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Urban Hazmat Transportation with Multi-factor

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Abstract In this paper, a urban hazmat transportation problem considering multiple factors that tangle with real-world applications (i.e., weather conditions, traffic conditions, population density, time window, link closure and half link closure) is investigated. Based on multiple depot capacitated vehicle routing problem, we provide a multilevel programming formulation for urban hazmat transportation. To obtain the Pareto optimal solution, an improved biogeography-based optimization (improved BBO) algorithm is designed, comparing with the original BBO and genetic algorithm (GA), with both simulated numerical examples and a real-world case study, demonstrating the effectiveness of the proposed approach.

Keywords Urban hazmat transportation · Multiple factors · Multilevel programming · Biogeography-based optimization · Pareto optimization

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1 Introduction

As the demands of hazardous material for industry and life continue to increase, dangerous goods transportation has remained as one of the major concerns for public safety and environmental protection. It is estimated that approximately 4 billion tons of hazmat are transported annually at the worldwide level (Carotenuto et al. 2007). As the shipments of long distance transportation carried hazardous materials increase gradually, there exist significant threats for catastrophic incidents with multiple fatalities, injuries, large-scale evacuations, and severe environmental damage. For example, when pass through the city of Lac-Megantic, Canada in 2013, an oil-tanker carrying hazardous materials and oil derailed and caused 72 train tankers occurred explode, resulting in 47 deaths and forty buildings damage. In 2016, the explosion of an oil tanker occurred at Mozambique caused 73 deaths with several dozens injured. Nowadays, this problem has become more serious – the number of hazmat incidents has surged from 12,651 in 2010 to 16,476 in 2016 in the United States alone, resulting in 77 deaths and 1316 injuries and a total property damage of \$ 626.2 million (U.S. Department of Transportation[1]).

The methods that avoid transportation risk for hazmat shipments can be categorized into two groups: risk evaluation approach and vehicle routing problem. The risk evaluation approaches aim to define the risk in a mathematical way which mainly incorporate accident occurrence probability and accident occurrence results. The different risk evaluation approaches can lead to different risk values. Therefore, the risk evaluation approaches' choice is also a significant consideration for

[1] U.S. Department of Transportation. See at: https://www.transportation.gov

hazmat transport. Vehicle routing problems (VRP) are classical combinatorial optimization problems that have been studied extensively in recent years due to their wide applicability and economic importance. Similarly, many approaches of VRP also have been employed in transport with hazmat. Generally, in urban areas, a majority of hazmat shipments (i.e., gas station, chemical institution) deliver goods to more than one destination once under the considerations of cost and travel convenience. This transportation mode is similar to that of non-fixed destination multiple depot capacitated VRP (MDCVRP), therefore the non-fixed destination MDCVRP is used as the transportation mode in our study. Filipec et al. (1997, 2000) formulated the problem of the non-fixed destination MDCVRP, where a fleet of homogeneous vehicles in depots find a set of links, originating and ending at different depots, to service all customers with known demand at minimum cost, while satisfying vehicle and depot capacity constraints (where a limit is imposed on the number of customers per vehicle's route).

Based on the realistic considerations in hazmat transportation, several previous studies proposed various issues involving multiple folds of considerations such as road closure (Fan et al. 2015), time window (Meng et al. 2005), congestion (Lozano et al. 2010; Assadipour et al. 2015). However, none of them provides the comprehensive considerations of multiple factors for urban hazmat transportation. In this study, multiple factors such as adverse weather condition, high population density, accident, congestion traffic flow, time window, link closure and half link closure, are investigated for urban hazmat transport. It is note that the closed link can not be used during some certain time segments for hazmat shipments. While half link closure ensures several links can be passed by adding penalty cost in certain segments. This model, modeled as a multilevel programming, entails considering multiple factors for all link so as to channel the hazmat shipment on the risk-less route. Nonetheless, our results indicated that multi-factor urban hazmat transport is more dynamic and effective than those of single-factor for mitigating transport risk.

Because of the MDCVRP, a complex multiple levels' planning, constitutes an integrated whole of multiple industrialized departments, the interest of each department cannot be ignored. Therefore, the administrative departments are classified as three levels: the upper level (carrier company) allocates customers to depots under the constraints of depot capacities and customer demands; the middle level (carrier subsidiary) assigns customers to vehicles for each group of depots and customers; the lower level (carrier) determines the optimal route for each group of vehicles and customers. In this approach, the process of decision-making is accomplished from a certain upper-level down to a lower-level, arranged hierarchically. Base the above framework, we also present an improved biogeography-based optimization (improved BBO) for obtaining the pareto solution, which is first proposed by Simon (2008a, b) and the experiment also demonstrates the effectiveness of the proposed approach. However, our main contribution is proposing the methodology of urban hazmat transportation of multiple factors. To this end, we present a mathematical programming of multiple levels for multifactor urban hazmat transport, which is more effective than those of single-factor. Moreover, an improved BBO algorithm is designed for optimizing the Pareto solutions, which is integrated with the Clarke and Wright saving mechanism (Clarke and Wright 1964) and neighborhood search for the generation of initial inhabits as well as Pareto elitism reserve. The results demonstrate that the improved BBO is able to lead to solutions that reach global optimality within an acceptable time.

This paper is organized as follows. Section 2 reviews relevant literature on hazmat transportation. In Section 3, the non-fixed destination MDCVRP with hazmat in urban areas is formulated as a multilevel programming problem, while considering multiple factors. Section 4 presents an improved BBO algorithm to find solutions inherent in such a model. Numerical examples and a real-world case study are provided in Section 5 in comparison with the existing techniques. Finally, Section 6 presents conclusions and points out further research.

2 Literature Review

In this section, we outline the existing research related to hazmat transportation in practical applications, including risk assessment, multiple affecting factors and routing optimization.

2.1 Risk Assessment

In general, hazmat transportation accidents are viewed as low probability high consequence events. The risk assessment over such events has been widely studied over the past few decades. Commonly used risk assessment models in hazmat transportation were summarized in Erkut et al. (2007). Recently, other type methods of risk measure have also been investigated. For instance, Kang et al. (2014) proposed a value-at-risk model and the route choice is implemented for hazmat transportation under the condition of giving the probability distribution of accident consequence on each link. Also, in order to mitigate risk in hazmat transportation (within a risk-averse framework), Toumazis et al. (2013) put forward a conditional value-at-risk model, considering various levels of risk acceptance by policy makers. Erkut and Verter (1998) validated different risk models that work usually by selecting different optimal paths for a hazmat shipment between a given origin-destination pair. They proposed to exploit the weighted combinations of different single-criterion risk models in order to reach the final decision, having recognized that different objectives may generate different optimal paths. Such work indicates that the choice of risk models is a key issue for hazmat transportation. Given that traditional risk models that involve the use of the concepts like incident probability and incident consequence are popular and important for hazmat transportation in sensitive urban areas, we will adapt such models in this work.

2.2 Multiple Affecting Factors for Hazmat Transportation

Weather conditions, high population density, and traffic congestion are generally recognized as the main issues of urban hazmat transportation. Considering such factors that may adversely affect urban hazmat transportation has long been an important topic in the literature. For example, work has been done which addresses the effect of the distance between the population center and the hazmat traffic route (Carotenuto et al. 2007; List and Mirchandani 1991). Bronfman et al. (2015, 2016) considered the distance between the route and its closest vulnerable centre, weighted by the centre's population. Here, a vulnerable centre with a highly concentrated population may be a school, a hospital and/or a residence zone.

Regarding weather influence, there have been a number of articles concerning the modeling of wind effects. Karkazis and Boffey (1995) proposed a method which incorporated meteorological conditions in the process of determining the dispersion of pollutants. Patel and Horowitz (1994) considered the diffusion of gases from spills during hazmat transportation. In order to minimize the risk of dangerous goods over the pathways, specific wind directions, uniform average wind direction, maximum concentration wind directions, windrose averaged wind directions and speeds, and multiday routing with uncertain weather conditions were all taken into account. There have also been studies that are focused on rainy and/or snowy weather. For example, Satterthwaite (1976) investigated the significant effect of wet weather upon accident number on the State Highways of California in 1970. Akgun et al. (2007) modeled the time-dependent attributes for route links by analyzing the impact of weather systems upon hazmat transportation routing.

Not much research has been conducted on traffic flow and link closure for hazmat transportation, however. Assadipour et al. (2015) formulated a rail-truck intermodal shipments of hazmat incorporating congestion at intermodal yards and that at terminals which may result in a certain non-negligible hazmat risk. Wang et al. (2012) developed a dual-pricing model for hazmat transportation which may avoid the delays and costs caused by traffic congestion by dealing with different types of traffic flow. Fan et al. (2015) proposed a bi-objection programming model while considering link closure, and Wang et al. (2016) investigated a dynamic system that covered multiple affecting factors such as people, vehicles, tanks, weather and road conditions.

Most of the above studies take into consideration only one or a highly selected few factors, but do not carry out a comprehensive coverage of many key factors that may affect urban hazmat transportation. In this study, we address multiple such factors conjunctively.

2.3 Routing Optimization

Much work has been carried out in the field of hazmat route planning, i.e., planning route choices for hazmat shipments between origin-destination pairs. Usually such research can be categorized into two fields: shortest path problems and vehicle routing problems. Many researchers have studied the first class such as Bronfman et al. (2015), Du et al. (2016), Toumazis and Kwon (2015). However, in many real world applications (i.e., transportation of gas cylinders), transportation of hazmats calls for the determination of a set of links used by a fleet of trucks to serve different customers, rather than merely the determination of a single optimal route as shortest path algorithms may produce.

Whilst approaches to vehicle routing problem (VRP) for hazmat transportation are generally very limited, there have been interesting work reported recently. Bula et al. (2017) presented a nonlinear function modeling the heterogeneous fleet VRP (shorthanded as HFVRP) in the context of hazmat transportation. A variable neighborhood search algorithm was employed to solve this problem. Fan et al. (2015) established a bi-objective mixed integer nonlinear model for VRP under the context of urban hazmat transportation, with a new heuristic algorithm to solve it. Pradhananga et al. (2014) proposed a meta-heuristic method for Pareto-based bi-objective optimization of hazardous materials in VRP (including scheduling). In Androutsopoulos and Zografos (2012), Androutsopoulos and Zografos (2012) put forward a technique to address the hazardous materials distribution problem within specified time windows that was modeled as a bi-objective time dependent VRP. A heuristic algorithm was used to solve this problem. Last but not least, Du et al. 2017 proposed a fuzzy bilevel programming model to minimize the total expected transportation risk for multi-depot VRP in hazmat transportation, using four different fuzzy simulation-based heuristic algorithms to solve the problem. In this study, the BBO algorithm is improved and integrated with the Clarke and Wright saving method and neighborhood search, in an effort to generate the initial inhabits as well as Pareto elitism retention for obtaining the optimal VRP solutions.

3 Proposed Approach

In this section, we first briefly introduce the urban hazmat transportation incorporating triple level programming and multi-factor, and discuss the influence of partial factors on objectives. Then, we proposed the mathematic programming for urban hazmat transportation and described their meanings.

3.1 Urban Hazmat Transportation

We consider a non-fixed destination MDCVRP on a hazmat transportation network which is formulated using a triple level integer linear programming model (Figure 1), taking into consideration the assignment strategies (customer assignment for depots, customer assignment for vehicles, route assignment) at the above three levels by minimizing risk, cost and time, respectively. Due to the real and complex situation faced by hazmat carrier such as weather conditions, road conditions, population exposed etc, we have to consider the multiple factors in our model conjunctively to be more realistic. Figure 2 shows such an example. Table 1 lists the status of partial links based on multiple factors in which the network is observed for 10 hours, between 08:00 a.m. and 18:00 p.m., divided into 1-hour time intervals. These factors are as follows: 1. weather condition; 2. population density; 3. traffic congestion; 4. link closure; 5. half link closure; 6. time window.

