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# Z-TRAPEZOIDAL RISK ASSESSMENT FOR MULTI-OBJECTIVE HAZMAT ROUTING MODEL WITH TIME WINDOWS

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**Abstract.** Hazardous material (Hazmat) transportation is an inseparable section of the industry, despite its major financial and health risks. In order to optimize Hazmat transportation, a multi-objective Hazmat routing model with time windows is employed where the risk and distance are minimized. Due to the uncertainty of Hazmat transportation risk, a Z-number fuzzy approach is used to estimate the risk, in which the probability of occurrence and the severity is considered in the context of Z-information. The severity of the event includes the affected population and depends on the amount of transported Hazmat and the number of individuals affected by the explosion. To tackle the proposed model, the present paper utilizes a multi-objective hybrid genetic algorithm, the validity of which is tested by Solomon's problems. Furthermore, the optimization of a case study concerning the Hazmat distribution in Iran is analyzed using the suggested approach to assess the efficiency of the proposed fuzzy problem in real-world applications.

**Mathematics Subject Classification.** 90B06, 90B50, 90C05, 90C29, 90C70, 68T20.

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## 1. Introduction

Hazmat mainly includes toxic gases, explosive materials, flammable liquids, and radioactive and corrosive substances. Because of the nature of these materials, their production, storage, and transportation activities may be accompanied by significant threats to society and the environment. Moreover, because Hazmat is commonly not consumed on the production site, but is used in factories and universities, the demand for this material is met by long-distance transportation. One of the most notable issues concerning Hazmat transport is the explosion event caused by a vehicle accident. Although, the probability of a vehicle accident is very low, the consequences can be very destructive [9]. If an accident occurs while transporting Hazmat, it may cause hazardous material leakage, explosion, poisoning, and some other events that probably will result in loss of life and property, environmental degradation, traffic disruption, etc. According to events and statistics reported in the oil and gas industry in 2004, there is an average of 1.09 lost time injuries (LTI) per million hours of work in Asia, Africa, and Europe. Statistics also highlights the fact that accident damage costs approximately \$70 billion annually [32]. Thus, regarding the industrialized countries' demand for Hazmat transportation and taking into account the statistics of accidents and injuries resulting from it, more research works are required to be conducted on this type of transportation, hoping to enhance safety and reduce its environmental impact.

*Keywords.* Vehicle routing problem with time windows, hazardous material, risk, Z-number.

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The nature of decisions related to Hazmat is multi-objective because each stakeholder (including transporters, managers, customers, and residents) has different and conflicting objectives that should be taken into account during the planning. The shortest path problem (SPP) of the vehicle routing problem (VRP) is often used to optimize Hazmat transportation [10]. The vehicle routing problem with time windows (VRPTW) optimizes the collection and distribution of goods from one depot to several customers using several vehicles with a specified time window [30]. Referring to the proportionality of the VRPTW problem to Hazmat transportation, utilizing the VRPTW with an additional objective function for the risk parameter can be useful in improving the transportation planning of this material.

As mentioned earlier, the nature of Hazmat transportation has the risk of accidents and explosions. In the real world, determining the risk parameters deterministically is not a simple task. As a result, the uncertain VRP can be employed, the majority of studies of which consists of the stochastic vehicle routing problem (SVRP) and the fuzzy vehicle routing problem (FVRP). The SVRP is used when parameters are random and the FVRP is utilized in when parameters are vague and unknown. Scholars have made great attempts so far to reach a desirable model to describe information uncertainty more rationally, a model that can accurately simulate human cognitive processes and decisions. Nonetheless, information related to the real-life is characterized not only by fuzzy constraints on the variable values but also by partial reliability. Hence, fuzzy assessments or other uncertainty modeling approaches cannot fully capture real-life problems. So, reliability should be considered in the risk assessment method [27]. The concept of Z-number was developed by Zadeh [54], which expresses both the limitations and the reliability of an assessment and is proposed as a more appropriate way to describe real-life information. Therefore, this paper presents a bi-objective Hazmat routing problem with time windows, the risk of which is estimated by a new Z-number formulation, and finally, the proposed problem is optimized using a multi-objective hybrid genetic algorithm.

The paper is organized as follows. Section 2 addresses the literature review on the research works in this realm to identify key problems and research gaps. Section 3 describes the mathematical model of the bi-objective Hazmat routing problem. In Section 4, Z-number risk calculations are provided and a genetic algorithm is designed. Section 5 analyzes and validates the results obtained by the algorithm. Section 6 examines a case study of a Hazmat distribution and, in the end, Section 7 provides a summary of the findings of the current research.

## 2. Literature review

The literature review of the paper addresses two subjects. The first is a review of the Hazmat routing problem and the second is a review of the fuzzy vehicles routing problem.

### 2.1. Hazmat routing problem

This section deals with the literature on the Hazmat routing problem. One of the first studies concerning Hazmat routing belongs to Tarantilis and Kiranoudis [48]. The authors attempt to select routes for Hazmat transportation in areas far from residential centers so that the number of people at risk is reduced in the event of an accident. Androutsopoulos and Zografos [2] presented a bi-objective time-dependent Hazmat routing problem with time windows. The risk in this study depends on the probability of the accident and the population around the event. Pradhananga *et al.* [39] also proposed a multi-objective vehicle routing problem with a time window for Hazmat transportation. Objective functions include minimizing the risk of accident and explosion of the vehicle and the total travel time. The authors optimized their proposed model using the multi-objective ant colony system (MOACS). Hamdi-Dhaoui *et al.* [25] presented a Hazmat routing problem considering two-dimensional loading. The proposed problem has two objectives: minimizing travel cost and load balancing between different routes. The authors solved their problem by a non-dominated sorting genetic algorithm II (NSGA-II). Kheirkhah *et al.* [28] proposed a bi-level vehicle routing problem for the hazardous materials transportation. The authors solved the bi-level optimization model by two metaheuristic algorithms.

Bula *et al.* [10] presented a heterogeneous vehicle routing problem for Hazmat transportation. The problem aimed to minimize the risk of routes. The risk considered in this paper depends on the accident rate, the probability of release of Hazmat, the vehicle load, the length of the link, the event-prone population, and the type of Hazmat. Finally, they solved the suggested model using the variable neighborhood search (VNS). In another study, Bula *et al.* [11] proposed a bi-objective heterogeneous vehicles routing problem for Hazmat transportation. Objectives of the problem include minimizing the risk and cost of transportation routes. The authors used a neighborhood search algorithm (NSA) to solve the model. Du *et al.* [16] described a multi-depot routing problem of Hazmat transportation. The authors first developed a fuzzy bi-level programming model to minimize the total transportation risk and optimized it using a metaheuristic algorithm.

Man *et al.* [33] presented a vehicle routing problem with limited capacity for Hazmat transportation. The objective function of the problem is to minimize the risk that depends on the accident rate, the probability of release of the Hazmat, the length of the link, and the population around the event. Additionally, the population density around the event is considered as a two-stage fuzzy parameter. Moghaddam and Azadian [34] dealt with a stochastic multi-objective vehicle routing problem to increase safety and speed of distribution of Hazmat. The authors also solved the model for a case study of the distribution of Hazmat in the U.S. In another study, Ouertani *et al.* [38] described a multi-objective dynamic vehicle routing problem with a time window for Hazmat distribution. The authors solved the given model using a GA combined with VNS. Ghannadpour *et al.* [21] presented a hazardous medical waste collection routing problem with sustainable development objectives, where the sustainable objective functions of the study consist of minimizing cost, fuel consumption, and risk.

Mohri *et al.* [35] presented a review paper for hazardous materials routing problems. They examined assumptions, constraints, objective functions, variables and parameters, solution approaches and case studies of hazardous material routing problems from 1980 to 2020. Rahbari *et al.* [42] proposed a location-inventory-routing problem for hazardous materials and waste management at two levels of the supply chain with considering a heterogeneous vehicle feet. The authors considered three objective functions for their problem, which include cost minimization, risk minimization, and greenhouse gas emission minimization. Zandieh and Ghannadpour [56] presented a time-dependent routing problem for Hazmat transportation. The authors determined the risk of Hazmat transportation by interval type-2 fuzzy logic controller. Then they designed a multi objective evolutionary algorithm based on decomposition to optimize the proposed problem. Table 1 provides a summary of the objective functions and risk characteristics of the problem along with the solution algorithm.

## 2.2. Fuzzy vehicles routing problem

Fuzzy vehicle routing problem includes one or more fuzzy variables or parameters. This section addresses some of these studies and the various types of fuzzy parameters considered in this problem. Brito *et al.* [8] proposed a close–open vehicle routing problems with time windows (COVRPTW), in which capacity and time window constraints are taken into account. The proposed problem is solved using a combination of three metaheuristic algorithms, namely, ant colony optimization (ACO), greedy randomized adaptive search procedure (GRASP), and VNS. Shi *et al.* [43] proposed a home treatment services routing problem with a time window in which customer demand was considered as a fuzzy parameter. As the demand is considered fuzzy in this study, the remaining capacity of the vehicle may be less than the customers' demand and a shortage may be encountered. To compensate for this shortage, the vehicle should return to the depot.

