, especially on vehicle routing problems, have considered the GHG emissions issue (e.g., Behnke, 2020 ; Bektaş and Laporte, 2011; Fan et al., 2015; Sim, 2017; Wang et al., 2019; Xiao and Konak, 2016). Hazmat shipment, like any type of transportation, emits GHG; additionally, an accident or incident that leads to Hazmat explosion will emit a large amount of GHG, especially when inflammable and pyrophosphoric materials are carried (Martínez-Alegría et al., 2003). As a result, it is especially important to consider GHG emissions in Hazmat transportation optimization.

To date, though, research on Hazmat location-routing has focused almost exclusively on cost and risk aspects, ignoring GHG emissions. Only a small handful of prior studies have considered GHG emissions in Hazmat optimization. In Hazardous waste transportation, both Yousefloo and Babazadeh (2020) and Farrokhi-Asl et al. (2018), while assuming that all parameters were deterministic, included the cost of CO_2 emission as part of a total cost of transportation, and developed a model to minimize total cost and risk of transportation. In a different approach, Pradhananga et al. (2014) utilized CO_2 emission as a criterion for selecting the final optimal solution among pareto optimal solutions obtained by minimization of cost and risk of routing and scheduling of Hazmat transportation.

Not only have GHG emissions been neglected in Hazmat optimization studies, but so have other environmental aspects of Hazmat transportation. Only a few relevant studies have thus far been published. Yilmaz et al. (2017) incorporated the environmental risk of hazardous waste transportation in their model by considering vulnerable elements, such as bodies of water, coastlines, forests and agricultural lands, located around transportation routes, and proposed a mixed integer model to minimize risks and transportation cost. Zhao and Verter (2015) developed a new method for assessment of environmental risk of Hazmat transportation and then utilized it in a bi-objective model of location-routing of waste oil in order to minimize the cost and environmental risk. Zhao and Ke (2017) then expanded upon that previous work in order to simultaneously optimize location, routing and inventory of Hazmat. Finally, Mahmoudsoltani et al. (2018) presented a model to determine the location of storage centers and the route, in which the risk of transportation route is a weighted linear sum of population risk and bioenvironmental risk. They used fuzzy numbers to model uncertain bioenvironmental risk and presented some multi-objective evolutionary algorithms to solve the problem.

Despite the rich body of literature in Hazmat transportation, there is little extant research on Hazmat transportation in multi-modal networks (but see, Assadipour et al., 2016; Coco et al. 2020; Mahmoudsoltani et al., 2018; Mohammadi et al., 2017; Xie et al., 2012). In a multi-modal transportation network, a combination of at least two modes is possible, and different modes connect to each other in a transfer point node. In this paper, we consider a capacitated multi-modal network of highways and railways with potential transfer points; we present a multi-objective model to determine the location of transfer points and the optimal routing for Hazmat shipment. While considering uncertainties of risk, CO_2 emissions, and cost, we utilize a robust counterpart approach to tackle the uncertainties, and employ a bounded objective method for minimizing CO_2 emissions alongside cost and risk.

To illustrate the differences between our current study and previous existing research, Table 1 outlines a taxonomy of relevant studies (studies that have considered uncertainties and/or environmental issues) on Hazmat location-routing.

Table 1

Summarized of relevant papers on Hazmat location-routing

Reference	Uncertainty				Objective function			Assumptions		
	SP[a]	FP[b]	Sb[c]	RP[d]	Cost	Risk	Other	Env[e] Impact	Multi-Modal	Cap[e]
Jia et al. (2011)	•	•				•				
Pradhananga et al. (2014)					•	•		GHG Emission		

Sun et al. (2015)				•	•	•				
Zhao and Verter (2015)					•	•		Env Risk		•
Ardjmand et al. (2016)	•				•	•				
Pamučar et al. (2016)		•			•	•				
Yilmaz et al. (2017)					•	•		Env Risk		•
Mohammadi et al. (2017)	•	•				•				•
Zhao and Ke (2017)					•	•		Env Risk		•
Taslimi et al. (2017)	•				•	•				
Mahmoudsoltani et al. (2018)		•				•		Env Risk	•	
Ydemir-Karadag (2018)							•	Env Risk		•
Farrokhi-Asl et al. (2018)					•	•		GHG Emission		•
Ghaderi and Burdett (2019)	•				•	•			•	•
Men et al. (2019)		•				•				•
Rabbani et al. (2019)	•				•	•				•
Sun et al. (2019)		•			•	•				•
Zero et al. (2019)		•				•				
Yousefloo and Babazadeh (2020)					•	•		GHG Emission		•
Jabbarzadeh et al. (2020)	•				•	•				•
Ke et al. (2020)			•		•	•			•	•
Saeidi-Mobarakeh et al. (2020)			•			•				

This study	•	•	•	•	GHG Emission	•	•

[a] Stochastic Programming [b] Fuzzy programming [c] Scenario-Based Optimization [d] Robust Programming [e] Environmental [f] Capacitated

As Table 1 demonstrates, Sun et al. (2015) is, to the best of our knowledge, the only prior study in the location-routing arena that has utilized the robust counterpart approach for handling uncertainty. Our work is somewhat similar, but nonetheless has substantial differences. Sun et al. considered a road network without capacity limitation, in which the government first determines the available road segments, and then a carrier chooses the route with minimum cost. In contrast, we study a capacitated multimodal network which, in addition to the optimal route, requires that the optimal transfer points should also be determined. Furthermore, Sun et al. (2015) only considered risk of transportation as an uncertain parameter, without considering any environmental aspects of hazmat transportation.

The main contributions of this paper can be summarized as follows:

1. We incorporate GHG emissions in Hazmat transportation optimization, an important topic that has been only barely addressed in prior papers on Hazmat location routing.
2. We consider uncertainties in multiple different parameters (cost, risk, and CO_2 emission), and employ "robust counterpart programming" which has important advantages over stochastic programming and fuzzy programming for coping with uncertainties in Hazmat transportation.
3. We base our study on realistic assumptions and modeling elements such as a multi-modal network as well as capacity constraints on both routes and transfer points, and we apply a bounded objective method for handling three conflicting objectives, rather than the common weighting method approach.

The rest of the paper is organized as follows. Section 2 elaborates the description of the given problem, the mathematical model, and the robust counterpart of the model. Section 3 applies the proposed model to a real-world case study and discusses the results. Finally, Section 4 discusses conclusions and future directions.

2. Problem description

For this research, we consider a multi-modal network consisting of highways and railways. The network is represented by a directed graph *G= (N, E)* where *N* is the set of

nodes and E is the set of arcs. E consists of subsets E_H and E_R, corresponding to highway roads and railway roads, respectively. N is the union of N_H, N_R and N_{HR}. Here, N_R is used for nodes where a railway ends or more railways join; N_H represents nodes where a highway ends or more highways connect; and N_{HR} is used for transfer points where highways and railways join, and, only in these nodes, mode-switching is possible. The origin and destination nodes are given, and the goal is to find the optimum route from the origin to the destination that minimizes total risk, cost and CO_2 emission of Hazmat transportation. The model also determines the activated transfer points.
The following notations are utilized to formulate the problem. It should be noted that uncertain parameters are distinguished by a tilde (~) on them.