3.2 Illustrative Example

To more clearly illustrate link factors, a simple example for a transportation network with two depots and two customers is presented in Figure 3, where A and B denote depots and 1 and 2 represent customers. To focus on the examination of the potential impact of various factors, the customers assignment problem that dealt with during the first and second level decision making processes is omitted here (but will be described later). Note that the link status will remain as it is once the hazmat vehicle enters this network. Considering the multi-factor's complexity, here in this example, three factors including link closure, half link closure and time window are explored. Two cases for the illustrate example without and with multi-factor are considered in Table 2 and Table 3. In the Table 3, partial factors including link closure, half link closure and time window are considered. In Figure 4, all route schemes for Case 1 and Case 2 are presented in a way of tree form. The time at each node indicates the arrival time at which the vehicle reaches that node. Three digit strings show the total risk, total cost and total time applied to the hazmat vehicle from the departure node to the current node. Take node 2 of route I in Case 1 for example, 09:02 is the time that the vehicle arrives node 2, and 9, 77, 62 represent the total risk, total cost and total time that it moves from node A to node 1 and then to node 2. Note that, in Case 2, since the link (1, B) is closed during [08:00, 09:00], this link is not feasible during that time segment.

The results can be observed in Figure 4 and Table 4. The optimal schemes in Case 1 and 2 are II and III. Due to the factor of link closure, scheme II in Case 2 is infeasible. From the Figure 4, one can observed that the cost of scheme I in Case 2 compared to that of Case 1 increases 20, which is incurred by the penalty cost of half link closure in scheme I for Case 2. Note that the cost of schemes III and IV in Case 2 compared to those of Case 1 increases 30. This is because the factor of time window for customer 2 in Case 2. Except for scheme II, the risk and time in the two cases remain unchanged, this is due to, for simplification, we only consider the factors of link closure, half link closure and time window in this example in which the former one is associated with route feasibleness and the latter two are in connection with the cost objective. The other factors such as weather condition, population density and traffic congestion are associated with risk model and time model. From the above analysis, we can see that the consideration of multiple factors affect significantly the scheme choice and the objective values of risk, cost and time. Hence, dealing with multi-factor is essential.

Whilst in the above trivial example, we only need to make a simple and direct comparison of risk, cost and time to derive the route schemes, there are a number of modeling and algorithmic challenges for a large-scale deployment problem typically encountered in urban hazmat transportation. Therefore, our research will focus on modeling formulation and algorithm improve-

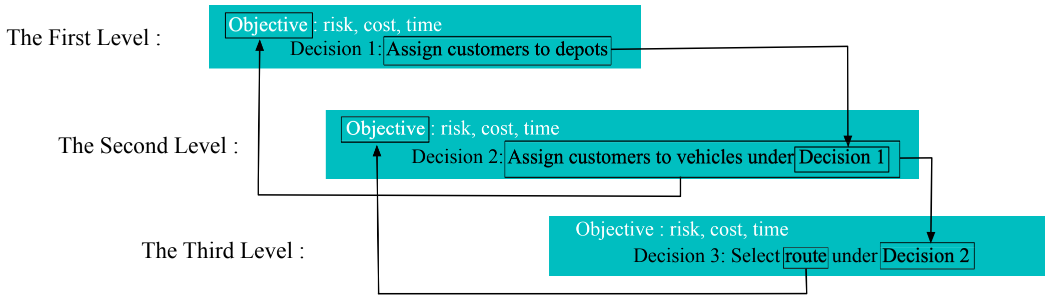


Fig. 1 Schematic representation of hierarchical decision planning

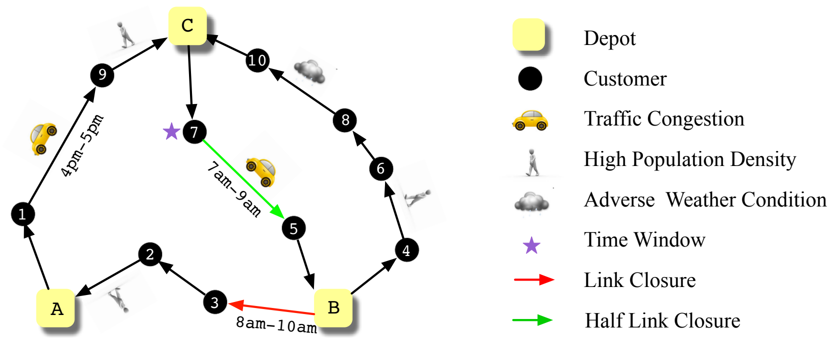


Fig. 2 Example of link status for non-fixed destination MDCVRP

Table 1 Example of link status

	$(A,1)$	$(2,A)$	$(3,2)$	$(B,3)$	$(1,9)$	$(9,C)$	$(5,B)$	$(7^*,5)$	$(C,7^*)$	$(B,4)$
08:00am-09:00am	☼⚀○→	☼⚂○→	☼⚀○→	≣⚂○✕	≣⚀◐→	☼⚄●→	☼⚀●→	☼⚀●→	☼⚀○→	☼⚀○→
09:00am-10:00am	☼⚀◐→	☼⚂○→	🌧⚂○→	☼⚀○✕	☼⚀◐→	☼⚂○→	☼⚀●→	☼⚀◐→	☼⚀○→	☼⚀○→
10:00am-11:00am	☼⚀○→	☼⚄○→	🌧⚂○→	☼⚂◐→	☼⚀●→	☼⚄○→	☼⚀○→	☼⚀●→	☼⚀○→	☼⚀○→
11:00am-12:00am	☼⚀◐→	☼⚂◐→	☼⚀◐→	☼⚂○→	☼⚀●→	☼⚄○→	☼⚀◐→	☼⚀◐→	☼⚀◐→	☼⚀◐→
12:00am-13:00pm	☼⚂○→	☼⚄○→	☼⚂○→	☼⚀○→	☼⚂◐→	☼⚂○→	☼⚀○→	☼⚂◐→	☼⚀◐→	☼⚂○→
13:00pm-14:00pm	☼⚀○→	☼⚂◐→	☼⚄●→	☼⚂◐→	☼⚂◐→	☼⚂○→	☼⚀◐→	☼⚀●→	☼⚂●→	☼⚀○→
14:00pm-15:00pm	☼⚀○→	☼⚂○→	☼⚀◐→	☼⚀○→	☼⚀◐→	☼⚄○→	☼⚀○→	☼⚀◐→	☼⚀○→	☼⚀◐→
15:00pm-16:00pm	☼⚂○→	☼⚄○→	☼⚄○→	☼⚀○→	☼⚀◐→	☼⚂○→	☼⚀○→	☼⚀◐⤫	☼⚀◐→	☼⚂○→
16:00pm-17:00pm	☼⚀○→	☼⚄○→	☼⚂○→	☼⚂○→	☼⚂●✕	☼⚄○→	☼⚀●→	☼⚀◐→	☼⚂○→	☼⚀◐→
17:00pm-18:00pm	☼⚀○→	☼⚂◐→	☼⚀◐→	☼⚀○→	☼⚀◐→	☼⚂○→	☼⚀●→	☼⚀◐→	☼⚀○→	☼⚀○→

[a] ☼ 🌧 ≣ represent weather conditions: Clear, Rain, Fog.
[b] ⚀ ⚂ ⚄ represent population density degree: Low, Crowded, Very crowded.
[c] ○◐●represent traffic congestion degree: Slight, Moderate, Heavy.
[d] → ⤫ ✕ represent open link, half link closure, link closure.
[e] N^* represents customer N has time window constraint.

ment for such complex problems. Specifically, the Pareto optimization will be used to effectively deal with the multiple objectives problem faced in the following large-scale examples and real-world case study.

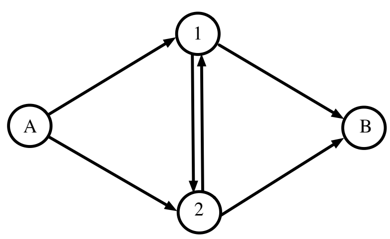


Fig. 3 Transport network in the illustrative example

3.3 Multilevel Programming Model

The multi-factor urban hazmat transportation can be modeled as the following multilevel programming. Table 5 presents the notation in this model.

3.3.1 Risk Model

Risk is a measure of the occurrence probability and consequence of accidents. Following the definition of

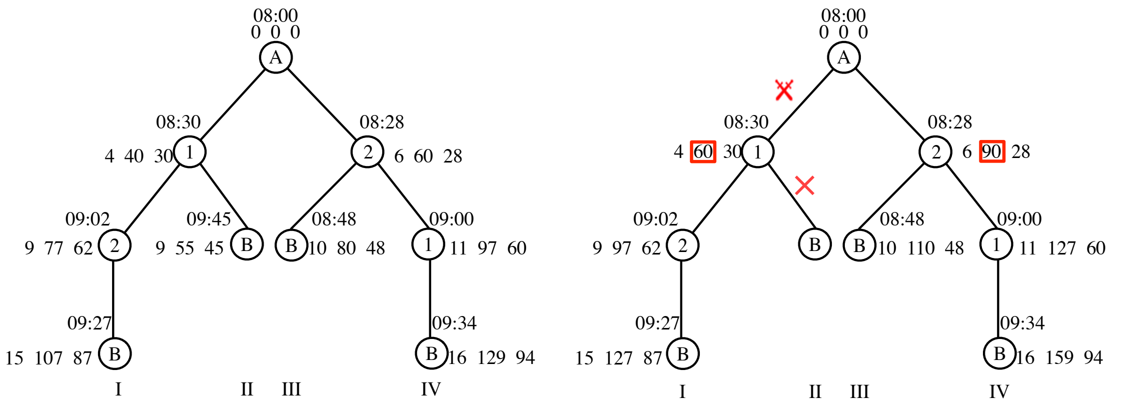
Table 2 Risk, cost and time of Case 1 without multi-factor

	(A , 1)			(A , 2)			(1 , 2)/(2 , 1)			(1 , B)			(2 , B)		
	Risk	Cost	Time	Risk	Cost	Time	Risk	Cost	Time	Risk	Cost	Time	Risk	Cost	Time
08-09:00	4	40	30	6	60	28	5	37	32	5	15	15	4	20	20
09-10:00	3	40	25	8	40	45	6	45	32	5	32	34	6	30	25
10-11:00	4	40	33	7	40	49	7	52	35	6	28	42	5	34	27

Table 3 Risk, cost and time of Case 2 with multi-factor

	(A,1)			(A,2*)			(1,2*)/(2*,1)			(1,B)			(2*,B)		
	Risk	Cost	Time	Risk	Cost	Time	Risk	Cost	Time	Risk	Cost	Time	Risk	Cost	Time
08-09:00	4✗	40✗	30✗	6	60	28	5	37	32	×	×	×	4	20	20
09-10:00 *	3✗	40✗	25✗	8	40	45	6	45	32	5	32	34	6	30	25
10-11:00 *	4	40	33	7	40	49	7	52	35	6	28	42	5	34	27

✗ represents half link closure. The penalty cost is 20, when the hazmat vehicles pass the link (A , 1) during [08:00, 10:00].
× represents link closure. The hazmat vehicles are prohibited to pass on link (1 , B) during [08:00, 09:00].
2* represents customer 2 has time window during [09:00, 11:00] and the penalty cost is 30.



(1) Route schemes of Case 1 without multi-factor

(2) Route schemes of Case 2 with multi-factor
(□ represents the cost including penalty cost)

Fig. 4 Route schemes for Case 1 and Case 2

Table 4 Route schemes for Case 1 and Case 2

Case	Scheme	Route	Risk	Traffic cost	Penalty cost	Total cost	Time
Case 1	I	A-1-2-B	15	107	0	107	87
	II	A-1-B	9	55	0	55	45
	III	A-2-B	10	80	0	80	48
	IV	A-2-1-B	16	129	0	129	94
Case 2	I	A-1-2-B	15	107	20	127	87
	II	A-1-B	×	×	×	×	×
	III	A-2-B	10	80	30	110	48
	IV	A-2-1-B	16	129	30	159	94

the risk described in Batta and Chiu 1988, the common used risk measure for hazmat transportation can be represented as follows:

$$R_{ab} = P_{ab} \times \rho_{ab} \times S_{ab}$$

where P_{ab} is the occurrence probability of a certain accident; ρ_{ab} represents the average population density surrounding the accidental spot; and S_{ab} denotes the affected area of the accident.