Ghannadpour and Zarrabi [18] presented a multi-objective model of heterogeneous vehicle routing with a time window that has three objective functions including minimizing fuel consumption, maximizing customer satisfaction, and minimizing the number of fleets. The fuzzy parameter of this paper is the customers' time window. To maximize customer satisfaction, customer service is provided as much as possible at a time with a maximum degree of membership. Zheng *et al.* [58] proposed a fuzzy electric vehicle routing problem with a time window that takes into account travel time, battery power consumption, and customer service time as fuzzy parameters. To optimize this problem, the adaptive large neighborhood search (ALNS) algorithm combined with fuzzy simulation was employed. Chen *et al.* [13] described a vehicle routing problem considering the type of transport between milk-run and cross-dock, in which the travel time was considered as a fuzzy number.

Table 1. A review of the literature focusing on the Hazmat routing problem.

| Reference | Objective(s) | | | Risk estimation parameters | Fuzzy risk | Solution algorithm |
|---|---|---|---|---|---|---|
| | Single | Multi | Items | | | |
| Androutsopoulos and Zografos [2] | | ✓ | TT, TR | pa, pop | | heuristic algorithm |
| Pradhananga *et al.* [39] | | ✓ | TT,TR | pa, pr, pi, pc, pdc, pop | | multi-objective ant colony optimization |
| Bula *et al.* [10] | ✓ | | TR | pa, pr, type, vl, length, ci | | variable neighborhood search |
| Du *et al.* [16] | ✓ | | TR | pa, area, ps | | heuristic algorithm |
| Bula *et al.* [11] | | ✓ | TC, TR | pa, pr, type, vl, length, ci | | neighborhood search algorithms |
| Men at al. [33] | ✓ | | TR | pa, pr, length, area, ps | ✓ | simulated annealing algorithm |
| Moghaddam and Azadian [34] | | ✓ | TD, TR | pu, pi | | hybrid game theory based compromise programming |
| Ouertani *et al.* [38] | | ✓ | TC, TR | pi, length, pop | | bi-population GA and the VNS |
| Ghannadpour *et al.* [21] | | ✓ | TC, TR, TFC | at, wv, type | | multi-objective self-adaptive genetic algorithm |
| Rahbari *et al.* [42] | | ✓ | TC, TR, TGE | – | | NSGA II, MOSA, and MOBWO |
| This study | | ✓ | TC, TR | pa, pop (area, ps), lo | ✓ | genetic algorithm |

**Notes.** TT: Travel Time, TR: Travel Risk, TC: Total Cost, TD: Total Distance, TFC: Total Fuel Consumption, TGE: Total greenhouse Gas Emission, MOSA: multi-objective simulated annealing algorithm, MOBWO: multi-objective black widow optimization.
pa: probability (rate) of accident, pop: expected population exposure, pr: (conditional) probability of release, pi: conditional probability of incident, pc: conditional probability of consequence, pdc: conditional probability of death consequence, type: type of Hazmat, vl: vehicle load, length: length of link, ci: consequences of incident, area: affected area of accident, ps: population density, pu: probability of using a link, at: arrival time, wv: waste volume, lr: load occupancy.

Zheng [59] suggested a VRPMTW (vehicle routing problem with multiple time windows) with respect to the time variation of traffic flow. The objective functions of the proposed problem include maximizing customer satisfaction and minimizing costs.

Figueroa–García *et al.* [17] presented an fuzzy capacitated VRP in which the travel cost and customer demand were formulated in the form of fuzzy numbers. The authors considered the membership function of the fuzzy parameters as a mix of triangular and Gaussian. Nozari *et al.* [36] proposed a multi-depot VRP for distribution of medical equipment in the COVID-19 pandemic. A robust fuzzy method controlled uncertain parameters, such as demand, transmission, and distribution costs. Raeisi and Jafarzadeh Ghoushchi [41] presented a multi-objective location-routing problem for hazardous wastes. The amount of generated waste and transportation costs were formulated as uncertain data in the form of trapezoidal fuzzy numbers. Singh *et al.* [45] presented a fuzzy stochastic capacitated vehicle routing problem. The authors assumed the demands as a stochastic parameter. Yang *et al.* [51] proposed a VRP with fuzzy demand and fuzzy time windows. This paper uses a fuzzy chance-constrained programming model based on credibility theory, minimizing the total logistics cost. Simultaneously, a random simulation algorithm is used to calculate the penalty cost of delivery failures caused by the demand that cannot be satisfied. Other studies of the vehicle routing problem in which at least one parameter is considered fuzzy can be mentioned [41, 53]. In some VRP studies, a fuzzy solution approach has been utilized (*e.g.* in [5, 40, 49, 57]).

Concerning the studies carried out so far, most of them consider fuzzy parameters in the vehicle routing, problem. Yet, fuzzy risk has rarely been considered in the conducted studies. Therefore, in this paper, a Hazmat routing problem is established by presenting a new formula for risk based on Z-number to provide appropriate risk analysis for the problem.

## 3. Fuzzy Hazmat routing problem

The vehicle routing problem with a time window includes $N$ customers. If the depot is assumed the 0-th customer, the set of customers of this problem is considered as $C = \{0, 1, 2, \ldots, N\}$. The maximum number of vehicles is represented by $K$. Link $ij$ connects two customers $i$ and $j$ and has a distance of $d_{ij}$and the risk of $r_{ij}$. Each customer has a time window in the form of $[e_i, l_i]$ , where $e_i$ and $l_i$are the earliest and latest service time to customer $i$, respectively. Customers' time window is hard, meaning that if the arrival time of a vehicle to the customer is less than $e_i$, the vehicle must wait for the start of the customer's time window, and if the time of arrival of the vehicle to the customer is greater than $l_i$, the goods will not be delivered. Customer $i$'s demand is $m_i$ and the capacity of the $k$-th vehicle is shown by $Q_k$. A route consists of a loop of several customers and the depot, in which the vehicle starts traveling from the depot and returns to the depot after providing service to all the customers on the route. The total demand of customers for a route should not exceed the capacity of the vehicle ($Q_k$). Moreover, the total travel time on a route should not violate the maximum service time of the vehicle ($r_k$). The decision variables of the proposed model are $x_{ijk}$, $u_i$, $w_i$, $D^k_{ij}$, $x_{ijk}$, $\tilde{S}_{ijk}$ and $\tilde{R}_{ijk}$. The indices, parameters, and variables related to the proposed model are summarized as follows.

**Nomenclature of mathematical formulation**

*Indices*

| | |
|---|---|
| $i, j, h$ | indices of customers and depot ($i, j \in C$) |
| $k$ | index of vehicles ($k \in K$) |

*Parameters*

| | |
|---|---|
| $d_{ij}$ | travel distance between node $i$ and node $j$ |
| $m_i$ | demand of customer $i$ |
| $e_i$ | earliest allowable service time for customer $i$ |
| $l_i$ | latest allowable service time for customer $i$ |
| $Q_k$ | capacity of vehicle $k$ |
| $s_i$ | time needed to service customer $i$ |
| $t_{ij}$ | travel time between nodes $i$ and $j$ |
| $r_k$ | maximum allowed time of vehicle $k$ |
| $\tilde{P}_{ij}$ | fuzzy probability of accident in link $ij$ |
| $p\tilde{o}p_{ij}$ | maximum number of people affected by the Hazmat in link $ij$ per maximum vehicle load |
| $M$ | A big number |

*Decision variables*

| | |
|---|---|
| $x_{ijk}$ | variable set to 1 if the vehicle $k$ travels from node $i$ to node $j$ |
| $u_i$ | arrival time at customer $i$ |
| $w_i$ | waiting time at node $i$ |
| $D^k_{ij}$ | the load of vehicle $k$ when travels from node $i$ to node $j$ |
| $\tilde{R}_{ijk}$ | the fuzzy risk of vehicle $k$ when travels from node $i$ to node $j$ |
| $\tilde{S}_{ijk}$ | fuzzy severity of accident of vehicle $k$ in link $ij$ |
| $\theta_{ijk}$ | Occupancy rate (The ratio of vehicle load to vehicle capacity in link $ij$) |

