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Abstract

In this study, we address an Inventory Routing Problem for hazardous and deteriorating pharmaceutical items in a healthcare network. Each hospital’s demand is assumed to be deterministic but time varying over a finite planning horizon. Demand can be satisfied through a supply network, either from the main central pharmacy, or from other related hospitals' drugstores by allowing the transshipment option. The medicines deteriorate under a constant rate during the storage period. The proposed model is a bi-objective mixed integer mathematical programming. The first objective aims to minimize the total cost of logistics including ordering, transportation, delivery, pickup, shortage and inventory holding costs. The second objective function attempts to minimize the maximum accident loss during distribution among all periods. To consider the accident loss, for each route, two essential parameters are estimated based on historical data; the occurrence probability and severity index of accident. The model therefore attempts to utilize the best configuration of the routes and transshipment option to satisfy the demand while minimizing the costs and accident loss simultaneously. Several numerical examples are generated and solved by CPLEX and compared with the solutions of an efficient Hybrid Genetic Algorithm (HGA). The results show that the transshipment option not only can be used as a lever to increase the economic supply network performance through saving the routes, but also it can help the system to avoid risky routes.

Keywords: *Inventory routing problem; deteriorating items; transshipment; accident risk; hybrid genetic algorithm*

1. Introduction

In recent years, the pharmaceutical sector has undergone profound changes, partially due to the aging of the population and rising costs in health care services. With margins that are getting lower and lower, the drug distribution problem to pharmacies has become much more important, particularly in large metropolitan areas (Magalhães and Sousa, 2006). As pharmacies demand shorter delivery times, inventory routing and scheduling problems become much more important for distributors. It is even more challenging when they deal with deteriorating items.

In the classic Inventory Routing Problem (IRP), the optimization's aim is to identify the best strategy for the inventory management of products, and determine the best configuration of the vehicles, routes, kind of products, and their quantity to be delivered to each customer while minimizing the total inventory and transportation costs (Rahimi et al. 2015). It is recognized that the traditional distribution system based on merely minimizing cost does not fulfil the expectations of pharmacies/hospitals and may, in some cases, be quite inefficient for them.

In the pharmaceutical supply chain, decision makers deal with deteriorating items and it is obvious that the deterioration rate of an inventory in stock during the storage period cannot be disregarded especially in the healthcare sector. Deteriorating products refer to items that get damaged, spoiled, dried, invalid, or degraded over time (Li et al. 2010) and can be classified into two groups: perishable items and decaying items. Products such as meat, green vegetables, and, flowers are known as perishable products. Commodities like alcohol, gasoline and radioactive substances are known as decaying products (Sazvar, et al., 2017, Goyal and Giri 2001).

In this paper, we are concerned with the radioactive pharmaceutical products which are widely used in the healthcare sector particularly for cancer patients. This kind of products are categorized in hazardous materials, the occurrence of an accident may lead to the damages, loss of health benefits of products, the inevitable delay in delivery, or even uncompensated effects. As stated by Van Raemdonck et al., (2013), the Western Europe is characterized by a high population density, a dense transportation network and high volumes of import, export and transit of dangerous substances. Although it is not yet mandatory to analyze whether the transport along a certain transport route generates a further risk for the society because of its cargo, it is quite important to gain an insight in not only the cost, but also the risk of hazardous materials transportation (Verma, 2009) and develop a level-headed policy concerning the transportation of hazardous goods.

In order to cope with these challenges as well as the consistency of deliveries, accuracy in inventory and demand management, and low-cost safety enhancement in distribution, we propose a Transshipment-enabled Inventory Routing Problem (TIRP). Our framework does not only focus on the economic performance of the TIRP but it is also concerned with the minimization of the accident risk and loss. Indeed, in a case of an accident, the consequence can be non-negligible from an environmental, social as well as economic point of view. We particularly discuss how the transshipment option can act as a lever to not only increase the economic performance of the pharmaceutical network but we will show that it permits to the model to manage the accident risk. We investigate the situations when the transshipment policy is efficient from economic and accident risk point of views in practice. Besides, the bi-objective modeling of the problem enables us to identify the link between the economic performance and the accident risk and consequently to derive the tradeoff between logistics operations costs and minimal accident risk by enabling the transshipment option.

The remainder of the paper is organized as follows: in Section 2, the related studies on IRP in the literature have been reviewed and the main contributions of this research are compared, in Section 3, we provide the assumptions, principles and particular configuration of our framework. The mathematical formulation of the problem is then presented in Section 4 and followed by Section 5, where a small sized example is illustrated. The proposed hybrid genetic algorithm is proposed in Section 6. In Section 7, several sensitivity analyses are conducted and the finding and managerial insights of this work are discussed. Finally, the conclusions of this research are presented in Section 8 alongside with some promising directions for further research in this area.

2. Literature review and motivation

The IRP problem is used when routing and inventory decisions must be made simultaneously (Persson, and Gothe-Lundgren, 2005, and Sindhuchao et al. 2005). Such a joint decision problem has recently attracted the attention of many researchers (e.g. Bertazzi and Speranza, 2002, Kleywegt, et al., 2002, Mishra, and Raghunathan, 2004, Cordeau, et al., 2007, Archetti, et al., 2007, Andersson, et al., 2010, Bertazzi, et al., 2013, Mirzapour Al-e-hashem, and Rekik, 2012, 2014, 2017). In Table 1, we present an overview of the main IRP investigations related to our framework. The Table shows that several studies were concerned with the management of deteriorating products. As previously mentioned, deteriorating products could be categorized in two different classes; perishable items and decaying ones. Despite the fact that the realistic assumption of "deterioration" has recently attracted the attention of several researchers (e.g. Coelho and Laporte 2014, Hauge et al. 2014, Mirzaei & Seifi 2015, Soysal et al. 2015), the research literature still misses studies investigating the impact of decaying products on IRPs. Besides, very few investigations on IRP have been devoted to the transshipment policy (Coelho et al. 2012, Jemai et al. 2012, Mirzapour al-e-hashem and Rekik 2014, Mirzapour al-e-hashem et al., 2017). Traditional IRPs focus mainly on the key logistical cost- related objective (Soysal, 2016), and only scarce studies (Rahimi et al., 2015, Dabiri et al. 2017, Mirzapour al-e-hashem and Rekik 2014, Mirzapour al-e-hashem et al., 2017) have applied a multi-objective analysis to reflect the possible conflicts which may exist between economic and other important aspects of decision making such as social issues and environmental concerns. We notice that only the last publication in Table 1 investigates the contribution of the transshipment option in the presence of different optimization criteria. More importantly, we notice that none of these publications considers specifically the accident risk and loss as an optimization criterion in the distribution of expensive or hazardous items which is the case of radioactive pharmaceutical products. For these reasons, our challenge in this paper is threefold: 1) modeling: how to integrate the accident risk and loss in the classical IRP, 2) mathematical: how to deal with a bi-objective setting of the IRP problem and 3) managerial: what tradeoffs between the classical economic performance of the IRP and the accident risk and loss and what is the impact of the transshipment option on both optimization criteria.

In real word situations, shortage, in which demand exceeds the inventory level of products, is considered in most of the studies in the context of IRP (e.g. Nolz et al., 2014, Etebari and Dabiri, 2016), but almost all above researches assumed that the unfulfilled demand is totally backordered to the next periods except Mirzaei & Seifi (2015) who conversely assumed the unfulfilled demand is completely lost while in our model partial backordering shortage is proposed. Both kinds of full backorder and full lost-sale demand are special cases of our approach where an adjusting parameter takes its ultimate values: zero or one.

As Table 1 shows, several other variants of IRP are also extended such as IRP with split deliveries (Yu et al., 2008), the IRP with vehicle failure (Huang and Lin 2010), the IRP with time windows (Liu and Lee 2011, Iassinovskaia et al. 2016), the IRP for waste collection (Hauge et al. 2014) and the IRP for closed-loop supply chain (Soysal 2016).

Table 1. Overview of the related literature on IRP

	Shortage		Deterioration		Modeling and resolution particularities					
	Back order	Lost sales	Fixed shelf life	Continuous decay	Transshipment	Accident risk	Multi-objective	Modeling	Resolution	Other
Sindhuchao et al. 2005	-	-	-	-	-	-	-	MIP	B&P + neighborhood search	Multi-item
Persson and Gothe-Lundgren 2005	-	-	-	-	-	-	-	MIP	Column generation	
Abdelmaguid and Dessouky 2006	√	-	-	-	-	-	-	MIP	GA	
Archetti et al. 2007	-	-	-	-	-	-	-	MIP	B&C	
Yu et al., 2008	-	-	-	-	-	-	-	MIP	Lagrange + sub-gradient	split delivery
Abdelmaguid et al. 2009	√	-	-	-	-	-	-	MIP	Heuristic	
Hvattum and Løkketangen 2009	√	-	-	-	-	-	-	Markov	Scenario-tree - heuristic	
Huang and Lin 2010	√	-	-	-	-	-	-	MIP	ACO	vehicle failure
Shen et al. 2011	√	-	-	-	√	-	-	MIP	Lagrangian Relaxation	Multi-mode
Moin et al. 2011	-	-	-	-	-	-	-	ILP	Hybrid GA	
Liu and Lee 2011	√	-	-	-	-	-	-	MIP	Tabu search	Time window
Mirzapour al-e-hashem and Rekik 2012	√	-	-	-	√	-	-	MIP	B&B	Greenness
Jemai et al. 2012	√	-	-	-	√	-	-	(R,s,S)	Exact	
Coelho et al. 2012	-	-	-	-	√	-	-	MIP	Neighborhood search heuristic	
Solyalı et al. 2012	√	-	-	-	-	-	-	MIP	B&C	Robustness
Bertazzi et al. 2013	√	-	-	-	-	-	-	DP	B&C + Rollout	
Le et al. 2013	-	-	√	-	-	-	-	MIP	Column generation	
Shukla et al. 2013	-	-	-	-	-	-	-	NLMIP	GA	
Coelho and Laporte 2014	-	-	√	-	-	-	-	MIP	B&C	Age-dependent price
Hauge et al. 2014	-	-	-	-	-	-	-	IP	Column generation	waste collection
Al Shamsi et al. 2014	-	-	√	-	-	-	-	MIP	Simulation	
Alkawaleet et al. 2014	-	-	-	-	-	-	-	IP	GAMS	
Jia et al. 2014	√	-	√	-	-	-	-	MIP	Decomposition+ Tabu	Loading Cost

