Modeling and Solving a Multi-Period Inventory Fulfilling and Routing Problem for Hazardous Materials

Hu, Hao; Li, Jian; Li, Xiang; Shang, Changjing

Published in:
Journal of Systems Science and Complexity

DOI:
10.1007/s11424-019-8176-2

Publication date:
2020

Citation for published version (APA):
Hu, H., Li, J., Li, X., & Shang, C. (2020). Modeling and Solving a Multi-Period Inventory Fulfilling and Routing Problem for Hazardous Materials. *Journal of Systems Science and Complexity*, *33*(3), 760-782. https://doi.org/10.1007/s11424-019-8176-2

J Syst Sci Complex (20XX) XX: 1–24

Modeling and solving a multi-period inventory fulfilling and routing problem for hazardous materials

HU Hao · LI Jian · LI Xiang · SHANG Changjing

DOI:
Received: x x 20xx / Revised: x x 20xx

Abstract Any potential damage may be severe once an accident occurs involving hazardous materials. It is therefore important to consider the risk factor concerning hazardous material supply chains, in order to make the best inventory routing decisions. In this paper, we address the problem of hazardous material multi-period inventory routing with the assumption of a limited production capacity of a given manufacturer. The goal is to achieve the manufacturer's production plan, the retailer's supply schedule and the transportation routes within a fixed period. As the distribution of hazardous materials over a certain period is essentially a multiple travelling salesmen problem, we formulate a loading-dependent risk model for multiple-vehicle transportation and present an integer programming model to maximize the supply chain profit. An improved genetic algorithm considering two dimensions of chromosomes that cover the aforementioned period and supply quantity is devised to handle the integer programming model. Numerical experiments carried out demonstrate that using the proposed multi-period joint decision-making can significantly increase the overall profit of the supply chain as compared to the use of single period decision repeatedly, while effectively reducing its risk.

Keywords Multi-period inventory routing problem, Integer programming model, Limited production capacity, Genetic algorithm.

HU Hao
College of Information Science and Technology, Beijing University of Chemical Technology, Beijing 100029, China. Email:huhao568@qq.com.
LI Jian
Research Base of Beijing Modern Manufacturing Development, College of Economics and Management, Beijing University of Technology, Beijing 100124, China. Email:lijiansem@bjut.edu.cn.
LI Xiang (Corresponding author)
College of Economics and Management, Beijing University of Chemical Technology, Beijing 100029, China; Department of Computer Science, Institute of Mathematics, Physics and Computer Science, Aberystwyth University, Aberystwyth SY23 3DB, UK. Email:lixiang@mail.buct.edu.cn.
SHANG Changjing
Department of Computer Science, Institute of Mathematics, Physics and Computer Science, Aberystwyth University, Aberystwyth SY23 3DB, UK. Email:cns@aber.ac.uk.
*This research was supported by the National Natural Science Foundation of China under Grant Nos. 71571010, 71722007, a Fundamental Research Funds for the Central Universities No XK1802-5, a Sêr Cymru II COFUND Research Fellowship, UK, and a Great Wall Scholar Training Program of Beijing Municipality under Grant No CIT&TCD20180305.
◇ *This paper was recommended for publication by Editor .*

1 Introduction

In recent years, with the development of economy, China has become a major Country in the field of chemical production, sale and use. Chemical industry is an important pillar industry of national economy, and there are tens of thousands of chemical manufacturing enterprises. For instance, by 2016 the total output value of petrochemical and chemical industry in the country had increased to about 14 trillion RMB according to the report of 'Economic Analysis of China Petroleum and Chemical Industry', which surpassed the United States to have become the number one nation in the world, in this regard. Ironically, hazardous materials have made a significant contribution to the improvement of people's living standards. Unfortunately, at the same time they have brought about serious potential harms to human health and environment, such as carcinogenesis, teratogenicity, environmental degradation and so on. Therefore, the safety management of hazardous materials is vital to the sustainable development of the country and the human society in general. Although China's hazardous materials safety management is improving continuously, the situation is still grim, and grave accidents frequently occur. For example, on March 1, 2014, two hazardous material transportation vehicles collided in Shanxi JinJi freeway, which killed 40 people, injured 12, and burned 42 cars. Worse still, on August 12, 2015, a fire caused by an explosion at a container terminal in Tianjin Binhai New Area, killed 165 people and injured more than 798 people.

Thus, how to reduce the risk of any accidents caused by hazardous materials has become a very important and urgent subject for safety management and chemical industrial development. Generally speaking, accidents involving hazardous materials mainly occur from the following six stages in their lifecycle: production, transportation, storage, sale, use and scrap. Among these, hazardous material inventory and transportation form a very important part and have attracted much attention. According to incomplete statistics, the number of accidents, deaths and injuries during the period from 2011 to 2015 are 1058, 1275 and 4175, respectively, in China[1]. Fig.1 shows the proportion of the above six aspects in accidents, deaths and injuries. It can be seen that the proportion of accidents occur in transportation and storage is indeed very high (accounting for 46.7%, 41.8%, and 36.2%, respectively). Although a great deal has been spent on the inventory and transportation processes regarding hazardous materials, accidents remain, typically arising from leakage, explosion, poisoning and other reasons, which are harmful to life, property and the environment. Consequently, an overall optimization mechanism is desirable for the inventory and transportation of hazardous materials from a supply chain perspective, considering not only the cost, but also the risk.

Inventory routing problem (IRP) mainly considers how to make decisions on suppliers and customers' inventory, and how to design the transportation routes. Considering limited production capacity of any given manufacturer, we should pay particular attention to the production plan and inventory arrangement. Hu, et al.[2] studied a hazardous material single period IRP for a three-level supply chain system. However, from the viewpoint of long-term effects of inventory and distribution, single period IRP does not take into account the continuity of time. As such, we cannot simply utilise a single period decision repeatedly in an attempt to solve the hazardous material multi-period IRP. For example, in order to avoid shortage of hazardous material supply over certain periods, sufficient amounts of the materials have to be produced in advance to increase inventory, which will therefore affect the supply chain production, inventory and transportation strategies. The use of IRP that considers multi-period is thus, more realistic. While existing studies regarding hazardous material multi-period IRP normally focus on profits, costs or service levels, they often ignore the risk issue on hazardous materials[3, 4]. In this investigation, we consider the risk factor during the process of multi-period inventory and transportation.

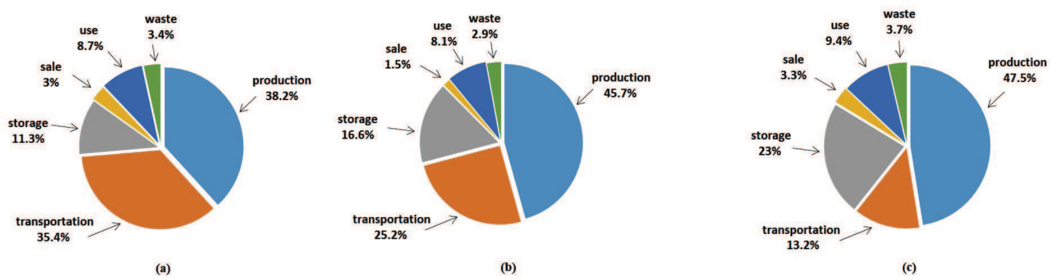

Figure 1: Proportion of six stages within hazardous material lifecycle regarding accidents, deaths and injuries

The contributions of this paper are summarized as follows: i) we consider multi-period joint decision on hazardous material supply chains under a limited production capacity, focusing on the formulation of manufacturer's production plan, retailer's supply schedule, and transportation routing programming for the entire hazardous material lifecycle; ii) we formulate a loading-dependent risk model for hazardous material multi-vehicle transportation, and propose an integer programming model to deal with hazardous material IRPs. The remainder of this paper is structured as follows. Section 2 provides a brief overview of the literature on IRP. Section 3 presents the loading-dependent risk model for hazardous material multi-vehicle transportation and describes the mathematical model for hazardous material multi-period IRP. A genetic algorithm is devised in Section 4. Section 5 shows an illustrative example to demonstrate the efficiency of the proposed model and solution algorithm. Section 6 concludes the study.