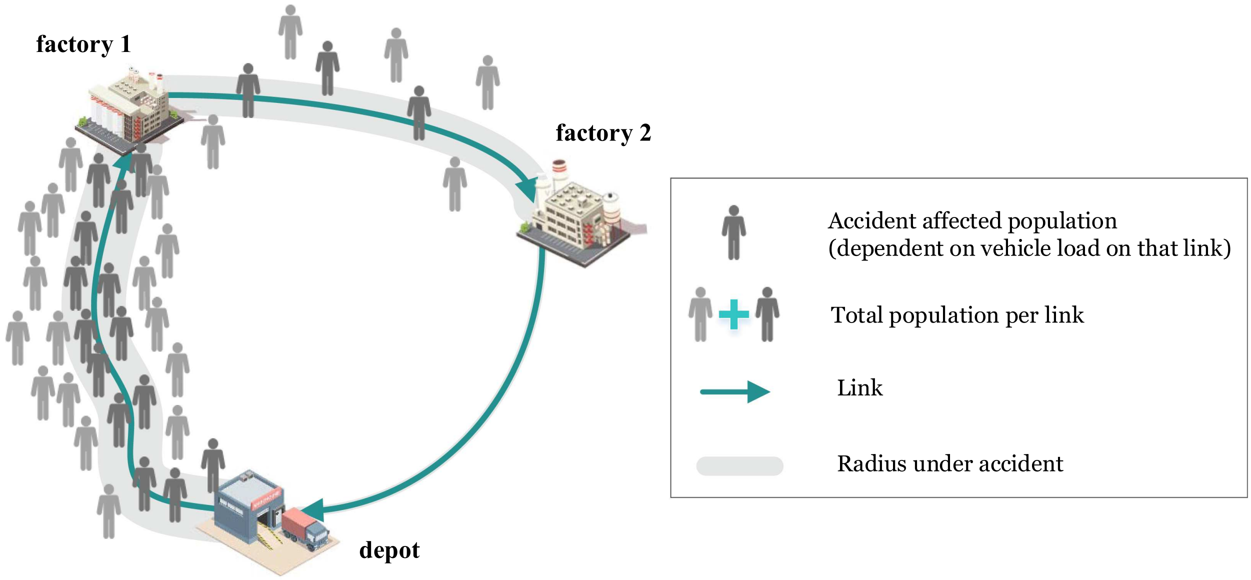


FIGURE 1. An instance of Hazmat routing problem with fuzzy risk.

### 3.1. Risk estimation

The Hazmat transportation risk includes a vehicle accident and the resulting explosion and fire. This risk depends on various factors that cannot be estimated with certainty. In this paper, the effective factors in the risk of the exposed population and the probability of the event are assumed as fuzzy parameters. Thus, the fuzzy equation (1) is presented to estimate the Hazmat transportation risk.

$$\tilde{R}_{ijk} = \tilde{S}_{ijk}\tilde{P}_{ij}\forall i,j \in C, \quad \forall k \in K \tag{1}$$

where $\tilde{R}_{ijk}$represents the risk of the fuzzy vehicle $k$ in link $ij$. The parameter $\tilde{P}_{ij}$indicates the fuzzy probability of occurrence of an accident in link $ij$, which is determined according to the expert's opinion. The variable $\tilde{S}_{ijk}$shows the severity of the effect of the accident. This variable represents the population affected by the explosion, which depends on the population density around the link and the amount of Hazmat transported. To put it simply, to calculate this variable, the approximate number of people close to the accident, who are affected depending on the amount of vehicle load, is estimated. Therefore, the value of $\tilde{S}_{ijk}$is calculated as equation (2).

$$\tilde{S}_{ijk} = p\tilde{o}p_{ij}\theta_{ijk}\forall i,j \in C, \quad \forall k \in K. \tag{2}$$

In this equation, $p\tilde{o}p_{ij}$ represents the maximum number of people affected by the accident in link $ij$ per maximum vehicle load. Also, $\theta_{ijk}$ denotes the ratio of vehicle load $k$ to the maximum load (vehicle capacity) in link $ij$.

Figure 1 shows a vehicle routing problem for Hazmat distribution from the depot to several factories. This figure illustrates the total population close to the accident site and the population affected by the accident. As seen in the figure, fleet routing planning is highly hazardous because the vehicle passes through crowd points when it carries the heaviest load. It is worth mentioning that because the vehicle load in the link connecting factory 2 to the depot is zero, there is no risk of explosion as a consequence of a vehicle accident.

### 3.2. Mathematical modeling

The bi-objective model of the Hazmat routing problem with minimizing the transportation distance and risk is described as follows.

$$\text{Min} f_1 = \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j \neq i, j=0}^{N} d_{ij} x_{ijk} \tag{3}$$

$$\text{Min} f_2 = \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j \neq i, j=0}^{N} \tilde{R}_{ijk} x_{ijk} = \tilde{S}_{ijk} \tilde{P}_{ij} = p\tilde{o}p_{ij} \theta_{ijk} \tilde{P}_{ij} \tag{4}$$

$$s.t. \tag{5}$$

$$\sum_{k=1}^{K} \sum_{j=0}^{N} x_{0jk} \leq |K|$$

$$\sum_{k=1}^{K} \sum_{\substack{i=0 \\ i \neq j}}^{N} x_{ijk} = 1 \forall j \in C \setminus \{0\} \tag{6}$$

$$\sum_{\substack{j=0 \\ j \neq i}}^{N} x_{ijk} \leq 1 \forall i \in C, \forall k \in K \tag{7}$$

$$\sum_{\substack{j=0 \\ j \neq i}}^{N} x_{jik} \leq 1 \forall i \in C, \forall k \in K \tag{8}$$

$$\sum_{i=0}^{N} x_{ihk} - \sum_{j=0}^{N} x_{hjk} = 0 \forall h \in C, \forall k \in K \tag{9}$$

$$\sum_{\substack{j=0 \\ j \neq i}}^{N} \sum_{k=1}^{K} D_{ji}^{k} - \sum_{\substack{j=0 \\ j \neq i}}^{N} \sum_{k=1}^{K} D_{ij}^{k} = m_i \forall i \in C \setminus \{0\} \tag{10}$$

$$\sum_{i=0}^{N} \sum_{\substack{j=0 \\ j \neq i}}^{N} m_i x_{ijk} \leq Q_k \forall k \in K \tag{11}$$

$$\theta_{ijk} = D_{ij}^{k} / Q_k \forall i, j \in C, \forall k \in K \tag{12}$$

$$u_i + s_i + w_i + t_{i0} - (1 - x_{i0k})\, M \le T_k \forall i \in C \setminus \{0\} \tag{13}$$

$$u_0 = w_0 = s_0 = 0 \tag{14}$$

$$u_i + s_i + w_i + t_{ij} - (1 - x_{ijk})\, M \le t_j \forall i \in C \setminus \{0\}\;, \forall i \ne j \in C, \forall k \in K \tag{15}$$

$$e_i \le (u_i + w_i) \le l_i \forall i \in C \setminus \{0\} \tag{16}$$

$$x_{ijk} \in \{0, 1\}\;, at_i \ge 0, w_i \ge 0, D_{ij}^k \ge 0, \theta_{ijk} \ge 0, \forall i, j \in C, \forall k \in K. \tag{17}$$

Equations (3) and (4) show the objective functions of the problem, with equation (3) minimizing the distance and equation (4) minimizing the risk. Constraint (5) guarantees a maximum $K$ routes out of the depot. Equations (6), (7), and (8) guarantee that each customer is serviced exactly once by a vehicle. Constraint (9) ensures that if a node is entered by a vehicle, it should leave from the same node. Equation (10) calculates the vehicle load. Constraint (11) applies the capacity constraint. Equation (12) calculates Occupancy rate of vehicle $k$ in link $ij$. Constraint (13) is related to the maximum service time of each vehicle. Equation (14) ensures that the starting time from the depot, the waiting time, and the service time of the depot are zero. Constraint (15) calculates the arrival time of each customer. Equation (16) applies the time window limit to customers.

# 4. The proposed solution approach

The proposed solution approach involves optimizing the problem by a multi-objective hybrid genetic algorithm in which the risk is calculated using Z-number. Therefore, in this section, first the Z-number risk assessment is described then the details of the proposed algorithm are explained. Figure 2 shows the conceptual model of the proposed solution approach.

## 4.1. Z-number risk assessment

As mentioned earlier, in this paper, the risk is considered a fuzzy Z-number. To this end, a triple Z-valuation is defined for risk assessment, in which risk assessment factors are expressed as Z-numbers. The Z-valuation of expert $e$ for risk factor $l$ ($S$ and $P$) is defined as equation (18).

$$\tilde{Z}_l^e = \left(FM_l, \tilde{A}_l^e, \tilde{B}_l^e\right) \begin{array}{c} i = 1, \ldots, \mathcal{M} \\ l = 1, \ldots, L \\ e = 1, \ldots, E \end{array} \tag{18}$$

where $FM_l$ gives the degree of risk factors of risk $l$. Also, $\tilde{A}_l^e = (a_{l1}^e, a_{l2}^e, , a_{l3}^e, a_{l4}^e)$ and $\tilde{B}_l^e = (b_{l1}^e, b_{l2}^e, b_{l3}^e)$ respectively denote risk prevention and reliability, where $a_{lh}^e\,(h = 1, 2, 3, 4) \in [0, 10]$ and $b_{lh}^e\,(h = 1, 2, 3) \in [0, 1]$. The Z-number can then be interpreted to mean that the fuzzy probability $FM_l$is equal to $\tilde{A}_l^e$and the fuzzy probability $\left(FM_l, \tilde{A}_l^e\right)$ is $\tilde{B}_l^e$.