Indices

k	index of potential transfer points
$(i, j) \in E$	index of transportation links

Parameters

n	number of shipments in each time of transportation
cap_k	Hazmat Capacity of transfer point *k*
cap_{ij}	Hazmat Capacity of link *(i, j)*
C_{ij}	per unit cost of Hazmat transportation at link *(i, j)*
$\widetilde{f_k}$	Fixed cost of activating transfer point *k*
$\widetilde{r_k}$	Hazmat transportation risk at transfer point *k*, $\widetilde{r_k} \in [r_{1k}, r_{2k}]$
$\widetilde{r_{ij}}$	Hazmat transportation risk at link *(i, j)*, $\widetilde{r_{ij}} \in [r_{1ij}, r_{2ij}]$
$\widetilde{e_{ij}}$	CO_2 emission of Hazmat transportation at link *(i, j)*, $\widetilde{e_{ij}} \in [e_{1ij}, e_{2ij}]$
M	a big number

Decision variables

x_k	1 if transfer point k is activated, and 0 otherwise

y_{ij} 1 if Hazmat flow uses link *(i, j)*, and 0 otherwise

2.1. Risk measurement

Several research studies have been conducted assessing the risk of Hazmat transportation, with different models quantifying risk in different ways. Kang et al. (2014) categorized the risk models used in Hazmat transport research into 10 categories: 1) Traditional Risk model, 2) Incident Probability model, 3) Population Exposure model, 4) Perceived Risk model, 5) Conditional Risk model, 6) Maximum Risk model, 7) Mean-Variance model, 8) Disutility model, 9) Mixed-Route model, and 10) Value at Risk (VaR). Hosseini and Verma (2018) subsequently added the conditional value-at-risk (CVaR) model to category 10.

For this paper, we use the Traditional Risk model, which is the most common approach in risk modeling (Kazantzi et al., 2011), for the following reasons:

- The Incident Probability model and the Population Exposure model can be viewed as two extreme cases of the Traditional Risk model. While the Traditional Risk model considers both accident probability and population on the impacted area, the Population Exposure model and the Incident Probability model consider only one parameter, which might lead to a biased output (Kang et al., 2014).
- While the Perceived Risk model, Maximum Risk model, Mean-Variance model, and Disutility model are all risk-averse, the Traditional Risk model is risk-neutral, which makes it a better fit with our robust counterpart approach. As we will explain later in this section, we consider risk as an uncertain parameter and control the degree of risk aversion by uncertainty level. By employing a neutral risk model and testing different uncertainty levels, we can cover the full range of risk averseness levels.
- The needed data for the Traditional Risk model (population and accident probability) are easier to gather. For the Conditional Risk model, mixed-route model, VaR, and CVaR, in addition to accident probability, we would need to have information on the consequences of accidents, which is difficult to obtain.

According to this model, transportation risk for transfer points is defined by Eq. (1).

$$r_k = p_k Pop_k \qquad (1)$$

where p_k is the accident probability (per shipment) at transfer point *k*, and Pop_k is the number of people affected (living) in the neighborhood of the transferred point *k*.
In a similar way, transportation risk for a link *(i, j)* is calculated according to Eq. (2).

$$r_{ij} = \sum_m r_{ijm} = \sum_m p_{ijm} Pop_{ijm} Len_{ijm} \qquad (2)$$

where Len_{ijm}, p_{ijm}, Pop_{ijm} are the length, accident probability and the population of mth segment of the link *(i, j)*, respectively. For convenience, paths are usually assumed to be homogeneous and Eq. (2) can be reformulated with Eq. (3).

$$r_{ij} = p_{ij} Pop_{ij} \qquad (3)$$

where Pop_{ij} is the total population of the link *(i, j)* and p_{ij} is the accident probability of the link *(i, j)*.

There are many factors such as driver's skill, road/rail conditions, vehicle conditions, and so on, which influence accident probability. Therefore, a precise estimation of accident probability is challenging. In this paper, we assign an uncertainty set for accident probability which means that the accident probability can be given any value belonging to this uncertainty set. Hence the new definitions for transportation risk are as below:

$$\begin{aligned} &\widetilde{p_{ij}} \in [p_{1ij},\ p_{2ij}] \ , \qquad \widetilde{r_{ij}} = \widetilde{p_{ij}} Pop_{ij} \\ &\widetilde{p_k} \in [p_{1k},\ p_{2k}] \ , \qquad \widetilde{r_k} = \widetilde{p_k} Pop_k \end{aligned} \qquad (4)$$

2.2. CO_2 emission measurement

There are two kinds of methodology for calculating CO_2 emission: fuel-based methodology and distance-based methodology. In the fuel-based methodology, which is based on the fraction of carbon in oxidized fuel, emission is calculated by multiplying fuel consumption by the CO_2 emission factor. In the distance-based methodology, emission is calculated by multiplying distance traveled by the CO_2 emission factor. Selection between these two approaches is generally based on data availability. Since most of the available data are in the form of distance traveled, we utilize the distance-based method. The CO_2 emission in the link *(i, j)* is expressed by Eq. (5).

$$e_{ij} = \varepsilon_{ij} d_{ij} \qquad (5)$$

where d_{ij} is the distance between the nodes *i* and *j*, and ε_{ij} is the distance-based emission factor for the link *(i, j)*. The emission factor depends on many variables such as vehicle type, fuel type, mass of vehicle and load, speed, road gradient, etc. Quantifying all these variables and implying them in calculating CO_2 emission is virtually impossible; even implying some of them like speed, velocity, and mass leads to a nonlinear formulation of CO_2 emission (Demir et al., 2011; Xiao and Konak, 2016). For this reason, we assume that the emission factor for the link *(i, j)* is only the function of vehicle type (highway or railway transportation), and the influence of other variables is modeled by uncertainty in the emission factor. Instead of assigning a unique number to the emission factor, an interval is assigned to it. So, the new definitions for CO_2 emission are as below:

$$\widetilde{\varepsilon_{ij}} \in \left[\varepsilon_{1ij},\ \varepsilon_{2ij}\right] \ , \qquad \widetilde{e_{ij}} = \widetilde{\varepsilon_{ij}} d_{ij} \qquad (6)$$

2.3. Model formulation

The multi-objective mathematical model is presented as follows.

$$Min\ OFV^c = \sum_{k \in N_{HR}} \widetilde{f_k}\, x_k + \sum_{(i,j)\in E} n c_{ij} y_{ij} \qquad (7)$$

$$Min\ OFV^r = \sum_{(i,j)\in E} n\widetilde{r_{ij}} y_{ij} + \sum_{k \in N_{HR}} \widetilde{r_k} x_k \qquad (8)$$
$$= \sum_{(i,j)\in E} \widetilde{p_{ij}} Pop_{ij} n y_{ij} + \sum_{k \in N_{HR}} \widetilde{p_k} Pop_k x_k$$

$$Min\ OFV^e = \sum_{(i,j)\in E} n\widetilde{e_{ij}} y_{ij} = \sum_{(i,j)\in E} n d_{ij} \widetilde{\varepsilon_{ij}} y_{ij} \qquad (9)$$

St.