2 Literature review

The earliest IRPs focused on problems involving a single period. Bell, et al.[5] first studied IRP to improve the distribution of Industrial Gases, and designed a Lagrangian relaxation algorithm to solve the mixed integer programming problem for the application. Daganzo, et al.[6] considered an IRP which transported items with different characteristics to a common destination at different rates from a finite number of supply points. They proposed a method for optimizing the number of transportation vehicles and the services provided by each. Chien, et al.[7] formulated the IRP as one of mixed integer programming, and developed a Lagrangian-based procedure to generate both good upper bounds and heuristic solutions. Zhao, et al.[8] addressed an IRP in a three-echelon logistics system following a fixed partition strategy, and established a variable large neighborhood search algorithm. Coelho and Laporte[9] proposed a branch-and-cut algorithm for the solution of IRPs with multiple products and multiple vehicles. Li, et al.[10] considered an IRP in which the objective is to minimize maximum route travel time, and presented a tabu algorithm to improve the search quality for each iteration. Although the single period IRPs take into account the joint decision of inventory and transportation, they may not reflect the underlying long-term plan of addressing such problems.

Multi-period IRPs have become a hot topic over the past two decades. In particular, Viswanathan and Mathur[11] considered a multi-period IRP involving one-warehouse, multi-retailer and multi-product distribution, and presented a new heuristic algorithm for building a stationary nested joint replenishment policy. Jaillet, et al.[3] dealt with a multi-period IRP regarding the request for repeated distribution of a commodity, such as heated oil from depot to customers, resolving the mathematical model based on Monte Carlo simulation. Zhao, et al.[12] tackled a multi-period IRP with a fixed partition policy, and designed a tabu search algorithm to find the retailers' optimal partition regions. Cheng-Hong[13] studied an IRP involving stochastic demands, via analyzing all of the cost, including the retailer's stocking, shortage penalty, and distribution center's replenishment, holding, distribution, and designed a heuristic algorithm by borrowing ideas from solving the conventional traveling-salesman problem. Huang and Lin[14] proposed an integrated model to address an IRP with multi-item replenishment and stochastic demands, and devised a modified ant colony optimization algorithm. Moin, et al.[15] investigated two representations using GAs for a multi-product and multi-period IRP, and made two significant modifications to the algorithm regarding its binary representation.

More recently, Al-E-Hashem and Rekik[16] proposed a multi-period multi-product IRP by examining the specific interrelationship between the transportation cost and the greenhouse gas emission level. For solving a multi-product and multi-period IRP in fuel delivery, Vidović, et al.[4] proposed a mixed integer programming model and devised a heuristic approach, with or without the consideration of fleet size costs. Roldán, et al.[17] investigated a multi-period IRP under three different customer selection methods: big orders first, lowest storage first, and equal quantity discount. Rahimi, et al.[18] studied a multi-period IRP by considering the service level and the greenhouse gas emissions in the distribution of perishable products, and applied a mechanism named NSGA-II to resolve the equivalent auxiliary crisp model. Although such investigations into multi-period IRPs exist, contributions for multi-period IRP concerning hazardous materials are rather scarce.

Different from ordinary goods, when dealing with the logistics of hazardous materials it is necessary to consider the risk factors, which will directly affect the inventory and transportation decisions associated with such problems. Wei, et al.[19] developed a chance-constrained programming model for the hazardous material IRP, and designed a GA to solve the model. Wei, et al.[20] first investigated fuzzy-randomness in location-scheduling programming for hazardous material transportation, and formulated a modified particle swarm optimization algorithm to minimize the en route risks and site risks. Du, et al.[21] also reported a chance-constrained programming model by assuming the distances between any two locations within a supply chain network to be fuzzy variables. A hybrid intelligent algorithm integrating fuzzy simulation and a GA was designed for solving the model. Du, et al.[22] studied a multi-depot vehicle routing problem for hazardous material transportation, and proposed four different fuzzy simulation-based heuristic algorithms, offering possible alternative solutions for the common problem addressed. Hu, et al.[23] considered a time-dependent hazardous material vehicle routing problem to obtain the optimal route and the departure time, and designed an improved GA to solve it. Last but not least, as indicated previously, Hu, et al.[2] studied a hazardous material single period IRP for a three-level supply chain network, and designed an improved GA whose chromosomes contain two types of gene to handle the proposed model. Nevertheless, these developments do not integrate inventory and transportation of hazardous materials and the consideration of risks from a multi-period perspective.

3 Problem definition and mathematical formulation

3.1 Problem description and notations

In this section, we consider a two-echelon hazardous material supply chain network including a single manufacturer and multiple retailers. The retailers need to collect the daily demand information for each specified period, and deliver such demand to the manufacturer. Then, the manufacturer arranges the daily inventory according to the supply quantities requested by the retailers, and designs the transportation routes. Suppose that in general, in the long run, the production capacity of the manufacturer can meet the demand of the market, but there may be a shortage of supply in certain periods. Therefore, in order to decrease the potential shortage and its associated cost, the manufacturer needs to produce the materials in advance and increase inventory. Such advanced production will inevitably affect the inventory, supply and transportation decision of the supply chain over the entire sequence of the periods concerned. The retailer's inventory is also required to be higher than a basic value at the beginning of each period, which mainly refers to a basic value set in response to some unexpected disasters. It is mandatory and fixed by the government. Under the premise of joint decision-making, the objective of the proposed multi-period IRP model (and the associated solution mechanism) is to maximize the profit of the complete supply chain while effectively control the system risk in each period. For this, practically working assumptions are made as listed below:

- The shortage at a certain retailer is allowed, but it will incur a shortage cost; replenishment is unnecessary.
- The number of vehicles is not restricted within each period.
- Vehicles depart from the manufacturer location to meet retailers' demands and return to the manufacturer at the end of the trip.

- It is possible for each retailer to be visited once and only once, when its inventory level falls to or below the reorder point.

Notationally, the proposed hazardous material multi-period IRP model adopts the following for shorthand:

Notation system

N	set of retailers, $N = \{1, 2, \cdots, n\}$,
M	set of manufacturer and retailers, $M = \{0\} \bigcup N$,
T	number of periods,
P	production capacity of the manufacturer in each period,
V	transportation capacity of a single vehicle,
I^0	initial inventory of the manufacturer,
I^t	inventory level of the manufacturer in period t,
h_0^t	unit mass inventory holding cost of the manufacturer in period t,
c^t	unit mass production cost of the manufacturer in period t,
μ	unit mass inventory risk of the manufacturer,
U_i	inventory capacity of retailer i,
U_i^*	maximum shortage level of retailer i,
u_i	basic inventory quantity of retailer i at the beginning of each period,
s_i^t	unit mass sale price of retailer i in period t,
I_i^0	initial inventory of retailer i,
I_i^t	inventory level of retailer i in period t,
O_i^t	shortage level of retailer i in period t,
h_i^t	unit mass inventory holding cost of retailer i in period t,
l_i^t	unit mass shortage cost of retailer i in period t,
d_i^t	demand of retailer i in period t,
c	fixed transportation cost of a single vehicle,
c_{ij}	unit mass variable transportation cost on arc (i, j),
α_i	unit mass inventory risk of retailer i,
β_{ij}	unit mass transportation risk on arc (i, j).

Decision variables

p^t	production quantity of the manufacturer in period t,
q_i^t	supply quantity from the manufacturer to retailer i in period t,
x_{ij}^t	1 if arc from i to j is active in period t; 0 otherwise.