In the next step, the values of risk factors (severity of effect, probability of occurrence) are determined between 0 to 10 according to Table 2. The population affected by the accident was determined based on a study [52]. According to this study, the population affected by the earthquake and its score is determined based on the statistics of people affected by real earthquakes in the world, which is available on reference [24]. The maximum population that has been under the earthquake so far is corresponding to 5 and other scores are specified based on it. In this paper, a similar approach has been taken. According to studies on the statistics of Hazmat transportation events, one of the most events with the greatest population affected by the event is related to an event in Ohio that affected approximately 3700 people [26]. Trapezoidal fuzzy numbers are also

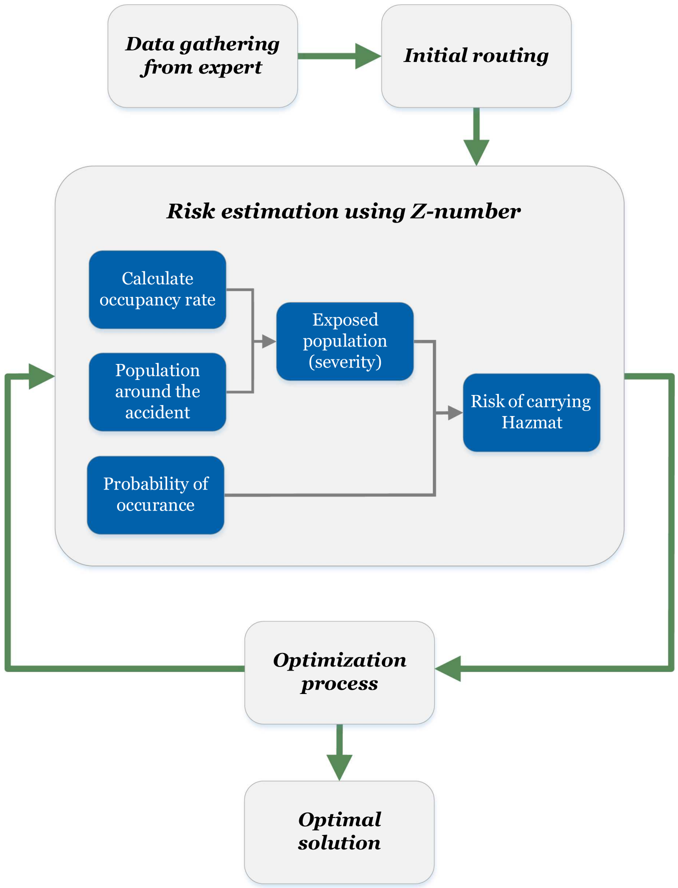


FIGURE 2. Conceptual model of the proposed solution approach.

TABLE 2. Risk index parameters for risk estimation.

| Linguistic variables | | Trapezoidal fuzzy numbers |
|---|---|---|
| Affected population | Probability of event | |
| very low (0–100) | very low | $(0, 1, 2, 3)$ |
| Low (100–1000) | low | $(1, 2, 3, 4)$ |
| Medium (1000–2000) | medium | $(3, 4, 5, 6)$ |
| High (2000–3000) | high | $(5, 6, 7, 8)$ |
| very high (>3000) | very high | $(7, 8, 9, 10)$ |

determined using trapezoidal fuzzy numbers of a study conducted by Zheng *et al.* [60]. Therefore, the scales of a population affected by the event are expressed according to Table 2.

The rules of transformation are listed in Table 3.

To transform the Z-number risk, initially, the second component of the Z-number (reliability) is transformed to a crisp number by equation (19).

$$\delta = \frac{\int x\mu_{\tilde{B}}(x)\,\mathrm{d}x}{\int \mu_{\tilde{B}}(x)\,\mathrm{d}x}. \tag{19}$$

TABLE 3. Transformation rules of linguistic variables of reliabilities [1].

| Linguistic terms | Very low | Low | Medium | High | Very high |
|---|---|---|---|---|---|
| Membership function | $(0, 0, 0.3)$ | $(0.1, 0.3, 0.5)$ | $(0.3, 0.5, 0.7)$ | $(0.5, 0.7, 0.9)$ | $(0.7, 1, 1)$ |

In the above equation, $\delta$ and $\mu_{\tilde{B}}\,(x)$ represent the reliability weight and degree of membership $x \in X$ in the set $\tilde{B}$, respectively. In the next step, the Z-number is transformed using equation (20).

$$\tilde{Z}^{\delta} = \left\{ \left(x, \mu_{\tilde{A}^{\delta}}\right) | \mu_{\tilde{A}^{\delta}}\,(x) = \delta \mu_{\tilde{A}}\,(x)\,, x \in [0, 10] \right\} \tag{20}$$

where $\mu_{\tilde{A}^{\delta}}\,(x)$ denotes the degree of membership $x \in X$ in the set $\tilde{A}^{\delta}$. Refer to [23] for more details on this method.

Given that the weight of each expert is different for the risk components, the fuzzy numbers $\tilde{V}$ corresponding to the expert $e$ are combined as given in equation 21.

$$\tilde{V} = \left( \sum_{e=1}^{E} w_e a_1^e, \sum_{e=1}^{E} w_e a_2^e, \sum_{e=1}^{E} w_e a_3^e, , \sum_{e=1}^{E} w_e a_4^e \right) = \left(\bar{a}_1, \bar{a}_2, \bar{a}_3, \bar{a}_4\right). \tag{21}$$

In the above equation, $\tilde{V}$ is the weight combination related to experts' fuzzy numbers $(\tilde{Z}^{\delta})$ and $w_e$is the weight of each of the experts. In the end, the risk of Z-number obtained for link $ij$ is defuzzified using equation (22) (for more details on this method, the reader can refer to [12]).

$$ZRPN_{ij} = \frac{\mathrm{M}_{ij} - \mathrm{N}_{ij}}{\mathrm{M}_{ij} + \mathrm{N}_{ij} + \left(100 - COG\left(A_{ij}\right)\right)} \tag{22}$$

where $\mathrm{M}_{ij} = LN_{ij} + RN_{ij}$and $\mathrm{N}_{ij} = LP_{ij} + RP_{ij}$are established. Also,$LN_{ij}$, $RN_{ij}$, $LP_{ij}$, and $RP_{ij}$ represent the left negative area, the right negative area, the left positive area, and the right positive area (as shown in Fig. 3), respectively. $COG\,(A_{ij})$ is the center of gravity of the fuzzy number $A_{ij}$, which is calculated using equation (23).

$$COG\left(A_{ij}\right) = \frac{\int_{x_1}^{x_2} x g_1\,(x)\,\mathrm{d}x + \int_{x_2}^{x_3} x g_2\,(x)\,\mathrm{d}x + \int_{x_3}^{x_4} x g_3\,(x)\,\mathrm{d}x}{\int_{x_1}^{x_2} g_1\,(x)\,\mathrm{d}x + \int_{x_2}^{x_3} g_2\,(x)\,\mathrm{d}x + \int_{x_3}^{x_4} g_3\,(x)\,\mathrm{d}x}. \tag{23}$$

## 4.2. Multi-objective hybrid genetic algorithm

The vehicle routing problem belongs to NP-hard problems due to its high computational complexity and many conditional constraints. Genetic algorithms has been successful in solving NP-hard problems [4,7,15]. The genetic algorithm is based on the evolution theory, and the solutions improve through repeated modification and natural selection [29]. This algorithms and related hybrids have many advantages over traditional optimization algorithms, such as being capable of handling complex and parallel problems. Genetic algorithms can deal with various optimization problems, including time-varying or fixed, linear or nonlinear, and continuous or non-continuous objective functions, or those with stochastic noise. Since various offspring in a population act like independent factors, the population (or each subset) can explore the search space in different directions. High robustness, excellent convergence, and effective global search are other advantages of this algorithm. Nonetheless, poor local search ability, low search efficiency in final iterations, and high dependence on parameters setting are some of its demerits [6,50].