									search	
Mirzaei & Seifi 2015	-	√	√	-	-	-	-	MIP	SA	
Soysal et al. 2015	√	-	√	-	-	-	-	Chance constraint	Simulation	Energy consumption
Rahimi et al. 2015	√	-	√	-	-	Driver injury	√	MIP	CPLEX	Social issue
Soysal et al. 2016	√	-	√	-	-	-	-	Chance constraint	CPLEX	Horizontal collaboration
Soysal 2016	√	-	-	-	-	-	-	MIP	CPLEX	Closed loop
Dabiri et al. 2017	-	-	-	-	-	-	√	MIP	MOPSO	Step cost function
Mirzapour al-e-hashem et al. 2017	√	-	-	-	√	-	√	MIP	L-shaped Method	Disposal
This research	√	√	-	√	√	√	√	MIP	HGA	Hazardous martials

One of the scientific contributions of this study is examining the transshipment option within the proposed inventory routing problem. Under this policy, the hospital orders might be provided either directly from the main supplier (radioactive pharmaceutical products center), or from the other related hospitals' drugstores (if available). In order to have a common sense, consider two retailers that are both in possession of the same company. A centralized planning department decides the inventory of both retailers before the start of the planning horizon. Due to carrier expenses, vehicles capacity limitations, and/or long lead time, the Decision Maker (DM) does not have the possibility to replenish extra inventory during the period. Imagine the case when the available inventory of one retailer exceeds its demand, and, conversely, the demand of the other retailer is unfulfilled due to the lack of inventory. Then, if the benefit surpasses the incurred costs of doing so, it would be advantageous, from a system perspective, to have the former retailer transfer some of its inventory to the latter retailer. This practice is called "*transshipment*", and is occasionally carried out in a variety of industries (Nonas, Jornsten, (2007)).

In this paper we show that the *transshipment option* not only can be used as a lever to increase the economic supply network performance through saving the routes, but also it can help the system to avoid risky routes and protect the supply network against catastrophic events especially when the cargos are categorized in decaying hazardous materials. Despite the existence of a rather wide variety of studies on IRP problem for deteriorating items (e.g. Soysal et al., 2015, 2016), the transshipment option has never been studied for hazardous items. The challenging research question in this context, therefore, is to identify the linkage between the deteriorating rate and the benefit brought by the transshipment policy in terms of economic and accident loss.

3. Problem Description

Assume a medicine supply chain composed of a set of hospitals {1, 2, ..., N} that provides the radio pharmacy services for the cancer patients and a central pharmacy as the only supplier of this type of products. For vital products like pharmaceutical radioactive substances, occurrence of an accident may lead to the loss of health benefits of products as well as uncompensated environmental effects; the transportation vehicles therefore must be endowed with special equipment. This central pharmacy has an internal contract with a vehicle rental company to ship the products from the supplier to the hospitals in each period. The routes between the supplier and hospitals are predetermined and the accident occurrence probability for each designated route as well as the degree of the accident loss severity are wisely specified. The network of this medical supply chain is depicted in Fig. 1.

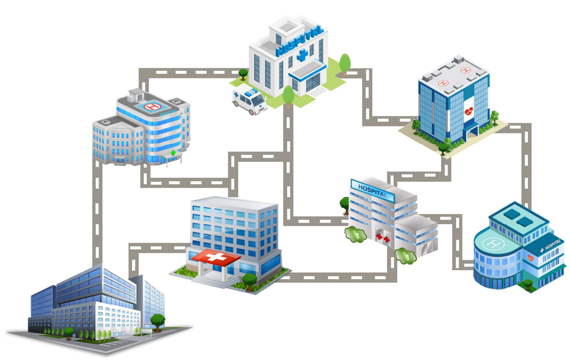


Figure 1. General schema of supply network

In order to manage the medicine availability more smoothly, a transshipment option is incorporated in the model with which the demand can be satisfied, either directly from the main supplier, or from the other hospitals' drugstores. The optimization problem is to determine the ideal configuration of the routes, pickups, deliveries and transshipments in each period in order to minimize the total cost of the supply chain (including ordering cost, inventory holding cost, fixed and variable transportation cost, shortage cost and pickup cost), and to minimize the maximum accident loss of distribution while satisfying the demand of all hospitals as much as possible. It should be noted that the shortage is allowed but the backordered demands must be satisfied at most in the last period.

In the proposed model, "partial backordering shortage" is incorporated in the model by introducing a parameter (β) which can be estimated based on historical data of patients in hospitals. When a hospital's drugstore encounters the shortage, two possible scenarios are recognized in real situations; β percent of patients can wait until the next period(s) (period can be defined as day, week, etc.) to receive the medications based on their clinical situations. Their demands are therefore considered as backorder in the inventory balance. The remaining (1-β) percent of the patients, who cannot wait, either use alternative medicines or leave the hospital and refer to other medical centers.

We use the following notations to formulate the proposed IRP model:

Sets

$\Omega=\{0,1,\ldots,N\}$	set of all nodes
$\omega=\{1, 2, \ldots, N\}$	set of hospitals
$O=\{0\}$	radio-pharmacy center
$\eta=\{1,2,\ldots,K\}$	fleet size

Parameters

D_{it}	demand of hospital i in period $t \in T = \{1, 2, \ldots, \|T\|\}$, *(product unit)*
d_{ij}	distance between nodes i and j, *(km)*
vc_k	variable transportation cost for vehicle k, *($/product unit×km)*
fc_k	fixed transportation cost for vehicle k, *($)*
cv_k	capacity of vehicle k, *(product unit)*
c	unit cost of product, *($)*
h_i	unit inventory holding cost in node i, *($/period×product unit)*
π_i	unit backorder cost in node i, *($/period×product unit)*
π'_i	unit lost sale cost in node i, *($/product unit)*
pr_{ij}	accident occurrence probability of arc (i, j), *(0≤prij≤1)*
Io_i	initial inventory level of product in hospital i, *(product unit)*
Ic_i	inventory capacity of product in hospital i, *(product unit)*
pc_i	the pickup cost (transshipment) in hospital i, *($/product unit)*
θ	the deterioration rate of product,
β_i	the fraction of unsatisfied demands carried over to future periods (backordering ratio) in node i, *(product unit)*
γ_{ij}	the severity of accident in arc (i, j) between 0 and 100%,
f_k	the value of vehicle k, *($)*
M	an arbitrary large number;

Decisions variables

I_{it}	the inventory level of product in hospital i in period t,
S_{it}	the shortage level of product in hospital i in period t,
X_{ijkt}	a binary variable that determines arc (i, j) is visited by vehicle k in period t,
Y_{ikt}	a binary variable that determines whether hospital i is visited by

vehicle k in period t,

Q_{ijkt} the quantity of product transported by vehicle k trough arc (i, j) in period t,

Qd_{ikt} the quantity of product delivered to hospital by vehicle k in period t,

Qp_{ikt} the quantity of product picked up from node i by vehicle k in period t,

XQ_{ijkt} an auxiliary variable for linearization,

u_t an auxiliary binary variable for linearization;

4. Mathematical formulation

The bi-objective mixed integer programming for the transshipment enabled IRP taking into account the accident risk is formulated as follows:

$$Min\, Z_1 = \sum_{i\in\omega,k,t} fc_k \cdot X_{0ikt} + \sum_{(i,j)\in\Omega}\sum_{k,t} vc_k \cdot d_{ij} \cdot Q_{ijkt} + \sum_{i\in\omega,t} h_i \cdot I_{it} + \sum_{i\in\omega,t} \pi_i \cdot \beta_i . S_{it} + \sum_{i\in\omega,t} \pi'_i \cdot (1-\beta_i).S_{it} + \sum_{i\in\omega,k,t} pc_i \cdot Qp_{ikt} \qquad (1)$$

$$Min\quad Z_2 = \underset{t}{Max} \sum_{i,j\in\Omega,k} \gamma_{ij}(c.Q_{ijkt} + f_k) \times pr_{ij} \times X_{ijkt} \qquad (2)$$

s.t.

$$I_{it} - S_{it} = (1-\theta) \times I_{i(t-1)} - \beta \times S_{i(t-1)} + \sum_k Qd_{ikt} - \sum_k Qp_{ikt} - D_{it} \qquad \forall i \in \omega, t \qquad (3)$$

$$\sum_{j\in\Omega} X_{jikt} = \sum_{j\in\Omega} X_{ijkt} = Y_{ikt} \qquad \forall i \in \Omega, k, t \qquad (4)$$

$$Y_{ikt} \le 1 \qquad \forall i \in \omega, t, k \qquad (5)$$

$$\sum_{j\in\Omega} Q_{jikt} - Qd_{ikt} + Qp_{ikt} = \sum_{j\in\Omega} Q_{ijkt} \qquad \forall i \in \omega, k, t \qquad (6)$$

$$Q_{ijkt} \le cv_k . x_{ijkt} \qquad \forall (i, j) \in \Omega, k, t \qquad (7)$$

$$\sum_k Qp_{ikt} \le (1-\theta) I_{i(t-1)} \le (1-\theta) Ic_i \qquad \forall i \in \omega, t \qquad (8)$$

$$Y_{0kt} \ge Y_{ikt} \qquad \forall i \in \omega, k, t \qquad (9)$$

$$\sum_{(i,j)\in S} X_{ijkt} \le |S|-1 \qquad \forall S \subseteq \omega, S \ne \phi \ \forall k,t \qquad (10)$$

$$X_{iikt} = Q_{i0kt} = 0 \qquad \forall i \in \Omega, k,t \qquad (11)$$

$$Y_{ikt}, X_{ijkt}, w_t \in \{0,1\}$$

$$Q_{ijkt}, Qp_{ikt}, Qd_{ikt}, I_{it}, S_{it} \ge 0 \qquad \forall (i,j) \in \Omega, k,t \qquad (12)$$