Auxiliary variables

x_{ij}^{kt} 1 if arc from i to j is active by running vehicle k in period t; 0 otherwise,

y^t number of vehicles required in period t,

r_i^{kt} the ith retailer on the transportation route of vehicle k in period t

z_k^t number of retailers served by vehicle k in period t,

w_k^t set of retailers served by vehicle k in period t.

3.2 Computation of risk

Transportation risk is usually expressed as a product of accident probability and consequence [24, 25]. Meanwhile, accident consequence could be measured as the total number of exposed people in an accident. The more quantity of hazardous materials a vehicle loads, the more number of exposed people there will be in the event of an accident. Therefore, in order to control the transportation risk more accurately, any change of the loading is required to be considered, which means that the transportation risk is in general a dynamic term. As not all the retailers are served in each period, the distribution of hazardous materials is essentially a multi-vehicle travelling salesmen problem. If we can determine the retailers served by vehicle k and their service order, we should be able to compute the transportation risk of a given route. The following risk modeling reflects these observations.

Firstly, we need to calculate the transportation loading of each arc in the route of vehicle k. Considering the general case where there are more than one vehicle starting from the manufacturer location, the first retailer served by each vehicle in period t can be captured as follows:

$$r_1^{1t} = \min\left(\arg\max_{j\in N}(x_{0j}^t)\right),$$
$$r_1^{kt} = \min\left(\arg\max_{j\in N\setminus\bigcup_{m=1}^{k-1}\{r_1^{mt}\}}(x_{0j}^t)\right),\ k=2,3,...,y^t,$$

and the ith retailer served by vehicle k in period t can be expressed as

$$r_i^{kt} = \arg\max_{j\in N}(x_{r_{i-1}^{kt}j}^t),\ i=2,3,...,z_k^t.$$

Furthermore, in period t, the loading of vehicle k on arc $(m-1,m)$ is

$$v^{kt} = \sum_{i=m}^{z_k^t} q_{r_i^{kt}}^t,$$

and the transportation risk of vehicle k on arc $(m-1,m)$ is $\beta_{r_{m-1}^{kt}r_m^{kt}}v^{kt}$, where $1\le m\le n$.

The transportation risk of vehicle k in period t can be estimated as $\sum_{k=1}^{y^t}\sum_{m=1}^{z_k^t}\beta_{r_{m-1}^{kt}r_m^{kt}}v^{kt}$. The inventory risk is also calculated by inventory quantity and unit mass inventory risk, which can be expressed as

$$R_t' = \mu I^t + \sum_{i=1}^{n}\alpha_i I_i^t.$$

Therefore, the total risk from the manufacturer to its retailers in period t can be expressed as

$$R_t = R'_t + \sum_{k=1}^{y^t} \sum_{m=1}^{z_k^t} \sum_{i=m}^{z_k^t} \beta_{r_{m-1}^{kt} r_m^{kt}} q_{r_i^{kt}}^t.$$

3.3 Formulation of overall problem

For enterprises, the pursuit of economic profit maximization is usually the first goal. Given the often changing sale price of the hazardous materials, in order to obtain the most economic benefits, any manufacturer wishes to accurately control the daily output while reducing any associated costs. The profit of a supply chain network within a certain period t can be expressed as

$$\begin{aligned} L_t = & \sum_{i=1}^{n} s_i^t \min\{I_i^{t-1} + q_i^t, d_i^t\} - c^t p^t - h_0^t I^t - \sum_{i=1}^{n} h_i^t I_i^t - \sum_{i=1}^{n} l_i^t O_i^t - cy^t \\ & - \sum_{k=1}^{y^t} \sum_{m=1}^{z_k^t} \sum_{i=m}^{z_k^t} c_{r_{m-1}^{kt} r_m^{kt}} q_{r_i^{kt}}^t, \end{aligned}$$

where $\sum_{i=1}^{n} s_i^t \min\{I_i^{t-1} + q_i^t, d_i^t\}$ is the revenue of the supply chain, $c^t p^t$ is the production cost at the manufacturer, $h_0^t I^t + \sum_{i=1}^{n} h_i^t I_i^t$ is the inventory cost, $\sum_{i=1}^{n} l_i^t O_i^t$ is the shortage cost at the retailers, cy^t and $\sum_{k=1}^{y^t} \sum_{m=1}^{z_k^t} \sum_{i=m}^{z_k^t} c_{r_{m-1}^{kt} r_m^{kt}} q_{r_i^{kt}}^t$ are fixed transportation cost and variable transportation cost, respectively.

Aiming at hazardous material IRPs, we add a new objective function which is targeted at minimizing the risk of a two-echelon supply chain network. Thus, we could formulate a bi-objective model to solve the problem. While in general, different types of hazardous material possess different hazard levels, and the chemical manufacturers always pursue the maximum profit possible subject to consideration of different risk levels. Thus, we could select the popular ε-constraint method to constrain the system risk. The ε-constraint method was originally proposed by Haimes[26], and is one of the best known approaches for solving multi-objective problems. In this method, one objective is selected as the main objective and other objectives are transformed into model constraints. In real-world practice, achieving the maximum profit is normally the goal. Hence, we can transform the risk aspect into a constraint condition imposed over the model. As such, we propose the following integer programming model:

$$\max \quad L = \sum_{t=1}^{T}\sum_{i=1}^{n} s_i^t \cdot \min\{I_i^{t-1} + q_i^t, d_i^t\} - \sum_{t=1}^{T} c^t p^t - \sum_{t=1}^{T} h_0^t I^t - \sum_{t=1}^{T}\sum_{i=1}^{n} h_i^t I_i^t - \sum_{t=1}^{T}\sum_{i=1}^{n} l_i^t O_i^t$$
$$- \sum_{t=1}^{T} c y^t - \sum_{t=1}^{T}\sum_{k=1}^{y^t}\sum_{m=1}^{z_k^t}\sum_{i=m}^{z_k^t} c_{r_{m-1}^{kt} r_m^{kt}} q_{r_i^{kt}}^t$$

$$\text{s.t.} \quad \mu I^t + \sum_{i=1}^{n} \alpha_i I_i^t + \sum_{k=1}^{y^t}\sum_{m=1}^{z_k^t}\sum_{i=m}^{z_k^t} \beta_{r_{m-1}^{kt} r_m^{kt}} q_{r_i^{kt}}^t \le \varepsilon_t \;, \quad t = 1, 2, \cdots, T \tag{1}$$

$$I^t = I^{t-1} + p^t - \sum_{i=1}^{n} q_i^t, \quad t = 1, 2, ..., T \tag{2}$$

$$I_i^t = (I_i^{t-1} + q_i^t - d_i^t)^+, \quad t = 1, 2, ..., T, \; i \in N \tag{3}$$

$$O_i^t = (I_i^{t-1} + q_i^t - d_i^t)^-, \quad t = 1, 2, ..., T, \; i \in N \tag{4}$$

$$\sum_{t=1}^{\theta}\sum_{i=1}^{n} q_i^t \le I^0 + \sum_{t=1}^{\theta} p^t, \quad \theta = 1, 2, \cdots, T \tag{5}$$

$$I_i^t \le U_i, \quad t = 1, 2, ..., T, \; i \in N \tag{6}$$

$$O_i^t \le U_i^*, \quad t = 1, 2, ..., T, \; i \in N \tag{7}$$

$$q_i^t \le U_i - I_i^{t-1}, \quad t = 1, 2, ..., T, \; i \in N \tag{8}$$

$$q_i^t \ge \max\{u_i - I_i^{t-1}, 0\}, \quad t = 1, 2, ..., T, \; i \in N \tag{9}$$

$$p^t \le P, \quad t = 1, 2, ..., T \tag{10}$$

$$\sum_{i=1}^{z_k^t} q_{r_i^{kt}}^t \le V, \quad t = 1, 2, ..., T, \; k = 1, 2, ..., y^t \tag{11}$$