In the proposed genetic algorithm, the initial population is formed randomly. In the next step, the parent population is selected by tournament selection, then crossover and mutation are applied to the parent population and the offspring population is formed. In the next step, the offspring population is improved by neighborhood

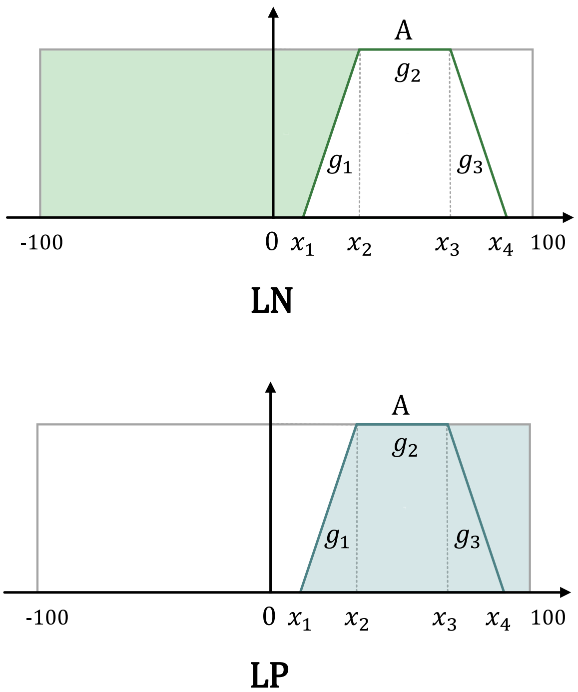


FIGURE 3. Areas in the positive and negative sides of the fuzzy number $\tilde{A}_{ij}$.

search algorithms. To maintain suitable solutions for each population, the elitism is performed in each iteration. In other words, several desirable solutions replace the undesirable solutions of the offspring population. Finally, this process continues until the best solution in each objective function converges (Refer to the Appendix to view the flowchart of the proposed algorithm).

*4.2.1. Crossover*

In this paper, the best cost route crossover (BCRC) [37] is used for crossover operation. In this method, a route is selected from one parent and the customers in that route are deleted in the other parent, and then the deleted customers on each chromosome are placed in the lowest possible and least risky position. This results in two parent chromosomes of the two offspring, which are likely to be less costly and risky. Figure 4 shows how to select a random route from each parent and remove the customers of that route from the opposite parent.

*4.2.2. Mutation*

To mutate the population solutions, three reverse, routes swaps, swap algorithms are used as follows.

*Reverse algorithm:* In this algorithm, two points are randomly selected from a route and the point between them is reversed [19].

*Route swaps:* Two points are selected randomly and their routes are swapped from two selected points [20].

*Swap:* In this algorithm, two points are randomly selected from one or more routes and then are swapped.

*4.2.3. Hill-climbing*

In the neighborhood search process, an algorithm is used to extract the solution space in the neighborhood of the current solution. In this algorithm, a point from a route is selected randomly and removed from its route. It is then placed in intra-route or inter-route so that a non-dominated solution is established. Figure 5 shows the neighborhood search algorithm.

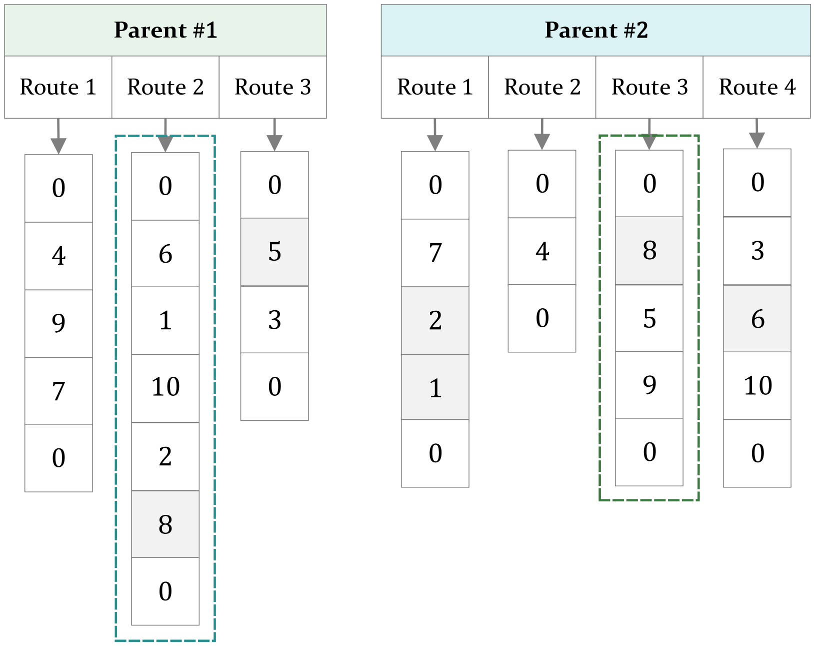


FIGURE 4. Graphical representation of customers deletion in BCRC.

TABLE 4. Parameter setting of the proposed genetic algorithm.

| Parameters | Lower bound (−1) | Upper bound (+1) | Optimum value |
|---|---|---|---|
| Number of population | 50 | 150 | 100 |
| Maximum iteration | 500 | 1000 | 600 |
| Probability of crossover | 0.1 | 0.9 | 0.7 |
| Probability of mutation | 0.1 | 0.9 | 0.4 |
| Probability of hill-climbing | 0.1 | 0.9 | 0.7 |
| Number of elitism | 1 | 4 | 4 |

## 5. Results and discussion

To evaluate the proposed algorithm, initially, the algorithm parameters are set and then its performance is measured by a set of Solomon's problems [46].

### 5.1. Parameter setting

Parameter setting is highly recommended when applying metaheuristics to any problem domain [3]. Appropriate design of the parameters and operators has a significant impact on the efficiency of the imperialistic competitive algorithm [44]. Thus, to achieve an effective and robust algorithm, parameter setting in an appropriate manner is a necessary step in establishing a meta-heuristic algorithm. In this paper, the response surface methodology (RSM) is employed as an effective approach to adjust the parameters of the proposed algorithm. The RSM method is considered as a design of the experiments (DOE) method which imposes an upper boundary and a lower boundary for each parameter. The upper and lower boundaries assumed for the parameters of the proposed algorithm along with its optimal value are tabulated in Table 4.

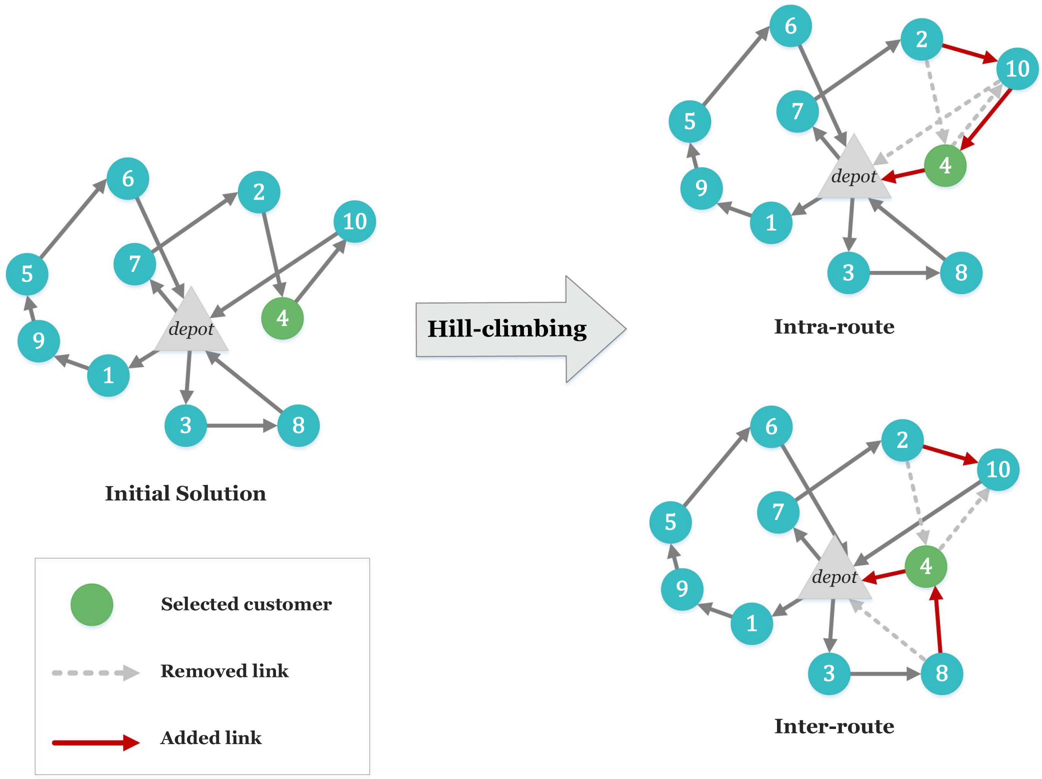


FIGURE 5. Single-point neighborhood search.

## 5.2. Numerical test

In this section, several Solomon problems in different sizes (25, 50, and 100) are optimized using the proposed algorithm and compared with the best-known solutions. The results of this evaluation are provided in Table 5. The best-known values for 25-and 50-customer problems are downloadable from the branch and value algorithm at [47] The best-known values of [22] are also used for 100-customer problems.