Constraints:

Constraints (3) model the inventory balance equation at hospitals and determine that the inventory position of product in hospital *i* in current period (*t*) is equal to *(1-θ)* percent of previous inventory level (I_{t-1}), plus the quantity delivered in period *t* (transshipped by the vehicles), minus the quantity picked up by the vehicles in period *t* minus the demand of the current period and *β* percent of the shortage in previous period. It is assumed that only *β* percent of the patients, who encounter the lack of medicines, will wait for the next period and the demand for the remaining (*1-β*) percent is definitely lost. It is also assumed that the inventory in stock deteriorates at a rate of *θ,* and only *(1-θ)* percent of previous inventory level remains safe for future use. Constraints (4 and 5) guarantee that each hospital should not be visited by one specific vehicle more than once in each period. Even so, a split delivery is possible meaning that the hospital can be visited more than one time by different vehicles in a period. If the split delivery is forbidden, then one can change this constraint to $\sum_k Y_{ikt} \le 1$.

Constraint (6) is the inventory balance equation for the vehicle that visits the arc (*i, j*) in period *t* and ensures that the quantity of product transported by the vehicle from node *i* to node *j* in period *t* is equal to the quantity of product shipped to node *i*, plus the quantity picked up by the vehicle from hospital *i*, minus the quantity delivered to this hospital in current period. Constraints (7) guarantee that the vehicle's capacity should not be exceeded and imply that the vehicles could visit arc (*i, j*) only once that the variable x_{ijkt} takes value. Constraint (8) ensures that the vehicles could not pick up the products from a hospital, more than their inventory level in previous period. This constraint also guarantees that the inventory capacity of the hospital cannot be exceeded. Constraint (9) ensures that a trip should start and finish at radio-pharmacy center (node 0). Constraint (10) is the classic sub-tour elimination constraint. Constraint (11) forbids the product returns and determines the impossible arcs and, finally constraint (12) defines the variable types. It should be noted that in constraints (3) and (8), the variable $I_{i(t-1)}$ for the particular case of $t=1$, is replaced by initial inventory (I_0).

Objective functions:

Equation (1) is the first objective function of the proposed model, which aims to minimize the total supply chain cost including the fixed and variable transportation costs, inventory holding cost, shortage cost, and transshipment (pickups) costs. Equation (2) is the second objective function and attempts to minimize the maximum expected loss of accident in distribution among all periods. The accident loss is computed based on the value of the vehicle and its cargo multiplied by an accident severity index γ_{ij}, which is estimated for each route.

We therefore notice that our modeling of the accident risk and loss includes components related to: ***i)*** where the accident occurs (γ_{ij}): one can assume that an accident occurring in the city center is more severe to handle than a one occurring in a sub urban location. ***ii)*** with which truck the accidents occurs (f_k): handling an accident of a big truck may be more penalizing than a small one, and ***iii)*** what is the content of the truck when the accident occurs ($c.Q_{ijkt}$): an accident occurring in the beginning of the vehicle tour (when the truck is still full) is more penalizing than an accident occurring at the end. Collectively the term $\gamma_{ij}(c.Q_{ijkt}+f_k)$ can model the unit loss for each arc (i, j) incurred if an accident occurs in this arc.

Since $\sum_{i,j\in\Omega,k} \gamma_{ij}(c.Q_{ijkt}+f_k)\times pr_{ij}\times X_{ijkt}$ has an explicit nonlinear term of $Q_{ijkt}\times X_{ijkt}$, at first, it is replaced by a new auxiliary variable, XQ_{ijkt} , and converted to a linear form by the help of the following additional constraints:

$$Q_{ijkt} - (1 - X_{ijkt}).M \le XQ_{ijkt} \le Q_{ijkt} \qquad \forall (i,j)\in\Omega, k, t \tag{13}$$

$$0 \le XQ_{ijkt} \le X_{ijkt}.M \qquad \forall (i,j)\in\Omega, k, t \tag{14}$$

Then, the minimax structure of Z_2 is linearized and rewritten as follows:

$$Min \quad Z_2 \tag{15}$$

s.t.

$$Z_2 \ge \sum_{i,j\in\Omega,k} \gamma_{ij}(c.Q_{ijkt}+f_k)\times pr_{ij}\times X_{ijkt} \qquad \forall t \tag{16}$$

$$Z_2 \le \sum_{i,j\in\Omega,k} \gamma_{ij}(c.Q_{ijkt}+f_k)\times pr_{ij}\times X_{ijkt} + u_t.M \qquad \forall t \tag{17}$$

$$\sum_{t\in T} u_t \le |T| - 1 \tag{18}$$

Constraints (16) state that Z_2 should be greater than the right hand side for all t, since Z_2 is the maximum of $\sum_{i,j\in\Omega,k} \gamma_{ij}(c.Q_{ijkt}+f_k)\times pr_{ij}\times X_{ijkt}$. Constraints (17) and (18) ensure that Z_2 must be lower than or equal to $\sum_{i,j\in\Omega,k} \gamma_{ij}(c.Q_{ijkt}+f_k)\times pr_{ij}\times X_{ijkt}$ at least for a single t, and prevent Z_2 approaching infinity. It should be noted that when the objective function is "*minimization*", these two constraints are not necessary, but when the objective function is "*maximization*" and/or the model structure is "*multi-objective*", these are very important constraints and should not be neglected.

Since the proposed model is a multi-objective integer programming model where the two objective functions are completely inconsistent, it is not possible to provide the decision makers with a single optimal solution, which contains the simultaneous minimum values for all objective functions. Instead, we attempt to approximate the set of all Pareto optimal solutions named the Pareto frontier. It contains the best compromise solutions that cannot be improved in any objective without causing degradation in another. Compromise programming (l_p-metrics) is one of the well-known Multi Objective Decision Making methods (MODM) in solving multi-objective problems with inconsistent objective functions (Aryanezhad et al., 2009, Mirzapour Al-e-Hashem et al., 2012). According to the compromise programming method, first the primary bi-objective model, with respect of each objective function, is solved separately, then a single objective model (l_p-metrics) is reformulated in order to minimize the weighted sum of each objective functions' normalized deviation from its optimum value.

Let us assume a multi-objective model as

$$\begin{array}{l} \text{Min } Z_1 \\ \text{Min } Z_2 \\ \vdots \\ \text{Min } Z_n \end{array}$$

If the best and nadir values of the single objective functions Z_1, Z_2, …, Z_n are equal to (Z_1^{min}, Z_1^{max}), (Z_2^{min}, Z_2^{max}) … and (Z_n^{min}, Z_n^{max}), respectively, the equivalent single objective compromise programming (l_p-metrics) can be therefore written as:

$$l_p\text{-metrics} = \left(w_1 \times \left| \frac{Z_1 - Z_1^{\min}}{Z_1^{\max} - Z_1^{\min}} \right|^p + w_2 \times \left| \frac{Z_2 - Z_2^{\min}}{Z_2^{\max} - Z_2^{\min}} \right|^p + \ldots + w_n \times \left| \frac{Z_n - Z_n^{\min}}{Z_n^{\max} - Z_n^{\min}} \right|^p \right)^{1/p},$$

where w_i is the relative weights of i_{th} component and p is an arbitrary positive integer number, both of them are chosen by the decision maker (Sazvar et al., 2014).

5. Numerical illustration

We propose in this section a small-sized illustrative example to numerically show the implication of the accident concern in the optimal solution as well as the contribution of the transshipment option on both the economic and accident objectives.

Assume a medicine supply network consists of 5 hospitals $H_1, \ldots, H_5$. The travel distances are given in Table 2. The matrix of routes is an asymmetric directed graph that meaning the roads can be one-way. The occurrence probability and the severity index of accident for each segment are provided in Table 3. These parameters can be obtained from governmental or community databases like as the data on road accidents which are collected through CARE (Community database on Accidents on the Roads in Europe), the European centralized database on road accidents resulting in death or injury across the EU. For the USA, one could use the NASS (National Accident Sampling System) which contains information on every police-reported accident including nonfatal accident and property damages. Generally, the occurrence probability and severity index of accidents to occur on each road segment, can be estimated based on the present infrastructure characteristics, the average speed of vehicles, the presence of vulnerable locations (e.g. schools, residential complexes, etc.) and the proximity to emergency services (Panwhar et al., 2000).

The deterioration and backorder ratios are assumed to be equal to 0.05 and 0.2, respectively. Table 4 shows the unit holding cost, unit backorder and lost sale costs (in terms of monetary unit per period per product), the initial inventories (product unit), and the forecasted demand (product unit) for each hospital in 5 periods. The fixed and variable transportation costs (in terms of monetary unit per product per km), the capacity (*product unit*) and value of each vehicle (monetary unit) are given at Table 5. For practical reasons, the delivery lots (Qd) and pickups (Qp) are assumed as multiplayers of 50 and 5, respectively. The unit pickup cost for all vehicles are set at 0.1 (*monetary unit).* The price of each unit of product is equal to 1000 (*monetary unit*). It is also assumed that the orders can be backordered at most until the last period (S_{iT}=0).