The risks in the hazmat transportation are associated with any accident's impacts on the surrounding environment. Apart from the population factor, weather condition is also an indispensable factor for hazmat

Table 5 Mathematical notation

Notation	Description
Parameters	
I	number of depots
J	number of customers
i	depot index $i = 1, 2, \cdots, I$
j	customer index $j = 1, 2, \cdots, J$
Cap_i	capacity of depot i, $i = 1, 2, \cdots, I$
d_j	demand of customer j, $j = 1, 2, \cdots, J$
M_i	number of vehicles in depot i, $i = 1, 2, \cdots, I$
m_i	vehicle index for depot i , $m_i = 1, 2, \cdots, M_i$, $i = 1, 2, \cdots, I$
N_i	number of customers served by depot i, $i = 1, 2, \cdots, I$
n_i	index of customer served by depot i, $n_i = 1, 2, \cdots, N_i, i = 1, 2, \cdots, I$
V_i	number of depots passed by vehicles in depot i, $i = 1, 2, \cdots, I$,
v_i	index of depots passed by vehicles in depot i, $v_i = 1, 2, \cdots, V_i$, $i \neq v_i, i = 1, 2, \cdots, I$
$q_{n_i}^{m_i}$	supply that vehicle m_i serves customer n_i, $m_i = 1, 2, \cdots, M_i, n_i = 1, 2, \cdots, N_i, i = 1, 2, \cdots, I$
Ca_{m_i}	vehicle capacity of vehicle m_i, $m_i = 1, 2, \cdots, M_i, i = 1, 2, \cdots, I$
k_{m_i}	number of customers assigned to vehicle m_i, $m_i = 1, 2, \cdots, M_i$, $i = 1, 2, \cdots, I$
u_{m_i}	depot passed by vehicle m_i,
G_{m_i}	set of depots and customers that vehicle m_i passes, $m_i = 1, 2, \cdots, M_i$, $i = 1, 2, \cdots, I$, i.e., $G_{m_i} = \left\{i, n_{i_1}, n_{i_2}, \cdots, n_{i_{k_{m_i}}}, u_{m_i}\right\}$
$R_{ab}^{m_i}$	risk from a to b with $a, b \in G_{m_i}$, $a \neq b$, $m_i = 1, 2, \cdots, M_i, i = 1, 2, \cdots, I$
$C_{ab}^{m_i}$	total cost from a to b with $a, b \in G_{m_i}$, $a \neq b$, $m_i = 1, 2, \cdots, M_i, i = 1, 2, \cdots, I$
$T_{ab}^{m_i}$	total time from a to b with $a, b \in G_{m_i}$, $a \neq b$, $m_i = 1, 2, \cdots, M_i, i = 1, 2, \cdots, I$
$[\underline{W}_{ab}^1, \underline{W}_{ab}^2]$	time slot of link closure from a to b, $a, b \in G_{m_i}$, $a \neq b$
CUC	the maximum number of customers visited by vehicle
ξ_{ab}	if the link from a to b with $a, b \in G_{m_i}$, $a \neq b$ is forbidden, it takes value 1; otherwise,it takes value 0
Decision variables	
x_{ij}	if depot i serves customer j, it takes value 1; otherwise, it takes value 0, $i = 1, 2, \cdots, I$, $j = 1, 2, \cdots, J$
e_{iu}	if depot i passes depot u, it takes value 1; otherwise, it takes value 0, $i = 1, 2, \cdots, I$, $u = 1, 2, \cdots, I, i \neq u$
$y_{n_i}^{m_i}$	if vehicle m_i serves customer n_i, it takes value 1; otherwise, it takes value 0, $m_i = 1, 2, \cdots, M_i$, $n_i = 1, 2, \cdots, N_i, i = 1, 2, \cdots, I$
$l_{v_i}^{m_i}$	if vehicle m_i passes depot v_i, it takes value 1; otherwise, it takes value 0, $m_i = 1, 2, \cdots, M_i$, $v_i = 1, 2, \cdots, V_i, i = 1, 2, \cdots, I$
$Z_{ab}^{m_i}$	if the link from a to b is active with $a, b \in G_{m_i}$, $a \neq b$, it takes value 1; otherwise, it takes value 0, $m_i = 1, 2, \cdots, M_i, i = 1, 2, \cdots, I$

transportation. Therefore, we consider the characteristic of weather in the geographical regions involved by the hazmat transportation, such that the risk is modeled by

$$R_{ab} = P_{ab} \times \rho_{ab} \times S_{ab} \times \tau_{ab}$$

where τ_{ab} is the weather influence factor that can be classified into a number of specific weather situations (which in this work include: clear, foggy, and rainy); and τ_{ab} may be assigned with different values corresponding to the different time segments (implementation details of which will be given later).

3.3.2 Cost Model

Generally, when scheduling transportation tasks, a carrier company looks for a route (between the origin and destination) for each shipment that would incur only the minimal overall cost. As such, in this study, the total cost modeled herein includes travel cost and penalty cost, with the latter composed of two sub-costing items: time window cost and half link closure cost. In particular, the travel cost c_{ab} and the total cost C_{ab} from node a to b within a given network are presented as follows:

$$c_{ab} = \frac{\zeta_{ab}}{\iota} \times \theta$$

$$\delta(TE_a, TE_b) = \begin{cases} 0, & TE_b \leq W_{ab}^1 \text{ or } TE_a > W_{ab}^2 \\ TE_b - W_{ab}^1, & TE_a \leq W_{ab}^1, W_{ab}^1 \leq TE_b \leq W_{ab}^2 \\ W_{ab}^2 - W_{ab}^1, & TE_a \leq W_{ab}^1, TE_b > W_{ab}^2, \\ TE_b - TE_a, & W_{ab}^1 < TE_a, TE_b \leq W_{ab}^2 \\ W_{ab}^2 - TE_a, & W_{ab}^1 \leq TE_a \leq W_{ab}^2, TE_b \geq W_{ab}^2 \end{cases}$$

$$C_{ab} = c_{ab} + \alpha \left[\delta(TE_a, TE_b)\right]^+ \lambda_{ab} + \left[\beta_1 (O_b^1 - TE_b)^+ + \beta_2 (TE_b - O_b^2)^+\right] \eta_b$$

$$[\delta(TE_a, TE_b)]^+ = \max\{0, \delta(TE_a, TE_b)\}$$
$$(O_b^1 - TE_b)^+ = \max\{0, (O_b^1 - TE_b)\}$$
$$(TE_b - O_b^2)^+ = \max\{0, (TE_b - O_b^2)\}$$

where ζ_{ab} is the link length from a to b; ι indicates the speed of the vehicle; θ denotes the fuel consumption cost per unit time; TE_a and TE_b represent the time that the vehicle arrives at node a and node b, respectively; $\left[W_{ab}^1, W_{ab}^2\right]$ is time window of half link closure from a to b; $\left[O_b^1, O_b^2\right]$ is the time window of the earliest and latest arrival on node b; α the penalty cost of unit time when the vehicle passes a half closed link; β_1 the penalty cost per unite time over increased waiting time that is earlier than the earliest arrival time; β_2 the cost penalty per unite time over increased delay time that is later than the latest arrival time; λ_{ab} takes value 1 if the vehicle violates the time window over the half closed link from a to b, else, it takes value 0; η_b takes value 1 if the vehicle violates the time window of node b, else it takes value 0.

3.3.3 Time Model

The link travel time function promoted by the Bureau of Public Roads (BPR) (Branston 1976; Esfandeh et al. 2016) is adopted here:

$$T_{ab} = \frac{\zeta_{ab}}{\iota}\left[1 + 0.15\left(\frac{f_{ab}}{\varphi_{ab}}\right)^4\right]$$

where f_{ab} and φ_{ab} express the traffic flow and traffic flow capacity from location a to b, respectively.

3.3.4 Overall Model

Based on the aforementioned component models, we formulate the following three-level programming model (**U1**, **U2**, **U3**) for non-fixed destination MDCVRP in urban hazmat transportation:

$$\min \sum_{i=1}^{I} (R1 = R(x_{i1}, x_{i2}, \cdots, x_{iJ}, e_{i1}, e_{i2}, \cdots, e_{iI})) \quad (1)$$
$$\sum_{i=1}^{I} (C1 = C(x_{i1}, x_{i2}, \cdots, x_{iJ}, e_{i1}, e_{i2}, \cdots, e_{iI})) \quad (2)$$
$$\sum_{i=1}^{I} (T1 = T(x_{i1}, x_{i2}, \cdots, x_{iJ}, e_{i1}, e_{i2}, \cdots, e_{iI})) \quad (3)$$
$$\text{s.t.} \sum_{j=1}^{J} d_j x_{ij} \le Cap_i, i = 1, \cdots, I \quad (4)$$
$$\sum_{i=1}^{I} x_{ij} = 1, j = 1, \cdots, J \quad (5)$$
$$x_{ij} \in \{0,1\}, i = 1, \cdots, I,\ j = 1, \cdots, J \quad (6)$$
$$e_{iu} \in \{0,1\}, i = 1, \cdots, I, u = 1, \cdots, J, i \ne u \quad (7)$$

where $R1$, $C1$, $T1$ in **U1** represent the following three objectives in **U2**, respectively.

The upper level formulation **U1** seeks the minimization of the total transportation risk, cost and time, which is affected by a feasible depot assignment strategy $(x_{i1}, x_{i2}, \cdots, x_{iJ}, e_{i1}, e_{i2}, \cdots, e_{iI})$. Specifically, constraint 4 ensures the capacity satisfaction of depots, and constraint 5 indicates that each customer is only served with one depot.

$$\min \sum_{m_i=1}^{M_i} \left(R2 = R\left(y_1^{m_i}, \cdots, y_{N_i}^{m_i}, l_1^{m_i}, \cdots, l_{V_i}^{m_i}\right)\right) \quad (8)$$
$$\sum_{m_i=1}^{M_i} \left(C2 = C\left(y_1^{m_i}, \cdots, y_{N_i}^{m_i}, l_1^{m_i}, \cdots, l_{V_i}^{m_i}\right)\right) \quad (9)$$
$$\sum_{m_i=1}^{M_i} \left(T2 = T\left(y_1^{m_i}, \cdots, y_{N_i}^{m_i}, l_1^{m_i}, \cdots, l_{V_i}^{m_i}\right)\right) \quad (10)$$
$$\text{s.t.} \sum_{n_i=1}^{N_i} d_{n_i} y_{n_i}^{m_i} \le Ca_{m_i}, m_i = 1, \cdots, M_i \quad (11)$$
$$q_{n_i}^{m_i} y_{n_i}^{m_i} = d_{n_i}, m_i = 1, \cdots, M_i, n_i = 1, \cdots, N_i \quad (12)$$
$$\sum_{n_i=1}^{N_i} y_{n_i}^{m_i} \le CUC, m_i = 1, \cdots, M_i \quad (13)$$
$$\sum_{m_i=1}^{M_i} y_{n_i}^{m_i} = 1, n_i = 1, \cdots, N_i \quad (14)$$
$$\sum_{v_i=1}^{V_i} l_{v_i}^{m_i} = 1, m_i = 1, \cdots, M_i \quad (15)$$
$$y_{n_i}^{m_i} \in \{0,1\}, m_i = 1, \cdots, M_i, n_i = 1, \cdots, N_i \quad (16)$$
$$l_{v_i}^{m_i} \in \{0,1\}, m_i = 1, \cdots, M_i,\ v_i = 1, \cdots, V_i \quad (17)$$

where $R2$, $C2$, $T2$ in **U2** represent the following three objectives in **U3**, respectively.