$$\sum_{j|(i,j)\in E} y_{ij} - \sum_{j|(j,i)\in E} y_{ji} = \begin{cases} 1 & if\ orig = i \\ -1 & if\ dest = i \\ 0 & else \end{cases} \qquad \forall\, i \in N \qquad (10)$$

$$\sum_{j|(i,j)\in E_H} y_{ij} - \sum_{j|(j,i)\in E_H} y_{ji} = 0 \qquad \forall\, i \in\ N_R \cup N_H\, , i\ \neq dest, i\ \neq orig \qquad (11)$$

$$\sum_{j|(i,j)\in E_R} y_{ij} - \sum_{j|(j,i)\in E_R} y_{ji} = 0 \qquad \forall\, i \in N_R \cup N_H\,, i \neq dest, i \neq orig \tag{12}$$

$$-Mx_k \leq \sum_{k|(i,k)\in E_H} y_{ik} - \sum_{k|(k,i)\in E_H} y_{ki} \leq Mx_k \qquad \forall\, i \in N_{HR} \tag{13}$$

$$-Mx_k \leq \sum_{k|(i,k)\in E_R} y_{ik} - \sum_{k|(k,i)\in E_R} y_{ki} \leq Mx_k \qquad \forall\, i \in N_{HR} \tag{14}$$

$$nx_k \leq cap_k \qquad \forall\, k \in N_{HR} \tag{15}$$

$$ny_{ij} \leq cap_{ij} \qquad \forall\, (i,j) \in E \tag{16}$$

$$x_k \in \{0,1\} \qquad \forall\, k \in N_{HR} \tag{17}$$

$$y_{ij} \in \{0,1\} \qquad \forall\, (i,j) \in E \tag{18}$$

Eq. (7), the cost objective function, minimizes the total cost, including the cost of establishing transfer points and cost of transporting Hazmat. Eq. (8), the risk objective function, minimizes the overall risk of Hazmat transportation including risk in links and transfer points of routes. Eq. (9), the CO_2 emission objective function, minimizes the total CO_2 emission of Hazmat transportation. Constraint (10) is used for modeling origin and destination of transportation. Constraint (11) guarantees that in a not-candidate transfer point, income highway flows are equal to outcome highway flows. Constraint (12) ensures that in a not-candidate transfer point, income railway flows are equal to outcome railway flows. Constraint (13) expresses that, if a candidate transfer point is not activated, income highway flows should be equal to outcome highway flows; and if a candidate transfer point is activated, there is no requirement for equality of income highway flows and outcome highway flows. Constraint (14) expresses that if a candidate transfer point is not activated, income railway flows should be equal to outcome railway flows; and if a candidate transfer point is enabled, there is no requirement for equality of income railway flows and outcome railway flows. Constraints (15) and (16) limit the total amount of transportation in transfer points and links. Constraints (17) and (18) show the type of variables.

2.4. Solution Procedure

In this paper, we use the bounded objective function method for simultaneous optimization of conflicting objectives. Since minimizing the risk in Hazmat transportation is the most concerning issue, we have chosen the risk objective function

(Eq. (6)) as the main objective function. The cost objective function and CO_2 emission objective function are imported in the model as constraints with the upper bound. Thus, the proposed model will be as following:

$$\min \sum_{(i,j)\in E} \widetilde{p_{ij}} Pop_{ij} n y_{ij} + \sum_{k\in N_{HR}} \widetilde{p_k} Pop_k n x_k$$

$$S.t \begin{cases} \sum_{k\in N_{HR}} \widetilde{f_k}\, x_k + \sum_{(i,j)\in E} n c_{ij} y_{ij} \le \theta_c \\ \sum_{(i,j)\in E} n d_{ij} \widetilde{\varepsilon_{ij}} y_{ij} \quad \le \theta_e \\ constraints\ (10) - (18) \end{cases} \tag{19}$$

2.5. Robust optimization model

In robust counterpart programming, uncertain data are assumed to be varying in a given uncertainty set, and robust optimization provides a framework that guarantees the optimality of the solution for any realization of uncertain parameters in the given uncertainty set.

In general, consider the following linear optimization problem:

$$\max\ \tilde{c}x$$
$$s.t. \sum_j \tilde{a}_{ij} x_j \le \tilde{b}_i \qquad \forall\, i \tag{20}$$

where $\tilde{a}_{ij}$, $\tilde{b}_i$, and $\tilde{c}$ are uncertain parameters and defined as follows

$$\tilde{c} = c + \xi\hat{c}$$
$$\tilde{a}_{ij} = a_{ij} + \xi_{ij}\hat{a}_{ij} \qquad \forall\, j \in J_i \tag{21}$$
$$\tilde{b}_i = b_i + \xi_{i0}\hat{b}_i$$

where c, a_{ij} and b_i express the nominal value of the uncertain parameters; $\hat{c}$, $\hat{a}_{ij}$ and $\hat{b}_i$ express positive constant perturbation; ξ, ξ_{ij} and ξ_{i0} are random variables which are subject to uncertainty; and J_i represents the index subset that contains the variable indices whose coefficients are subject to uncertainty (Li et al., 2011).

With the above definitions and incorporating auxiliary variable x_0 which $x_0 = -1$, the original ith constraint can be reformulated as

$$\sum_j a_{ij}\, x_j + b_i x_0 + \left[\xi_{i0}\hat{b}_i x_0 + \sum_{j\in J_i} \xi_{ij}\hat{a}_{ij} x_j\right] \leq 0 \tag{22}$$

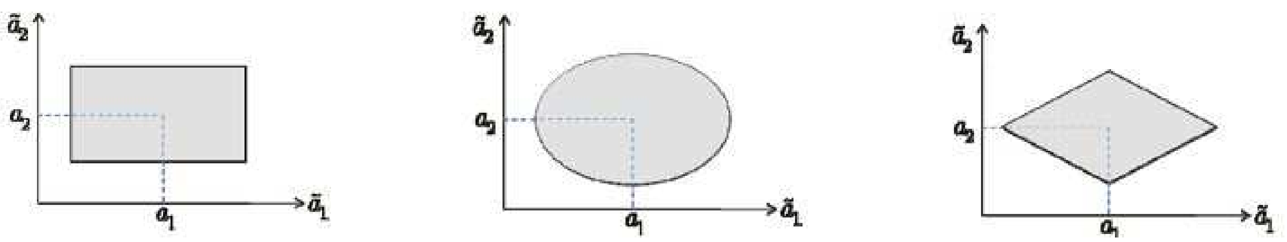
The set induced robust optimization method, with a predetermined uncertainty set U for ξ_{i0} and ξ_{ij} , explores solutions that remain feasible for any ξ_{i0} and ξ_{ij} in the given uncertainty set U, that is:

$$\sum_j a_{ij}\, x_j + b_i x_0 + \left[\max_{\xi\in U}\left\{\xi_{i0}\hat{b}_i x_0 + \sum_{j\in J_i} \xi_{ij}\hat{a}_{ij} x_j\right\}\right] \leq 0 \tag{23}$$

The set-induced robust counterpart formulations (23) depend upon the selection of the uncertainty set U. The most common uncertainty sets in robust optimization are box, ellipsoidal, polyhedral, and the intersection of them. Each of these uncertainty sets has unique characteristics that make it different from the others; thus, the proper uncertainty set should be chosen according to the problem structure and the type of uncertainty involved in it.

As we explained before, the fixed cost of activating transfer points, CO_2 emission factor at links, and accident probability in transfer points and links are the uncertain parameters in our Hazmat model. The distributions of these parameters are unknown; however, the intervals in which these parameters could vary are determined:
$\widetilde{f_k} \in [f_{1k},\ f_{2k}]$, $\widetilde{\varepsilon_{ij}} \in [\varepsilon_{1ij},\ \varepsilon_{2ij}]$, $\widetilde{p_k} \in [p_{1k},\ p_{2k}]$, $\widetilde{p_{ij}} \in [p_{1ij},\ p_{2ij}]$

For determining the construction of the uncertainty sets of these parameters in a 2-dimensional space, illustrations of box, ellipsoidal and polyhedral uncertainty sets are presented in Fig. 1 (respectively from left to right).



a. Box uncertainty set b. Ellipsoidal uncertainty set c. Polyhedral uncertainty set

Figure 1. Illustration of different uncertainty sets

Among the three constructions, the box uncertainty set is the most pessimistic one; in the box uncertainty set, it is assumed that all the uncertain parameters could get their worst-case value simultaneously (Fig. 1-a). Although the box uncertainty set gives the maximum immunity to infeasibility, the high conservatism of this approach has been harshly criticized (Bertsimas and Sim, 2004). Since we do not need such a high degree of protection in our model (especially for cost and CO_2 emission factor), the box uncertainty set is not a suitable construction for our uncertain parameters. The other two uncertainty sets (ellipsoidal and polyhedral) are more realistic than the box uncertainty set, and by using them, we achieve a balanced trade-off between the robustness of the achieved solution and cost of robustness (Pishvaee et al., 2012). As can be seen in Fig.1-b, the ellipsoidal uncertainty set induces nonlinearity in the model. Our model, though, is linear and we prefer that the counterpart of our problem becomes linear as well.