Table 2. *The distance between the nodes, d_{ij} (km)*

	0	H_1	H_2	H_3	H_4	H_5
0	-	31	-	73	21	31
H_1	31	-	-	-	13	62

H_2	78	-	-	-	90	-
H_3	73	-	-	-	62	96
H_4	21	13	90	62	-	-
H_5	31	62	-	96	-	-

- means that there is no direct road between the respected nodes.

***Table 3**. The occurrence probability (pr_{ij}) and severity index of accident (γ_{ij})*

	0		H_1		H_2		H_3		H_4		H_5	
	pr	γ	*pr*	γ	*pr*	γ	*pr*	γ	*pr*	γ	*pr*	γ
0	-	-	0.2	0	-	-	0.08	0.12	0.05	0	0.08	0.04
H_1	0	0	-	-	-	-	-	-	0.01	0.09	0	0.12
H_2	0.2	0.12	-	-	-	-	-	-	0.16	0.03	-	-
H_3	0.2	0.12	-	-	-	-	-	-	0	0.06	0.09	0.02
H_4	0	0.08	0.15	0.08	0.19	0.12	0.28	0	-	-	-	-
H_5	0.14	0.03	0.2	0.06	-	-	0.15	0.04	-	-	-	-

***Table 4**. Hospitals Data*

Hospital	IC_i	I_0	Demand in Period *t*					π'_i	π_i	h_i
			1	2	3	4	5			
1	300	0	0	470	310	100	0	200	20	22
2	500	0	500	0	120	480	120	100	10	12
3	300	0	0	150	320	0	390	400	40	25
4	500	0	210	0	230	0	115	200	20	30
5	300	0	330	120	0	180	0	100	10	15

***Table 5**. The vehicles' data*

Vehicle k	f_k	fc_k	vc_k	cv_k
1	50000	400	0.1	120
2	70000	600	0.08	210
3	90000	700	0.06	270
4	100000	800	0.04	380
5	150000	900	0.02	530

The proposed TRIP model and *lp*-metric reformulation are coded under the Optimization Programming Language (OPL) and the CPLEX script accessed via IBM ILOG CPLEX Optimization Studio 12.6.

Considering only 3 periods, and solving the given example twice for each objective function, the optimum values of each one are obtained which allow to build the *lp*-metric model, $l_p - metrics = w \times \left| \frac{Z_1 - 14509}{326070 - 14509} \right| + (1-w) \times \left| \frac{Z_2 - 6696}{28551 - 6696} \right|$. Here, 1-$w$ means that how much the decision maker is concerned about the accident loss when compared to total costs. We then solve the *lp*-metric problem under $w = 0.8$ (as an illustrative example) and the result is shown in Table

6. Tables 7 and 8 report the details of the optimal solution of the problem for w=1 and w=0.8, for the most important decision variables, deliveries (*Qd*), Pickups (*Qp*) and the routes (*X*).

Table 6. *Payoff table*

	Min Z_1 (w=1)	Min Z_2 (w=0)	Min l_p-metrics (w=0.8)
Z_1 (total cost)	14509	326070	29596
Z_2 (accident loss)	28551	6696	8466

Table 7. *The optimal solution for w=1*

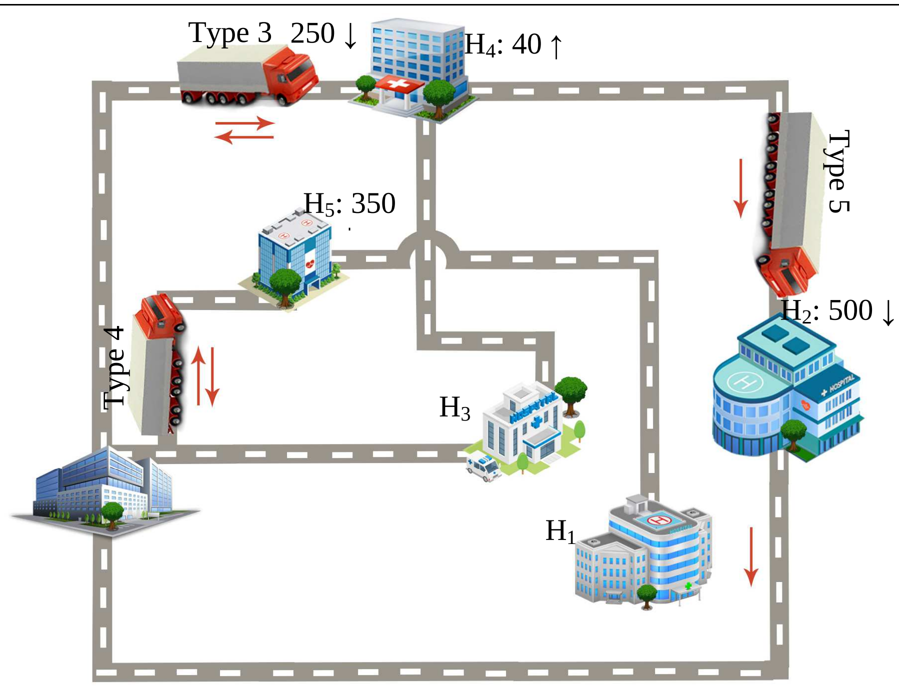
Period 1		Period 2		Period 3	
$X_{(i, j, k, t)}$	*value*	$X_{(i, j, k, t)}$	*value*	$X_{(i, j, k, t)}$	*value*
X(0, 4, 3, 1)	1	X(0, 1, 4, 2)	1	X(0, 4, 3, 3)	1
X(4, 1, 3, 1)	1	X(1, 5, 4, 2)	1	X(4, 0, 3, 3)	1
X(0, 5, 4, 1)	1	X(5, 0, 4, 2)	1	X(0, 1, 4, 3)	1
X(5, 0, 4, 1)	1	X(0, 1, 5, 2)	1	X(1, 4, 4, 3)	1
X(0, 4, 5, 1)	1	X(1, 4, 5, 2)	1	X(4, 2, 4, 3)	1
X(4, 2, 5, 1)	1	X(4, 3, 5, 2)	1	X(2, 0, 4, 3)	1
X(2, 0, 5, 1)	1	X(3, 0, 5, 2)	1	X(0, 3, 5, 3)	1
-		-		X(3, 5, 5, 3)	1
-		-		X(5, 1, 5, 3)	1
-		-		X(1, 4, 5, 3)	1
-		-		X(4, 2, 5, 3)	1
-		-		X(2, 0, 5, 3)	1
$Qd_{(i,, k, t)}$	*value*	$Qd_{(i,, k, t)}$	*value*	$Qd_{(i,, k, t)}$	*value*
Qd(4, 3, 1)	250	Qd(1, 4, 2)	150	Qd(4, 3, 3)	250
Qd(5, 4, 1)	350	Qd(5, 4, 2)	100	Qd(1, 4, 3)	300
Qd(2, 5, 1)	500	Qd(1, 5, 2)	350	Qd(2, 4, 3)	50
-		Qd(3, 5, 2)	150	Qd(3, 5, 3)	350
-		-		Qd(2, 5, 3)	100
$Qp_{(i, k, t)}$	*value*	$Qp_{(i, k, t)}$	*value*	$Qp_{(i, k, t)}$	*value*
Qp(4, 5, 1)	40	-		Qp(1, 5, 1)	15

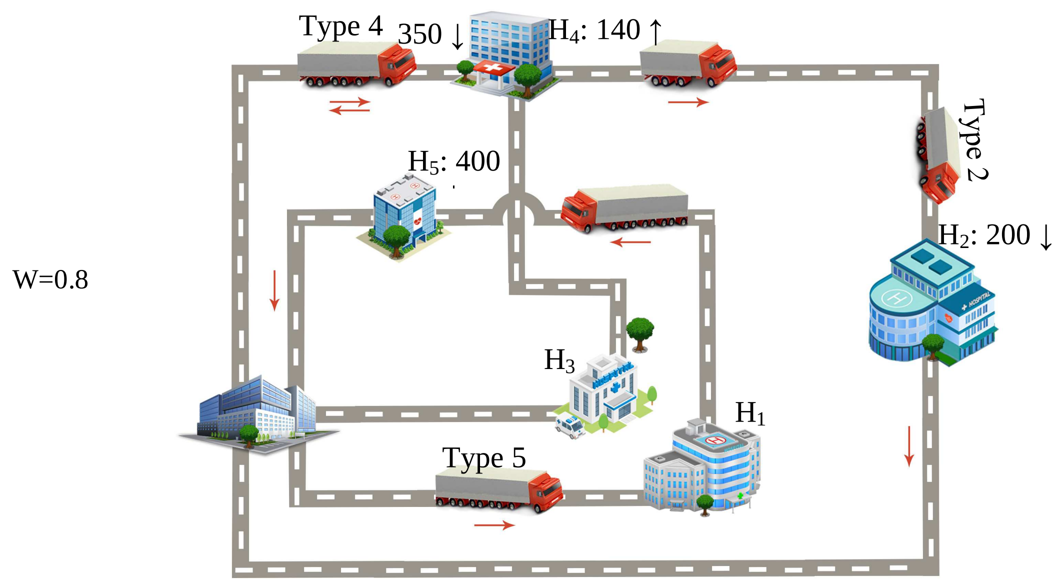
Table 8. *The optimal solution for w=0.8*