The medium level formulation **U2** models the second level decision maker's behavior of minimizing the total transportation risk, cost and time, which is influenced by a feasible vehicle assignment strategy $(y_1^{m_i}, y_2^{m_i}, \cdots, y_{N_i}^{m_i}, l_1^{m_i}, l_2^{m_i}, \cdots, l_{V_i}^{m_i})$ and which is subject to a number of constraints. Particularly, constraint 11 ensures the capacity satisfaction for the vehicles, constraint 12 guarantees the demand satisfaction for the customers, constraint 13 dictates that the number of customers served by each vehicle is no more than the maximum customer number, constraint 14 indicates that each customer is visited by a vehicle exactly once, and constraint 15 demands that each vehicle only visits one destination depot.

The lower level formulation **U3** models the third level decision maker's behavior, minimizing the total transportation risk, cost and time that is influenced by a feasible route assignment strategy $(Z_{ab}^{m_i})$. Again, a number of constraints are imposed, including: constraints 21-24 that are the same as those conventionally imposed while addressing the traveling salesman problem (in which the origin and destination depot are different) and satisfying the flow conservation requirements; constraint 25 ensures time continuity; and constraint 26 that expresses the status of link closure. Note that obviously, constraints 6, 7, 16, 17 and 27 define the domains of the relevant decision variables.

$$\min \sum_{a,b\in G_{m_i},a\neq b} R_{ab}^{m_i} Z_{ab}^{m_i} \tag{18}$$

$$\sum_{a,b\in G_{m_i},a\neq b} C_{ab}^{m_i} Z_{ab}^{m_i} \tag{19}$$

$$\sum_{a,b\in G_{m_i},a\neq b} T_{ab}^{m_i} Z_{ab}^{m_i} \tag{20}$$

$$\text{s.t.} \sum_{\substack{a\in G_{m_i}\\ a\neq i,u_{m_i}}} Z_{ia}^{m_i} - \sum_{\substack{a\in G_{m_i}\\ a\neq i,u_{m_i}}} Z_{ai}^{m_i} = 1, i \in G_{m_i} \tag{21}$$

$$\sum_{\substack{b\in G_{m_i}\\ b\neq a}} Z_{ab}^{m_i} = 1, a \in G_{m_i},\ a \neq i, u_{m_i} \tag{22}$$

$$\sum_{\substack{a\in G_{m_i}\\ b\neq a}} Z_{ab}^{m_i} = 1, b \in G_{m_i},\ b \neq i, u_{m_i} \tag{23}$$

$$\sum_{\substack{a\in G_{m_i}\\ a\neq i,u_{m_i}}} Z_{au_{m_i}}^{m_i} - \sum_{\substack{a\in G_{m_i}\\ a\neq i,u_{m_i}}} Z_{u_{m_i}a}^{m_i} = 1, u_{m_i} \in G_{m_i} \tag{24}$$

$$Z_{ab}^{m_i}(TE_a + T_{ab}^{m_i} - TE_b) = 0, a \neq b \in G_{m_i} \tag{25}$$

$$\xi_{ab} Z_{ab}^{m_i}(\underline{W}_{ab}^1 - T_{ab}^{m_i} - TE_a) (\underline{W}_{ab}^2 - TE_a) \geq 0, a \neq b \in G_{m_i} \tag{26}$$

$$Z_{ab}^{m_i} \in \{0,1\}, a, b \in G_{m_i}, a \neq b \tag{27}$$

4 Algorithm

In this section, we propose an improved heuristic framework that is effective for solving the proposed multi-factor urban hazmat transportation, which is based on the method of Simon (2008a, b). First, we discuss the original biogeography-based optimization algorithm. By considering the multi-level programming, the improved heuristic framework is provided.

4.1 Original Biogeography-Based Optimization Algorithm

The original Biogeography-Based Optimization (BBO) algorithm based on the biogeography theory of the distribution of species, investigates the relationships between different species (habitants) in terms of immigration, emigration and mutation.

BBO starts with an initial set of random solutions in the problem space, forming the initial population. Each solution in a population is called a habitat. The algorithm assigns each habitat a vector of habitants (similar to genes in a GA), representing the variables of a certain problem. The habitats evolve through successive iterations, called generations. Within each generation, the habitats are evaluated using Habitat Suitability Index (HSI) (Mirjalili et al. 2014). The habitats evolve over time based on three main rules as follows (Ma et al. 2013): (1) Habitants living in habitats with high HSI are more likely to emigrate to habitats with low HSI. (2) Habitats with low HSI are more prone to attract new immigrant habitants from those with high HSI. (3) Habitats might face random changes in their habitants regardless of their HSI values.

Each habitat has its own immigration, emigration, and mutation rates. A good solution has higher emigration rate and lower immigration rate, and vice versa. The emigration rate (χ_ϱ) and the immigration rate (σ_ϱ) are functions of the number of species in the habitat. These are calculated as follows:

$$\chi_\varrho = \frac{E \times \phi}{\Phi} \tag{28}$$

$$\sigma_\varrho = A \times \frac{1-\phi}{\Phi} \tag{29}$$

where E is the maximum possible emigration rate; ϱ the number of species of the ϱth individual in the ordered population according to their fitness; ϕ the number of habitants; Φ the allowed maximum number of habitants, which is increased by HSI (the more suitable the habitat, the higher the number of habitants); and A the maximum possible immigration rate.

Note that in running the algorithm, the involvement of the emigration and immigration operation speeds up the search process for reaching better solutions, and that the mutation operation maintains the diversity in the population to avoid being trapped in a local optimum. The mutation rate is defined as follows:

$$\epsilon_\varrho = \varepsilon \times \left(1 - \frac{B_\varrho}{B_{max}}\right) \tag{30}$$

where ε is an initial value for mutation defined by the user, B_ϱ is the mutation probability of the ϱth habitat, and $B_{max} = \text{argmax}(B_\phi), \phi = 1, 2, ..., \Phi$. The general steps of the BBO algorithm are as follows:

1. Initial set of random habitats.
2. Evaluate habitats by using HSI.
3. Update habitats by using emigration, immigration and mutation phases.

4. The BBO algorithm is terminated by the satisfaction of a termination criterion.

4.2 Improved Biogeography-Based Optimization Algorithm

As indicated previously, the present formulation of urban hazmat transportation problem is regarded as an integration of three optimization problems, including depot assignment strategy, vehicle assignment strategy and routing assignment strategy. We propose an improved BBO to solve such a complex and difficult problem, as shown in Figure 5. The main difference between the original BBO and the improved version is that the latter hybridizes the Clarke and Wright saving method (Clarke and Wright 1964), the neighborhood search algorithm and the Pareto elitism strategy.

Due to the hazmat transportation is a typical multi-objective problem that is complicated to resolve. In this work, three objectives are addressed and the Pareto optimization is utilized to choice the Pareto sets which have higher chances to be retained in the next generation. An example Pareto set is illustrated in Figure 6, where there are seven possible solutions with regard to two objectives: objective 1 and objective 2. In this example, suppose that the overall aim is to minimize both objectives. Then, solution 1 is superior to solutions 4, 6 and 7; and solutions 2 and 3 are better than 5, whilst 1, 2 and 3 can not be distinguished in terms of their relative pros and cons. There is no other set better than 1, 2 and 3. As such, these three possible solutions form the Pareto set for the given example.

4.2.1 Representation Structure

Route representation is used to encode the solution of the non-fixed destination MDCVRP. The idea of route representation is that the customers are listed in the delivery order within each route. For instance, suppose that there are six customers numbered 1- 6. If the route representation is (A 2 4 1 B B 3 6 5 A), then two routes are required to serve all these six customers. In the first route, a vehicle departs from the depot, which is denoted as A, travels to customers 2, 4, and finally customer 1. After that, the vehicle returns back to the depot B. In the second route, the vehicle starts with customer 3, then customer 6, and finally customer 5. Similarly, the vehicle travels back to the depot A after serving the customers.

4.2.2 Initialization

Three steps are implemented to generate a feasible initial habitat. First, the upper decision maker assigns customers to each depot. Customers are assigned to the nearest depots according to the distances from depots to customers and the destination depot is selected randomly. The way that customers assign to depots is presented as follows:

If $d(A, c) < d(B, c)$, c is assigned to A

If $d(A, c) > d(B, c)$, c is assigned to B

If $d(A, c) = d(B, c)$, c is assigned to depot randomly where $d(\cdot)$ is the distance between a depot and a customer, A and B are depots, and c denotes a customer.

The second step is for vehicle assignment where the customers are ranked from the farthest distance to the nearest distance from the depots. The service regions are segmented subject to the vehicle capacity constraint. The third step employs the Clarke and Wright algorithm to solve the routing assignment problem, finding the travel routes for every service region. This Clarke and Wright algorithm can be described as follows. Firstly, the distance matrix should be calculated. Secondly, the saving value is defined as $l_{i,j} = d(A, i)+d(A, j)-d(i, j)$, in which A is depot and i, j represent customers. All saving values are collected in the saving list. Thirdly, the values in the savings list are sorted in decreasing order. Finally, the route merging procedure starts from the top of the savings list. The route merging procedure is repeated until no feasible merging in the savings list is possible.

4.2.3 Improvement

This step may be implemented through the use of neighborhood search. In this case, the neighborhood of a solution is interpreted as a set of similar solutions attainable by making relatively simple modifications to the original solution. Given an initial habitat, two habitants are randomly selected from it. The two habitants and their neighbors are swapped to generate the new habitats. Taking Figure 7 for example, habitants 6 and 8 are those chosen from the original Habitat. Then, habitant 6 can be swapped with its neighbors habitant 5 and 7 to generate the populations of Habitat 1 and Habitat 3. Similarly, habitant 8 in the original Habitat can be swapped with its neighbors 10 and 9 to generate Habitat 2 and Habitat 4. So can Habitat 5 be generated, etc. For Habitat 1, the habitants 1, 4, 6, 5 and 7 are assigned to Depot A and the rest habitants are assigned to Depot B by the above mentioned Clarke and Wright algorithm.

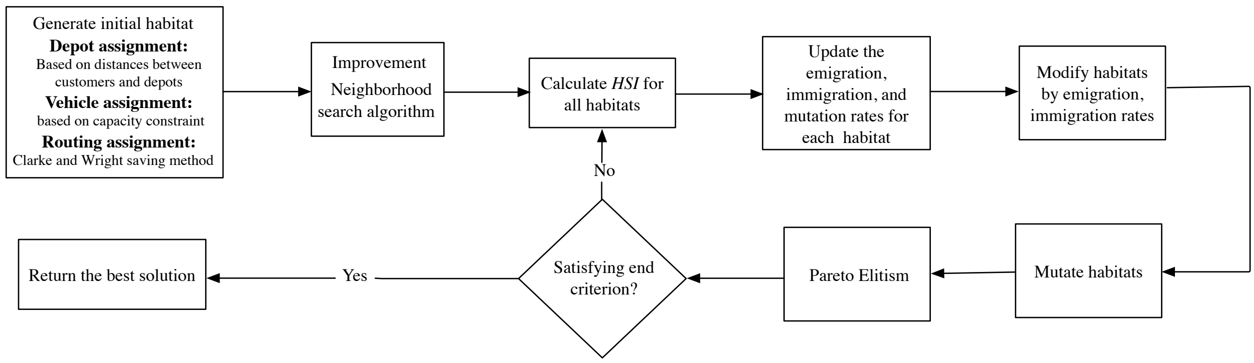


Fig. 5 Flowchart of improved BBO

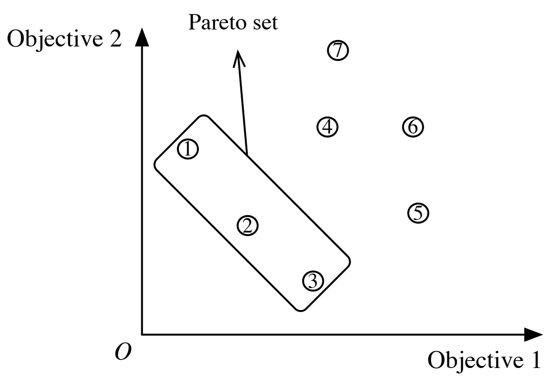


Fig. 6 Pareto set

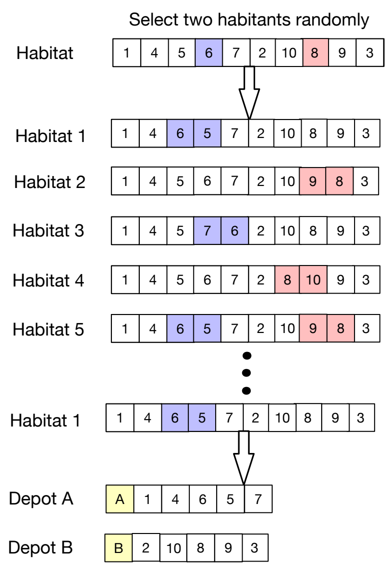


Fig. 7 Neighborhood search algorithm

4.2.4 Habitat Suitability Index (HSI)

In general, a fitting function is used to evaluate the habitats within a newly generated Habitat. For the urban hazmat transportation problem, an HSI is introduced to reflect the minimality of objectives related to total risk, cost and time among all depots involved.