These two advantages (being realistic and being linear) of the polyhedral uncertainty set permit us to assume that the uncertain parameters in our model vary in polyhedral uncertainty sets, and we develop our approach based on the polyhedral uncertainty set. Therefore, we continue this section by expressing the formulation for the polyhedral uncertainty.

The polyhedral uncertainty set is described using the 1-norm of the uncertain data vector as follows:

$$U_1 = \{\xi \mid \|\xi\|_1 \leq \Gamma\} = \left\{\xi \,\middle|\, \sum_{j \in J_i} |\xi_j| \leq \Gamma \right\} \tag{24}$$

where Γ is the adjustable parameter controlling the size of the uncertainty set.

The polyhedral uncertainty set given in Eq. (24) is incorporated in robust counterpart Eq. (22) and is equivalent to:

$$\begin{aligned} &\sum_j a_{ij}\, x_j + \Gamma \mu_i \leq b_i \\ &\hat{a}_{ij} |x_j| \leq \mu_i \qquad \forall\, j \in J_i \\ &\hat{b}_i \leq \mu_i \end{aligned} \tag{25}$$

where μ_i is a new variable.

As we explained earlier in regard to robust counterpart programming based on polyhedral uncertainty set, the robust counterpart of our Hazmat transportation model is as follows:

$$Min\ W \tag{26}$$

S.t.

$$\sum_{(i,j)\in E} p_{ij} Pop_{ij} n y_{ij} + \sum_{k\in N_{HR}} p_k Pop_k n x_k + \Gamma_p \mu_1 \leq W \tag{27}$$

$$\widehat{p_{ij}} Pop_{ij} n y_{ij} \leq \mu_1 \quad \forall (i,j) \in E \tag{28}$$

$$\widehat{p_k} Pop_k n x_k \leq \mu_1 \quad \forall k \in N_{HR} \tag{29}$$

$$\sum_{k\in N_{HR}} f_k\, x_k + \sum_{(i,j)\in E} n c_{ij} y_{ij} + \Gamma_f \mu_2 \leq \theta_c \tag{30}$$

$$\widehat{f_k} x_k \leq \mu_2 \quad \forall k \in N_{HR} \tag{31}$$

$$\sum_{(i,j)\in E} n d_{ij} \varepsilon_{ij} y_{ij} + \Gamma_\varepsilon \mu_3 \leq \theta_e \tag{32}$$

$$n d_{ij} \widehat{\varepsilon_{ij}} y_{ij} \leq \mu_3 \quad \forall (i,j) \in E \tag{33}$$

$$Constranits\ 10-18$$

Where Γ_f, Γ_p, and Γ_ε are uncertainty level related to activation cost, CO_2 emission factor, and accident probability respectively.

3. Model implementation

To assess the performance of the proposed model and the solution methodology, a selected multi-modal network for Iran is considered.

3.1. Case problem

Iran is one of the largest oil-producing countries in the world; one of the main Hazmat transported in this country is petroleum products. Unfortunately, the rate of accidents in Iran is one of the world's highest, even higher than countries with much larger transportation network size (e.g., US), and the safety level of its transportation system is comparatively low (Kheirkhah, 2012). Several high-profile Hazmat incidents have occurred in the country so far. For instance, on 20th March 1999, one railway car carrying naphtha overturned and caused the explosion of 46 other railway cars. This was the most catastrophic transportation accident in Iranian history, causing 283 deaths and hundreds of injuries. More recently, on 25th June 2005, because of brake failure, a gas truck collided with a bus at a checkpoint station in southeast Iran, causing 90 fatalities and more than a hundred other injuries (Ghazinoory and Kheirkhah, 2008).

In addition, air pollution is a serious issue in Iran. On some days, air pollution in cities such as Tehran, Esfahan, Ahvaz, and Mashhad is so extreme that governments shut down schools and restrict the movements of vehicles[1]. Therefore, presenting a model for Iran's Hazmat transportation which reduces risk and CO_2 emission is essential.

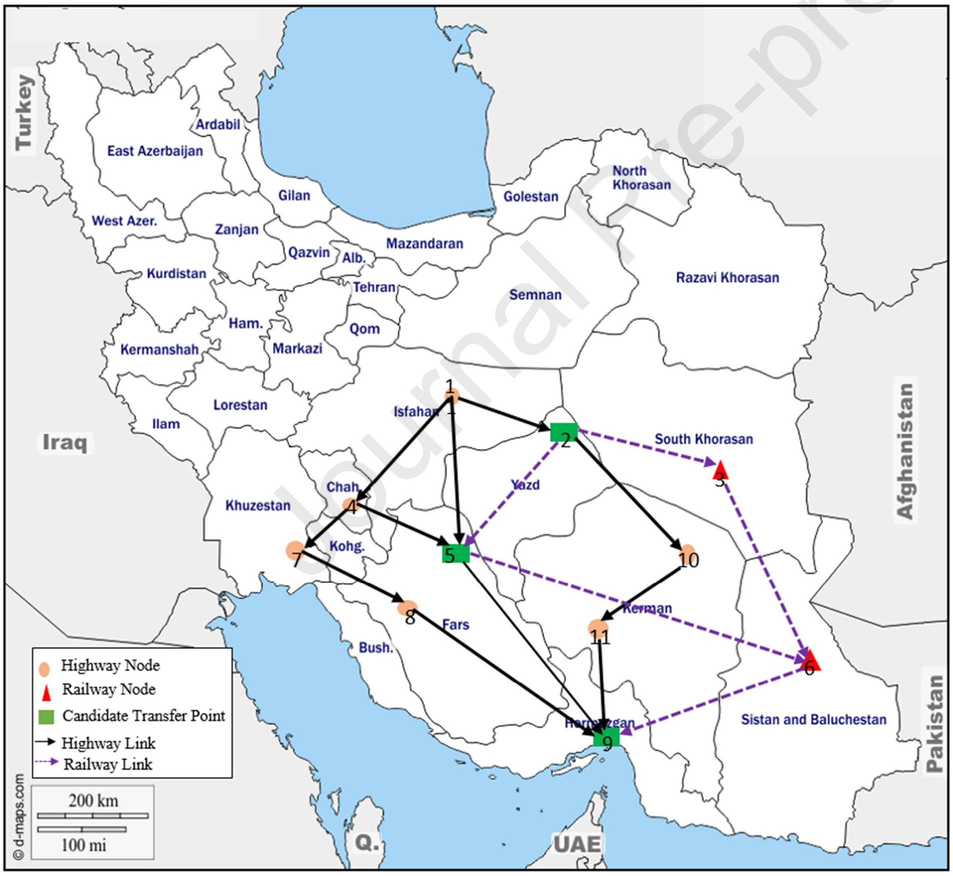


Figure 2. Transportation network of Petroleum Products in Iran

[1] https://www.tehrantimes.com/news/443416/Air-pollution-choking-Iranian-cities-some-14-000-hospitalized

Esfahan Oil Refining Company, located in Isfahan City, is one of the main refining companies of Iran which produces petroleum products such as liquefied petroleum gas, unleaded gasoline, kerosene, light and heavy lube cut, light and heavy fuel oil, solvents and sulfur. We considered the Esfahan Oil Refining Company as the origin node and Bandar-Abbas City as the destination node of this case study. This network, with corresponding nodes, links and candidate transfer points, is shown in Fig. 2.
The reported CO_2 emission factor, declared by Iran's Ministry of Roads & Urban Development, is 89 g CO_2/km for road transportation and 32 g CO_2/ km for rail transportation. As previously mentioned, in this paper, the CO_2 emission factors are modeled as uncertain parameters and represented through uncertainty sets. Hence, we assigned the interval of [88, 94] for the CO_2 emission factor of road transportation and [30, 35] for the CO_2 emission factor of rail transportation.