Period 1		Period 2		Period 3	
$X_{(i, j, k, t)}$	*value*	$X_{(i, j, k, t)}$	*value*	$X_{(i, j, k, t)}$	*value*
X(0, 4, 2, 1)	1	X(0, 4, 2, 2)	1	X(0, 4, 2, 3)	1
X(4, 2, 2, 1)	1	X(4, 2, 2, 2)	1	X(4, 2, 2, 3)	1
X(2, 0, 2, 1)	1	X(2, 0, 2, 2)	1	X(2, 0, 2, 3)	1
X(0, 4, 4, 1)	1	X(0, 4, 3, 2)	1	X(0, 1, 4, 3)	1
X(4, 0, 4, 1)	1	X(4, 3, 3, 2)	1	X(1, 4, 4, 3)	1
X(0, 1, 5, 1)	1	X(3, 5, 3, 2)	1	X(4, 0, 4, 3)	1
X(1, 5, 5, 1)	1	X(5, 0, 3, 2)	1	X(0, 1, 5, 3)	1
X(5, 0, 5, 1)	1	X(0, 1, 5, 2)	1	X(1, 4, 5, 3)	1
-		X(1, 0, 5, 2)	1	X(4, 3, 5, 3)	1
-		-		X(3, 5, 5, 3)	1
-		-		X(5, 0, 5, 3)	1
-		-		-	
$Qd_{(i,, k, t)}$	*value*	$Qd_{(i,, k, t)}$	*value*	$Qd_{(i,, k, t)}$	*value*
Qd(2, 2, 1)	200	Qd(2, 2, 2)	200	Qd(4, 2, 3)	50
Qd(4, 4, 1)	350	Qd(3, 3, 2)	150	Qd(2, 2, 3)	150

Qd(5, 5, 1)	400	Qd(5, 3, 2)	50	Qd(1, 4, 3)	300
-		Qd(1, 5, 2)	500	Qd(4, 4, 3)	50
-		-		Qd(4, 5, 3)	150
				Qd(3, 5, 3)	350
$Qp_{(i, k, t)}$	*value*	*$Qp_{(i, k, t)}$*	*value*	*$Qp_{(i, k, t)}$*	*value*
Qp(4, 2, 1)	140	-		Qp(1, 5, 1)	15

For $w = 0.8$, the economic performance of the system accounts for 80% of the decision maker concern and the accident loss accounts for 20%. Under this value of w, according to Table 6, the values for Z_1 and Z_2 are respectively equal to 29596 and 8466. By changing the relative weight (w), a Pareto set solutions can be obtained. In order to investigate the integration of the accident loss in the optimization procedure, let's compare a 100% economic performance optimization based only on the first objective function (Z^*_1) with a l_p-metrics* ($w = 0.8$) for the first period (Figure 2).

	Period 1
W=1	



a↑: means that the truck picks up "a" product units from the related hospital(transshipment).
b↓: means that the truck delivers "b" product units to the related hospital.

Figure 2. *Optimum solution obtained for w=0.8 vs. w=1.*

As illustrated in Figure 2, the transshipment option plays a significant role in the optimal solutions. In the first solution in which the accident risk is ignored, a truck type 3, at first period, begins its tour by visiting to hospital 4 to deliver 250 units of medication. A truck type 4 visits hospital 5 and delivers 350 units, and finally a truck type 5 visits hospital 4, and picks up 40 units and then goes to hospital 3 and delivers 500 units of medication. It should be noted that hospital 4 is visited twice in the first period, with truck type 3 and 5. The former truck delivers the medication to this hospital and the latter one picks up medication (transshipment). Despite that the two last tours (0 → 5 → 0 and 0 → 4 → 2 →0) are among the risky tours (estimated occurrence probability and severity index of accident for the route 2→0, are very high and equal to 0.2 and 0.12, respectively), the model ignores the accident concern (see Table 3) and the trucks use the mentioned risky routes, since the model only minimizes the total cost (w=1).

In the second solution (obtained by solving the l_p-metrics method for *w=0.8*), first, a truck type 4 delivers 350 units of product to hospital 4, then a vehicle type 2 visits this hospital and picks up 140 units and left this hospital to hospital 2, and delivers 200 units. It is observed that in this solution, the transshipment (*Qp*) increases that meaning it helps the system to adopt with changes in decision maker's preferences about total cost versus accident loss. Finally, a truck type 5 (the biggest one), visits hospital 5 and delivers 400 units and returns to the central pharmacy. Although there is a direct road between nodes zero and 5, but the truck chooses middle node 1, and takes the tour 0 → 1 → 5, rather than 0 → 5. The former tour seems reasonable when we discover that the accident severity indexes or occurrence probability of accident for this tour is zero. Besides, when passing a route like as 4 → 2 is inevitable, in contrast with the first solution, a small truck (type 2) cross this risky route to avoid a costly accident.

It is worthwhile to notice that by taking into account the second objective function (minimizing the maximum accident loss) with a relative weight of 0.2 (1- *0.8*=0.2), the accident loss decreases from 28551 to 8466 (~ two third saved), and this is even more interesting to notice that this considerable reduction in the accident loss occurs when the total cost is almost doubled (the total cost shifts up from 14509 to 29596).

Enabling the transshipment option has an important impact on the tradeoff between the two objective functions. One may ask the question that whether without considering transshipment option the above solution (provided in Figure 2) is applicable. The answer is "NO". When we solve the problem without the transshipment option, the accident loss average decreases but the total cost increases to reach 30600, which is about 4% more expensive than the transshipment enabled case for this small example.

Our framework permits consequently to the decision maker to judgmentally integrate the accident concern in his/her optimization of the IRP problem: this could be done by letting him/her judgmentally choosing the value of w. More importantly, thanks to this illustrative example, it is clear that transshipment option may allow the system to reduce the accident loss without an equivalent increase in the logistics costs. It would be interesting to investigate in a more detailed manner (in Section 7) at which level the transshipment option operates as a coordinator between the two objective functions.

6. Solving procedure (HGA)

As shown by Zhao, et al., (2007), the IRP is NP-hard. As a consequence, exact solution methods cannot find the optimum solution for large-sized problems in a reasonable time. Alternatively, several heuristic (Siswanto et al., 2011; Nambirajan et al., 2016) and metaheuristic approaches have been developed in the last few decades to discover the near optimal solutions. The most widely adopted methods are: genetic algorithm (Moin et al., 2011; Park, 2016), simulated annealing (Shaabani and Nakhai Kamalabadi, 2016; Ghorbani and Akbari Jokar, 2016), particle swarm optimization (Kumar et al., 2016; Chen and Lin, 2009), ant colony (Huang and Lin, 2010), and hybrid approaches (Avci and Topaloglu, 2016).

Since the proposed model is a multi-objective IRP and the computation time of determining the optimal solution is heavily dependent on the dimensions of the problem, we develop a Hybrid Genetic Algorithm (HGA) by taking the advantage of compromise programming (l_p-metrics) which makes the proposed HGA capable to generate the Pareto solutions. The flowchart of the proposed metaheuristic is depicted in Figure 3. As seen in Figure 3 in each inner loop of the proposed algorithm, GA is recalled five times. In the first four times, it is executed to obtain the best and worst values of each objective function separately, and last time it is executed to solve the problem with a compromise fitness function called l_p-metrics.

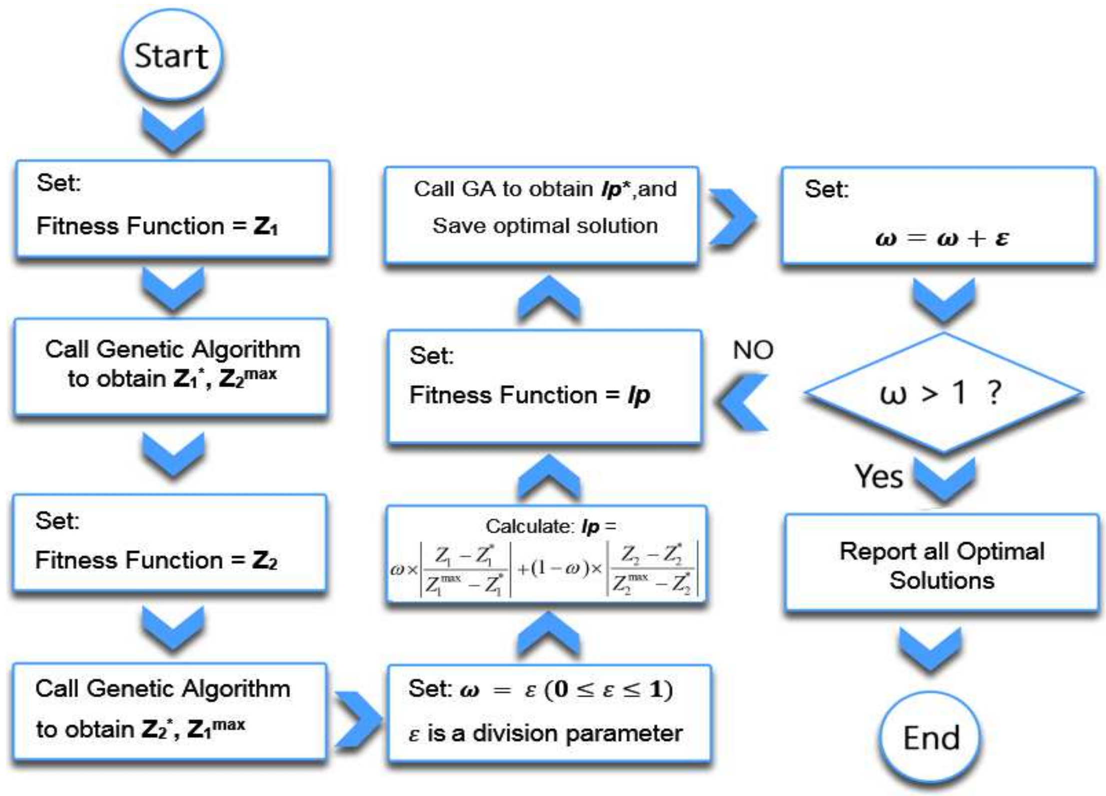


Figure 3. *The flowchart of hybrid GA*

6.1. Fitness function

In genetic algorithm, the fitness function is a criterion to evaluate the quality of the feasible solutions (chromosomes). Since the proposed model is a bi-objective programming, we have two inconsistence fitness functions. As previously explained, we merge both objectives to create a single fitness function called l_p-metrics (see Figure 3). This fitness function is the weighted sum of each objective functions' normalized deviation from its optimum value. The optimum values themselves are obtained separately by running GA where the fitness function is set to its respected objective function.