4.2.5 Migration and Mutation

To see how the proposed method works, a conceptual picture of the migration between the habitats for non-fixed destination MDCVRP using the improved BBO is visualized in Figure 8. In this figure, given the minimization objectives, habitat 1 is the fittest, followed by habitat 2, habitat 3, habitat 4. The habitat represents the customers order that will be visited. It can be seen that habitat 1 has the highest emigration, whereas habitat 4 provides the highest immigration. The fourth habitat accepts many habitants from other habitats as illustrated in different colors. The green nodes and connections also depict mutation which happen for all the habitats regardless of their HSI values.

After these operations, the new habitats are generated using the vehicle assignment and routing assignment strategies. The last step of the proposed method is Pareto elitism selection, in which some of the Pareto habitats are saved in order to prevent them from being corrupted by the evolutionary and mutation operators in the next generation. These steps are iterated until a given termination criterion is satisfied (i.e., when the number of iterations reaches the maximum iteration).

4.3 Genetic Algorithm

Genetic algorithm (De Jong, 2002) is a common method proposed to deal with optimal problems. It has drawn considerable attention and successfully applied to a wide range of areas in real-world problems according to the biological evolutional behavior and mechanism. This method constructs a set of feasible solutions and the excellent fittest individuals are selected for reproduction through the crossover and mutation operators until the algorithm converges achieving the stopping criterion.

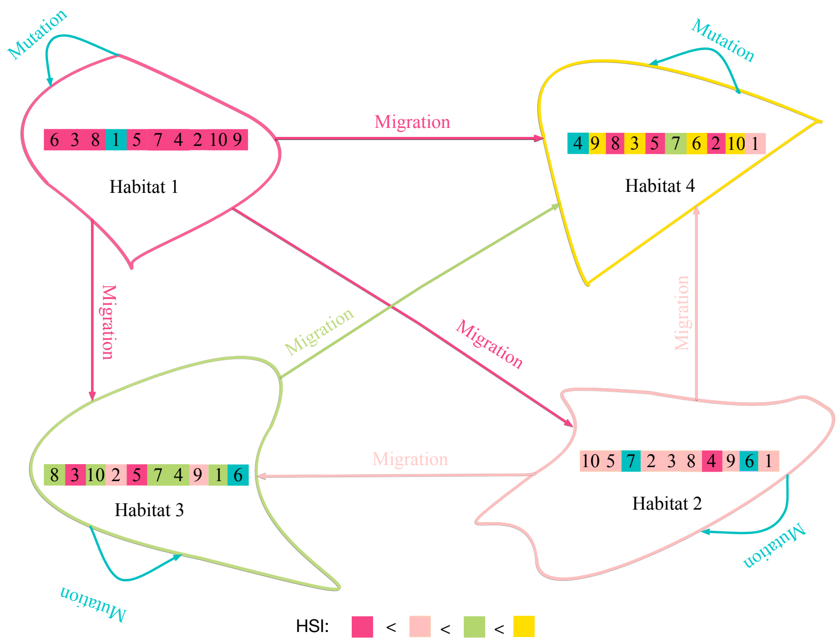


Fig. 8 Emigration and immigration

Genetic algorithm has been utilized as a compared algorithm in many optimization problems. For example, Elbeltagi et al. (2005) designed a genetic algorithm and other four evolutionary algorithms for solving the continuous and discrete optimization functions and compared the performance of this five algorithms. Hassan et al. (2005) compared the performance of the particle swarm optimization and genetic algorithm by a set of benchmark test problems and two space system design optimization problems. Therefore, this genetic algorithm in our study is designed to compare the performance with the original BBO algorithm and the improved BBO algorithm.

In this paper, the processes of genetic algorithm incorporates initialization, evaluation, selection, crossover and mutation operators. The initial solutions are generated similar to the improved BBO using these three steps: depot assignment, vehicle assignment as well as routing assignment. The evaluation function is generated by the calculation of HSI for all generated solutions. The common used roulette gambling approach is exploited for the solution selection process. The crossover operator is implemented in a way of single-point. The mutation operator in genetic algorithm is similar to that of improved BBO algorithm, but the mutation probability is a constant generated by random way.

4.4 Summarizing Note

The improved BBO algorithm is an Evolutionary Algorithm (EA) that offers specific evolutionary mechanisms to each individual in a population. The HSI of all habitats are improved over the generations since the habitants of better habitats tend to migrate to the worse habitats. This guarantees the improvement of all habitats during generations. Mutation operator enhances their exploitation capability. Moreover, different mutation constants for each habitant in a population may also help BBO outperform GA, which usually has a single mutation operator for the whole population. Finally, the intrinsically different adaptive mechanisms of evolutionary operators and mutations for each individual assist BBO to provide diverse exploration and exploitation behaviors while solving problems with a different scale. A pre-defined number of the Pareto habitats are retained as elites for the next generation. In contrast to GA, improved BBO has not only the additional migration operator, but also the Clarke and Wright saving method, neighborhood search, and Pareto elitism retention which are additional to the original BBO. These significantly enhance the algorithm's diverse exploration and exploitation capability. These properties of the proposed approach are experimentally verified below.

5 Experiments

This section presents experimental evaluation of the proposed model, using both numerical examples and a real-world case, and discusses the results.

5.1 Numerical Examples

Numerical experiments are herein carried out to compare improved BBO algorithm that is integrated with the Clarke and Wright saving method, neighborhood search and Pareto elitism retention, against BBO and GA, over three randomly simulated transportation networks of different scales. This is set to demonstrate the solution optimality and computational efficiency. Note that all systems implemented are coded in Matlab.

5.1.1 Experimental Setup

The three transportation networks tested consist of the following details: (1) 10 depots and 80 customers, (2) 12 depots and 100 customers, and (3) 14 depots and 120 customers. In terms of naming schemes for easy cross reference, within these three networks, the depots and customers are labelled as 1-10 and 11-90, 1-12 and 13-112, and 1-14 and 15-134, respectively. The locations of the depots and customers are randomly generated using a uniform distribution in the space of size 400 by 400 (which is sufficiently large empirically). Each link involves multiple factors: weather situations, traffic flow, population density, time window, link closures and half link closures. These networks are constructed for a segment of 24 hours, between 0:00 mid-night and 11:59 p.m., divided into 1-hour time intervals, with the assumption that the link status remains unchanged once the hazmat vehicle enters a certain link. The experiment environment and the parameter settings are depicted as follows:

1. The accident probabilities are calculated according to link lengths, $P_{ij} = l_{ij} \times 10^{-6}$ where l_{ij} is the length of a link (Abkowitz and Cheng 1988; Kang et al. 2014).
2. The population density is assumed within the range of [1131, 1678] people per square kilometer.
3. The affected area by a certain accident is assumed to be a rectangle centered at the accident location. Assume that all people within the rectangle will be affected and people outside this area will not be affected. The affected area can be written as $l_{ij} \times \Theta$. In our case, we consider $\Theta = 0.5km$.
4. The traffic flow and maximum traffic flow capacity are assumed within the range of [80, 200] and [300, 500] vehicles per hour, respectively.
5. The classification of days into weather types was done by checking against the parameter of τ (as per the notion τ_{ab} over the link from location a to b in formula A given previously) such that
   If $\tau = 0.2$, the day was classified as clear day.
   If $\tau = 0.5$, the day was classified as foggy day.
   If $\tau = 1$, the day was classified as rain day.
6. Time window, link closure and half link closure are set as follows: Customer 40 is served within the time window [14:00, 19:00]pm; link (17, 18) in [12:00, 13:00]pm is half closed; link (21, 28) in [10:00, 11:00] am is closed; and the number of customers served by a vehicle is no more than 6. We adopt Euclidean distance to measure the length of links. The vehicle speed is assumed to be in the interval [55, 65] km/h. The fuel consumption cost per kilometer is 0.15\$. The penalty cost per unit time from the time window and that for half link closure are set to be 50\$ and 30\$, respectively. The departure times of vehicles are assumed at 8:00 am. The customer demand is within the range [80, 260] and capacity of vehicle is 300.

To ensure appropriate settings for the parameters used in all implemented algorithms, the problems have been run 16 times with different values of all the parameters and those led to the best result are selected. For example, Figure 9 illustrates the allowed maximum number of habitants in terms of Pareto solution number. As shown in this figure, the maximum number of habitants of 150 gives the best result. Therefore, we set the maximum number of habitants=150. This is common practice in the literature and all compared algorithms have been treated equally, in the manner that they all use the empirically evaluated best parameters. The resulting parameters in the improved BBO algorithm and also, in the original BBO and GA algorithms are shown in Table 6.

5.1.2 Results and Discussion

Given the above experimental settings, to demonstrate the performance of our approach, all compared algorithms are each run for 30 times. The resultant optimal proportion of Pareto solutions, percentage deviations (Gap) and run time are shown in Figure 10 and Table 7, where the index of proportion of Pareto solution and Gap are defined as follows:

$$\text{Pareto proportion} = \frac{\text{Pareto number for an algorithm}}{\text{Total number of Pareto}}$$

$$\text{Gap} = -\frac{\text{Obtained solution} - \text{Best obtained solution}}{\text{Best obtained solution}}$$

The results of improved BBO in these numerical examples are explicitly compared with those of BBO and GA. In Table 7, the first-fourth columns of Table 7 list the number of depots, the number of customers which have to be served, the iteration number and population size, respectively. The proportion of Pareto solutions, Gap and CPU running time are presented in the sixth-eighth columns, respectively.

A number of observations can be obtained from these results. First of all, our improved BBO algorithm provides more optimal solutions than BBO and GA algorithms for all examples in terms of solutions' quality, with (i) more superior proportion Pareto solutions, and (ii) smaller percentage deviations. Particularlly, the number of superior Pareto solutions returned by the improved BBO is obviously more than that achievable by the use of either of the other two algorithms. This is reflected from sub-figures (d), (e) and (f) in Figure 10. For example, the proportions of Pareto solutions for the improved BBO, the original BBO and GA in the network of 10 depots and 80 customers are 78%, 20%, and 2%, respectively.

The results also show that the original BBO algorithm performs better than the improved BBO and GA, in terms of CPU run time. For example, the run times for the improved BBO, BBO and GA in the network of 10 depots and 80 customers are 629s, 100s, and 116s, respectively. However, this is expected as the improved BBO involves more computation than BBO itself. This is due to the fact that improved BBO incorporates the Clarke and Wright saving method and the neighborhood search algorithm for generating the initial inhabits. Importantly, the sacrifice of a limited extra amount of computational effort leads to significantly improved system performance. Indeed, the optimum proportion of Pareto solutions for the network of 10 depots and 80 customers is found while the computation time is increased to 629s. According to Table 7, the percentage deviations of improved BBO are lower than those of BBO and GA algorithms. For the network of 14 depots and 120 customers, the Gaps of proportion of Pareto solutions for the improved BBO as compared to those of the original BBO and GA algorithm are 0%, 100%, 100%.

Overall, these numerical experimental results demonstrate that the proposed approach with hybridized initialization procedure plays an important role in finding solutions to non-fixed destination MDCVRP, while the Pareto elitism retention procedure helps transmit the excellent habitants.