Referring to Table 5, the effect uncertainty of Z-number on the distance and safety of Hazmat transportation is investigated. If the problem is optimized only by the distance objective function, the distance is reduced but the transportation risk is increased, which indicates increased damage to the population around the event. As can be seen in the risk difference column for minimum distance response and the minimum risk response, when the problem is optimized with distance and risk minimization objectives, the risk is greatly reduced, which can help improve transportation safety and reduce the damage caused by vehicle explosions. For instance, in the R105 problem, the proposed bi-objective solution approach reduces the risk of accident and explosion of a vehicle by 35.35% by increasing the transportation distance up to 29.69%.

Also, the performance of the proposed algorithm is compared with NSGA-II [14], which is represented in Table 6.

As can be seen in Table 6, the proposed algorithm outperforms the NSGA-II algorithm on average. So that the proposed algorithm is 0.82% better than NSGA-II in the distance objective function and −34.99% better than NSGA-II in the risk objective function.

Nonetheless, it is worth noting that since risk and distance objective functions are inversely correlated, reducing the risk leads to increasing the distance and, as a result, increases the transportation system costs.

TABLE 5. Results of the proposed genetic algorithm.

| Problem | $\|N\|$ | BKS (distance) | Min distance | | Min risk | | Dev._B% | Dev._D% | Dev._R% |
|---|---|---|---|---|---|---|---|---|---|
| | | | TD | TR | TD | TR | | | |
| C201 | 25 | 214.7 | 216.25 | 1.05 | 469.07 | 0.55 | 0.71 | 54.23 | 47.62 |
| C207 | 25 | 214.5 | 215.34 | 1.11 | 446.16 | 0.53 | 0.39 | 54.73 | 52.25 |
| R105 | 25 | 530.5 | 531.53 | 0.99 | 755.96 | 0.64 | 0.19 | 29.69 | 35.35 |
| R210 | 25 | 404.6 | 410.60 | 1.01 | 730.28 | 0.54 | 0.18 | 43.77 | 46.53 |
| RC104 | 25 | 306.6 | 307.14 | 1.32 | 782.00 | 0.79 | 0.18 | 60.72 | 40.15 |
| R101 | 50 | 1044.0 | 1069.51 | 2.03 | 1494.34 | 1.83 | 2.39 | 28.70 | 9.85 |
| R211 | 50 | 535.5 | 563.73 | 2.41 | 1075.03 | 1.79 | 5.00 | 47.56 | 25.73 |
| RC102 | 50 | 822.5 | 840.27 | 2.60 | 1630.00 | 1.64 | 2.11 | 48.45 | 36.92 |
| RC107 | 50 | 642.7 | 645.58 | 3.19 | 1725.78 | 1.71 | 0.45 | 62.59 | 46.39 |
| RC204 | 50 | 444.2 | 444.97 | 2.28 | 1772.90 | 1.47 | 0.17 | 74.69 | 35.52 |
| C102 | 100 | 828.94 | 828.94 | 6.20 | 2214.57 | 4.87 | 0.00 | 62.57 | 21.45 |
| C202 | 100 | 591.56 | 591.56 | 6.76 | 2562.16 | 4.10 | 0.00 | 76.91 | 43.60 |
| C207 | 100 | 588.29 | 591.62 | 6.10 | 1810.42 | 4.05 | 0.56 | 67.32 | 33.60 |
| R108 | 100 | 960.26 | 1011.11 | 5.62 | 1683.22 | 4.56 | 5.03 | 39.93 | 18.86 |
| R111 | 100 | 1096.72 | 1206.04 | 5.05 | 1489.70 | 4.73 | 9.07 | 19.04 | 6.34 |
| R112 | 100 | 976.99 | 1085.92 | 5.70 | 1596.14 | 4.93 | 9.03 | 31.97 | 13.51 |
| R204 | 100 | 789.72 | 808.63 | 4.29 | 1437.76 | 3.58 | 2.34 | 43.76 | 16.55 |
| RC102 | 100 | 1470.26 | 1553.23 | 5.62 | 1786.56 | 4.94 | 5.34 | 13.06 | 12.10 |
| RC203 | 100 | 1026.61 | 1054.18 | 4.33 | 1751.00 | 3.52 | 2.62 | 39.80 | 18.70 |
| RC205 | 100 | 1300.25 | 1220.19 | 3.67 | 1797.08 | 3.46 | −6.56 | 32.10 | 5.72 |

**Notes.** Best Known solution for distance objective; Dev._B: distance deviation of BKS and solutions with the best distance; Dev._D: distance deviation of solutions with the best distance and solutions with the best risk; Dev._R: risk deviation of solutions with the best distance and solutions with the best risk.

Yet, given that the damage caused by the accident and the explosion of the vehicle concerns humans and the environment, sometimes the cost saved by using the solution with the minimum distance may damage the Hazmat transportation system and lead to irreparable damage. Figure 6 indicates the inverse relationship between risk and distance objective functions in the Pareto fronts of R105 and R210 problems.

### 5.3. Sensitivity analysis

In this part, a small-sized example is designed, and the performance of the Z-number approach in estimating the risk is evaluated. The example is optimized by the proposed approach and the classic method (with certain parameters and variables). Then, the solutions are compared. The example includes five customers and one depot. The best risk value in the approach based on Z-number is 0.3435. Also, the risk associated with the solution to the classic approach with the best risk is calculated using Z-number. This is because the accuracy of the Z-number is more than that of the classic method, and the solution of the classic method contains an error. The risk associated with the solution to the classic method is 0.4067. Therefore, the solution of the classic method has an error of 18% compared with the Z-number approach. Figure 7 represents these solutions in detail. The average risk for the links of the two solutions is 0.0535. If the links with a risk higher than this value are considered the risky links, the solution of the Z-number approach includes two risky links, while that of the classic solution contains four risky links.

TABLE 6. Transformation rules of linguistic variables of reliabilities.

| Problem | $\|N\|$ | Proposed genetic algorithm | | NSGA-II | | Dev._D% | Dev._R% |
|---|---|---|---|---|---|---|---|
| | | Min TD | Min TR | Min TD | Min TR | | |
| C201 | 25 | 216.25 | 0.55 | 235.20 | 0.63 | −8.76 | −14.55 |
| C207 | 25 | 215.34 | 0.53 | 231.57 | 0.68 | −7.54 | −28.30 |
| R105 | 25 | 531.53 | 0.64 | 556.43 | 0.71 | −4.68 | −10.94 |
| R210 | 25 | 410.60 | 0.54 | 415.31 | 0.54 | −1.15 | 0.00 |
| RC104 | 25 | 307.14 | 0.79 | 307.14 | 0.79 | 0.00 | 0.00 |
| R101 | 50 | 1069.51 | 1.83 | 1091.44 | 4.92 | −2.05 | −168.85 |
| R211 | 50 | 563.73 | 1.79 | 569.73 | 2.38 | −1.06 | −32.96 |
| RC102 | 50 | 840.27 | 1.64 | 840.31 | 1.64 | 0.00 | 0.00 |
| RC107 | 50 | 645.58 | 1.71 | 490.41 | 1.47 | 24.04 | 14.04 |
| RC204 | 50 | 444.97 | 1.47 | 444.97 | 1.47 | 0.00 | 0.00 |
| C102 | 100 | 828.94 | 4.87 | 828.94 | 8.19 | | −68.17 |
| C202 | 100 | 591.56 | 4.10 | 687.40 | 5.45 | −16.20 | −32.93 |
| C207 | 100 | 591.62 | 4.05 | 620.35 | 2.82 | −4.86 | 30.37 |
| R108 | 100 | 1011.11 | 4.56 | 1042.38 | 5.56 | −3.09 | −21.93 |
| R111 | 100 | 1206.04 | 4.73 | 1229.82 | 10.60 | −1.97 | −124.10 |
| R112 | 100 | 1085.92 | 4.93 | 1132.00 | 10.10 | −4.24 | −104.87 |
| R204 | 100 | 808.63 | 3.58 | 875.36 | 9.25 | −8.25 | −158.38 |
| RC102 | 100 | 1553.23 | 4.94 | 1714.25 | 9.96 | −10.37 | −101.62 |
| RC203 | 100 | 1054.18 | 3.52 | 648.18 | 2.01 | 38.51 | 42.90 |
| RC205 | 100 | 1220.19 | 3.46 | 1276.50 | 3.10 | −4.61 | 10.40 |
| Average | | | | | | −0.82 | −34.99 |