$$r_1^{1t} = \min\left(\arg\max_{j \in N}(x_{0j}^t)\right), \quad t = 1, 2, ..., T \tag{12}$$

$$r_1^{kt} = \min\left(\arg\max_{j \in N \setminus \bigcup_{m=1}^{k-1}\{r_1^{mt}\}}(x_{0j}^t)\right), \quad t = 1, 2, ..., T, \; k = 2, 3, ..., y^t \tag{13}$$

$$r_i^{kt} = \arg\max_{j \in N}(x_{r_{i-1}^{kt} j}^t), \quad t = 1, 2, ..., T, \; i = 2, 3, ..., z_k^t, \; k = 1, 2, ..., y^t \tag{14}$$

$$\sum_{j=0}^{n} x_{ji}^t - \sum_{j=0}^{n} x_{ij}^t = 0, \quad t = 1, 2, ..., T, \; i \in M \tag{15}$$

$$\sum_{j=0}^{n} x_{ij}^{t} = \mathrm{sgn}(q_i^t), \quad t = 1,2,...,T,\ i \in N \tag{16}$$

$$y^t = \sum_{j=1}^{n} x_{0j}^{t}, \quad t = 1,2,...,T \tag{17}$$

$$z_k^t = \sum_{i=0}^{n}\sum_{j=0}^{n} x_{ij}^{kt} - 1, \quad t = 1,2,...,T,\ k = 1,2,...,y^t \tag{18}$$

$$x_{ij}^{t} = \sum_{k=1}^{y^t} x_{ij}^{kt}, \quad t = 1,2,...,T,\ i \in M,\ j \in M \tag{19}$$

$$w_k^t \in \{r_i^{kt} | r_i^{kt} \in \{1,2,\cdots,n\}, i = 1,2,\cdots,z_k^t\}, \quad t = 1,2,...,T,\ k = 1,2,...,y^t \tag{20}$$

$$\sum_{i,j \in S} x_{ij}^{kt} \le |S| - 1,\ 2 \le |S| \le z_k^t,\ S \subset w_k^t, \quad t = 1,2,...,T,\ k = 1,2,...,y^t \tag{21}$$

$$p^t \ge 0, q_i^t \ge 0, \quad t = 1,2,...,T,\ i \in N \tag{22}$$

$$x_{ij}^{t} = \{0,1\}, x_{ij}^{kt} = \{0,1\}, \quad t = 1,2,...,T,\ k = 1,2,...,y^t,\ i \in M,\ j \in M. \tag{23}$$

In this model, constraint (1) is the ε-constraint of risk, where ε_t is a value between the maximum and minimum risk of the supply chain addressed, which is usually determined empirically, by considering the type and hazard level of hazardous materials. Constraints (2) and (3) define the inventory level at the manufacturer and retailers in period t, respectively. Constraint (4) specifies the shortage level at the retailers in period t. Constraint (5) guarantees that the cumulative supply quantity for retailers in each period is not more than the sum of initial inventory and cumulative production quantities of the manufacturer. Constraint (6) ensures that the inventory level of retailers can not be greater than the inventory capacity. Constraint (7) ensures that the shortage level of retailers can not be greater than the maximum shortage level. Constraint (8) describes the supply quantity ceiling of retailer i in period t. Constraint (9) imposes that retailer i must be served in period t if its inventory quantity in the previous period is lower than a basic inventory quantity. If we replace hazardous materials by general cargo, the safety inventory is not necessary because the model assumes the demands are known in advance without any uncertainty. Constraint (10) shows the production capacity for the manufacturer. Constraint (11) restricts the vehicles' transportation capacity. Constraints (12)-(14) dictates the way in which retailer i be served by vehicle k in period t. Constraint (15) indicates the flow conservation. Constraint (16) depicts the relationship between arc (i, j) and the supply quantity in period i. Constraint (17) represents the number of vehicles in period t. Constraint (18) states the number of retailers served by vehicle k in period t. Constraint (19) links up two related variables. Constraint (20) gives the set of corresponding retailers served by each vehicle k in period t. Constraint (21) implements a sub-tour elimination over the vehicles. Constraints (22) and (23) present basic domain ranges.

4 Model solution and solution algorithm

Since an IRP is a NP-hard problem[27], it is generally impracticable to be solved via traditional operations, even just for moderately sized problems. Instead, evolutionary algorithms have shown feasibility and have been widely exploited to solve such problems[28, 29]. In particular, for the present multi-period IRPs, the change of supply quantities in each period will affect the decision in the later periods, thus we design a genetic algorithm to work with the above-proposed model, aiming at identifying satisfactory solutions.

4.1 Retailers assignment

Retailers that are to be served and the corresponding supply quantities will directly affect their inventory level and also, the manufacturer's production plan, the number of vehicles and the transportation routing, in any future period. As reflected in Fig.2, if inventory levels $I_1^0, I_3^0, I_4^0, ..., I_n^0$ fall to or below the basic inventory quantity, the respective retailers will be served in period 1, where the supply quantities are set to $q_1^1, q_3^1, q_4^1, ..., q_n^1$. The rest of the retailers are likely to be supplied as well. After meeting the market demands, a new inventory level of each retailer is obtained and the retailers that need to be served in period 2 are identified. Once the retailers' supply quantities are determined, the distribution of hazardous materials is essentially a basic multi-traveling salesman problem. If the actual calculation scale is small, we can use enumeration method or branch and bound algorithm[30]; if the calculation scale is large, we can use heuristic algorithm for each cycle of distribution[31, 32]. There will be no detailed description here. To reflect this observation, we take those retailers which are served and the corresponding supply quantities as the basis upon which to design the chromosome structure, as shown in Fig.3.

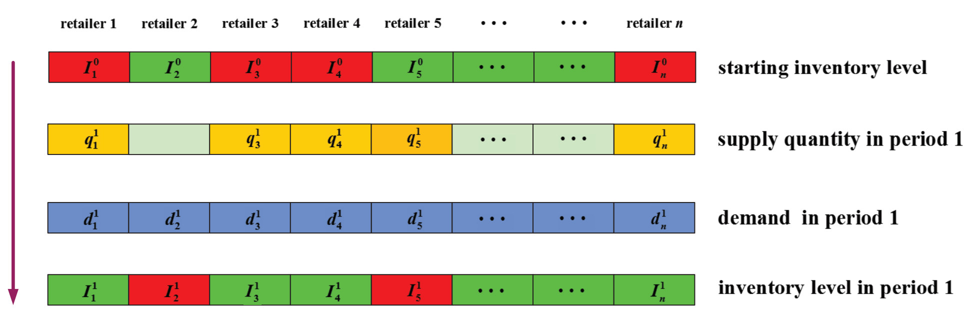

Figure 2: Operating process at retailers

From this determination of the delivery scheduling we can make a decision regarding the production plan.

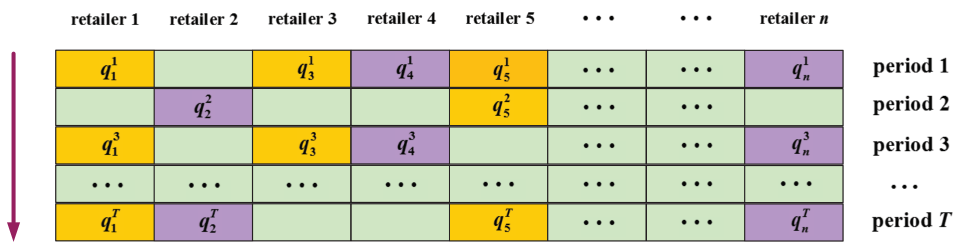

Figure 3: Chromosome structure

4.2 Production plan assignment

The production plan of the manufacturer is formulated on the basis of the supply schedule of the retailers in each period. Due to limited production capacity, the manufacturer needs to produce in advance to satisfy the demand beyond the production capacity in certain periods. Fig.4 shows the production plan assignment, where a green block means overcapacity in the period, and a red block means insufficient capacity that needs to be produced in advance. Once the retailer's supply quantity in each period is determined, the manufacturer's production quantity in each period can be obtained by minimizing the manufacturer's total production and inventory costs, which is a simple linear programming problem and can be easily solved by MATLAB.