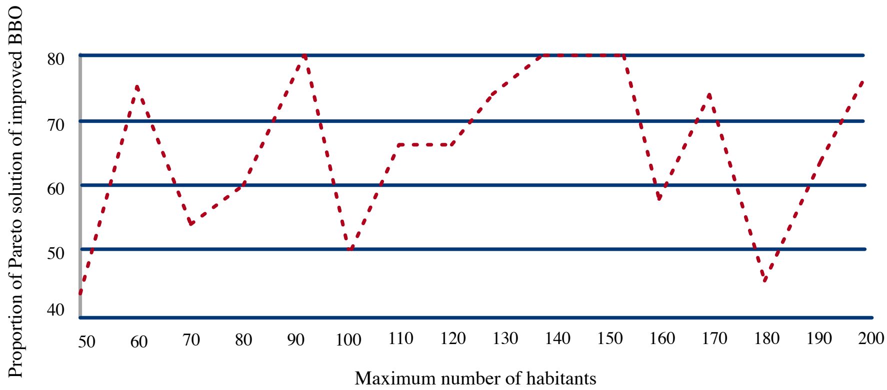


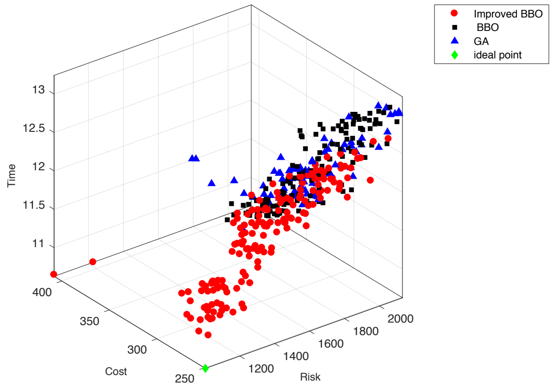
Fig. 9 Parameter tuning for maximum number of habitants

Table 6 Parameters of heuristic algorithms

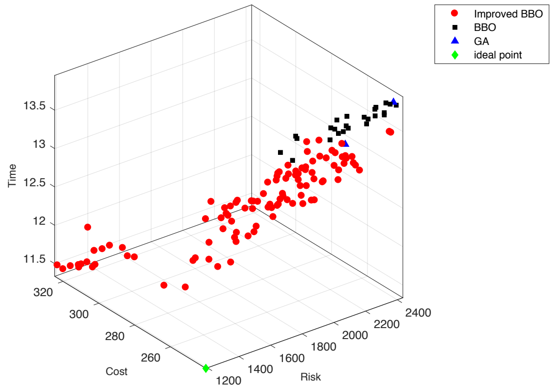
Improved BBO	Max emigration rate 1	Max immigration rate 1	Max habitants number 150	Initial mutation probability 0.005
BBO	Max emigration rate 1	Max immigration rate 1	Max habitants number 150	Initial mutation probability 0.005
GA	Crossover probability 1	Mutation probability 0.01		

Table 7 The results in different transportation network

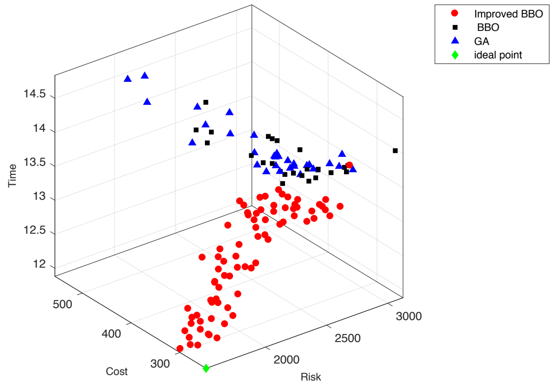
Depot/customer No.	Generation	Pop size	Algorithm	Proportion of Pareto (%)	Gap (%)	Runtime (s)
10/80	2000	150	Improved BBO	78	0	629
			BBO	20	74	100
			GA	2	97	116
12/100	1000	50	Improved BBO	80	0	889
			BBO	18	78	120
			GA	2	98	140
14/120	2000	50	Improved BBO	100	0	1188
			BBO	0	100	138
			GA	0	100	180



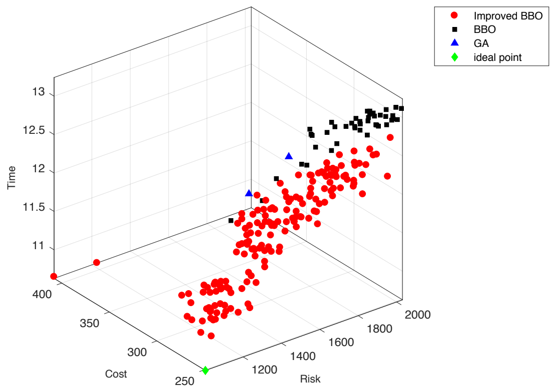
(a) example of 10 depots and 80 customers



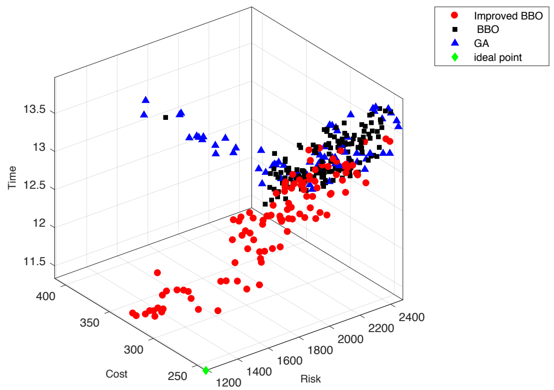
(b) example of 12 depots and 100 customers



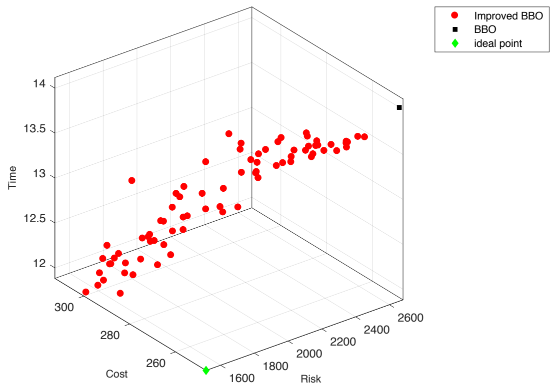
(c) example of 14 depots and 120 customers



(d) example of 10 depots and 80 customers



(e) example of 12 depots and 100 customers



(f) example of 14 depots and 120 customers

Fig. 10 Pareto solutions comparison of three different algorithms in different scales networks

5.2 Case Study

To further illustrate the effectiveness of the proposed approach, we present an empirical real case study, applying the proposed model and solution algorithm to the problem of liquefied petroleum gas transportation in Beijing City. Beijing is one of the most highly populated metropolitan areas in the world. Like most major cities, its traffic is heavy, especially during the morning and afternoon rush hours. The hazmat transportation vehicles are often restricted on certain roads during time windows specified by the local government. For example, in order to assure the safety in highways during the May Day holiday (from the 1st to 3th of May), no hazmat trucks from other provinces are allowed to pass through highways in Beijing. There are nevertheless certain customers (i.e., research institutes) requiring hazardous materials to be supplied over certain time windows. To make the case study realistic, we also consider situations involving half link closure links (i.e., construction areas) where hazmat vehicles may pass a certain link by adding penalty cost.

5.2.1 Case Specification

Beijing Oil Products Company of China Petroleum & Chemical Corporation is one of the large-scale subsidiaries of Sinopec, which is the main supplier of petroleum and petrochemicals for the Chinese capital. Petrochemical Logistics are responsible for shipping petrochemical products from regional depots to distributors mainly by road.

This case study is a realistic non-fixed destination MDCVRP instance derived from the real road network of Sinopec Group, Haidian District of Beijing City. The problem considered is a virtual distribution of liquefied petroleum gas oil depots to a set of geographically distributed gas stations[2]. The road network consists of 2 oil depots and 27 gas stations shown in Figure 11, where A-B and 1-27 represent the labels of all relevant nodes involved in the transportation network. The case study is constructed for a segment of 24 hours, between 0:00 mid-night and 11:59 p.m., divided into 1-hour time intervals. It is presumed that the link status remains unchanged once a hazmat vehicle enters a given link. The required data for the case study is collected in the format of maps from official websites, and the population density along each link is estimated by linking Beijing Census data to the route data based on geographic information. The accident probabilities are calculated according to link lengths, $P_{ij} = l_{ij} \times 10^{-6}$ where l_{ij} is the length of a link (Abkowitz and Cheng 1988; Kang et al. 2014). It is practically assumed that a hazmat accident will affect an area that is of a 500m radius circle, based on the recommendations in Fan et al. (2015). The traffic flow and maximum traffic flow capacity are provided by Beijing Traffic Management Bureau[3]. The dataset of weather conditions is obtained from Beijing Meteorological Service[4]. The number of customers served by a vehicle is no more than 6. The vehicle speed is set to be within the interval [55, 65] km/h. The fuel consumption cost is 0.15$ per kilometer. The penalty cost per unit time for the given time window and that for passing through a half link closure are 30$ and 30$, respectively. The departure times of vehicles are assumed to be at 8:00 am. The customer demand is within the range [80, 130] and the capacity of each vehicle is 400. Details on time window, link closure and half link closure are given in Table 9. The parameters in the improved BBO algorithm and those in the original BBO and GA are as shown in Table 6.

5.2.2 Results and Analysis

To assess the quality of the solutions provided by the proposed approach, we compare the improved BBO algorithm with the original BBO and GA. Figure 12 shows the results of Pareto solutions comparison, where Figure 12.a) illustrates the Pareto solutions for each algorithm, and Figure 12.b) depicts the Pareto solutions obtained by Pareto optimization for the solutions of Figure 12.a). From these figures we can see that the improved BBO algorithm provides more superior Pareto solutions as compared to BBO and GA.

Table 8 presents a tabular representation of the results of Figure 12. The first twenty results from row 2 to 21 are obtained by the improved BBO. The latter eighteen results from row 23 to 40 are solved by using the original BBO, and the remaining solutions are obtained by GA. The first column shows the routes of Pareto solutions for each of the three algorithms, where the numbers and letters represent gas stations and oil depots, respectively. For example, the number 1 represents Beianhe gas station. Columns 2-4 of Table 8 present the total risk, total cost and total time of the Pareto solutions. These results show that the average risk, average cost of the improved BBO are 6690 and 30, which are less than 7580 and 33 obtained by BBO and 7974 and 31 by GA, although the average transpo

[2] Electronic map of China petroleum & chemical corporation Beijing oil products company. See at: http://wap.bjoil.com/portal/map.jsp

[3] Beijing traffic management bureau. See at: http://cgs.bjjtgl.gov.cn/roadpublish/Map/trafficOutNew1.jsp