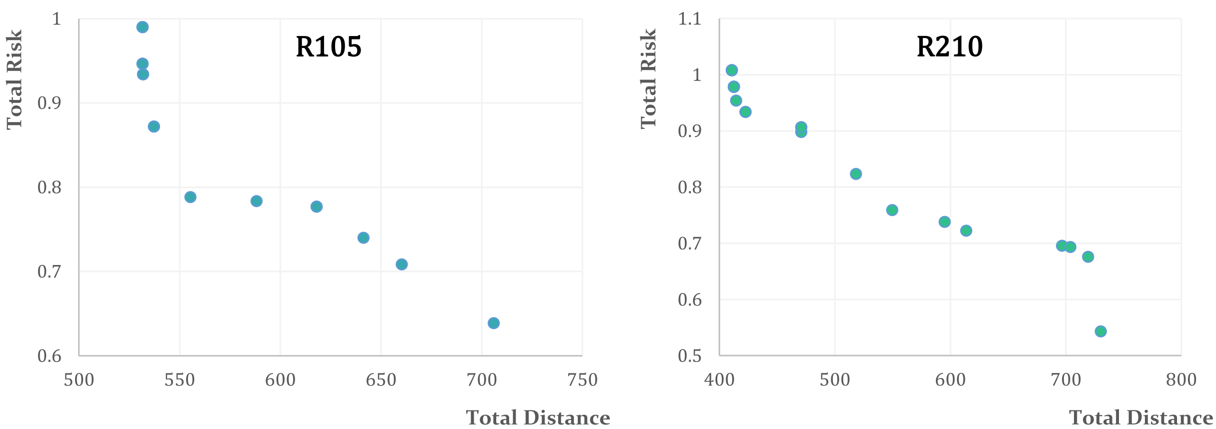


FIGURE 6. Pareto solutions to R105 and R210 problems.

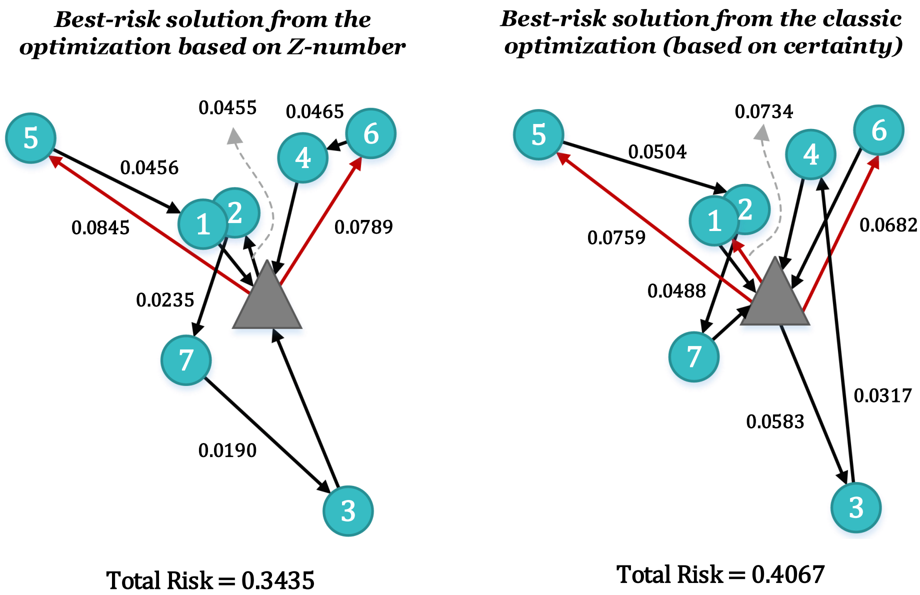


FIGURE 7. Comparison of risk estimation by Z-number and classic approach.

## 6. Case study

With the economic growth and the ever-increasing need to provide equipment for daily consumption in Iran, a large amount of chemicals and other Hazmat products are transported daily. Besides, since Iran is an exporting country, many chemicals must be processed for export purposes. As mentioned earlier, planning the Hazmat transportation is of great importance as it leads to irreparable damage to nature and the population around the event. There are no official statistics on the amount of damage caused by accidents involving Hazmat carrier vehicles in Iran. However, a brief review of the news and published events reveals that this problem is serious [55]. Hence, this section examines a case study of the distribution of hazardous material among a number of demand points (factories and chemical laboratories). The case study includes 24 points (23 factories and chemical laboratories and 1 depot) in Tehran and Karaj (located in Iran). Figure 8 depicts the dispersion of case points in the two cities and their communication routes.

Among the Pareto solutions obtained, two solutions with the minimum distance and risk are considered. Figure 9 shows the routes to this solution. The solution with the minimum distance includes three vehicles that distribute Hazmat with the minimum distance. This solution carries considerable risk because the vehicle passes through crowded places with a large load. For instance, in Route 1, the vehicle with large Hazmat by passing through links 8–1, 7–17, and 23–16, passes through crowded places three times, which increases the Hazmat transportation risk. The total distance of this solution is 198.82 km and the total value of risk is 1.28.

Figure 10 shows a solution with minimum risk to illustrate how to reduce risk. In the given solution, the vehicle passes through less crowded points as much as possible, and if it passes through crowded places it will pass through with less Hazmat. For example, the vehicle on Route 2 passes through a densely populated area through link 1–7 but does not carry much Hazmat. Therefore, Hazmat transportation risks are reduced. The total risk of this solution is 0.74 and the total distance of this solution is 397.86 km.

## 7. Conclusion

Given the importance of Hazmat transportation and its significant damage to individuals and the environment, this paper presents an approach to the vehicle routing problem with time windows to optimize distribution

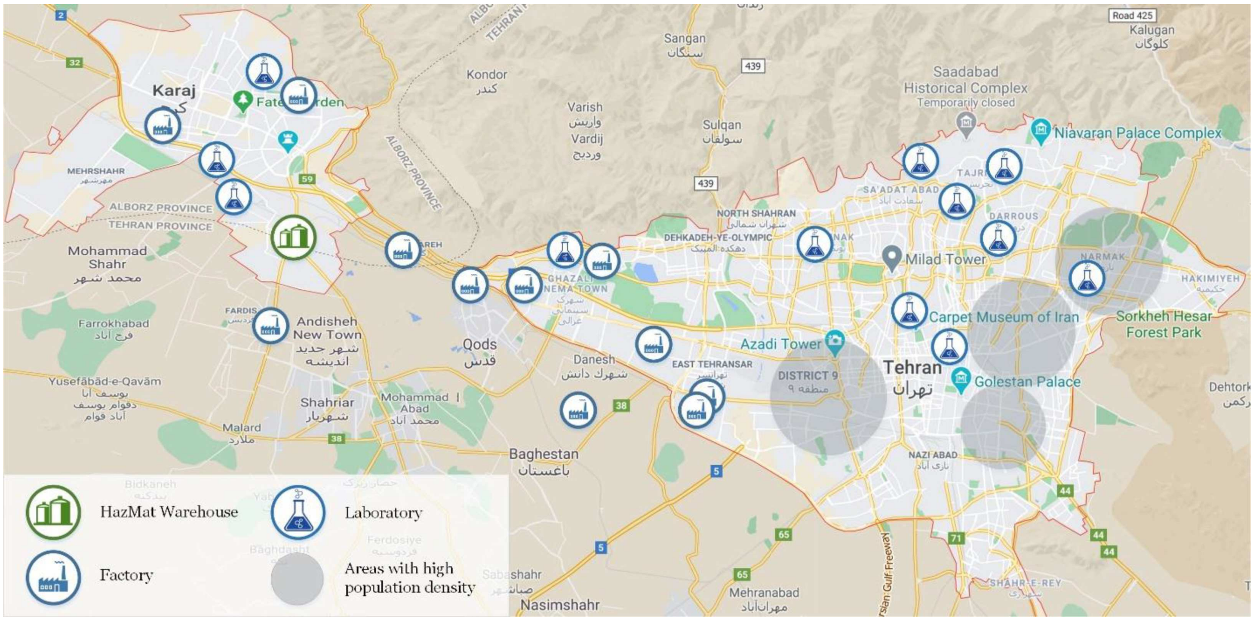


Figure 8. Dispersion of points in the case study.