6.2. Chromosome structure (Solution encoding)

A chromosome is composed of a set of genes. A solution of the developed model is consisting of some variables presented in Figure 4-a, where $g_{vt}=[X, Q_p, Q_d]_{vt}$ are matrices with dimensions of $i \times j$, $1 \times i$ and $1\times i$ and show the routes ($i \rightarrow j$), pickups and deliveries of vehicle v in hospital i and in period t, respectively. It is obvious that there are many zeros in above matrices. So, in order to make the algorithm more efficient, the encoding of a feasible solution is proposed differently as Figure 4-b.

(4-a)

		Period			
		1	2	…	T
Vehicle	1	$[X,Q_p,Q_d]_{11}$	$[X,Q_p,Q_d]_{12}$	…	$[X,Q_p,Q_d]_{1T}$
	2	$[X,Q_p,Q_d]_{21}$	$[X,Q_p,Q_d]_{22}$	…	$[X,Q_p,Q_d]_{2T}$
	⋮	⋮	⋮	…	⋮
	V	$[X,Q_p,Q_d]_{V1}$	$[X,Q_p,Q_d]_{V2}$	…	$[X,Q_p,Q_d]_{VT}$

(4-b)

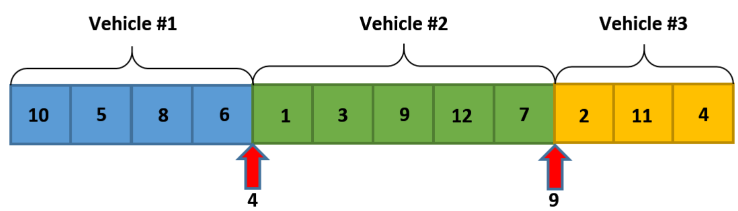


Figure 4. *The solution and chromosome structure*

In Figure 4-b, a network composed of 12 hospitals is considered. First, a random permutation between one and the number of hospitals is generated. Then a random number between 1 and the number of available vehicles are generated. In this example, three vehicles are selected. After that two (i.e. 3-1=2) random cuts (e.g. 4 and 9) are generated between 1 and the number of hospitals minus one (11) which are shown by the arrows, then the hospitals separated by the cuts create the routes for each vehicle. Therefore, vehicle 1, for example, visits the hospitals 10, 5, 8, and 6, respectively.

6.3. Initial population

Genetic algorithm is inspired by the natural biological evolution of a population during many generations. Although convergence of the genetic algorithm is not dependent on its initial population but it is important enough to create a diversified initial population to get a better result. For this purpose, we define the following steps:

1- Set $n=1$ as the counter of population.
2- Calculate the average demand ($\bar{D}$) and its standard deviation (S_D) for each period *(t)*.
3- Vehicles in each period are selected based on probability $Cv/\bar{D}$ and the upper bound (fleet size).
4- The routes for the selected vehicles are generated randomly, and the hospitals which should be visited are determined accordingly (Figure 4-b).
5- Matrix Q_p (pickups) is generated by the random numbers between zero and the hospital's previous period inventory minus its current demand, on condition that the truck has enough empty places, otherwise a random number between zero and the empty places of the truck is instead generated.
6- Matrix Q_d (deliveries) is generated by the random numbers in interval ($\bar{d} \pm S_D$), on conditions that: 1) the vehicle has enough cargo, 2) the hospital's available inventory cannot satisfy its current demand, and 3) the pickup operation is not already planned for this hospital in this period. If condition (2) is not met a random number in interval (0, the truckload) is instead generated.
7- Determine the inventory and shortage levels of the hospitals for the chromosome generated and check if it meets the hospital capacity constraint (Equations 29-30).
8- If the created chromosome violates the constraints, then modify it by the modification procedure (explained in sub-section 4.6).
9- If $n=N$, stop; otherwise set $n=n+1$ and go to step 3.

In this way, N feasible chromosomes are generated, which form the initial population.

6.4. Crossover Operator

In random crossover operation, the first two parent chromosomes are randomly paired, and then a new offspring chromosome is generated such that it inherits part of the genes from each parent. According to Figure 5, a route in Parent 2 is first chosen randomly and a sub-route is randomly selected from that route. The sub-route contains at least one hospital and at most the whole route. Before inserting the sub-route into Parent 1, if the split delivery is forbidden, all its hospitals are deleted from this parent to avoid duplications in the solution, otherwise; only the hospitals visited with same vehicles are deleted. Then, the sub-route is inserted in the best possible place, which is found by a greedy heuristic called Best-Insertion (Bjarnadóttir, 2004). The heuristic finds both the route in which the sub-route is inserted and the two hospitals it is inserted between. Consider H_1 denoting the first hospital in the sub-route and H_n the last one and h_m and h_{m+1} being two consecutive hospitals in a route in the offspring. The payoff of inserting the sub-route between h_m and h_{m+1} is measured by the formula:

$$payoff(m) = d(h_m.h_{m+1}) - d(h_m.H_1) - d(H_n.h_{m+1})$$

where $d(h_m.h_{m+1})$ is the cost/distance of the arc $m_{\rightarrow}m+1$. The algorithm searches through the whole offspring and inserts the sub-route in the place giving the largest payoff, and a new offspring has been generated. Then this operator is applied again to the other parent, to create the second offspring.

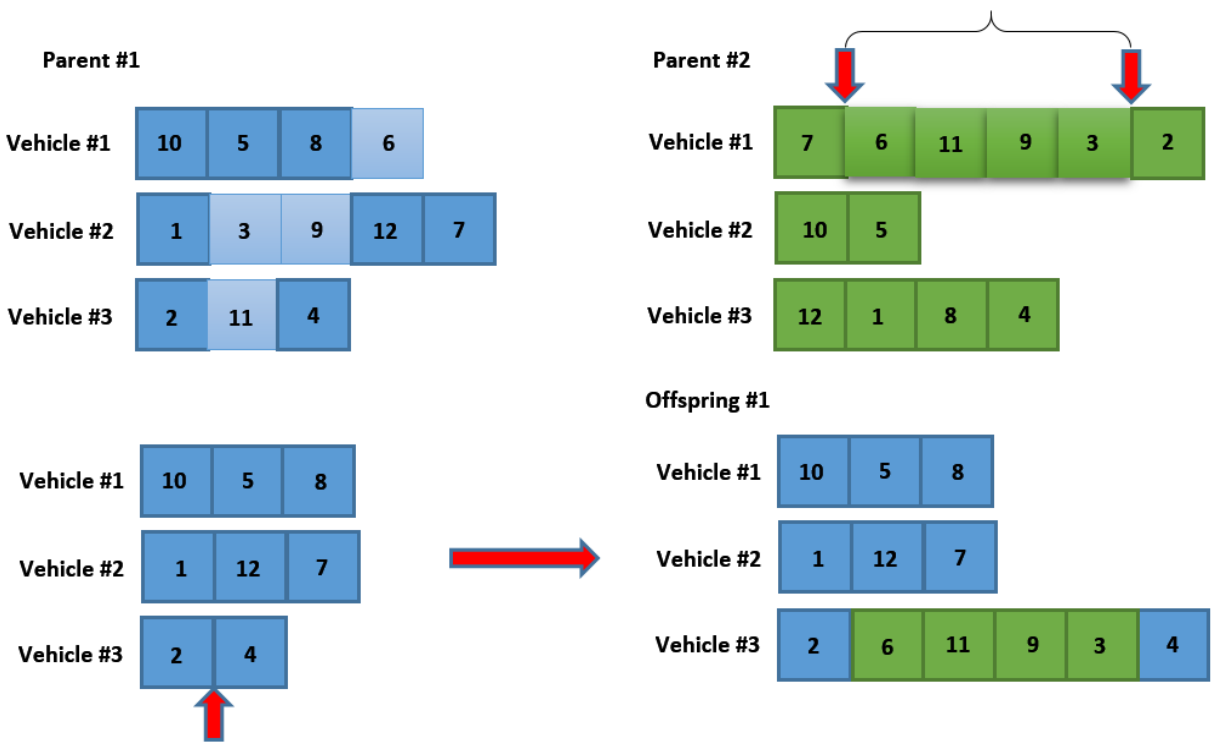


Figure 5. *Random Crossover operator*

6.5. Mutation operator

The mutation operation increases the possibility that the whole feasible space to be explored, and reduces the tendency of being trapped in local optimal solutions by changing the contents of one or more genes of the chromosomes. In our proposed HGA three parallel mutation operators are developed. Under mutation type 1 (α_{m1}), one random vehicle at a random period is first selected and its designated routes and associated pickups/deliveries are completely omitted. Under mutation type 2 (α_{m2}), one hospital is selected randomly, at its deliveries at a random period converted to pickups and vice versa, and finally, under mutation type 3 (α_{m3}), the deliveries (pickups) are randomly altered ($Q_d(Q_p) \pm\ 0.1 \times Q_d(Q_p)$).