In our case study, Hazmat rail transportation is done only by diesel haulage, so calculation of CO_2 emission in rail transportation is based on diesel haulage. The lengths and populations of the links are presented in Tables 2 and 3, respectively. The opening cost, populations, and capacities of transfer points are tabulated in Table 4. The transportation costs of highways and railways are 500 Rials (Iran's currency) and 1,800 Rials, respectively, per kilometer per shipment. Also, the capacity of highway and railway links is 500,000 and 440,000 shipments per year, respectively.

Table 2
Distance between nodes (Km)

Nodes	1	2	3	4	5	6	7	8	9	10	11
1	-	323	-	102	327	-	-	-	-	-	-
2	323	-	627	-	381	-	-	-	-	364	-
3	-	627	-	-	-	452	-	-	-	-	-
4	102	-	-	-	274	-	441	-	-	-	-
5	327	381	-	274	-	1,225	-	-	764	-	-
6	-	-	452	-	1,225	-	-	-	750	-	-
7	-	-	-	441	-	-	-	527	-	-	-
8	-	-	-	-	-	-	527	-	580	-	-
9	-	-	-	-	764	750	-	580	-	-	307
10	-	364	-	-	-	-	-	-	-	-	182
11	-	-	-	-	-	-	-	-	307	182	-

Table 3
Population of links

Nodes	1	2	3	4	5	6	7	8	9	10	11
1	-	834,000	-	301,200	222,100	-	-	-	-	-	-
2	834,000	-	418,700	-	300,100	-	-	-	-	561,300	-
3	-	418,700	-	-	-	209,100	-	-	-	-	-
4	301,200	-	-	-	254,100	-	841,600	-	-	-	-
5	222,100	300,100	-	254,100	-	421,500	-	-	398,000	-	-
6	-	-	209,100	-	421,500	-	-	-	450,100	-	-
7	-	-	-	841,600	-	-	-	1,109,100	-	-	-
8	-	-	-	-	-	-	1,109,100	-	832,900	-	-
9	-	-	-	-	398,000	450,100	-	832,900	-	-	297,100
10	-	561,300	-	-	-	-	-	-	-	-	18,200
11	-	-	-	-	-	-	-	-	297,100	18,200	-

Table 4
Transfer point information

nodes	Establishing Cost (Million Rials/year)	Population	Capacity (Million shipments/year)
2	[210, 230]	5,500	0.4
5	[170, 188]	1,010	0.3
9	[200, 226]	4,380	0.8

3.2. Numerical results and practical implications

The proposed robust model is coded in GAMS 24.1.3 on a laptop with Intel Core Duo CPU, 2.8 GHz and 4 GB of RAM. The runtime of the model is only about 0.01 Seconds. We assume that the uncertain parameters have an equal level of uncertainty (i.e., $\Gamma_f = \Gamma_p = \Gamma_\varepsilon = \Gamma$), and the optimal solutions according to different uncertainty levels are presented in Table 5.

Table 5 illustrates that the objective values of robust models are worse than those of the deterministic model. This is because, in robust models, infeasibility of solutions is reduced at the expense of deterioration of objective functions. Also, Table 5 shows that with an increase in uncertainty level, the values of all the objective functions increases. The reason behind this observation is related to the nature of robust optimization.

According to Ben-tal and Nemirovski (2008), in robust optimization, the solution is the "best immunized against uncertainty." Thus, with an increase in uncertainty level, the model adapts itself to the worst case and generates the solutions that remain feasible for nearly all realizations of uncertain data.

An interesting insight from the case study's results is that the optimal route and activated transfer points for different uncertainty levels are the same. This increases our confidence that the delivered solutions of our proposed model for this case study are optimal regardless of the extent to which decision-makers are risk-averse.

Table 5
Optimal values

Uncertainty level (Γ)	Optimal routes	Activated transfer point	Risk (people)	Cost (Million Rials)	CO_2 emission (kg)
0.1	(1,2)-(2,3)-(3,6)-(6,9)	2	2,134,978.329	1,139,942	28,459,900
0.3	(1,2)-(2,3)-(3,6)-(6,9)	2	2,143,867.935	1,139,944	28,558,900
0.5	(1,2)-(2,3)-(3,6)-(6,9)	2	2,152,757.541	1,139,946	28,657,900
0.7	(1,2)-(2,3)-(3,6)-(6,9)	2	2,161,647.147	1,139,948	28,756,900
0.9	(1,2)-(2,3)-(3,6)-(6,9)	2	2,170,536.753	1,139,950	28,855,900
1	(1,2)-(2,3)-(3,6)-(6,9)	2	2,174,981.556	1,139,951	28,905,400

3.3. Sensitivity Analysis

Cost threshold (θ_c) and emission threshold (θ_e) are the parameters which have significant effects on the bounded objective method and, therefore, on the delivered solutions. Tables 6 and 7 illustrate the sensitivity analysis of different values of θ_c and θ_e. First, we separately optimized the model for each objective function and found the optimal values of each objective function (θ_e^* and θ_c^* are the optimal values of CO_2 emission objective function and cost objective function, respectively). Then, we conducted a sensitivity analysis based on these ideal objective values. According to Table 6, when the value of θ_e is larger than $1.008\theta_e^*$, the optimal route is (1,2)-(2,3)-(3,6)-(6,9) and the transfer point 2 is activated. However, when the value of θ_e is smaller than $1.008\theta_e^*$, there is no feasible solution for the model. Table 7 demonstrates that different cost thresholds can lead to different optimal solutions.

Table 6
Solutions vs. different values of θ_e

Emission Threshold (θ_e)	Optimal routes	Activated transfer point	Risk (people)	Cost (Million Rials)
$\theta_e \leq 1.008\theta_e^*$	Infeasible			
$1.008\theta_e^* < \theta_e$	(1,2)-(2,3)-(3,6)-(6,9)	2	2,152,757.541	1,139,946

Table 7
Solutions vs. different values of θ_c

Cost Threshold (θ_c)	Optimal routes	Activated transfer point	Risk (people)	CO_2 emission (kg)
$\theta_c < \theta_c^*$	Infeasible			
$\theta_c^* \leq \theta_c \leq 6.33\theta_c^*$	(1,5)-(5,9)	-	3,505,614.750	33,140,900
$6.33\theta_c^* < \theta_c$	(1,2)-(2,3)-(3,6)-(6,9)	2	2,152,757.541	28,657,900

We performed an additional sensitivity analysis on the number of shipments. The effects of varying number of shipments on the risk objective function, CO_2 emission objective function, and cost objective function are shown in Figs. 3, 4 and 5, respectively. The results demonstrate that, below a specific number of shipments (400,000), an increase in the number of shipments leads to a linear increase in total risk, total cost, and total CO_2 emission. At the level of 400,000 shipments, though, a dramatic shift occurs for all three objectives; after this point, a linear relation with a different slope form emerges. These results are not surprising; as long as capacity constraints are satisfied, regarding the Eqs. (7), (8) and (9), the total cost, total risk and total CO_2 emission are all linear functions of the number of shipments. Shipment more than 400,000, though, exceed the capacity of node 2, the optimal transfer point, and so the optimal location-routing will be different. An interesting observation is that the total cost for more than 400,000 shipments is considerably less than the ones for shipments lower than 400,000. The reason: the new optimal location-routing has lower total cost but with the tradeoff of having higher total risk and higher total CO_2 emission.