[4] Beijing meteorological service. See at: http://www.bjmb.gov.cn

Table 8 Results with different algorithms

Route	R	C	T	PC	TW	HC	Pa(%)
A-25-26-B,A-24-23-B,A-21-18-B,A-19-16-B,A-15-12-10-B,A-14-11-B,A-7-9-B, A-4-2-B,A-6-5-B,B-3-1-13-A,B-8-17-20-A,B-22-27-A	5897	36	4.51	—	10:24	—	
A-27-26-B,A-24-23-B,A-21-18-B,A-19-17-B,A-16-15-12-B,A-10-14-B,A-11-7-B,A-9-2-B,A-6-5-B,B-3-1-4-A,B-8-13-20-A,B-22-25-A	5914	35	4.43	—	11:24	—	
A-25-26-B,A-24-23-B,A-21-18-B,A-19-16-B,A-15-10-12-B,A-14-11-B,A-7-9-B,A-4-2-B,A-6-5-B,B-3-1-13-A,B-8-17-20-A,B-22-27-A	5930	34	4.30	—	10:18	—	
A-25-27-B,A-26-24-B,A-23-22-B,A-21-18-B,A-17-16-13-B,A-12-10-B,A-11-7-B,A-9-2-B,A-6-5-B,B-1-3-4-A,B-8-15-14-A,B-19-20-A	6019	34	4.30	—	11:23	—	
A-25-26-B,A-24-20-B,A-21-18-B,A-19-17-B,A-15-12-10-B,A-14-11-B,A-7-9-B,A-4-2-B,A-6-5-B,B-3-1-13-A,B-8-16-22-A,B-23-27-A	6020	34	4.29	—	10:27	—	
A-25-27-B,A-26-24-B,A-23-22-B,A-21-18-B,A-19-17-B,A-16-13-12-B,A-11-7-B,A-9-2-B,A-6-5-B,B-1-3-4-A,B-8-10-15-A,B-14-20-A	6042	33	4.15	—	11:13	—	
A-25-27-B,A-26-23-B,A-20-21-B,A-18-19-B,A-17-16-15-B,A-14-10-B,A-7-1-B,A-4-2-B,A-6-5-B, B-8-9-13-A,B-12-11-3-A,B-22-24-A	6084	32	3.99	—	10:01	—	
A-25-27-B,A-26-24-B,A-23-21-B,A-18-19-B,A-17-16-15-B,A-14-10-B,A-7-1-B,A-4-2-B,A-6-5-B,B-9-8-13-A,B-12-11-3-A,B-20-22-A	6116	31	3.89	—	09:55	—	
A-25-27-B,A-26-24-B,A-23-20-B,A-18-19-B,A-17-16-15-B,A-14-10-B,A-7-1-B,A-4-2-B,A-6-5-B,B-8-9-13-A,B-12-11-3-A,B-22-21-A	6246	31	3.87	—	10:02	—	
A-25-27-B,A-26-23-B,A-20-21-B,A-18-19-B,A-17-16-15-B,A-14-10-B,A-7-1-B,A-4-2-B,A-6-5-B, B-8-9-13-A,B-12-11-3-A,B-22-24-A	6379	31	3.83	—	10:03	—	
A-25-27-B,A-26-23-B,A-20-21-B,A-18-19-B,A-17-16-15-B,A-14-10-B,A-7-1-B,A-4-2-B,A-6-5-B,B-9-8-13-A,B-12-11-3-A,B-22-24-A	6431	30	3.74	—	10:01	—	91%
A-25-26-B,A-24-23-B,A-20-21-B,A-18-19-B,A-17-16-15-B,A-14-10-B,A-7-1-B,A-4-2-B,A-6-5-B,B-8-9-13-A,B-12-11-3-A,B-22-27-A	6474	30	3.69	—	09:59	—	
A-27-26-B,A-24-23-B,A-20-21-B,A-18-19-B,A-17-16-15-B,A-14-10-B,A-7-1-B,A-4-2-B,A-6-5-B,B-8-9-13-A,B-12-11-3-A,B-22-25-A	6478	29	3.67	—	10:12	—	
A-25-27-B,A-26-24-B,A-23-20-B,A-18-19-B,A-17-16-15-B,A-14-10-B,A-7-1-B,A-4-2-B,A-6-5-B,B-8-9-13-A,B-12-11-3-A,B-22-21-A	6520	29	3.61	—	09:56	—	
A-25-27-B,A-26-24-B,A-23-20-B,A-21-18-B,A-17-15-B,A-10-13-B,A-4-3-B,A-7-1-8-B,A-6-5-B,B-9-12-A,B-11-16-A,B-14-2-A,B-19-22-A	6824	29	3.59	—	09:47	—	
A-25-27-B,A-26-23-B,A-20-21-B,A-18-19-B,A-17-16-15-B,A-14-10-B,A-7-1-B,A-4-2-B,A-6-5-B,B-8-9-13-A,B-12-11-3-A,B-22-24-A	6946	28	3.44	—	09:37	—	
A-25-27-B,A-26-24-B,A-23-21-B,A-19-17-B,A-13-12-10-B,A-16-11-B,A-4-1-B,A-9-2-B,A-6-5-B,B-7-3-A,B-8-15-14-A,B-18-20-A,B-22-A	7069	27	3.32	—	09:11	—	
A-25-27-B,A-26-24-B,A-22-21-B,A-19-17-B,A-13-12-10-B,A-16-11-B,A-4-1-B,A-9-2-B,A-6-5-B,B-7-3-A,B-8-15-14-A,B-18-20-A,B-23-A	7637	26	3.22	—	09:31	—	
A-26-24-B,A-20-18-B,A-19-17-B,A-15-12-10-B,A-14-11-B,A-7-4-B,A-1-9-B,A-2-8-B,A-6-5-B,B-13-16-A,B-22-3-A,B-21-23-A,B-25-27-A	8401	25	3.11	—	09:23	—	
A-25-27-B,A-26-24-B,A-23-20-B,A-18-19-B,A-17-16-15-B,A-10-13-B,A-14-11-B,A-7-2-B,A-6-5-B,B-1-3-4-A,B-9-8-12-A,B-22-21-A	10364	25	3.10	—	10:05	—	
Average	6690	30	3.80	0.00			
A-24-6-B,A-27-4-12-B,A-13-19-B,A-7-9-B,B-15-18-A,B-25-21-A,B-20-23-1-A,B-11-15-A,B-14-3-A,B-26-16-8-A,B-2-10-A,B-22-17-A	6584	43	4.33	12.0	08:36	—	
A-24-23-1-B,A-22-21-B,A-16-27-B,A-20-5-B,B-18-10-A,B-15-13-19-A,B-8-11-12-A,B-14-3-A,B-17-2-A,B-4-6-A,B-26-7-A,B-9-25-A	6636	33	4.18	—	10:59	—	
A-10-24-B,A-27-4-12-B,A-13-19-B,A-7-6-B,B-15-18-A,B-25-21-A,B-20-23-1-A,B-11-5-A,B-14-3-A,B-16-26-8-A,B-2-9-A,B-22-17-A	6646	41	3.95	13.5	08:33	—	
A-10-19-B,A-27-17-12-B,A-13-24-B,A-7-6-B,B-15-18-A,B-25-21-A,B-20-23-1-A,B-11-5-A,B-14-3-A,B-26-16-8-A,B-2-9-A,B-22-4-A	6804	32	4.02	—	11:51	—	
A-10-19-B,A-27-17-12-B,A-13-2-B,A-7-21-B,B-15-18-A,B-25-6-A,B-20-23-1-A,B-11-5-A,B-14-3-A,B-26-4-8-A,B-9-24-A,B-22-16-A	6850	31	3.89	—	10:49	—	
A-10-6-B,A-25-9-B,A-21-5-B,A-4-3-8-B,B-18-19-A,B-7-15-A,B-23-17-A,B-22-2-A,B-13-20-12-A,B-11-14-A,B-27-26-A,B-16-24-1-A	6879	30	3.75	2.5	08:55	—	
A-24-18-B,A-25-9-B,A-21-16-B,A-4-15-27-B,B-6-17-A,B-7-3-A,B-19-8-1-A,B-12-13-20-A,B-23-2-A,B-14-5-A,B-26-22-A,B-10-11-A	6980	28	3.53	—	09:00	—	
A-10-9-B,A-16-2-B,A-12-13-19-B,A-7-21-B,B-15-18-A,B-25-6-A,B-20-23-1-A,B-11-5-A,B-14-3-A,B-26-4-8-A,B-17-24-A,B-22-27-A	7132	28	3.52	—	10:47	—	
A-10-6-B,A-25-9-B,A-21-5-B,A-4-3-8-B,B-18-22-A,B-7-15-A,B-23-17-A,B-19-2-A,B-13-20-12-A,B-11-14-A,B-27-26-A,B-16-24-1-A	7641	35	3.31	10.5	08:39	—	
A-10-6-B,A-25-9-B,A-21-5-B,A-4-27-8-B,B-18-19-A,B-26-15-A,B-23-7-A,B-22-11-A,B-13-20-12-A,B-2-14-A,B-24-17-A,B-16-3-1-A	7754	36	3.20	10.5	08:39	10:41-10:45	4.5%
A-10-6-B,A-25-9-B,A-21-5-B,A-4-3-8-B,B-18-19-A,B-7-15-A,B-23-17-A,B-22-2-A,B-13-20-12-A,B-11-14-A,B-27-26-A,B-16-24-1-A	7856	35	3.29	10.5	08:39	—	
A-10-9-B,A-16-17-12-B,A-13-19-B,A-7-21-B,B-15-18-A,B-25-6-A,B-20-23-1-A,B-11-5-A,B-14-3-A,B-26-4-8-A,B-2-24-A,B-22-27-A	7918	27	3.4	—	10:29	—	
A-2-6-B,A-25-9-B,A-21-5-B,A-4-3-B,A-19-B,B-18-8-A,B-7-15-A,B-27-17-A,B-22-10-A,B-13-20-12-A,B-11-14-A,B-23-26-A,B-16-24-1-A	8183	35	3.24	10.5	08:37	—	
A-10-6-B,A-25-17-B,A-7-5-B,A-20-27-B,A-9-B,B-26-19-A,B-18-15-A,B-14-4-A,B-21-11-A,B-13-3-12-A,B-2-1-A,B-23-24-A,B-16-22-8-A	8282	26	3.34	—	09:34	—	
A-10-6-B,A-25-9-B,A-21-5-B,A-4-3-8-B,B-18-19-A,B-7-15-A,B-23-17-A,B-22-2-A,B-13-20-12-A,B-11-14-A,B-27-26-A,B-16-24-1-A	8291	34	3.27	10.5	08:39	—	
A-10-11-B,A-25-9-B,A-21-5-B,A-4-3-8-B,B-18-19-A,B-13-15-23-A,B-17-22-A,B-2-7-A,B-20-12-A,B-6-14-A,B-27-26-A,B-16-24-1-A	8442	34	3.26	10.0	08:40	—	
A-10-11-B,A-25-9-B,A-21-5-B,B-4-3-8-A,B-18-19-A,B-13-15-23-A,B-17-22-A,B-2-7-A,B-20-12-A,B-6-14-A,B-27-26-A,B-16-24-1-A	8502	33	3.14	10.0	08:40	—	
A-22-6-B,A-1-9-B,A-21-16-B,A-4-3-B,A-5-B,B-18-8-15-A,B-13-19-A,B-17-11-A,B-12-24-20-A,B-14-2-A,B-27-23-A,B-26-7-A,B-10-25-A	9068	32	3.31	7.5	08:45	—	
Average	7580	33	3.55	6.00			
A-9-22-B,A-26-7-B,A-23-16-1-B,A-19-10-B,B-17-20-A,B-14-15-A,B-13-8-27-A,B-18-3-A,B-11-4-12-A,B-24-21-A,B-6-25-A,B-5-2-A	6652	37	4.26	8.5	10:43	11:14-11:19	
A-14-25-B,A-7-11-B,A-24-21-B,A-17-1-13-B,B-19-27-A,B-20-22-A,B-23-3-16-A,B-15-4-A,B-18-2-A,B-6-10-A,B-26-5-A,B-12-9-8-A	6690	30	3.71	—	10:02	—	
A-25-2-B,A-8-11-1-B,A-16-26-B,A-19-14-B,B-23-7-A,B-6-20-A,B-17-4-15-A,B-12-13-3-A,B-10-5-A,B-27-22-A,B-18-9-A,B-21-24-A	6876	29	3.66	—	09:57	—	
A-14-5-B,A-9-20-B,A-15-1-22-B,A-10-21-B,B-13-12-25-A,B-7-19-A,B-8-23-4-A,B-16-6-A,B-11-3-A,B-24-27-A,B-18-17-A,B-26-2-A	7010	30	3.42	5.0	09:50	10:44-10:49	
A-15-13-5-B,A-26-22-B,A-23-24-B,A-11-B,B-21-10-A,B-4-8-9-A,B-19-2-A,B-12-27-3-A,B-18-25-A,B-17-20-A,B-7-1-A,B-14-16-A,B-6-A	7510	29	3.66	—	09:18	—	
A-13-22-15-B,A-11-5-B,A-16-2-B,A-19-26-B,B-7-10-A,B-6-20-A,B-27-3-12-A,B-23-1-8-A,B-18-24-A,B-14-9-A,B-4-21-A,B-17-25-A	7545	28	3.49	—	11:00	—	4.5%
A-6-2-B,A-26-18-B,A-13-5-1-B,A-19-16-B,B-3-14-A,B-27-12-17-A,B-10-4-A,B-23-24-8-A,B-15-7-A,B-20-25-A,B-21-22-A,B-9-11-A	7621	28	3.46	—	09:39	—	
A-17-5-B,A-22-7-B,A-24-2-B,A-18-10-B,A-3-B,B-26-14-A,B-4-1-12-A,B-16-8-20-A,B-13-25-A,B-21-23-A,B-6-19-A,B-27-11-A,B-9-15-A	8065	27	3.36	—	09:25	—	
A-17-5-B,A-12-15-24-B,A-14-16-B,A-9-26-B,B-20-27-A,B-7-18-A,B-1-8-11-A,B-13-4-3-A,B-23-19-A,B-6-21-A,B-10-22-A,B-25-2-A	8308	27	3.32	—	10:06	—	
A-7-1-8-B,A-12-13-18-B,A-26-17-B,A-5-B,B-11-16-A,B-10-9-A,B-22-19-A,B-24-15-A,B-14-27-A,B-25-4-A,B-20-3-A,B-23-6-A,B-21-2-A	9101	26	3.29	—	10:07	09:35-09:39	
A-5-2-B,A-23-19-B,A-3-4-1-B,A-7-6-B,B-17-21-A,B-18-25-A,B-26-27-A,B-24-22-A,B-9-8-15-A,B-12-20-16-A,B-14-10-A,B-13-11-A	9459	35	3.24	8.5	08:43	09:57-10:00	
A-15-12-13-B,A-9-16-B,A-2-4-B,A-5-7-B,B-14-27-A,B-20-25-A,B-19-8-A,B-17-10-A,B-22-26-A,B-23-11-A,B-18-21-A,B-24-3-1-A,B-6-A	10852	43	3.13	16.5	08:27	10:30-10:35	
Average	7974	31	3.5	3.20			