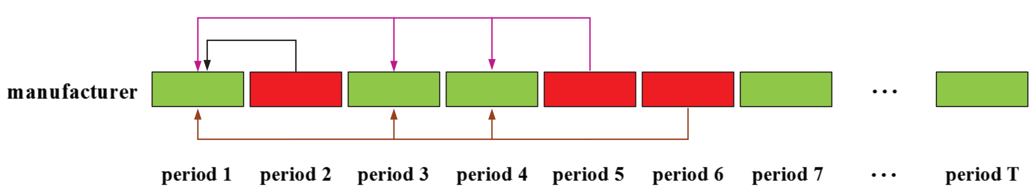

Figure 4: Production plan assignment

$$
\begin{aligned}
\min \quad & C = \sum_{t=1}^{T} c^t p^t + \sum_{t=1}^{T} h_0^t I^t \\
\text{s.t.} \quad & I^t = I^{t-1} + p^t - \sum_{i=1}^{n} q_i^t, \quad t = 1, 2, ..., T \\
& \sum_{t=1}^{\theta} \sum_{i=1}^{n} q_i^t \leq I^0 + \sum_{t=1}^{\theta} p^t, \quad \theta = 1, 2, \cdots, T \\
& p^t \leq P, \quad t = 1, 2, ..., T \\
& p^t \geq 0, \quad t = 1, 2, ..., T.
\end{aligned}
$$

4.3 Initialization Process

Let *pop_size* denote the size of population generated by retailers assignment process. The initialization process can then be summarized as given in Table 1.

Table 1 GA initialization process

Step 1. Define an integer number *pop_size* as the number of chromosomes. Set $i = 1$ and $j = 1$.
Step 2. For period j, find retailers whose inventory level is lower than a given threshold, and ran -domly generate supply quantity for these retailers ($u_i - I_i^{t-1} < q_i^t \leq U_i - I_i^{t-1}$); the retail -er of which inventory is higher than the given threshold is randomly selected to supply (If the retailer is supplied, $0 \leq q_i^t \leq U_i - I_i^{t-1}$) .
Step 3. If new inventory level does not exceed inventory capacity of retailers, set $j = j + 1$; other -wise, go to step 2.
Step 4. If $j \leq T$, go to step 2.
Step 5. Set $i = i + 1$. If $i \leq pop\_size$, set $j = 1$ and go to step 2.
Step 6. Return initial chromosomes.

4.4 Evaluation Function

Let V_i be a feasible chromosome. Arrange the chromosomes in descending sort according to the target value, and calculate the fitness values. The evaluation function is defined as follows:

$$eval(V_i) = a(1-a)^{i-1}, \quad i = 1, 2, ..., pop\_size$$

where a is a real number taking value in interval $(0, 1)$. Thus, by computing the above equations, *pop_size* objective values are obtained for all chromosomes.

4.5 Selection Process

We employ the classical method of spinning the roulette wheel to select chromosomes for constructing a population. For any $i = 1, 2, \cdots, pop\_size$, calculate

$$\gamma_i = \sum_{j=1}^{i} eval(V_j).$$

Then, generate a random number $r \in (0, \gamma_{pop\_size}]$ and select the ith chromosome V_i if $\gamma_i < r \leq \gamma_{i+1}$. Repeat the above process *pop_size* times to obtain the required *pop_size* chromosomes.

4.6 Crossover Process

First, select chromosomes for crossover using a random number r and crossover probability p_c, with the selected ones denoted by $v_1, v_2, ..., v_c$. Divide them into pairs $((v_1, v_2), (v_3, v_4), ...)$. Without losing generality, we illustrate the crossover operation with (v_l, v_{l+1}). Second, consider the real-world problem in that for two different chromosomes, even the same retailer may have different supply strategies in different periods. Therefore, if retailer k within parents v_l and

v_{l+1} are both served in period j, the crossover operator regarding the supply quantities can be designed as follows:

$$\lambda q_{k,l}^{j} + (1-\lambda) q_{k,l+1}^{j}, (1-\lambda) q_{k,l}^{j} + \lambda q_{k,l+1}^{j}, \lambda \in (0,1).$$

Finally, we check the feasibility for each child before accepting it. The crossover process can be summarized in Table 2.

Table 2 Crossover procedure

Step 1. Set crossover probability p_c and $i=1$.

Step 2. Randomly generate $r \in (0,1)$.

Step 3. If $r \le p_c$, select a chromosome as a parent and set $i=i+1$.

Step 4. If $i \le pop\_size$, go to step 2.

Step 5. Denote selected parents by $v_1, v_2, ..., v_L$, divide them into pairs, and set $l=1$ and $k=1$.

Step 6. Randomly select a period $j \in [1,T]$, and randomly generate a real number $\lambda \in (0,1)$; if retailer k within parents v_l and v_{l+1} are both served in period j, produce two new supply quantities $\lambda q_{k,l}^{j} + (1-\lambda) q_{k,l+1}^{j}$ and $(1-\lambda) q_{k,l}^{j} + \lambda q_{k,l+1}^{j}$; if both supply quantities are fea -sible for retailer k in period j, replace supply quantities of parents with them, else, retain them and generate supply strategy as with initialization process for retailer k after period j.

Step 7. Set $k=k+1$; if $k \le n$, go to step 6.

Step 8. Update chromosomes and set $l=l+2$; if $l \le L$, set $k=1$ and go to step 6.

Step 9. Return chromosomes.

4.7 Mutation Process

Let P_m denote the mutation probability. Select the chromosomes using P_m and a random number r. For each retailer within the selected chromosome, randomly select a period to perform mutation. If retailer k in parents is served in period j, the mutation operator is applied such that

$$\overline{q}_k^j = q_k^j + \lambda \min\{(q_k^j - u_i + I_k^{j-1}), (U_k - I_k^{j-1} - q_k^j)\}.$$

The mutation process is summarized in Table 3.

Table 3 Mutation procedure

Step 1. Set mutation probability p_m, $i=1$ and $k=1$.

Step 2. Randomly generate $r \in (0,1)$.

Step 3. If $r \le p_m$, randomly select a mutation period $j \in [1,T]$, and randomly generate $\lambda \in [-0.5, 0.5]$; if retailer k is served in period j, replace its supply quantities q_k^j with $\overline{q}_k^j$ where $\overline{q}_k^j = q_k^j + \lambda \min\{(q_k^j - u_i + I_k^{j-1}), (U_k - I_k^{j-1} - q_k^j)\}$; generate supply strategy as with initializati -on process for retailer k after period j.

Step 4. Set $k=k+1$; if $k \le n$, go to step 2.

Step 5. Update chromosomes and set $i=i+1$; if $i \le pop\_size$, set $k=1$ and go to step 2.

Step 6. Return chromosomes.

A new generation of population is generated after the evaluation, selection, crossover and mutation operations. Repeat this cycle G times, and we may obtain a satisfactory solution with the smallest fitness value.

5 Numerical experiments

To illustrate the efficacy of the proposed model, we apply it to two multi-period hazardous material IRP case studies. We first describe the problem-related data in detail and then discuss the numerical results.

5.1 Experimental data

This experimental investigation considers a two-echelon supply chain IRP with a single manufacturer and eight retailers. The data in Table 4 shows the unit mass sale prices of the product at individual retailers. The unit mass variable transportation costs of the hazardous materials are listed in Table 5. The unit mass inventory risks of the hazardous materials at the manufacturer and retailers are given in Table 6. The unit mass transportation risks of hazardous materials among the manufacturer and retailers are presented in Table 7. The demands of the retailers are shown in Table 8.