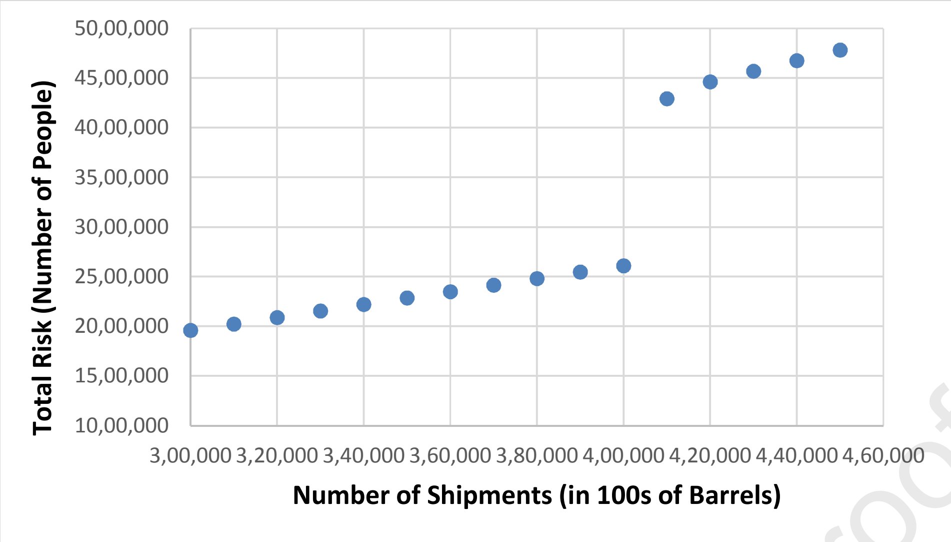


Figure 3. Risk vs. Number of shipments

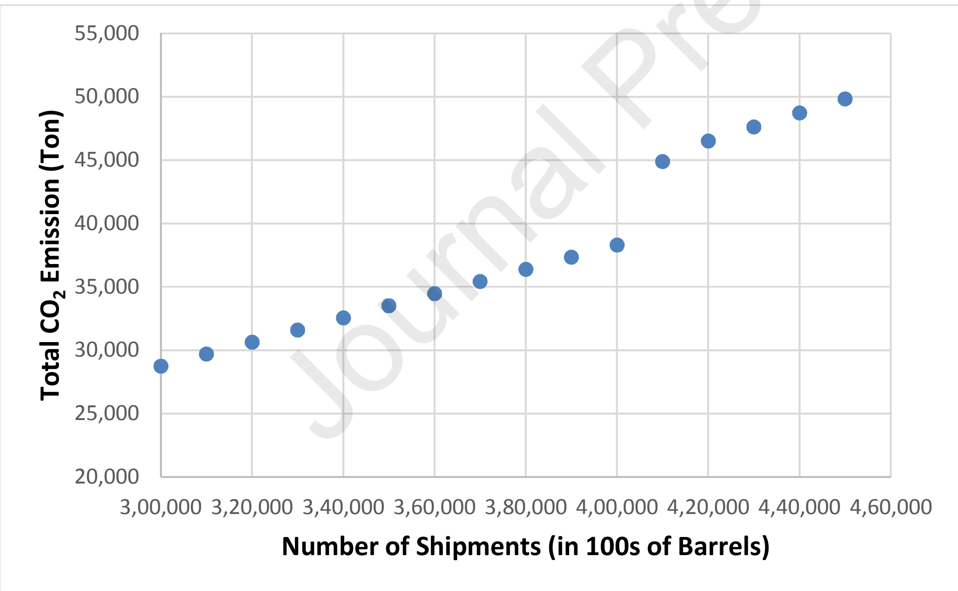


Figure 4. CO_2 emission vs. Number of shipments

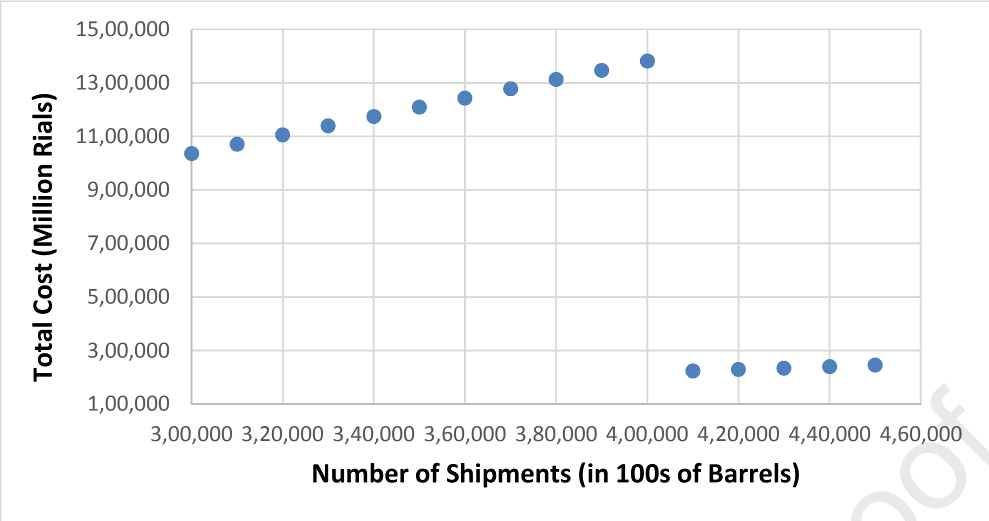


Figure 5. Cost vs. Number of shipments

3.4. Discussion & Managerial Insights

To illustrate the practicality of the presented model, we compared the results of our model applied in the case study with its current situation. The comparison is presented in Table 6; it shows that by applying the proposed model to our case study, the total risk decreases by 37.66%. It also generates a 12.53% reduction in CO_2 emission. Although the current situation has lower cost, since the vital issue of Hazmat transportation is a salient risk, we can assert that our presented model is efficient and practical for the described case-study. To be more specific, if the governmental authority (Hazmat carrier in our case study) can be persuaded to spend 959,931 million Rials (approximately equivalent to 4.7 million dollars), the annual CO_2 emitted by Hazmat will decrease by an expected 4,104,800 Kg and the Hazmat risk will decrease by an expected 1,300,290 people; i.e. 873 grams fewer CO_2 emission and 0.28 fewer individual at risk for every additional dollar spent. Quantifying the value of reducing CO_2 emission is challenging; however, "social cost of carbon" (SCC), which is a term referring to economic damage caused by one ton of CO_2 emission, is used as a metric for it (Diaz and Moore, 2017). According to the United States Environmental Protection Agency (EPA), the SCC in 2020 is around $123 (EPA, 2017). Considering this SCC amount and the importance of reducing the number of people at risk, the incremental practical value of the solution presented by our robust model is compelling.