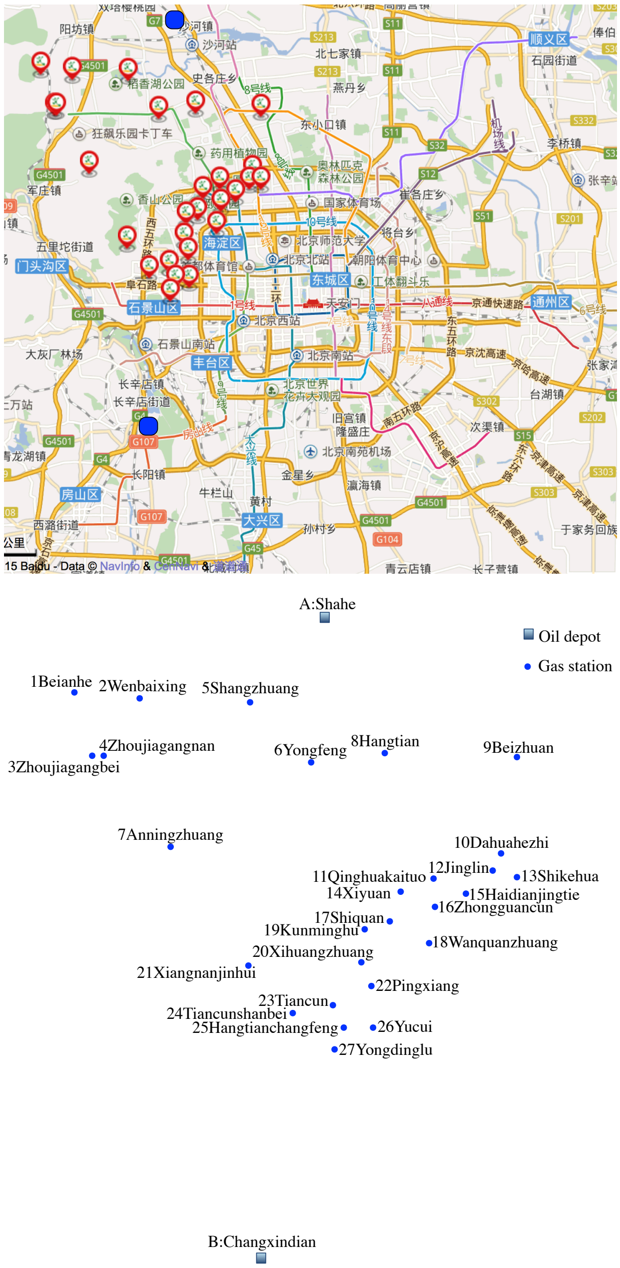
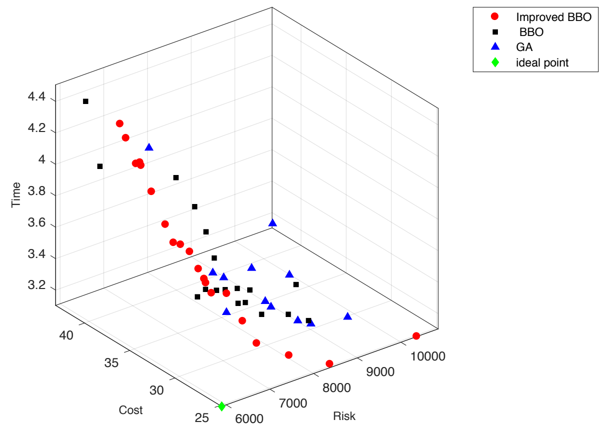


Fig. 11 Case study network

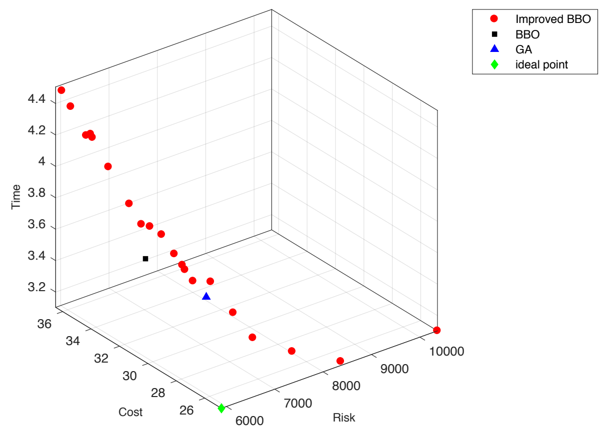
Table 9 Time window, link closure and half link closure

Link/ node	(4,8)	(4,15)	(5,18)	6
Time window				[9-12]
Link closure	[11-13]	[12-13]		
Half closure			[12-13]	

rtation time of improved BBO is higher than that of BBO or GA. We can see that the total risk increases drastically as the total cost and total time decrease



(a) Pareto solutions for three algorithm



(b) Superior Pareto solutions

Fig. 12 Pareto solutions comparison

for improved BBO. This indicates that the total risk and the total cost and total time are in conflict with each other, in this multi-objective optimization problem (of hazardous materials transportation network). It can also be seen that in order to avoid the use of a link with high risk, the total cost and total time are increased in the optimization solutions. As the population density and weather conditions are associated with the total risk, and traffic congestion is related with the total time, we can observe that the Pareto solutions from the improved BBO algorithm opt for a link with congestion for decreasing risk, while avoiding the use of any high risk link.

Columns 5-6 in Table 8 show the penalty cost and the arrival time of node 6 regarding time window and ”TW” represents time window. In the penalty cost column, the line ”—” indicates that the route does not generate any penalty cost. As the time of arriving at node 6 along a certain route exceeds the allowable time window [9:00, 12:00], the corresponding solutions generate penalty costs that vary as the time segment exceeds the allowable time. For example, the first solution in BBO, due to the arrival time at node 6 being 08:36, and the time window at node 6 is [09:00, 12:00], transporting through this route generates a penalty cost of $12. Note that the average penalty cost returned by the improved BBO algorithm is lower than that of running the original BBO and GA algorithms.

The column under “Half link closure” represented by “HC” of Table 8 lists the start and end time of passing half closed link and the line ”—” indicates that the corresponding route does not include any half link closure. For example, the 10th solution returned by BBO, the time segment passing through the link (5, 18) is (10:41, 10:45) while the no entry time is [12:00, 13:00]. By looking at the ”Half link closure” column, most routes do not include this half closed link and the time segments that pass the half closed link do not fall within the forbidden time segment. Thus, the algorithm does not generate any penalty cost for all solutions. Therefore, the only penalty costs come from the constraint of time window. These results imply that the Pareto solutions returned by three algorithms avoid the use of the half closed link, thereby helping minimize the total cost.

All solutions obtained from these three algorithms also meet the link closure constraints. The last column is ”Pareto proportion” obtained by implementing Pareto optimization for all Pareto solutions. The proportions of superior Pareto solutions (blue font) for improved BBO, BBO and GA are 91%, 4.5% and 4.5%, respectively. These results demonstrate that the improved BBO algorithm provides more superior Pareto solutions than BBO and GA.

Jointly drawn from the above results, it can be summarized that the Pareto solutions returned by the improved BBO algorithm are superior to those obtained by the original BBO and GA. They effectively avoid closed links, while achieving considerable reductions in the associated penalty cost due to half link closures and time window (by altering the assignment and scheduling schemes). This is at the small expense of the computation times required (which are 313.3s, 32.3s and 39.7s, respectively for improved BBO, BBO and GA). The longer CPU run time required by the improved BBO is largely attributed to the increased computational burden in search for the superior Pareto solutions. Importantly, the improved BBO provides the more superior Pareto solutions still within a practically acceptable time. In short, the above experimental results have shown that the improved BBO algorithm is efficient and practical to analyze and solve the non-fixed destination MDCVRP with hazmat transportation problems that involve multiple factors.

6 Conclusions and Further Research

This paper has presented a novel formulation of the non-fixed destination MDCVRP for urban hazmat transportation. A multilevel programming model has been proposed to minimize the total transportation risk, cost and time, with many other factors potentially adversely affecting these three key issues also addressed, including: weather conditions, traffic conditions, population density, time window, link closures, and half link closures. This enables the model and solutions to take into better account of the specificities of real-life applications. To obtain optimal solutions to the programming model given a particular problem, an improved BBO algorithm has been designed to effectively search for the best strategies allocating customers to depots and customers to vehicles, and determining the optimal routing solutions with respect to a certain group of depots, vehicles and customers. This improved BBO algorithm integrates the Clarke and Wright saving method and the neighborhood search algorithm for generating the initial inhabits as well as Pareto elitism retention for finding the optimal solutions. Comparative experiments have been carried out to evaluate the performance of the proposed approach, with both simulated numerical examples and a real-world problem case.

The experimental results indicate that the proposed work entails more diverse exploration and exploitation of the potential solutions, than typical existing techniques. Whilst the improved BBO performs the best on optimality, but the time consumed still seems to be in a practically acceptable order or magnitude. The results also confirm the modeling hypotheses in that the population density and weather conditions are associated with total risk, and that traffic congestion is related with total time. Due to the high congestion link may have the low risk, the The Pareto solutions returned by the improved BBO algorithm are able to choose the congestion link for decreasing risk, avoiding the use of high risk links. This is very important for dangerous goods transportation in urban areas.

In future studies, it would be interesting to investigate the other transportation patterns of urban hazmat transportation, addressing further factors such as special-line transportation, road toll, and fatigue driving. Also, making use of Big Data to exploit the real historical statistics of road accidents is worth investigating, in an attempt to derive more realistic urban hazmat transportation models and their solutions. Typically, for catering the large scale transportation corporations (Amozon, FedEx, UPS), the artificial intelligence (machining learning, deep learning) would be applied to deal with the complex and large scale cases.

Compliance with ethical standards

Conflict of interest

Author Jiaoman Du declares that she has no conflict of interest. Author Xiang Li declares that he has no conflict of interest. Author Lei Li declares that he has no conflict of interest. Author Changjing Shang declares that she has no conflict of interest.

Human and animal rights

This article does not contain any studies with human or animal participants performed by the author.

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