6.6. Inversion

Similar to the mutation operator, it is applied to a single chromosome at a time. Two random cuts are first chosen within a randomly selected tour of an offspring. The order of the nodes between the cuts is then reversed.

6.7. Modification

Since the offsprings generated by either crossover/mutation operators or the initial population procedure may not satisfy the hospital/vehicle capacity constraints, we check these two limitations and alter the pickups and deliveries accordingly till reach the feasible solution. If after many attempts of this procedure (e.g. 10 times) the chromosome is still remained infeasible, either the infeasible chromosome is completely removed and a substitute chromosome is randomly generated by the help of initial population procedure or penalized in fitness function.

6.8. The proposed Genetic Algorithm (GA)

The essential steps of the proposed hybrid genetic algorithm are summarized as follows:

1. Initialize GA parameters; P (population size), N (the number of generations), α_c (the probability of the crossover operation), αm_1 and αm_2 (the probability of mutation type 1 and 2, respectively).
2. Initialize the division parameter for l_p-metrics (ε)
3. Generate the initial feasible population of size P according to algorithm given in Section 6.3.
4. Initialize counter $n=1$ (counter of generation).
5. Set up the mating pool including P parents (chromosomes).

6. Pair the P chromosomes (parents) randomly and exercise crossover to create offsprings according to algorithm given in Section 6.4.
7. Pick the chromosomes randomly and apply mutation and inversion operation to create new offsprings according to algorithm given in Sections 6.5 and 6.6.
8. Check the feasibility of new offsprings and modify the infeasible ones to satisfy the constraints (Section 6.7).
9. Update the mating pool with all parents and feasible offsprings.
10. Compute the fitness values for each chromosome based on ε and the given function in Figure 3, and rank them accordingly (the ties are removed).
11. If $n=N$; stop and report the first ranked solution, otherwise; go to next step.
12. Transfer the first one-third of ranked chromosomes ($P/3$) directly to the next generation's mating pool (elitism) and fill the rest of mating pool by randomly selection of remaining chromosomes ($2P/3$).
13. Set $n=n+1$, and go to step 6.

7. Sensitivity analysis and managerial implications

In order to demonstrate the efficiency of the proposed metaheuristic, and to derive managerial insights about our proposed framework, several numerical examples are generated and solved using both CPLEX and the hybrid GA. Then, three sensitivity analyses are performed; 1) to study the role of transshipment option to reduce the total cost as well as the accident loss, 2) to identify the range of deterioration rate over which the transshipment is still cost effective and, 3) to discuss the impact of unit transportation costs (fixed and variable), and backorder ratio on the optimal solution and the associated two objective functions.

7.1. Performance of HGA

In order to show the efficiency of the proposed metaheuristic, 15 test problems with different dimensions are generated and solved by the HGA presented in the previous section and then compared with the lower bound of CPLEX. The proposed HGA is coded in MATLAB R2015a, and all computations are run on a workstation with 3.3 GHz and 4 GB RAM under Microsoft Windows 7.

The number of hospitals and periods are respectively ranging from 5, 2 (in small sized problems) to 50, 12 (in large sized problems). Each problem is first solved by using the l_p-metrics method accessed via CPLEX script and then solved by the proposed hybrid GA. the variable cost and demand are randomly generated between (0-130) and (0-500), respectively. The relative weights are set as 0.2, 0.4, 0.6 and 0.8 to generate Pareto solutions and the results are reported in Table 9. The Gap_1 (in percentage) in Tables 9 is the percentage deviation of the average first objective function's best values (Total cost) among Pareto solutions obtained by HGA (AOV^1_{HGA}) from the one obtained by CPLEX (AOV^1_{LB}) and calculated as follows:

$$Gap_1 = \frac{AOV^1_{HGA} - AOV^1_{LB}}{AOV^1_{LB}} \times 100$$

Similarly, Gap_2 is defined as the deviation of the average of the second objective function's best values (Accident risk) among Pareto solutions obtained by HGA (AOV^2_{HGA}) from that obtained by CPLEX (AOV^2_{Opt}).

$$Gap_2 = \frac{AOV^2_{HGA} - AOV^2_{LB}}{AOV^2_{LB}} \times 100$$

Except some large sized instances in which the workstation could not even generate the model to solve it, wherever the CPLEX cannot solve the problem in two hours, the lower bound reported by CPLEX is used to compute the gaps. As seen in Table 8, in all cases the reported gaps are reasonable and never exceed 13%.

Table 9. *Performance of the proposed metaheuristics*

# Problem	# Hospitals	# Period	HGA			CPLEX			GAP$_1$	GAP$_2$
			AOV^1_{HGA}	AOV^2_{HGA}	CPU Time*	AOV^1_{LB}	AOV^2_{LB}	CPU Time***		
1	5	2	210,742	1240	0:15:00:00	186497	1218	0:17:44:09	0.13	0.018
2	5	3	299,038	1938	0:15:49:00	97725	317	0:22:19:21	2.06	5.111
3	6	3	381,444	2774	0:15:20:00	45682	441	0:47:52:03	7.35	5.290
4	10	5	588,906	14337	0:22:22:00	70443	2233	1:17:26:93	7.36	5.421
5	12	6	614,333	17673	0:55:18:00	55798	2773	1:22:12:17	10.01	5.374
6	15	6	721,110	25385	1:05:29:00	72039	3504	1:48:47:23	9.01	6.244
7	18	9	1,006,555	49111	1:55:50:00	96321	5371	1:59:59:59	9.45	8.144

8	20	9	1,165,445	55373	2:20:00:00	115620	6912	1:59:59:59	9.08	7.011
9	22	9	1,502,606	59012	2:20:00:00	123367	6318	1:59:59:59	11.18	8.348
10	24	10	1,719,024	67614	2:30:00:00	154867	5315	1:59:59:59	12.10	11.721
11	26	10	1,880,417	69935	2:17:00:00	153880	5413	1:59:59:59	11.22	11.92
12	28	10	2,099,907	71375	2:26:10:00	165347	6456	1:59:59:59	11.70	10.056
13	30	11	2,330,447	105493	2:25:09:00	210139	8454	1:59:59:00	10.09	11.478
14	30	12	2,924,103	112776	2:45:00:00	N/A	N/A	3:00:00:00	-	-
15	50	12	5,666,211	289998	5:00:00:00	N/A	N/A	3:00:00:00	-	-

* Running time is reported for the best experience in the format of hr:min:sec:millisec.
** The time taken to generate the initial population and respected l_p-metrics parameters are both excluded from the solving time.
*** For large scale problems the lower bounds (LB) of CPLEX, reported after two hours, are used for comparison.
N/A: CPLEX cannot reach the feasible solution after three hours.

7.2. Transshipment vs no transshipment scenarios

In order to shed more light on the importance of the transshipment policy, we compare the solutions with and without the transshipment option to demonstrate that the latter is not only beneficial for the first objective function (total cost) through saving in routes but also it enables the model to avoid the routes with higher degree of accident loss, and ensures the supply against catastrophic consequences of possible accident. Thus, several numerical examples are generated and solved by using the proposed hybrid algorithm to study the impact of the transshipment option on the optimal solution for a given weight *w*. We solve 10 more test problems twice; with transshipment option ($Z_i^*{}_{TR}$) and without transshipment option ($Z_i^*{}_{WTR}$). The optimal solutions for the problems with and without transshipment option are then reported and the gap between them is calculated by $\Delta i = \frac{Z_{i\,TR}^{*} - Zi^{*}{}_{WTR}}{Zi^{*}{}_{WTR}}$. As seen in Table 10, the average, minimum and maximum of Δ_1 are 0.196, 0.11 and 0.31, respectively. Similarly, the average, minimum and maximum of Δ_2 are 0.176, 0.10 and 0.28, respectively. With no exception, the transshipment policy leads to better solutions based on total cost and accident loss, concurrently. For instance, in test problem 4, the transshipment option enables a 23% saving in the total cost, and a decrease of 16% in the accident loss.

Table 10. *The overall impact of transshipment on objective functions*

#Problem	With	Without	Δ_1	Δ_2

	Transshipment		Transshipment			
	Z_1	Z_2	Z_1	Z_2		
1	60261	7576	76532	9394	0.27	0.24
2	49102	14455	54503	15900	0.11	0.1
3	44646	10833	50896	12783	0.14	0.18
4	48621	15662	59804	18168	0.23	0.16
5	52241	10455	61122	11500	0.17	0.1
6	57540	5980	70774	7056	0.23	0.18
7	61630	14105	80735	17490	0.31	0.24
8	65144	15040	72961	17747	0.12	0.18
9	54308	7560	67342	8316	0.24	0.1
10	69289	10888	78990	13937	0.14	0.28
Average					0.196	0.176

7.3. Impact of the deterioration rate

Due to the perishability nature of the products under study, the transshipment benefit is upper bounded by the deterioration occurring during the horizon periods. In this section a sensitivity analysis is performed to discuss the impact of the deterioration rate (θ) on the optimal solution and to identify the appropriate range of θ over which the transshipment option keeps on its beneficial role. For this purpose, the test problem with 18 periods is solved for different values of θ ranging from zero (Non-deteriorating items) to 0.1 while the other parameters remain unchanged. The number of periods is assumed equal to 18, such that the impact of deterioration rate can be observed. The results are depicted in Figure 6. As illustrated in Figure 6, although the deterioration rate has no meaningful impact on the accident loss, it is determinant to distinguish the positive role of the transshipment option (pickups) on the total cost. Since we consider in Z_2 the min max of accident loss and not the cumulative sum of the accident loss, there is small variations in cumulative sum but the max boundary is almost the same for changing θ. As illustrated, for higher rates of θ, the transshipment option is more solicited (higher pickup quantities) leading to increasing values of the first objective. If the transshipment option is not enabled, the situation would be worse since the products may perish and more logistics costs may be incurred. Indeed, for higher values of θ, the extra inventories of medications in hospitals' drugstore (when the available inventory in a hospital exceeds its demand) are rapidly perishing. So, it would be advantageous, from a system perspective, to transfer some of its inventory to other hospitals where its demand is unsatisfied due to the lack of inventory, and prevent a great part of medications from perishing of the deterioration process.