Table 8
Comparison of current situation and proposed model

	Risk (people)	Cost (Million Rials)	CO_2 emission (kg)
Current situation	3,453,047.730	180,015	32,762,700
Proposed model	2,152,757.541	1,139,946	28,657,900
Gap (%)	-37.6563051%	+84.2084625%	-12.5288819%

In the first analyses discussed in this paper, we considered the same level of uncertainty for our uncertain parameters (cost, risk, emissions). However, it is not ecologically realistic to assume that the degree of uncertainty is equal among the three parameters. For instance, there are more unpredictable contributors (e.g., human error, weather conditions, etc.) affecting the risk of Hazmat transportation than affecting its cost. To consider the implications of this ecological asymmetry, we experimentally investigated how different levels of uncertainty for each uncertain parameter could influence the optimal solution. For this experiment, we analyzed different levels of uncertainty for each parameter, one at a time, keeping the uncertainty level of the other two parameters fixed at 0.5, and calculated the percentage change of the objective function with respect to the value of the objective function when uncertainty level is 0.5 for all three uncertain parameters. As Figure 6 shows, the uncertainty level of risk has the strongest effect on the value of the objective functions. This makes sense intuitively because total risk is the main function that we consider in our bounded objective function method. While cost uncertainty level has a weak effect on the objective function, emission uncertainty level has a considerably stronger effect. This further highlights the importance of considering uncertainty in CO_2 emission (in addition to risk uncertainty) for Hazmat transportation problems.

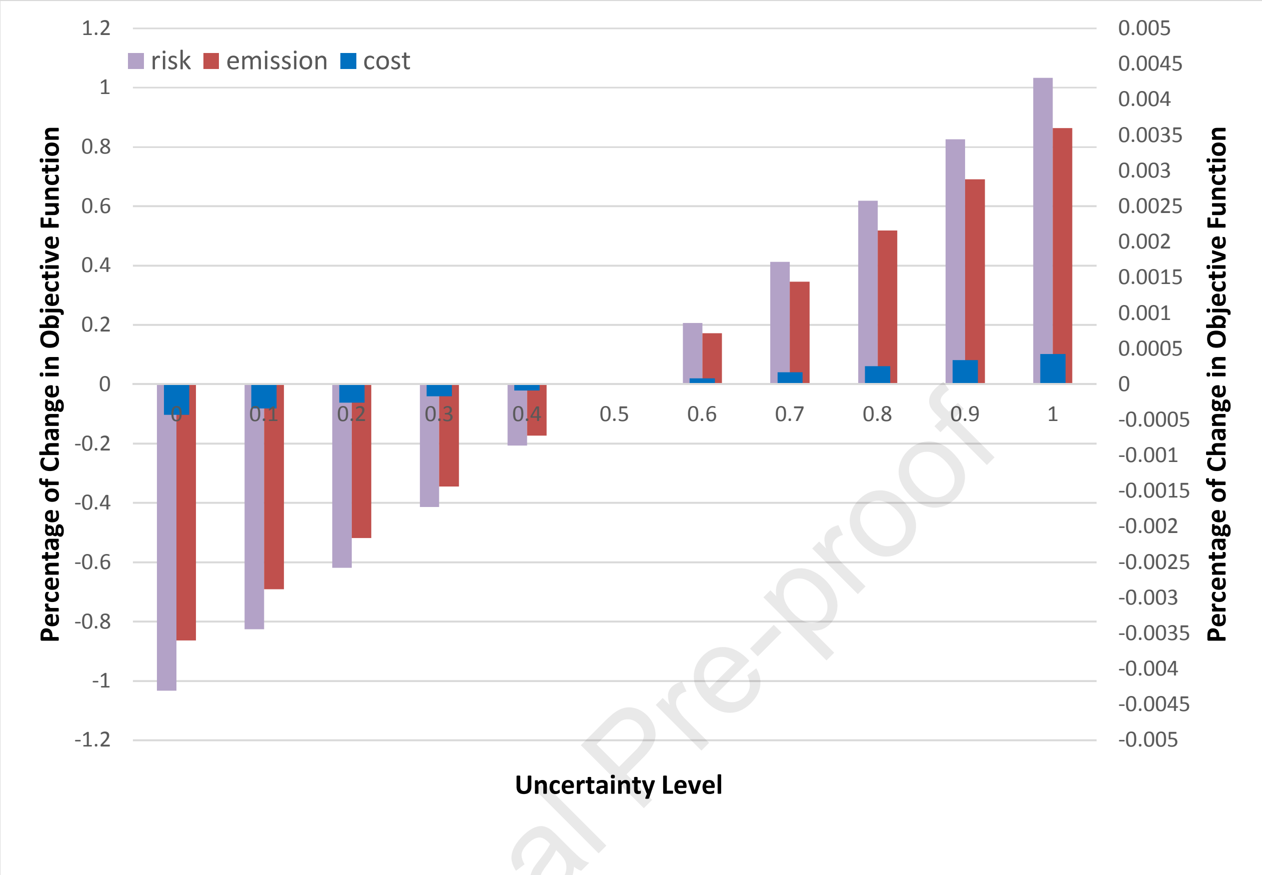


Figure 6. Percentage Change in Objective Function vs. Uncertainty Level

As our sensitivity analysis in section 3.3 demonstrates, an increase in the number of shipments not only increases the total cost, total risk, and total CO_2 emission of transportation for the optimal path, but also, because of capacity limitation, may sometimes force the carrier to deviate from the optimal path and choose a different path with relatively higher risk (Figure 3) and environment damage (Figure 4). In our study, the capacities of potential transfer points are exogenously determined. Thus, in order to investigate how the optimal solutions would change if we considered different transfer points' capacities, we conducted an additional experiment. We considered three sets of capacities for candidate transfer points: the current capacities, 90% of current capacities, and 150% of current capacities. By assuming that a transfer point's establishment cost linearly changes with its capacity, we obtained the optimal objective functions by number of shipments for each three sets of capacities (Figure 7-9). As shown in Figures 7-9, the general pattern for each specific objective function does not differ depending on capacity, but changes in capacity shift the pattern at differing points.

A number of managerial insights emerge from this experiment. First, as long as we can predetermine the capacity of transfer points that are reasonable given the number of shipments, there is no need to consider capacities as decision variables and optimize them; this helps to reduce the complexity and computational intensity of the model. Second, if decision makers know that the number of shipments will increase significantly in the future, considering the possible future number of shipments in the current optimization will enhance the longer-term value of the decision model.

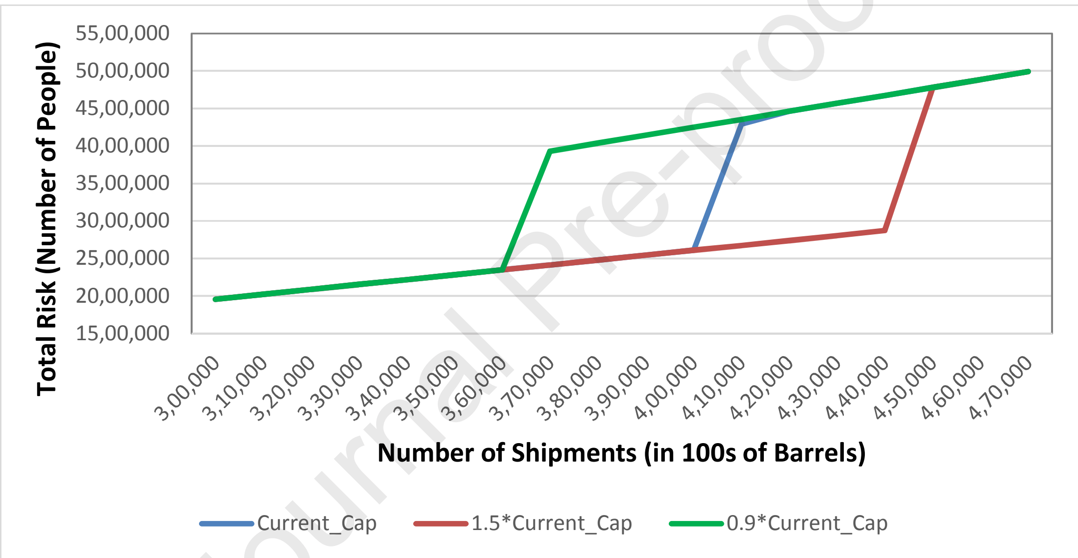


Figure 7. Risk vs. Number of shipments for different capacities of transfer points