Table 4 Unit mass sale prices of retailers ($\times 10^3$ dollars)

	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}
R_1	3.725	3.725	3.725	3.725	3.825	3.825	3.825	3.825	3.825	3.825
R_2	3.8	3.8	3.8	3.8	4.025	4.025	4.025	4.025	4.025	4.025
R_3	3.75	3.75	3.75	3.75	3.8	3.8	3.8	3.8	3.8	3.8
R_4	3.625	3.625	3.625	3.625	3.875	3.875	3.875	3.875	3.875	3.875
R_5	3.825	3.825	3.825	3.825	3.9	3.9	3.9	3.9	3.9	3.9
R_6	3.875	3.875	3.875	3.875	4.025	4.025	4.025	4.025	4.025	4.025
R_7	3.7	3.7	3.7	3.7	3.9	3.9	3.9	3.9	3.9	3.9
R_8	3.8	3.8	3.8	3.8	3.975	3.975	3.975	3.975	3.975	3.975

Table 5 Unit mass variable transportation costs (dollar per ton)

	M	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
M	0	25	26	25	30	23	32	26	27
R_1	25	0	51	31	38	46	31	18	15
R_2	26	51	0	41	39	15	48	49	50
R_3	25	31	41	0	54	28	53	16	42
R_4	30	38	39	54	0	47	13	50	26
R_5	23	46	15	28	47	0	52	39	49
R_6	32	31	48	53	13	52	0	46	17
R_7	26	18	49	16	50	39	46	0	31
R_8	27	15	50	42	26	49	17	31	0

Table 6 Unit mass transportation risks among manufacturer and retailers ($\times 10^{-2}$)

	M	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
M	0	17.25	26.125	18.125	26.5	25.25	25.75	24.875	30.125
R_1	17.375	0	43.75	17	25.625	27.75	21.625	12	11.375
R_2	26.25	43.875	0	25.125	22.125	12.375	25.375	38.125	38.875
R_3	17.75	17	25.5	0	38	22.375	44.125	23	30.125
R_4	26.875	25.5	22.625	38.25	0	32.625	17.875	33.875	27.875
R_5	25.125	27.375	12.25	22.5	33	0	33.125	40.5	38.75
R_6	25.875	21.375	25.125	44.125	17.375	33	0	38	27.125
R_7	25	12.125	37.875	23	34.125	40.625	38.375	0	27.625
R_8	30.25	11.5	39	30.125	28.375	39.125	27.25	27.25	0

Table 7 Unit mass inventory risks of manufacturer and retailers ($\times 10^{-2}$)

M	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
2	3.2	3.6	4.2	3.6	3.8	3.2	3.6	3.5

Table 8 Demands of retailers (ton)

	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
period 1	10	14	10	6	8	14	8	11
period 2	13	7	10	14	8	8	10	6
period 3	7	11	7	14	12	12	14	9
period 4	6	13	14	14	7	13	12	10
period 5	12	11	11	12	6	10	10	14
period 6	11	12	10	9	11	12	14	13
period 7	8	11	8	10	6	11	10	8
period 8	14	10	14	15	12	14	11	12
period 9	6	8	10	11	8	7	12	13
period 10	15	14	14	12	14	16	12	6

The following parameters are used in the experimentation: the production capacity of the manufacturer is $P = 80$ ton per day; the starting inventory at the manufacturer is $I^0 = 120$ ton; the starting inventory level, the basic inventory quantity and the inventory capacity at retailer i are $I_i^0 = 10$ ton, $u_i = 6$ ton and $U_i = 60$ ton, respectively; the maximum shortage level $U_i^* = 60$ ton; the transportation capacity of a single vehicle is $V = 50$ ton; the number of the periods is $T = 10$; the risk boundary value and the unit mass production cost of the manufacturer at period t are $\varepsilon_t = 65$ and $s_i^t = 1775$ dollars, respectively; the unit mass inventory holding cost at the manufacturer is $h_0^t = 10$ dollars per ton; the unit mass inventory holding cost and the unit mass shortage cost at retailer i in period t are $h_i^t = 20$ dollars per ton and $l_i^t = 80$ dollars per ton, respectively; and the fixed transportation cost of a single vehicle is $c = 200$ dollars $(i = 1, 2, \cdots, 8; t = 1, 2, \cdots, 10)$. The parameters of the genetic algorithm are set as follows: $G = 200$, $pop\_size = 50$, $P_c = 0.8$, $P_m = 0.2$.

5.2 Results and discussions

By running GA-based method as proposed, the optimum results are obtained as shown in Tables 9 and 10. Fig.5 shows the convergence process. The maximum profit of the supply chain system is 1.8485×10^6 dollars. In particular, Table 9 gives the retailers' supply schedule in each period, and Table 10 shows the transportation routes and supply chain network risk in each period. Fig.6 describes the manufacturer's arrangement for inventory in advance. From the results of Table 10, it can be seen that the system risk in each period is less than 65, and the total risk is 394.334.

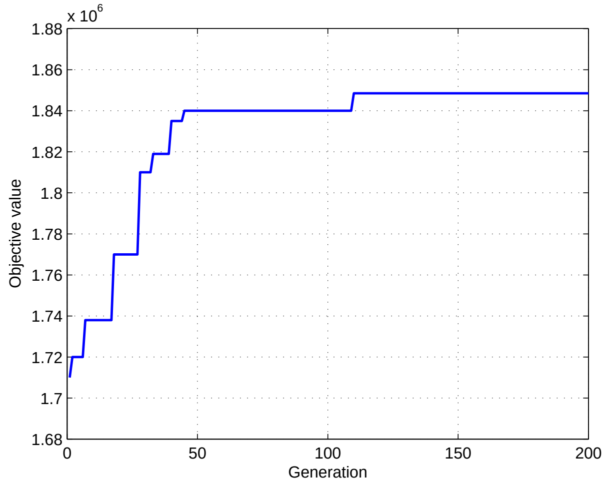

Figure 5: Convergence curve of GA

Table 9 Retailers' supply schedule in each period (ton)

	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
period 1	0	0	0	0	0	0	0	0
period 2	28	12	17	32	26	23	28	30
period 3	0	23	8	0	0	0	0	0
period 4	5	0	6	11	10	27	22	0
period 5	8	10	19	18	0	0	0	35
period 6	22	20	14	0	15	12	22	0
period 7	0	0	0	12	9	9	0	0
period 8	21	16	18	20	0	25	23	9
period 9	0	16	9	12	20	0	0	23
period 10	9	0	6	0	0	7	8	0

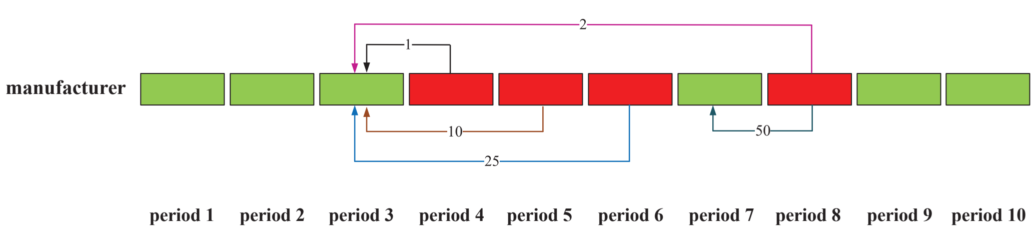

Figure 6: Arrangement for inventory in advance

Table 10 Transportation route, production plan and supply chain network risk in each period