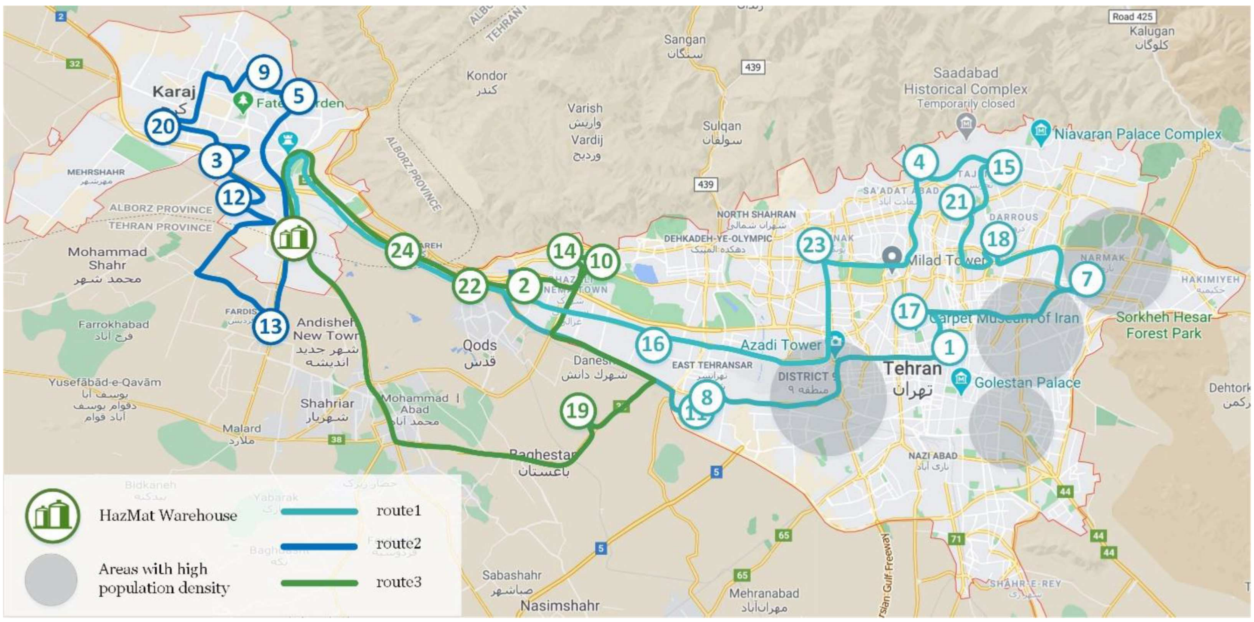


Figure 9. The solution with the best distance.

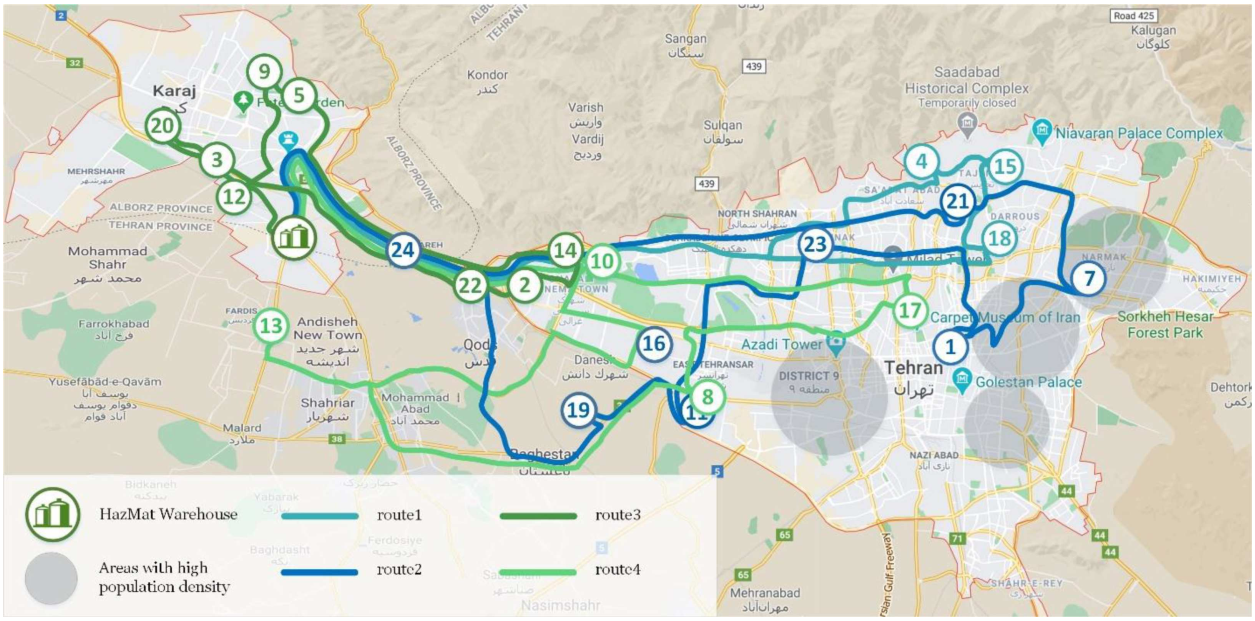


Figure 10. The solution with the best risk.

and reduce damage caused by vehicle accidents. Due to the uncertainty in this problem, the transportation risk was assumed fuzzy in which the probability of an accident and its severity of the effect are is considered in the context of Z-information. The severity of the accident is the population impacted by the accident, the number of which can vary in proportion to a load of vehicles.

To solve the proposed model, a bi-objective hybrid genetic algorithm that incorporated with a neighborhood search algorithm was proposed to improve performance. The algorithm was evaluated using Salmon problems. The results of the distance and risk objective functions show the relatively desirable performance of the solution method. Additionally, from the distance objective function results concerning the risk objective function, it can be observed that these two objectives are inversely correlated, and as the amount of risk is reduced, the transportation system distances escalate. Eventually, the proposed problem was evaluated in a case study in Iran, the results of which show a reduced risk of Hazmat transportation.

## Appendix A. Supplement to algorithm

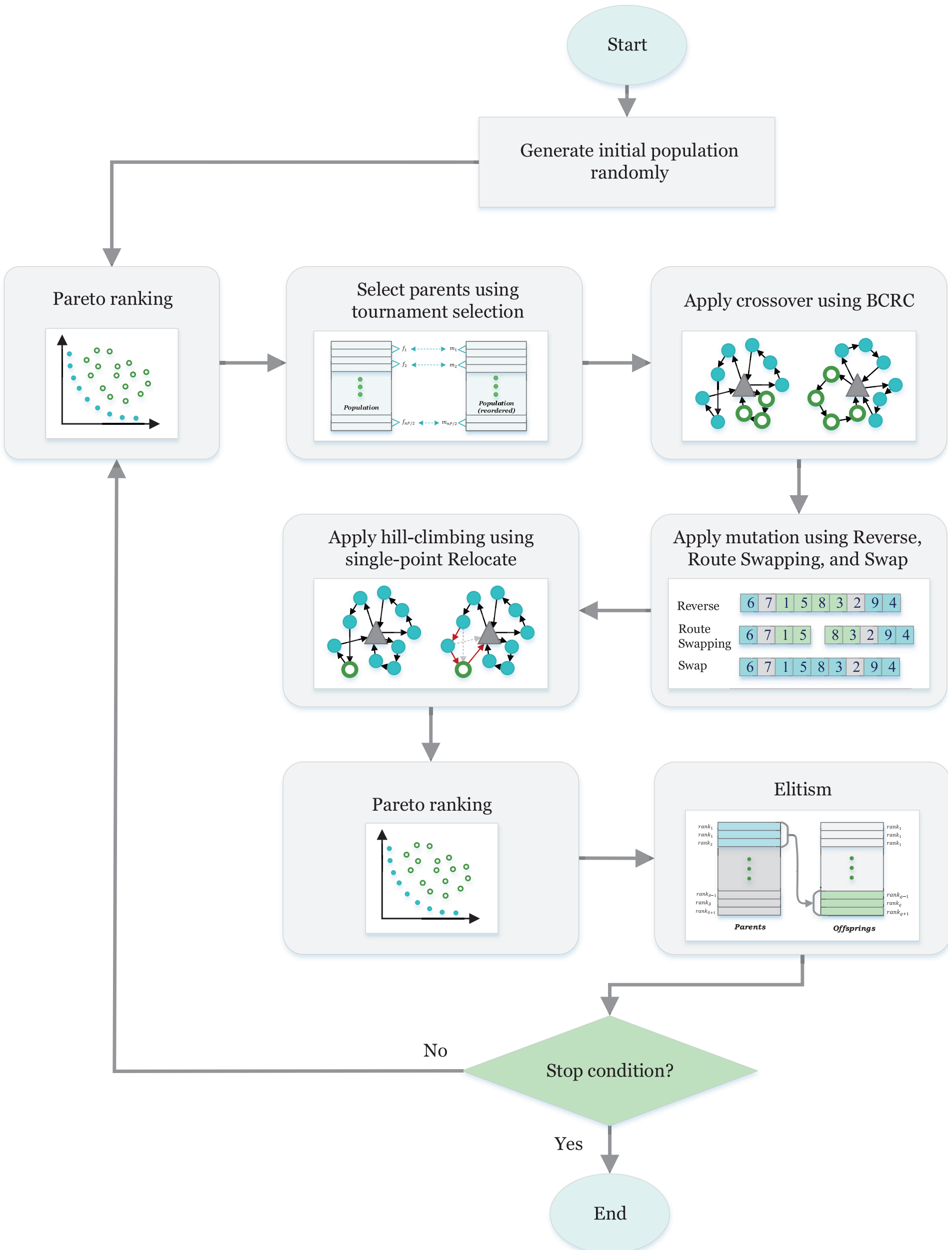


Figure A.1. The flowchart of the proposed algorithm.

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