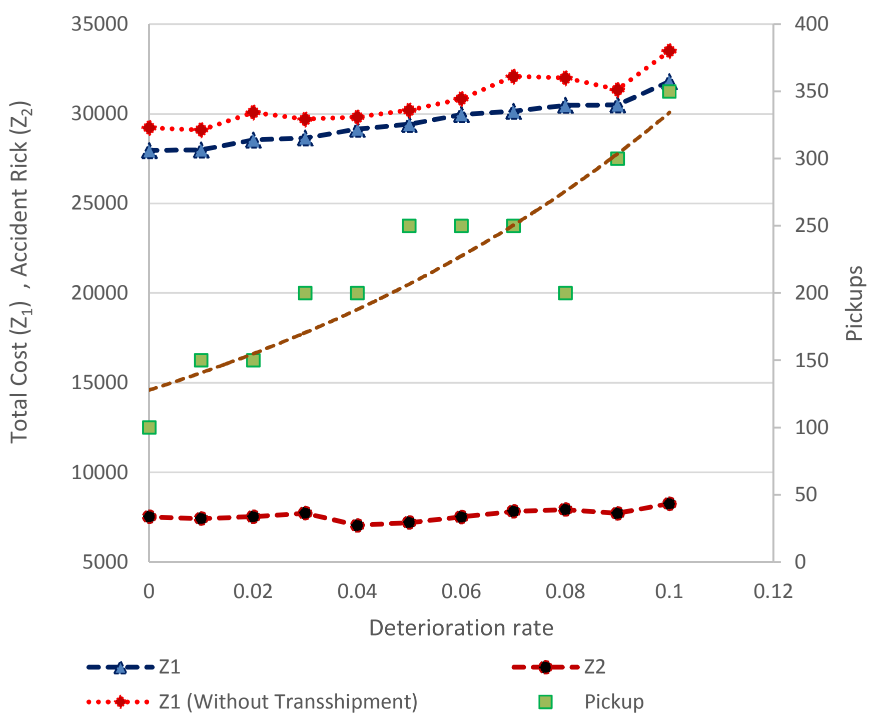


Figure 6. *Accident loss and total cost as a function of the deterioration rate*

7.4. Impact of the backorder rate

As previously discussed, one significant characteristic of the proposed model is the modeling and the integration of the partial backordering β. It is very helpful to identify at which range of β, the ratio of demand backlogged, the need to use transshipment option is more profitable and for which reason. For this purpose and to study the impact of the backorder ratio on the optimal strategy, we solve the test problem under different values of β ranging from zero (all unfulfilled demand is lost) to 1 (all unfulfilled demand completely backordered) while we keep the other parameters unchanged. The objective values Z_1 and Z_2 as a function of the transshipment quantity (pickups) are depicted in Figure 7. This Figure shows that the transshipment option is more beneficial for the lost sale shortage case rather than the case in which demand is totally backordered. That means that the transshipment option acts as an excellent emergency solution to avoid lost sales. The less the ratio of unsatisfied demand is backordered, the more often transshipment will be visible in optimal solutions for range $0.3<\beta<0.7$. Afterward, the trend is inverted and the transshipment option is first satiated, and then decreased but never collapsed. The rationale behind this observation is that the transshipment option generally depends on the vehicle capacity, so in order to take advantage of the transshipment; the inventory manager has rather to utilize vehicles that are more spacious.

By observing the stable behavior of the accident loss (in Figures 6 and 7) for increasing pickup quantities and associated total cost, we notice that the transshipment option plays the role of a coordinator between the economic and the safety criteria of the problem. For instance, for increasing values of β, one could expect the use of more routes (including risky ones) to fulfill the backordered demands and as a consequence, we may expect a worse evolution of the accidents loss for higher β. As shown in Figure 6, this is not the case, because the system is soliciting more the transshipment option in order to avoid the risky routes. Besides, in our test problems, the unit lost sale penalty cost is assumed almost ten times larger than that of backorder cost.

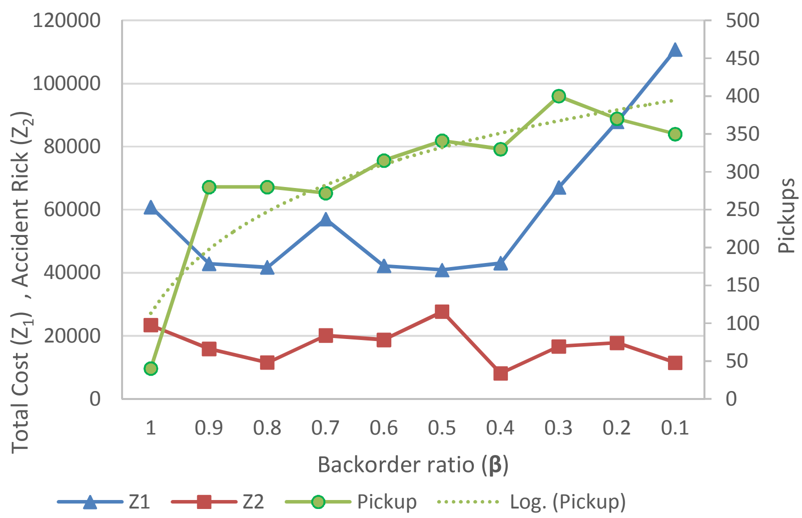


Figure 7. *Transshipment for different backorder ratios.*

7.5. Impact of the fixed and variable transportation cost

We finally perform a sensitivity analysis on the fixed (d_k) and variable transportation cost (vc_k), to show the attractiveness of the transshipment option when they increase. We multiplied the unit fixed and variable cost by a coefficient ranges from 1 to 3 as illustrated in the horizontal axis of Figure 8. As intuitively expected, when the fixed cost increases, the total pickups (transshipment) increases rapidly. The rationale behind this observation is that when the fixed cost increases, the transshipment policy attempts to merge the cargos to reduce the number of vehicles utilized. It implies that the transshipment option is an interesting option in the presence of a small fleet of vehicles. Conversely, the transshipment is not very attractive when the variable cost increases, especially when the variable cost depends on the both distance and the size of vehicle's cargo.

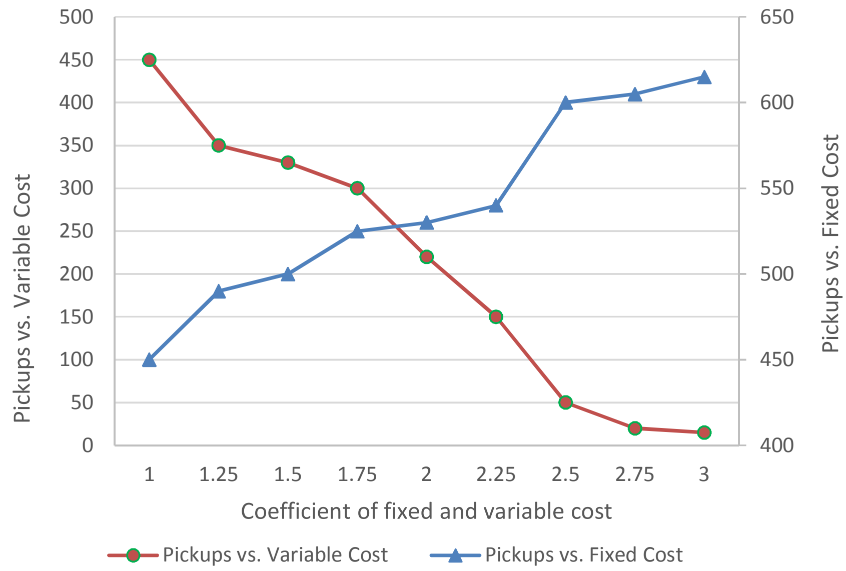


Figure 8. *Transshipment versus fixed and variable transportation cost*

8. Conclusion and future research

In this research, a mixed integer mathematical model is presented to deal with a bi-objective transshipment enabled inventory routing problem for deteriorating items in a supply chain network. Two distinguishing features of the proposed model are; i) transshipment option is incorporated in the model as a possible solution to increase the performance of the distribution, ii) minimizing the maximum accident loss as an additional objective function is added to the classic form of IRP model to avoid the possible catastrophic accidents that may lead to uncompensated effects that is particularly vital for radio pharmaceutical products. These features enable the model to select the appropriate routes as well as the transshipment alternative to reduce the total costs of supply chain and keep the distribution as safe as possible. The results show that the model is capable to make a rational balance between the conflicting criteria. The model permits to decision maker to judgmentally choose the tradeoff between the safety and the economic performance by setting the weight assigned for each optimization criterion. A problem modeling effort is performed in order to integrate the accident issue in the classical IRP. We formulate it as an average loss function based on the location of the accident as well the type and the content of the truck when the accident happens.

An efficient hybrid Genetic Algorithm is developed as a resolution procedure and sensitivity analyses are conducted to derive managerial insights for decision makers. We particularly illustrate the particular cases where the transshipment option brings an important added value to the economic performance while the accident loss is kept under control. The transshipment option does not only play the role of a lever to decrease the costs but also, it operates as a coordinator between the economic and the safety criteria.

Examining other heuristic and metaheuristic methods, extending the model for multi-product situation and under uncertain conditions, and developing the model for reverse side of the supply network are some promising directions for future research.

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