	transportation route	production plan	system risk
period 1	-	0	2.6920
period 2	$M \to R_2 \to R_1 \to M, M \to R_5 \to R_6 \to M,$ $M \to R_4 \to M, M \to R_7 \to M, M \to R_8 \to R_3 \to M$	76	63.2685
period 3	$M \to R_2 \to R_3 \to M$	69	50.7418
period 4	$M \to R_3 \to R_1 \to M, M \to R_4 \to M, M \to R_5 \to M,$ $M \to R_6 \to M, M \to R_7 \to M$	80	60.0635
period 5	$M \to R_1 \to R_8 \to M, M \to R_2 \to M, M \to R_3 \to M,$ $M \to R_4 \to M$	80	54.1760
period 6	$M \to R_1 \to R_7 \to M, M \to R_2 \to M, M \to R_3 \to M,$ $M \to R_5 \to M, M \to R_6 \to M$	80	33.0175
period 7	$M \to R_4 \to R_6 \to M, M \to R_5 \to M$	80	62.8852
period 8	$M \to R_1 \to R_8 \to M, M \to R_2 \to M, M \to R_3 \to M,$ $M \to R_4 \to M, M \to R_6 \to M, M \to R_7 \to M$	80	33.5500
period 9	$M \to R_3 \to M, M \to R_4 \to M, M \to R_5 \to R_2 \to M,$ $M \to R_8 \to M$	80	25.4800
period 10	$M \to R_1 \to R_7 \to M, M \to R_3 \to M, M \to R_6 \to M$	30	8.4595

In order to reflect the effectiveness of the proposed model, we compare the above results with those of the following two cases: i) the results obtained using the single period decision repeatedly; and ii) the results for multi-period problems, whose risk function is defined by the total risks of all periods. Case 1 is obvious, but more specifically, case 2 involves a new risk function, which can be expressed as follows:

$$R = \sum_{t=1}^{T} \mu I^t + \sum_{t=1}^{T} \sum_{i=1}^{n} \alpha_i I_i^t + \sum_{t=1}^{T} \sum_{k=1}^{y^t} \sum_{m=1}^{z_k^t} \sum_{i=m}^{z_k^t} \beta_{r_{m-1}^{kt} r_m^{kt}} q_{r_i^{kt}}^t \tag{24}$$

The optimum results for case 1 are summarized in Tables 11 and 12, and the maximum profit of the supply chain network is 1.7554×10^6 dollars, which decreases by 93,100 dollars as compared to that of the proposed model. As can be seen from Table 12, the network risk in each period is low. The reason for this is that the manufacturer tries to meet the retailers' demands in the current period and minimizes inventory as much as possible. Due to the limited production capacity, the retailers may face significant shortages of supplies in certain periods, thereby leading to the reduction of profits. From this regard the results confirm that it is practically more effective to address multi-period IRPs.

Table 11 Retailers' supply schedule of case 1 (ton)

	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
period 1	0	4	0	0	0	4	0	1
period 2	13	7	10	14	8	8	10	6
period 3	7	11	7	14	12	12	14	9
period 4	6	13	14	6	7	13	11	10
period 5	11	11	6	12	6	10	10	14
period 6	6	12	6	6	11	12	14	13
period 7	8	11	8	10	6	11	10	8
period 8	6	10	6	9	12	14	11	12
period 9	6	8	10	11	8	7	12	13
period 10	6	14	6	6	14	16	12	6

Table 12 Transportation route, production plan and supply chain network risk of case 1

	transportation route	production plan	system risk
period 1	$M \to R_2 \to M, M \to R_6 \to R_8 \to M$	0	5.1158
period 2	$M \to R_1 \to R_7 \to M, M \to R_4 \to R_6 \to M,$ $M \to R_3 \to R_8 \to M, M \to R_5 \to R_2 \to M$	0	21.157
period 3	$M \to R_1 \to R_8 \to M, M \to R_4 \to R_6 \to M,$ $M \to R_5 \to R_2 \to M, M \to R_7 \to R_3 \to M$	51	24.8645
period 4	$M \to R_3 \to R_2 \to R_5 \to M, M \to R_6 \to R_4 \to M,$ $M \to R_7 \to R_1 \to R_8 \to M$	80	22.922
period 5	$M \to R_1 \to R_8 \to R_7 \to M, M \to R_4 \to R_6 \to M,$ $M \to R_2 \to R_5 \to R_3 \to M$	80	24.3882
period 6	$M \to R_1 \to R_8 \to M, M \to R_5 \to R_2 \to M,$ $M \to R_6 \to R_4 \to M, M \to R_7 \to R_3 \to M$	80	24.4707
period 7	$M \to R_2 \to R_1 \to M, M \to R_3 \to R_5 \to M,$ $M \to R_6 \to R_4 \to M, M \to R_7 \to R_8 \to M$	72	20.4345
period 8	$M \to R_2 \to R_3 \to M, M \to R_6 \to R_4 \to M,$ $M \to R_7 \to R_1 \to M, M \to R_8 \to R_5 \to M$	80	24.6032
period 9	$M \to R_4 \to R_6 \to M, M \to R_5 \to R_2 \to M,$ $M \to R_7 \to R_1 \to M, M \to R_8 \to R_3 \to M$	75	22.3645
period 10	$M \to R_3 \to R_1 \to M, M \to R_5 \to R_2 \to M,$ $M \to R_6 \to R_4 \to M, M \to R_7 \to R_8 \to M$	80	22.622

In order to compare the proposed model with the situation as described in case 2, we again employ the ε-constraint method and set $\varepsilon = 650$. By running the GA, the optimum results for case 2 are summarized in Tables 13 and 14. The maximum profit of the supply chain network is 1.8531×10^6 dollars, which increases by 4,600 dollars compared with that of the proposed, a factor of 0.25%. However, the total network risk in case 2 is 470.9582, increased 19.43% as compared to the proposed model. Indeed, the risks are rather high in certain periods, significantly more than 65 (see period 2, period 3 and period 5). Overall, the proposed model performs much better. As such, we should take the proposed approach to solve the given hazardous material multi-period IRP.

Table 13 Retailers' supply schedule of case 2 (ton)

	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
period 1	0	0	0	0	0	0	0	0
period 2	21	11	24	21	24	11	14	19
period 3	12	28	0	0	0	21	10	0
period 4	0	0	11	27	20	0	24	21
period 5	7	10	13	0	0	11	0	0
period 6	12	6	18	27	0	29	15	22
period 7	9	29	0	0	19	0	9	0
period 8	16	0	13	7	0	8	19	22
period 9	9	12	20	22	19	22	0	0
period 10	6	0	0	0	0	0	13	8

6 Conclusion

In this paper, we have investigated hazardous material multi-period IRPs with the assumption of limited production capacity by the manufacturer concerned. An integer programming model has been proposed to maximize the overall profit of given multi-period supply chain networks. To solve the resulting integer programming model, an improved genetic algorithm has been devised to help searching for a quality solution. The main contributions of this study are as follows: (i) the necessity of the multi-period joint decision for hazardous material IRPs is revealed; and (ii) an original loading-dependent risk model for multi-vehicle travelling salesmen problem is formulated. Numerical experiments have been carried out, demonstrating that multi-period joint decision can effectively improve the profits of a given supply chain, while the proposed risk model helps reducing the overall risk of the supply chain.

Future research may be conducted in several direction. First, more real-life factors will be considered, such as traffic restriction, more flexible distribution mode, customer satisfaction, and third-party logistics. Second, it would be useful to improve the efficiency of the proposed solution method for large-scale multi-period IRPs. Last but not least, it would be interesting to extend the proposed model to deal with more complex supply chain structures, such as three-level supply chain networks.

Table 14 Transportation route, production plan and supply chain network risk of case 2

	transportation route	production plan	system risk
period 1	-	0	2.692
period 2	$M \to R_1 \to R_8 \to M, M \to R_3 \to M, M \to R_7 \to M,$ $M \to R_4 \to R_6 \to M, M \to R_5 \to R_2 \to M$	64	81.92
period 3	$M \to R_1 \to M, M \to R_6 \to R_2 \to M,$ $M \to R_7 \to M$	80	68.0075
period 4	$M \to R_3 \to R_5 \to M, M \to R_4 \to M,$ $M \to R_7 \to M, M \to R_8 \to M$	80	57.6665
period 5	$M \to R_2 \to M, M \to R_3 \to R_1 \to M,$ $M \to R_6 \to M$	80	75.569
period 6	$M \to R_1 \to R_8 \to M, M \to R_2 \to M, M \to R_3 \to M,$ $M \to R_4 \to M, M \to R_6 \to M, M \to R_7 \to M$	80	52.3922
period 7	$M \to R_1 \to R_7 \to M, M \to R_2 \to M, M \to R_5 \to M$	80	47.9548
period 8	$M \to R_1 \to R_8 \to M, M \to R_3 \to M, M \to R_4 \to M,$ $M \to R_6 \to M, M \to R_7 \to M$	80	47.635
period 9	$M \to R_1 \to M, M \to R_3 \to M, M \to R_4 \to M,$ $M \to R_6 \to M, M \to R_5 \to R_2 \to M$	80	28.832
period 10	$M \to R_1 \to R_8 \to M, M \to R_7 \to M$	24	8.2892

Acknowledgements This work was partly supported by the National Natural Science Foundation of China (Nos. 71571010, 71722007), partly a Fundamental Research Funds for the Central Universities (No XK1802-5), partly by a Sêr Cymru II COFUND Research Fellowship, UK, and partly by a Great Wall Scholar Training Program of Beijing Municipality (CIT&TCD20180305).

References

[1] Li J, Feng Y, Yu Y, et al., Research on the statistics of hazardous chemical accidents in China during the "twelfth five-year" period and recommendations, *Journal of Wuhan University of Technology*, 2016, **38(5)**: 543–547.

[2] Hu H, Li J, and Li X, A credibilistic goal programming model for inventory routing problem with hazardous materials, *Soft Computing*, 2018, **22(17)**: 5803–5816.

[3] Jaillet P, Bard J F, Huang L, et al., Delivery cost approximations for inventory routing problems in a rolling horizon framework, *Transportation Science*, 2001, **36(3)**: 292–300.

[4] Vidović M, Popović D, and Ratković B, Mixed integer and heuristics model for the inventory routing problem in fuel delivery, *International Journal of Production Economics*, 2014, **147**: 593–604.

[5] Bell W, Dalberto L, Fisher M, et al., Improving the distribution of industrial gases with an on-line computerized routing and scheduling optimizer, *Interfaces*, 1983, **13**: 4–23.

[6] Daganzo, C F, Supplying a single location from heterogeneous sources, *Transportation Research Part B: Methodological*, 1985, **19(5)**: 409–419.

[7] Chien T W, Balakrishnan A, and Wong R T, An integrated inventory allocation and vehicle routing problem, *Transportation Science*, 1989, **23(2)**: 67–76.

[8] Zhao Q H, Chen S, and Zang C X, Model and algorithm for inventory/routing decision in a three-echelon logistics system, *European Journal of Operational Research*, 2008, **191(3)**: 623–635.

[9] Coelho L C and Laporte G, A branch-and-cut algorithm for the multi-product multi-vehicle inventory-routing problem, *International Journal of Production Research*, 2013, **51(23-24)**: 7156–7169.

[10] Li K, Chen B, Sivakumar, A I, et al., An inventory-routing problem with the objective of travel time minimization, *European Journal of Operational Research*, 2014, **236(3)**: 936–945.

[11] Viswanathan S and Mathur K, Integrating routing and inventory decisions in one-warehouse multiretailer multiproduct distribution systems, *Management Science*, 1997, **43(3)**: 294–312.

[12] Zhao Q H, Wang S Y, and Lai K K, A partition approach to the inventory/routing problem, *European Journal of Operational Research*, 2007, **177(2)**: 786–802.

[13] Cheng-Hong F U, Optimization on stochastic inventory-routing problem in multi-cycle two-echelon system, *Computer Engineering and Applications*, 2010, **46(9)**: 198–201.

[14] Huang S H and Lin P C, A modified ant colony optimization algorithm for multi-item inventory routing problems with demand uncertainty, *Transportation Research Part E: Logistics and Transportation Review*, 2010, **46(5)**: 598–611.

[15] Moin N H, Salhi S, and Aziz N A B, An efficient hybrid genetic algorithm for the multi-product multi-period inventory routing problem, *International Journal of Production Economics*, 2011, **133(1)**: 334–343.

[16] Al-E-Hashem S M J M and Rekik Y, Multi-product multi-period inventory routing problem with a transshipment option: a green approach, *International Journal of Production Economics*, 2014, **157**: 80–88.

[17] Roldán R F, Basagoiti R, and Coelho L C, Robustness of inventory replenishment and customer selection policies for the dynamic and stochastic inventory-routing problem, *Computers and Operations Research*, 2016, **74**: 14–20.

[18] Rahimi M, Baboli A, and Rekik Y, Multi-objective inventory routing problem: a stochastic model to consider profit, service level and green criteria, *Transportation Research Part E: Logistics and Transportation Review*, 2017, **101**: 59–83.

[19] Wei M, Yu L, and Li X, Credibilistic location-routing model for hazardous materials transportation, *International Journal of Intelligent Systems*, 2015, **30(1)**: 23–39.

[20] Wei M, Li X, and Yu L, Time-dependent fuzzy random location-scheduling programming for hazardous materials transportation, *Transportation Research Part C: Emerging Technologies*, 2015, **57**: 146–165.

[21] Du J, Yu L, and Li X, Fuzzy multi-objective chance-constrained programming model for hazardous materials transportation, *International Journal of General Systems*, 2016, **45(3)**: 286–

310.

[22] Du J, Li X, Yu L, et al., Multi-depot vehicle routing problem for hazardous materials transportation: A fuzzy bilevel programming, *Information Sciences*, 2017, **399**: 201–218.

[23] Hu H, Guo S, Ma H, et al., A Credibilistic Mixed Integer Programming Model for Time-Dependent Hazardous Materials Vehicle Routing Problem, *Journal of Uncertain Systems*, 2017, **11(3)**: 163–175.

[24] Batta R and Chiu S S, Optimal obnoxious paths on a network: transportation of hazardous materials, *Operations Research*, 1988, **36(1)**: 84–92.

[25] Revelle C, Cohon J, and Shobrys D, Simultaneous siting and routing in the disposal of hazardous wastes, *Transportation Science*, 1991, **25(2)**: 138–145.

[26] Haimes Y Y, Lasdon L S, and Wismer D A, On a bicriterion formulation of the problems of integrated system identification and system optimization, *Systems Man and Cybernetics IEEE Transactions on*, 1971, **SMC-1(3)**: 296–297.

[27] Coelho L C, Cordeau J F, and Laporte G, The inventory-routing problem with transshipment, *Computers and Operations Research*, 2012, **39(11)**: 2537–2548.

[28] Xu Y and Cui J, Multitask n-vehicle exploration problem:complexity and algorithm, *Journal of Systems Science and Complexity*, 2012, **25(6)**: 1080–1092.

[29] Zhang X and Waller S T, Mixed-vehicular aggregated transportation network design considering en-route recharge service provision for electric vehicles, *Journal of Systems Science and Complexity*, 2018, **31(5)**: 1329–1349.

[30] Padberg M and Rinaldi G, A branch-and-cut approach to a traveling salesman problem with side constraints, *Management Science*, 1989, **35(35)**: 1393–1412.

[31] Marinakis Y and Marinaki M, A hybrid genetic C particle swarm optimization algorithm for the vehicle routing problem, *Expert Systems with Applications*, 2010, **37(2)**: 1446–1455.

[32] Zhou Y, Runtime analysis of an ant colony optimization algorithm for tsp instances, *IEEE Transactions on Evolutionary Computation*, 2009, **13(5)**: 1083–1092.