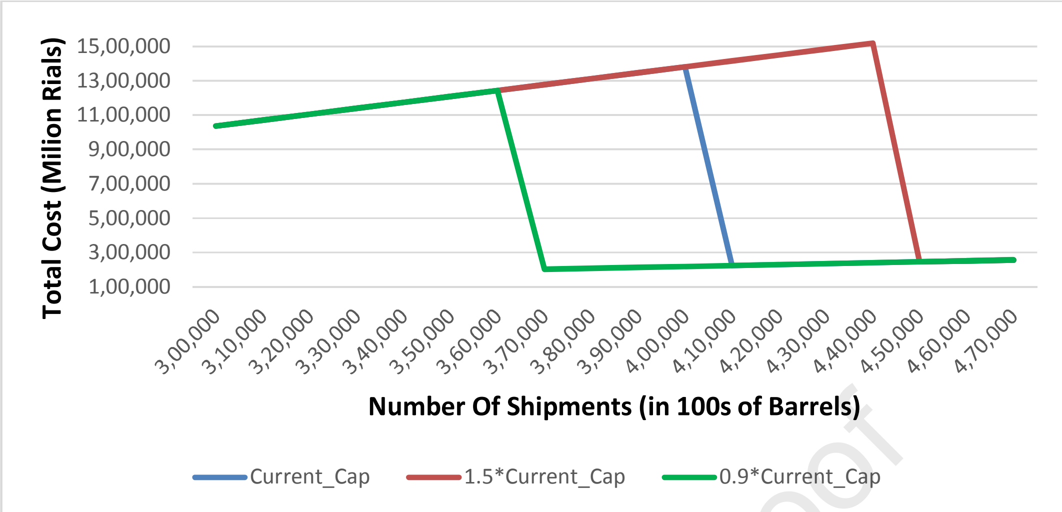


Figure 8. Cost vs. Number of shipments for different capacities of transfer points

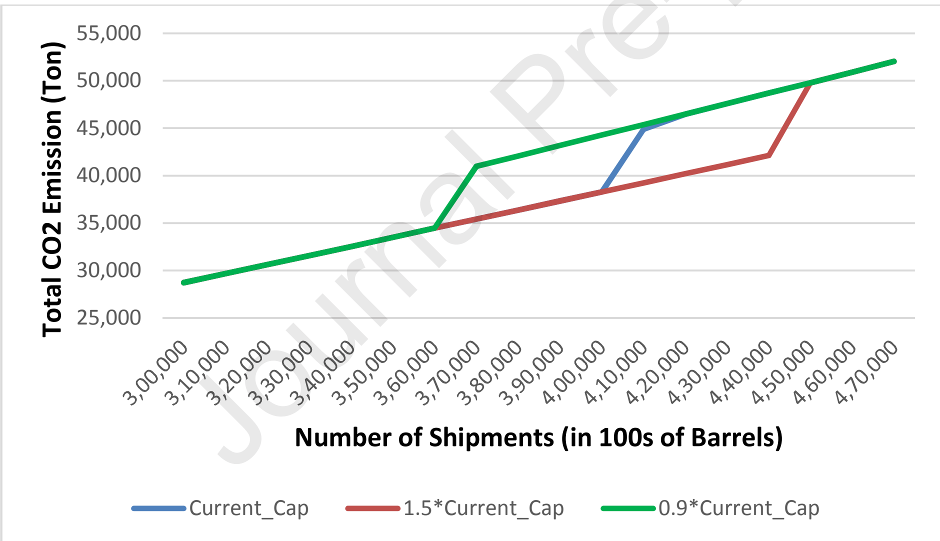


Figure 9. CO_2 emission vs. Number of shipments for different capacities of transfer points

A final managerial insight emerging from this paper is the importance of regulatory agencies setting realistic expectations for maximum allowed CO_2 emission. As the results of Table 8 show, if the required upper bound of CO_2 emission is less than a particular threshold, for our case $1.008\theta_e^*$, then the problem is infeasible. Hence, simply adopting the international level of allowable CO_2 emission may not work. The regulator, an environmental protection agency in our case, should instead determine a threshold which is feasible given the country's infrastructure.

4. Conclusion

This research presented a location-routing model for Hazmat transportation in a multi-modal network of highways and railways. We developed a mixed integer model to minimize total cost, risk, and CO_2 emission in Hazmat transportation. Cost of establishing transfer points, CO_2 emission factor, and accident probability were considered as uncertain parameters. These uncertainties were modeled by polyhedral uncertainty sets which allowed to obviate the need to know exact probability distribution functions of uncertain parameters. The proposed model was implemented in a real case study of the transportation of petroleum products. The results of the case study tentatively confirmed the robustness of the proposed model, as well as the incremental practical value of the solution presented by the robust model. Applying the model, we found that we can reduce CO_2 emissions by 873 grams, and individuals at risk by 0.28, for every additional dollar spent. Our analyses also showed that uncertainty of CO_2 emissions can have significant effects on optimal solutions, and hence highlighted the importance of considering uncertainty in parameters beyond only risk. Furthermore, we found that for a Hazmat transportation system, there is a minimum possible threshold for CO_2 emission, and aiming to have lower CO_2 emissions than this threshold renders the problem infeasible. This observation is particularly important for regulatory decision makers, pointing them to understand that the international level of allowable CO_2 emission may not work for the Hazmat transportation system in their particular country context.

The literature review of this paper, in conjunction with Holeczek's (2019) structured overview of the past half century of literature on Hazmat transportation problems, indicated that environmental issues have not been addressed sufficiently in Hazmat research. In this paper, we addressed CO_2 emission, though there are still other environmental aspects that future research can address. One of the most important of these issues is incorporating environment risk in Hazmat transportation decision making. Environment risk is distinguishable from direct bodily risk to humans. It is possible that a hazmat release may not directly injure or kill human beings but may rather cause severe damage to components of the natural environment such as water, soil, and ecology. Hence, future research direction could present optimization models that minimize environmental damage as well as population exposure and transportation cost.

Finally, we conducted our research in a multi-modal network with one origin-destination and for one type of Hazmat. However, in many real cases, a shared network is used for transportation of different types of Hazmat. Cordeiro et al. (2016) demonstrated that the Hazmat risk is strongly dependent on the type of transported Hazmat. Hence, designing a network that works well for different types of hazardous materials with different risks and costs offers an intriguing future direction for research. Finally, more analyses and tradeoff investigations at operational planning levels can be completed in future research. In this case, it might be required to develop new heuristics and metaheuristics that can solve larger problem instances within reasonable length of time.

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A green approach to location-routing for hazardous materials transportation under uncertainty

Highlights

- A robust location and routing model for hazardous materials is proposed.
- Co_2 emissions and risks of hazardous materials transportation are incorporated.
- Location costs, Co_2 emission factors and accident probabilities are uncertain.
- A multi-modal transportation network with limited capacity is considered.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: