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Multi-objective inventory routing problem: A stochastic model to consider profit, service level and green criteria

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A B S T R A C T

The Inventory Routing Problem has been mainly studied in recent decades under an economic performance perspective. In this paper, we develop a multi-objective mathematical framework for the IRP to link: (i) the economic performance, (ii) the achieved server level in terms of shortage and delivery delays and (iii) the environmental footprint. The framework developed addresses the uncertainty by considering fuzzy distributions for certain problem inputs, such as the demand and the transportation costs. We show the negative impact on the economic performance when service level targets are exogenously chosen without coordination with the logistics components (inventory and distribution).

1. Introduction

In its traditional mathematical modeling and optimization approaches, the Inventory Routing Problem (IRP) identifies the best inventory and distribution joint strategy, i.e., the inventory control of products, the determination type and number of vehicles, the type of products, their quantity to be delivered to each customer and the best routing in each period.

The main objective in the traditional IRP is the minimization of the total inventory and transportation cost as well as the traveling time or distance (Li et al., 2014; Madadi et al., 2010). However, this classical approach does not consider certain important criteria such as the inventory and distribution service levels and the environmental footprint of the IRP solution. Currently, managers must make their decisions by considering these different criteria in addition to the economic criterion; these may, in certain cases, conflict with each other.

It is obvious that the classical IRP should be extended in its modeling and in its optimization to consider the service levels and the green considerations in addition to the economic performance. The modeling and optimization extension may be more challenging when it is performed for perishable items where both the product non-freshness and the need to recycle perished products should also be modeled and considered.

With regards to the service level extension for IRP, it is worthwhile to note that the increasing competitiveness between firms in a global marketplace generates increasingly more pressure. The firms need to improve their efficiency as much as possible to ensure customer satisfaction. A high service level is indeed one of the key factors to strengthening customer satisfaction and loyalty. However, despite the positive impact on sales in the long-term, providing a higher service level to the customer may increase the associated inventory and distribution costs. From a business perspective, the service level presents a tradeoff between the opportunity costs and the operation costs (Schalit and Vermorel, 2014). Despite its importance

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for practitioners, very few investigations have integrated the service level into the IRP framework. With regard to the green footprint extension for IRP, it is obvious that ‘greenness’ has become a very much needed condition in the transportation industry. The IRP is naturally among the most interesting framework to deploy innovative and new decisions striving to decrease the CO_2 footprint of a supply chain.

The objective of this paper is to extend the classical IRP framework to integrate both the service level and the green considerations. We develop a multi-objective version of the IRP problem where we add to the classical economic objective two new objective functions that model and measure the inventory and transportation service level as well as the green footprint of the IRP solution. Our proposal is applicable for perishable items where we additionally model the products’ non-freshness as well as the reverse supply chain management of the perished products. To remain close to real IRP business cases, we allow certain problem parameters such as demand, variable transportation costs and vehicle speed to be uncertain. We model these parameters using fuzzy distribution; our framework is solved by using an adequate and well-motivated mathematical resolution approach. More importantly, a numerical study permits us to derive managerial insights about the following issues:

- We explore the linkage between the three objective measures; the framework permits us to numerically calculate the impact on costs and the green footprint of x% increase in the service level.
- Consequently, the framework permits us to derive the cost penalty if the service levels are exogenously decided without coordination with the logistics components of the IRP (inventory + transportation).
- We explore the non-freshness implication of the IRP three objective functions.

Regarding the practical applicability of our framework, we notice that the developed problem fits particularly with the IRP of fresh products in the last mile urban distribution where green considerations are important components of the decision making process. The problem developed in the paper is step forward making the IRP framework closer to a real distribution business case. Indeed:

- We introduce the service level measure as a second objective functions: service levels are very used in practice, particularly in the inventory control arena where they can be preferred for their ease of use from a technical point of view. The Cycle Service Level and the Fill Rate (both of them are modeled in the second objective function) are well known and very used measures for practitioners (SCHNEIDER, 1981). We also model the distribution time windows which may be an important constraint in practice particularly for urban vehicle touts and we model the non-respect of a visit time windows with a third service level measure.
- We introduce the environmental footprint as a third objective function and we measure it by the GHG emission during vehicles’ routes, product loading and unloading tasks. Nowadays, there are international standards permitting the calculation of the GHG output of an IRP solution (please cf. the World Resources Institute and the World Business Council on Sustainable Development reports (WRI;WBCSD, 2001)). Adding the green footprint of the IRP solution is not motivated by a wish to make the framework more sophisticated but we do believe that it is linked to a real need for practitioners. In some countries (Germany and France for instance) and in some urban cities (Berlin in Germany and Saint-Etienne in France for instance), the access to the city center is conditional to the green footprint of the vehicle performing the delivery. More and more legislation rules are set to at least track and limit the GHG emission particularly in urban zones.
- We introduce the non-freshness cost by either an extra holding cost (a cost to inspect items before transferring them to the next selling period) or/and by a need to discount non-fresh products if they are transferred from previous selling periods. Both practices are common in the management of fresh food products.
- We model some of the problem parameters as uncertain for the purpose to make the problem closer to real cases. We model these uncertain parameters by a possibility triangular distribution based on the pessimistic, optimistic and most likely values. We don’t claim that the triangular distribution is the best choice but we notice that the resolution approach presented in the paper will still apply for any discrete distribution of these parameters.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature and motivates as well as positions the contribution of our extended IRP proposal. Section 3 details the problem description and its mathematical modeling. The resolution approach of our extended IRP is presented in Section 4. A numerical analysis is performed in Section 5 in which the associated managerial insights are also provided. Finally, Section 6 presents the paper’s conclusions and suggests further research directions.

2. Literature review

This section presents the literature review and shows the existing gap in research on IRPs to highlight and position the contribution of our proposal. A significant amount of research has previously been done on IRPs: the reader is referred to Coelho et al. (2013) for an excellent and comprehensive overview of the subject. We limit our literature review to investigations addressing one or many of the following issues: product perishability, service level, and environmental considerations.

Custódio and Oliveira (2006) propose a deterministic mathematical model to minimize the total inventory and distribution costs for frozen food. To solve their problem, the authors use a heuristic approach by considering a periodic review policy and an optimization procedure while assuming that the problem parameters are deterministic. Hsu et al. (2007) consider perishable products in the vehicle routing problem and model the need for a special vehicle fleet with cold storage equipment. The researchers model the deterioration rate of foods as a function of the temperature. The researchers' objective function minimizes the total cost, including inventory, transportation, energy and penalty costs incurred when the delivery time window constraint is not respected. Hemmelmayr et al. (2008, 2010) investigate the inventory control of blood banks and the distribution of blood to hospitals with a stochastic demand and predetermined fixed routes. The researchers solve the proposed model by using a variable neighborhood search. Yu et al. (2012) propose a mathematical IRP model by assuming that the demand is subject to uncertainties and by introducing a service level measure. The researchers define two uncommon IRP constraints where demand must be satisfied by limiting the probability of a stock out, and the warehouse should not be overfilled in any period. Mirzapour Al-e-hashem and Rekik (2013) present a cost minimization IRP under a Greenhouse Gas (GHG) emissions constraint. The authors propose the transshipment option as a lever to decrease the environmental footprint of the IRP. Le et al. (2013) present a IRP framework for distribution of perishable product where total cost should be minimized. Moreover, they introduce a column generation-based algorithm to solve the proposed model and show its efficiency in obtaining the good result.

Amorim and Almada-Lobo (2014) contribute to the impact of the perishability of products in vehicle routing problems by proposing a multi-objective mathematical model where the first objective minimizes the related costs, while the second objective attempts to maximize the freshness of the delivered products. The researchers solve the model by using an ε-constraint for small sizes and adapting a multi-objective evolutionary algorithm for large problems. Coelho and Laporte (2014) study the IRP for perishable products by maximizing the profit function under the assumption that products have different ages. The supplier decides the number of products with differing ages delivered to each customer. The researchers consider two inventory policies where the supplier can sell fresher first or older first; they solve it using a branch-and-cut algorithm. Hauge et al. (2014) consider the collection of the industrial waste from different sites and assume that full containers should be driven to dump sites. Sazvar et al. (2014) propose a multi-objective mathematical model to show the effect of environmental criteria on the total cost function in the pharmaceutical industry under an uncertain demand. The researchers consider the recycling cost of the expired products and the quantity of GHG emissions generated by recycling the perished products. In this problem, a percentage of stocked products is assumed to deteriorate in each period. Al Shamsi et al. (2014) attempt to find trade-offs between the cost resulting from GHG emissions and the inventory and distribution of perishable products. The researchers consider the effect of the weight and speed of the vehicles on GHG emissions. Nolz et al. (2014) examine the collection of pharmaceutical waste in IRPs by introducing a multi-objective mathematical model to minimize the public health risk and the total cost function. Treitl et al. (2014) consider environmental issues in IRP in petrochemical industry. The authors convert amount of produced GHGH emission in distribution process to cost and try to minimize total cost. Jia et al. (2014) propose a two-echelon supply chain by considering production step in IRPs to minimize the total costs. The authors take into account limited production capacity in supplier side where one supplier distribute one perishable product to retailers. They present a two-phase algorithm to solve the problem and show efficiency of their proposed algorithm.

Mirzaei and Seifi (2015) propose a multi-objective IRP for perishable products to investigate the impact of the lost sales minimization on the total cost. Niakan and Rahimi (2015) propose a multi-objective model for the distribution the medical equipment. The authors attempt to forecast demand and minimize the error of this forecast. Bertazzi et al. (2015) present a cost minimization IRP where the supplier has a limited production capacity in which the retailers are encountering a stochastic demand. Soysal et al. (2015) propose the distribution of a fresh perishable vegetable and consider fuel consumption, which is converted into a cost, as an environmental consideration. Singh et al. (2015) apply IRPs in the distribution of liquefied industrial gases to maximize both the service level and the efficiency of the operations. There are three components in the objective function: the satisfaction of all orders, the interruption of stock-out, and the efficiency of the bulk gas distribution; the latter is measured by the ratio of total distribution costs to total delivered product. Ghorbani and Akbari Jokar (2016) propose a hybrid imperialist competitive-simulated annealing algorithm for location-allocation, inventory and routing decisions. Dayarian et al. (2016) present and show the performance of an adaptive large-neighborhood search with specific operators for optimizing product collection and redistribution in routing problems. Li et al. (2016) consider the replenishment lead-time and inventory inaccuracy in IRPs to minimize the related inventory and distribution costs of fresh products. Zhalechian et al. (2016) propose a multi-objective nonlinear model for IRPs that integrates the location-allocation issue in a closed-loop supply chain. The researchers consider the total cost minimization as well as the environmental and social issues maximization. Ghorbani and Akbari Jokar (2016) propose a hybrid imperialist competitive-simulated annealing (IC-SA) algorithm to solve a three-level supply chain including suppliers, depots and customers for IRPs. Soysal et al. (2016) take into account the produced GHG emission due to distribution of perishable products in IRPs. The authors consider uncertainty in the demand. They show applicability of propsoed model by applying a real case in food industry. Soysal (2016) integrates closloop supply chian in IRP for collection of wastes of prodcuts. The author considers demand uncertainty in the model. He applied the propsoed model for a real case where a distributer delivers a soft drink to retailers. Azadeh et al. (2017) integrate transshipment option in IRPs where supplier delivers one perishable product to customers. Authors assume that product deteriorates at the exponential rate during the time at the warehouse. They proposed a genetic algorithm to solve the problem. Hiassat et al. (2017) apply location decisions in the IRPs to find location of required warehouses in addition to classical decisions of IRPs. In order to solve the model they propose a genetic algorithm. Cheng et al. (2017) present a comprehensive model to consider environmental issue in IRPs. The authors concern on fuel consumption where it is measured based on load, distance, speed and vehicle characteristics. Iassinovskaia et al. (2017) propose a model where a producer, produces returnable products and delivers them to customers. Moreover, distributer is responsible of collection the empty returnable items. There exist two different storage area for delivered and empty products at customers. The authors propose a heuristic to solve the proposed problem.

Table 1 illustrates the classification of the previously presented papers in the IRP literature. As shown, the IRP economic performance was historically the unique objective function, but recently the research community has begun to be interested in the green issues and/or perishable products. Except for the investigations by Yu et al. (2012), Singh et al. (2015) and Mirzaei and Seifi (2015), who introduce a service level measure in the IRP by considering it as a problem constraint, there is no other study that considers such issues in IRPs. In this paper, we define the service level as a quantity-oriented performance measure, and we integrate it as an objective function.

Our paper contributes to the existing literature by developing a new multi-objective mathematical model considering the following issues:

- We integrate the service level in IRPs, and we explore the linkage between conflictual criteria such as the IRP transportation and inventory costs, the service level and the environment. We consider a service level measuring both the inventory control and the transportation performances. Therefore, we measure the service level with the joint rate of delays, the rate of backorder as well as the rate of backorder frequency.
- We model the vehicles with different technologies (electric and diesel) to obtain insights on the link between the technology under consideration and its GHG footprint. In fact, certain practitioners would be interested in studying the impact of using electrical energy in urban transportation for the distribution of perishable products. Assuming that this type of vehicle has a higher fixed and variable transportation cost than the alternative, it produces very low volumes of GHG emissions when compared with diesel vehicles.

Table 1
Classification of the presented papers.

Author	OF[a]	DN[b]	PP[c]	Green	SL[d]	Solving method
Custódio and Oliveira (2006)	*Single*	*Certain*	✓			*Heuristic*
Hsu et al. (2007)	*Single*	*Uncertain*	✓			*Time-Oriented Nearest-Neighbor*
Hemmelmayr et al. (2008, 2010)	*Single*	*Certain*	✓			*VNS*
Yu et al. (2012)	*Single*	*Certain*			✓	*Lagrangian & Linearization*
Mirzapour and Rekik (2013)	*Single*	*Certain*		✓		*Exact (CPLEX)*
Le et al. (2013)	*Single*	*Certain*	✓			*Heuristic*
Amorim and Almada (2014)	*Multi*	*Certain*	✓			*NSGA-II*
Coelho and Laporte (2014)	*Single*	*Certain*	✓			*Branch-and-cut*
Hauge et al. (2014)	*Single*	*Certain*		✓		*Hybrid (CG and TS)*
Sazvar et al. (2014)	*Multi*	*Uncertain*	✓	✓		*Weighted sum*
Al Shamsi et al. (2014)	*Multi*	*Certain*	✓	✓		*Exact (GAMS)*
Nolz et al. (2014)	*Multi*	*Certain*				*ALNS*
Treitl et al. (2014)	*Single*	*Certain*		✓		*Exact*
Jia et al. (2014)	*Single*	*Certain*	✓			*TS & NS*
Mirzaei and Seifi (2015)	*Multi*	*Certain*	✓		✓	*Hybrid (SA&TS)*
Niakan and Rahimi (2015).	*Multi*	*Uncertain*	✓	✓		*Exact*
Bertazzi et al. (2015)	*Single*	*Uncertain*				*Rollout algorithm*
Soysal et al. (2015)	*Single*	*Uncertain*	✓	✓		*Simulation*
Singh et al. (2015)	*Single*	*Certain*			✓	*Randomized local-search*
Ghorbani and Akbari (2016)	*Single*	*Certain*				*Hybrid*
Dayarian et al. (2016)	*Single*	*Certain*				*Heuristic*
Li et al. (2016)	*Single*	*Certain*				*Genetic Algorithm*
Zhalechian et al. (2016)	*Multi*	*Uncertain*	✓	✓		*Hybrid (SAG & VNS)*
Ghorbani and Akbari (2016)	*Single*	*Certain*				*Hybrid (IC-SA)*
Soysal et al. (2016)	*Single*	*Uncertain*		✓		*Exact*
Soysal (2016)	*Single*	*Uncertain*		✓		*Exact*
Azadeh et al. (2017)	*Single*	*Certain*	✓			*Genetic Algorithm*
Hiassat et al. (2017)	*Single*	*Certain*	✓			*Genetic Algorithm*
Cheng et al. (2017)	*Single*	*Certain*		✓		*Exact (Branch-and-cut)*
Iassinovskaia et al. (2017)	*Single*	*Certain*		✓		*Heuristic*

[a] Objective function.
[b] Data nature.
[c] Perishable product.
[d] Service level.

- We model the products' perishability in IRPs using two methodologies; we model the non-freshness of products that are transferred from one period to another using a step-wise nonlinear unit holding cost that is equivalent to a price discount performed on these non-fresh products. Our IRP proposal also enables the modeling of the management of the reverse logistics of perished products that should be recycled. In addition, we assume that recycling these perished products has an impact on the economic performance of the IRP as well as on its GHG footprint.
- In contrast to most investigations in the IRP literature and for a better modeling of perishable products, we enable the holding cost function to behave as a nonlinear step function. Such modeling is motivated by extra inspection tasks that the products need before transferring them to the next period. Such modeling could also be interpreted as a price discount offered for non-fresh product in the forthcoming periods.

Moreover, to be close to real IRP business cases, we assume that certain parameters such as demand, variable transportation costs and vehicle speed are uncertain, and we model them with a fuzzy possibilistic distribution.

3. Problem description and mathematical model

The objective of this section is to describe our extended IRP framework and to model is as a multi-objective mathematical framework for perishable products that allows the service level and environmental considerations in addition to the economic performance to be considered.

The IRP under study in this research can be described as follows. We consider T selling periods where one supplier distributes F perishable products to M retailers. The distribution of products could be performed with three vehicle types of different sizes (small, medium and large) and different energy technologies (diesel and electric).

Most researchers have investigated the IRP by considering the Vender Managed Inventory (VMI) concept where the vendor determines the product quantity and the delivery date based on the minimum and maximum levels defined jointly with the retailer. Such a concept is not easily applicable for perishable products due to the difficulty of defining the responsibility of each member of the supply chain with regard to the perished products. Therefore, as with (Pezeshki et al., 2013), we assume that the supply chain is coordinated by a contract that enables the decision maker to have access to all information about the inventory levels of products for the supplier and retailers, as well as information about the final customer requests. The decision maker is furthermore provided the opportunity to launch a negotiation between the supplier and the retailers regarding the quantity and delivery date. The final decisions must consider both the supplier's and the retailers' constraints to derive the best solution for the whole supply chain. The decision maker's objective is not only to maximize the expected profit of the supply chain but also to maximize the service level considerations and to consider the environmental footprint of the solution.

3.1. Economic criteria: Profit maximization

The economic performance of the IRP is measured by the profit function, which is equal to the sales revenue minus the related inventory and distribution costs, including holding, backorder, recycling, fixed and variable transportation, ordering, and loading and unloading costs.

To better model product perishability, we model the unit holding cost as a nonlinear step function depending on the stock remaining at the end of each period. Therefore, the higher the ending stock is, the higher the unit holding cost will be. The unit holding cost (h_{if}) associated with product f at retailer i depends on the inventory level (I_{ift}) at the end of period t, as modeled in Eq. (1).

$$h_{if} = \begin{cases} h_{if1} & \text{if } 0 \leqslant I_{ift} \leqslant i_1 \\ h_{if2} & \text{if } i_1 \leqslant I_{ift} \leqslant i_2 \\ \vdots & \\ h_{ifm} & \text{if } i_{m-1} \leqslant I_{ift} \end{cases} \quad (h_{if1} \leqslant h_{if2} \leqslant \ldots \leqslant h_{ifm}) \tag{1}$$

This assumption is motivated by the following:

- For perishable products, the unsold items in a given period may need inspections and possibly treatments before their transfer to the next selling period. The cost associated with such a process is directly linked to the quantity needing the inspection. To push the decision maker to limit the quantity of unsold items, our assumption directly impacts such a scenario and indirectly leads to a decrease of the perished products. We show that the proposed holding cost function assumption impacts the trade-off between the economic, service level and environmental criteria.
- The holding cost in the inventory control area is mainly composed of three components: (i) the investment (warehousing) needed to retain stocks; (ii) the financial penalty of not investing in the value of the stock and (iii) the obsolescence risk linked with holding a stock. In the presence of perishable items, the last component is important and can motivate the holding unit cost modeling proposed in Eq. (1). For a higher stock level remaining in a given period, the obsolescence risk is higher for the following period.

It is worth noting that

- Our assumption is a generalization of the classical holding function assumption. Assuming that the unit holding cost is independent of the end of period stock level, the latter assumption is simply a particular case of our assumption.
- Our assumption is equivalent to the case where the holding unit cost is assumed to be fixed but where the retailers propose a discount price for non-fresh products that are transferred from one period to another. In other words, the product non-freshness could either be modeled by higher holding costs or by a lower revenue for items remaining from previous periods. We will propose in Section 5.2, a particular case of Eq. (1) permitting to model the non-freshness cost as a price discount.

3.2. Service level

In addition to the classical economic objective described in the last section, we integrate a service level measure in our IRP. The service level defines a degree of satisfaction offered to the customer. Therefore, under an inventory and distribution context, the service level may include many possible measures among which we have chosen the following:

- The rate of delivery delay; a delay occurs if the vehicle visits a retailer after the allowed time window
- The rate of backorder
- The rate of the backorder frequency

The first service measure is associated with the distribution side of the IRP. Delays are one of the largest problems confronting food distribution in the UK. According to (McKinnon et al., 2003), 29% of the retailers surveyed in the food supply chain in the UK had experienced delivery delays that were shown to directly impact their customer's satisfaction. We model the delay rate by considering the total number of delays that we divide by the total number of visits.

The second and third service level measures are linked to the inventory side of the IRP. For a given product, the backorder rate is modeled by the total quantity backordered divided by the total demand. The frequency backorder rate is modeled by the total number of backorders divided by the total number of selling periods.

In the presence of different measures for the service level, we use three weighting factors (β_d, β_B, β_r), whose sum is equal to one, to address the relative importance of each one when compared with the others. Due to the differences in the nature of the three service levels, we furthermore proceed to a normalization of the three measures.

3.3. Environmental issue

In addition to the economic and service level considerations described in the previous sections, we introduce an environmental criterion in our extended IRP. Currently, there is increasing pressure on companies, stemming from the governmental and non-governmental communities and, more generally, from public opinion, to encourage them to master and decrease their GHG footprint. This reduction is not only to protect the environment but is also economically motivated, because new regulations provide for environmental penalties if this emission is higher than certain thresholds (Mirzapour Al-e-hashem and Rekik, 2013). If products perish, we assume that they need to be collected and recycled. For comprehensiveness, in addition to the GHG emissions resulting from the distribution and the loading/unloading operations, we include those associated with the recycling of perished products.

3.4. Problem assumptions

In addition to the description and assumptions previously presented, we consider that the supply chain under study is subject to the following additional assumptions to make it as close as possible to real IRP business cases:

- There is an urban logistics network in which various types of perishable products are distributed from one supplier to a set of retailers in each period.
- The supplier uses a heterogeneous fleet of vehicles with different capacities, different modes of technology (electric and diesel), different fixed and variable costs, and different GHG emissions levels per kilometer.
- The supplier and retailers have two types of equipment (gas and electric) for loading and unloading, with different costs and GHG emissions.
- The Just-in-time (JIT) and cross-docking philosophies are considered on the supplier side, leading to a scenario with no inventory for the supplier and the assumption that the products delivered to the retailers are fresh. Therefore, we also assume that the products for all orders should be received from the producer and merged together to be delivered to retailers as soon as possible.
- For each retailer, we consider that the inventory capacity and the initial inventory level for each product are known.
- The demand for each retailer is independent of the service level achieved in the IRP.

- Each product has a given shelf life (L_f), and we assume that products cannot be sold after the expiration date and should be recycled with an additional cost. Such a recycling operation will produce GHG emissions, which are included in the calculation of the environmental criterion.
- There is a time window constraint defined by the earliest and the latest possible distribution time for each retailer. It is assumed that a delay occurs if the vehicle arrives after the latest possible time. If the vehicle arrives sooner than the earliest time window, it must wait.
- The unloading time within the retailers' warehouses is considered and is calculated based on the quantity of products delivered. This time is considered in the vehicle route schedule.

The objective of the proposed model is to determine the set of retailers and delivery sequences for each vehicle (by considering type and technology), as well as the quantities of products delivered to each retailer in each period over the planning horizon.

3.5. Notation

The following notations are used in the proposed model. In particular, the uncertain parameters are described with a tilde and are differentiated from the crisp parameters.

Sets	
M	set of retailers, index for retailer $(1,2,\ldots, M)$
M'	set of retailer and supplier, $M\&\{0\}$
f	index for product $(1,2,\ldots, F)$
k	index for vehicle type $(1,2,\ldots, K)$
u	index for vehicle technology $(1,2,\ldots, U)$
d	index for loading equipment type $(1,2,\ldots, D)$
d'	index for unloading equipment type $(1,2,\ldots, D')$
t, t'	index for period $(1,2,\ldots, T)$
Parameters	
I_{if0}	initial inventory level of product f at retailer i
h_{if}	inventory holding cost at retailer i per unit of product f per period
IC_{if}	maximum inventory capacity of retailer i for product f
γ_{if}	backordering cost of one unit of product f at retailer i
O_{if}	ordering cost of product f for retailer i
R_{ft}	revenue of whole system for one unit product f at period t
c_{ij}	distance between retailer i and j
$\tilde{v}_{ku}$	variable transportation cost per unit distance for vehicle type k with technology u
fc_{ku}	fixed transportation cost for vehicle type k with technology u per trip
cap_{ku}	capacity of vehicle type k with technology u
$\tilde{d}_{ift}$	demand of retailer i for product f at period t
L_f	shelf life of product f
sp_{ku}	required time to unload one unit product from vehicle k with technology u
$[ai, bi]$	earliest and latest possible arrival time at retailer i
$\tilde{s}_{ijku}$	speed of vehicle type k with technology u in the route between i and j
LC_d	loading cost of one unit product through equipment type d
$UC_{d'}$	unloading cost of one unit product through equipment type d'
GL_d	GHG emissions produced through equipment type d for loading $1\ kg$ of product
$GU_{d'}$	GHG emissions produced through equipment type d' for unloading $1\ kg$ of product
MA_f	mass of one unit product f
GT_{ku}	GHG emissions produced by vehicle type k with technology u in one unit of distance
GE	average of emissions produced by recycling one unit of expired product
θ_f	recycling cost of one unit of expired product f
wt	maximum working time of tours
G	a large value number
$B = \|M\|,\ A = \|M\|.\|T\|$	
Variables	
x_{ijkut}	1 if retailer j is visited exactly after retailer i by vehicle type k and technology u at period t, otherwise 0

(continued on next page)

I_{ift}	inventory level of product f at retailer i at the end of period t
y_{kut}	quantity of transportation type k with technology u at period t
$q^{dd'}_{ifkutt'}$	quantity of product f received by retailer i through vehicle k with technology u at period t for use at period t', and which is loaded by equipment d and unloaded by equipment d'
B_{ift}	quantity of backordered product f of retailer i at the end of period t
EX_{ift}	quantity of expired products f in inventory of retailer i at the end of period t
n_{it}	1 if delay occurred in visiting retailer i at period t, otherwise 0
r_{it}	1 if backorder occurred in visiting retailer i at period t, otherwise 0
z_{ikut}	1 if retailer i is served at period t by vehicle k with technology u, otherwise 0
T_{ikut}	arrival time at retailer i by vehicle k with technology u at period t
C_{ift}	1 if product f is delivered to retailer i at period t, otherwise 0

3.6. Mathematical formulation

The mathematical model associated with the presented framework is provided in this section. Each equation in this model is detailed below.

$$\begin{aligned} Max \quad f_1 = {} & \left[\sum_{i\in M,f,k,u}\sum_{d,d',t,t'} R_{ft}.[q^{dd'}_{ifkutt'} - EX_{ift}]\right] - \sum_{i\in M}\sum_{f,t} h_{if} I_{ift} - \sum_{i\in M}\sum_{f,t}\gamma_{if} B_{ift} - \sum_{i\in M}\sum_{f,t}\theta_f EX_{ift} - \sum_{i\in M}\sum_{f,t} O_{if} C_{ift} \\ & - \sum_{k,u,t} fc_{ku} z_{0kut} - \sum_{(i,j)\in M'}\sum_{k,u,t}\tilde{v}_{ku} y_{kut} c_{ij} x_{ijkut} - \sum_{i\in M,f,k,u}\sum_{d,d',t,t'} LC_d q^{dd'}_{ifkutt'} - \sum_{i\in M,f,k,u}\sum_{d,d',t,t'} UC_{id'} q^{dd'}_{ifkutt'} \end{aligned} \tag{2}$$

profit
=revenue -
cost

$$Min \quad f_2 = \beta_d\left(\frac{\sum_{i,t} n_{it}}{\sum_{i,k,u,t} z_{ikut}}\right) + \beta_B\left(\sum_{i\in M}\sum_{f,t}\frac{B_{ift}}{\tilde{d}_{ift}}\right) + \beta_r\left(\frac{\sum_{i,t} r_{it}}{\sum_{i,k,u,t} z_{ikut}}\right) \tag{3}$$

service level

$$\begin{aligned} Min \quad f_3 = {} & \sum_{(i,j)\in M'}\sum_{k,u,t} GT_{ku} y_{kut} c_{ij} x_{ijkut} + \sum_{i\in M}\sum_{f,t} GEEX_{ift} + \sum_{i\in M,f,k,u}\sum_{d,d',t,t'} MA_f GL_d q^{dd'}_{ifkutt'} \\ & + \sum_{i\in M,f,k,u}\sum_{d,d',t,t'} MA_f GU_{id'} q^{dd'}_{ifkutt'} \end{aligned} \tag{4}$$

environmental

S.t.

$$I_{ift} - B_{ift} = I_{if(t-1)} - \tilde{d}_{ift} + \sum_{k,u,d,d',t'} q^{dd'}_{ifkutt'} - EX_{ift} - B_{if(t-1)} \quad \forall i\in M, f, t \tag{5}$$

$$B_{ift} r_{it} \geqslant \sum_{k,u,d,d'}\sum_{t>t'} q^{dd'}_{ifkutt'} \quad \forall i\in M, f, t \tag{6}$$

$$I_{ift}\times B_{ift} = 0 \quad \forall i\in M, f, t \tag{7}$$

$$\sum_{k,u,d,d',t'} q^{dd'}_{ifkutt'} \leqslant IC_{if} - I_{if(t-1)} \quad \forall i\in M, f, t \tag{8}$$

$$q^{dd'}_{ifkutt'} \leqslant IC_{if}.z_{ikut} \quad \forall i\in M, f, k, u, d, d', t, t' \tag{9}$$

$$\sum_{k,u,d,d'}\sum_{t'>(t+L_f)} q^{dd'}_{ifkutt'} \leqslant EX_{ift} \quad \forall i\in M, f, t \tag{10}$$

$$\frac{C_{ift}}{G} \leqslant \sum_{k,u,d,d',t'} q^{dd'}_{ifkutt'} \leqslant C_{ift} G \quad \forall i\in M, f, t \tag{11}$$

$$T_{ikut} + \sum_{f,d,d',t'} q^{dd'}_{ifkutt'}.sp_{ku} + \frac{c_{ij}}{\tilde{s}_{ijku}} \leqslant T_{jkut} + G(1 - x_{ijkut}) \quad \forall (i,j)\in M', k, u, t \tag{12}$$

$$a_i \leqslant \sum_{k\in K}\sum_{u\in U} T_{ikut} \leqslant (b_i + (wt - b_i).n_{it}) \quad \forall i \in M, t \tag{13}$$

$$\sum_{i\in M}\sum_{f,d,d',t'} q^{dd'}_{ifkutt'} \leqslant cap_{ku} y_{kut} z_{0kut} \quad \forall k, u, t \tag{14}$$

$$\sum_{j\in M'} x_{ijkut} = \sum_{j\in M'} x_{jikut} = z_{ikut} \quad \forall i \in M', k, u, t \tag{15}$$

$$\sum_{k,u} z_{ikut} \leqslant 1 \quad \forall i \in M, t \tag{16}$$

$$\sum_{k,u,t} z_{ikut} \geqslant 1 \quad \forall i \in M \tag{17}$$

$$\sum_{i\in M} x_{0ikut} = 1 \quad \forall k, u, t \tag{18}$$

$$\sum_{i\in M} x_{i0kut} = 1 \quad \forall k, u, t \tag{19}$$

$$x_{ijkut}, n_{it}, r_{it}, z_{ikut}, C_{ift} \in \{0, 1\} \quad \forall (i,j) \in M, k, u, t, i \neq j \tag{20}$$

$$q^{dd'}_{ifkutt'}, I_{ift}, B_{ift}, EX_{ift}, y_{kut}, T_{ikut} \geqslant 0, Integer \quad \forall i \in M, f, k, u, d, d', t \tag{21}$$

Objective function (2) maximizes the profit, which is equal to the sales revenue of products minus the costs including (in the order of presentation in (2)) the holding cost, the backordering cost, the recycling of expired products costs, the ordering costs, the fixed and variable transportation costs, and the loading and unloading costs. The second objective function (3) optimizes the weighted service level criterion through the minimization of the rate of delays that may occur when visiting the retailers, the rate of the number of backordered products, and the backorder frequency rate. The third objective function (4) minimizes the quantity of GHG emissions resulting from the transportation, the loading/unloading the products and the GHG emissions due to the recycling of expired products.

Constraint (5) balances the inventory level between each two successive periods. Constraint (6) calculates the volume of backordered products. With this constraint, if the quantity of the backordered products is positive, then r_{it} should be equal to one, meaning that the supplier finds a retailer with a backorder situation when visiting him/her. Therefore, the frequency of backorders is calculated by using this equation. Eq. (7) guarantees that the remaining stock (I_{ift}) and the backordered quantity (B_{ift}) cannot be simultaneously positive. Eqs. (8) and (9) guarantee that the retailers' capacity for each product is well respected. Constraint (10) calculates the number of expired products. Constraint (11) checks whether a retailer receives any product. Eq. (12) determines the arrival time at the next retailer, which is calculated as the visiting time of the immediate previous retailer increased by the unloading duration of products and the traveling time between the two retailers visited. Eq. (13) checks the time window constraint and calculates the number of delays. Constraint (14) guarantees that the capacity of each vehicle is well respected. Eqs. (15)(19) serve to determine routes and to eliminate sub-routes. Finally, (20) and (21) place bounds on the variables.

3.7. Linearization

Due to the existence of nonlinear equations in the objective functions and of constraints, four linearization techniques are applied to convert the model to its equivalent linear form.

3.7.1. Linearization of the nonlinear holding cost function

As noted above, the inventory holding cost (h_{if}) provided in Eq. (1) is non-linear. The linearization technique proposed by Sazvar et al. (2014) can be applied. Therefore, binary variables, p_{iftm}, and non-negative variables, I_{iftm}, are defined, and the following constraints (22)(24) are added:

$$I_{ift} = \sum_{m} I_{iftm} \quad \forall i \in M, f, t \tag{22}$$

m^* s.t. $\bar{i}_{m^*} \le I_{ift} \le i_{m^*+1}$

$$i_m . p_{iftm} \leqslant I_{iftm} \leqslant i_{m+1} . p_{iftm} \quad \forall i \in M, f, t \tag{23}$$

$\Rightarrow P_{iftm^*} = 1$

$$\sum_{m} p_{iftm} = 1 \quad \forall i \in M, f, t \tag{24}$$

3.7.2. Linearization of the nonlinear variable resulting from the division of two variables

The division of two variables, $\left(\frac{\sum_{i,t} n_{it}}{\sum_{i,k,u,t} z_{ikut}} \& \frac{\sum_{i,t} r_{it}}{\sum_{i,k,u,t} z_{ikut}}\right)$, as written in the second objective function (3), the results in nonlinearity. Therefore, the relaxation technique proposed by McCormick (1976) could be applied. The technique can be explained briefly as follows:

$$If k = x_1 x_2 \text{ and } x_1 \in [x_1^L, x_1^U], x_2 \in [x_2^L, x_2^U] \tag{25}$$

The four equations can then be added as new constraints:

$$k \geqslant x_1^L x_2 + x_2^L x_1 - x_1^L x_2^L \tag{26}$$

$$k \geqslant x_1^U x_2 + x_2^U x_1 - x_1^U x_2^U \tag{27}$$

$$k \leqslant x_1^L x_2 + x_2^U x_1 - x_1^L x_2^U \tag{28}$$

$$k \leqslant x_1^U x_2 + x_2^L x_1 - x_1^U x_2^L \tag{29}$$

To apply this technique in our case, we define two non-negative variables W and V. The lower and upper bounds are then defined as follows:

$$W = \sum_{i,t} n_{it} \cdot \frac{1}{\sum_{i,k,u,t} z_{ikut}} \quad V = \sum_{i,t} r_{it} \cdot \frac{1}{\sum_{i,k,u,t} z_{ikut}}$$

$$\sum_{i,t} n_{it} \in [0, A] \quad \sum_{i,t} r_{it} \in [0, A] \quad \frac{1}{\sum_{i,k,u,t} z_{ikut}} \in \left[\frac{1}{A}, \frac{1}{B}\right]$$

The reformulation of the second objective function (3) and the following new constraints are added to convert it into a linear form:

$$Min \quad f_2 = \beta_d(W) + \beta_B\left(\sum_{i \in M} \sum_{f,t} \frac{B_{ift}}{\tilde{d}_{ift}}\right) + \beta_r(V) \tag{30}$$

$$W \geqslant \left[\sum_{it} n_{it}/A\right] \tag{31}$$

$$W \geqslant \left[A/\sum_{i,k,u,t} z_{ikut}\right] + \left[\sum_{it} n_{it}/B\right] - [A/B] \tag{32}$$

$$W \leqslant \sum_{i,t} n_{it}/B \tag{33}$$

$$W \leqslant \left[A/\sum_{i,k,u,t} z_{ikut}\right] + \left[\sum_{it} n_{it}/A\right] - 1 \tag{34}$$

$$V \geqslant \left[\sum_{it} r_{it}/A\right] \tag{35}$$

$$V \geqslant \left[A/\sum_{i,k,u,t} z_{ikut}\right] + \left[\sum_{it} r_{it}/B\right] - [A/B] \tag{36}$$

$$V \leqslant \sum_{i,t} r_{it}/B \tag{37}$$

$$V \leqslant \left[A/\sum_{i,k,u,t} z_{ikut}\right] + \left[\sum_{it} r_{it}/A\right] - 1 \tag{38}$$

This equation remains nonlinear $\left[A/\sum_{i,k,u,t} z_{ikut}\right]$; however, this should be linearized. Therefore, we replace this equation with a sum of binary variables (as illustrated in Eq. (39)), assuming that only one of the binary variables is non-zero (Eq. (40)). We can therefore rewrite the nonlinear equation as proposed in constraint (41).

$$\sum_{i,k,u,t} z_{ikut} = \sum_{i,k,u,t} \sum_{l=B}^{A} l.z_{ikutl} \tag{39}$$

$$\sum_{l=B}^{A} z_{ikutl} = 1 \quad \forall i \in M, k, u, t \tag{40}$$

$$\frac{A}{\sum_{i,k,u,t} z_{ikut}} = \sum_{i,k,u,t} \sum_{l=B}^{A} A.\frac{z_{ikut}}{l} \tag{41}$$

3.7.3. Linearization of the nonlinear variable resulting from the multiplication of a binary with an integer variable

The multiplication of integer and binary variables, as defined in constraints (6) and (14), the results in non-linearity. The same occurs in the first and third objective functions. The nonlinear equations could be converted into linear equations by omitting the binary variable and considering the new Eqs. (42)(46).

$$B_{ift} \geqslant \sum_{k,u,d,d'} \sum_{t>t'} q_{ifkutt'}^{dd'} \quad \forall i \in M, f, t \tag{42}$$

$$\frac{r_{it}}{G} \leqslant \sum_{f \in F} B_{ift} \leqslant G.r_{it} \quad \forall i \in M, t \tag{43}$$

$$\sum_{i \in M} \sum_{f,d,d',t'} q_{ifkutt'}^{dd'} \leqslant cap_{ku} y_{kut} \quad \forall k, u, t \tag{44}$$

$$\frac{z_{0kut}}{G} \leqslant y_{kut} \leqslant z_{0kut} G \quad \forall k, u, t \tag{45}$$

$$\frac{x_{ijkut}}{G} \leqslant y_{kut} \leqslant x_{ijkut} G \quad \forall i, k, u, t \tag{46}$$

3.7.4. Linearization of the nonlinear variable resulting from the multiplication of two integer variables

Due to the multiplication of the two integer variables (I_{ift}) and (B_{ift}) in constraint (7), a new binary variable F_{ift} and two new constraints (48) and (49) replace the previous one as follows:

$$F_{ift} = \begin{cases} 1 & I_{ift} = 0 \\ 0 & B_{ift} = 0 \end{cases} \quad \forall i, f, t \tag{47}$$

$$B_{ift} \leqslant G \times F_{ift} \quad \forall i, f, t \tag{48}$$

$$I_{ift} \leqslant G \times (1 - F_{ift}) \quad \forall i, f, t \tag{49}$$

4. Resolution approach

To solve our extended IRP model, the following two steps are applied:

1. First, we proceed with the conversion of the original model into an equivalent auxiliary crisp model by applying fuzzy possibilistic approach.
2. Second, due to the NP-hardness of the IRP (Coelho et al., 2012; Shukla et al., 2013), we apply the NSGA-II proposed by Deb et al. (2002) to solve the equivalent auxiliary crisp model and to derive the optimal Pareto.

We notice that the choice of the NSGA-II method is motivated by the fact that it has been proved as an efficient meta-heuristic for IRPs (Amorim and Almada-Lobo, 2014). In addition to efficiency, the procedure of this algorithm does not allow a previously found Pareto optimal solution to be deleted. In addition, the run time of the algorithm is generally acceptable.

4.1. The equivalent auxiliary crisp model

The IRP literature (Abdul Rahim et al., 2014; Bertazzi et al., 2013; Chen and Lin, 2009) shows that IRPs encounter a high degree of uncertainty in the retailers' demand. Moreover, variations in the energy price, the weather conditions, and the traffic status have a significant impact on transportation costs (Cui and Sheng, 2012) and lead to a high degree of uncertainty of these costs even in the short term. For applicability, the IRP should be designed in a manner that is able to consider the uncertainty of certain parameters; otherwise its solution leads to a high risk for the enterprise (Abdul Rahim et al., 2014; Chen and Lin, 2009).

Motivated by the above explanation, we assume that the demand, the variable transportation cost and the vehicle speed are subject to uncertainty and are modeled with fuzzy distributions. First, we define for each uncertain variable s the pattern set of a triangular fuzzy number (s^p, s^m, s^o) where s^p defines the most pessimistic value, s^m defines the most likely value, and s^o defines the optimistic value of s. Then, we use the principle of the fuzzy possibilistic approach by Niakan and Rahimi (2015), to transform the extended IRP model to the equivalent multi-objective crisp model. Such a conversion leads to the following formulation:

$$\begin{aligned} Max \quad f_1 = & \left[\sum_{i\in M, f, k, u, d, d', t, t'} R_{ft}.[q_{ifkutt'}^{dd'} - EX_{ift}]\right] - \sum_{i\in M}\sum_{f,t,m} h_{ifm} I_{iftm} - \sum_{i\in M}\sum_{f,t}\gamma_{if}B_{ift} - \sum_{i\in M}\sum_{f,t}\theta_f EX_{ift} - \sum_{i\in M}\sum_{f,t} O_{if}C_{ift} \\ & -\sum_{k,u,t} fc_{ku} z_{0kut} - \sum_{(i,j)\in M'}\sum_{k,u,t}\left(\frac{v_{ku}^p + 2v_{ku}^m + v_{ku}^o}{4}\right) y_{kut} c_{ij} - \sum_{i\in M}\sum_{f,k,u,d,d',t,t'} LC_d q_{ifkutt'}^{dd'} - \sum_{i\in M}\sum_{f,k,u,d,d',t,t'} UC_{id'} q_{ifkutt'}^{dd'} \end{aligned} \tag{50}$$

$$Min \quad f_2 = \beta_d(W) + \beta_B\left(\sum_{i\in M}\sum_{f,t} 4.\frac{B_{ift}}{d_{ift}^p + 2d_{ift}^m + d_{ift}^o}\right) + \beta_r(V) \tag{51}$$

$$\begin{aligned} Min \quad f_3 = & \sum_{(i,j)\in M'}\sum_{k,u,t} GT_{ku} y_{kut} c_{ij} + \sum_{i\in M}\sum_{f,t} GEEX_{ift} + \sum_{i\in M}\sum_{f,k,u,d,d',t,t'} MA_f GL_d q_{ifkutt'}^{dd'} \\ & + \sum_{i\in M}\sum_{f,k,u,d,d',t,t'} MA_f GU_{id'} q_{ifkutt'}^{dd'} \end{aligned} \tag{52}$$

S.t.

$$\begin{aligned} I_{ift} - B_{ift} \leqslant I_{if(t-1)} + & \sum_{k,u,d,d',t'} q_{ifkutt'}^{dd'} - \left[\left(\frac{\alpha}{2}\right) \times \frac{d_{ift}^m + d_{ift}^o}{2} + \left(1 - \frac{\alpha}{2}\right) \times \frac{d_{ift}^p + d_{ift}^m}{2}\right] \quad \forall i \in M, f, t \\ & -EX_{ift} - B_{if(t-1)} \end{aligned} \tag{53}$$

$$\begin{aligned} I_{ift} - B_{ift} \geqslant I_{if(t-1)} + & \sum_{k,u,d,d',t'} q_{ifkutt'}^{dd'} - \left[\left(1 - \frac{\alpha}{2}\right) \times \frac{d_{ift}^m + d_{ift}^o}{2} + \left(\frac{\alpha}{2}\right) \times \frac{d_{ift}^p + d_{ift}^m}{2}\right] \quad \forall i \in M, f, t \\ & -EX_{ift} - B_{if(t-1)} \end{aligned} \tag{54}$$

$$B_{ift} \geqslant \sum_{k,u,d,d'}\sum_{t>t'} q_{ifkutt'}^{dd'} \quad \forall i \in M, f, t \tag{55}$$

$$\frac{r_{it}}{G} \leqslant \sum_{f\in F} B_{ift} \leqslant G.r_{it} \quad \forall i \in M, t \tag{56}$$

$$B_{ift} \leqslant G \times F_{ift} \quad \forall i \in M, f, t \tag{57}$$

$$I_{ift} \leqslant G \times (1 - F_{ift}) \quad \forall i \in M, f, t \tag{58}$$

$$\sum_{k,u,d,d',t'} q_{ifkutt'}^{dd'} \leqslant IC_{if} - I_{if(t-1)} \quad \forall i \in M, f, t \tag{59}$$

$$q_{ifkutt'}^{dd'} \leqslant IC_{if}.z_{ikut} \quad \forall i \in M, f, k, u, d, d', t, t' \tag{60}$$

$$\sum_{k,u,d,d'}\sum_{t'>(t+L_f)} q_{ifkutt'}^{dd'} \leqslant EX_{ift} \quad \forall i \in M, f, t \tag{61}$$

$$\frac{C_{ift}}{G} \leqslant \sum_{k,u,d,d',t'} q_{ifkutt'}^{dd'} \leqslant C_{ift}G \quad \forall i \in M, f, k, u, t \tag{62}$$

$$\begin{aligned} T_{jkut} + G(1 - x_{ijkut}) \geqslant T_{ikut} + \sum_{f,d,d',t'} q_{ifkutt'}^{dd'}.sp_{ku} \\ + \frac{c_{ij}}{\left[(\alpha)\times\left(\frac{s_{ijku}^{m}+s_{ijku}^{o}}{2}\right)+(1-\alpha)\times\left(\frac{s_{ijku}^{p}+s_{ijku}^{m}}{2}\right)\right]} \quad \forall (i,j) \in M', k, u, t \end{aligned} \tag{63}$$

$$a_i \leqslant \sum_{k\in K}\sum_{u\in U} T_{ikut} \leqslant (b_i + (wt - b_i).n_{it}) \quad \forall i \in M, t \tag{64}$$

$$\sum_{i\in M}\sum_{f,d,d',t'} q_{ifkutt'}^{dd'} \leqslant cap_{ku}y_{kut} \quad \forall k, u, t \tag{65}$$

$$\frac{z_{0kut}}{G} \leqslant y_{kut} \leqslant z_{0kut}G \quad \forall k, u, t \tag{66}$$

$$\frac{x_{ijkut}}{G} \leqslant y_{kut} \leqslant x_{ijkut}G \quad \forall i, k, u, t \tag{67}$$

$$\sum_{j\in M'} x_{ijkut} = \sum_{j\in M'} x_{jikut} = z_{ikut} \quad \forall i \in M', k, u, t \tag{68}$$

$$\sum_{k,u} z_{ikut} \leqslant 1 \quad \forall i \in M, t \tag{69}$$

$$\sum_{k,u,t} z_{ikut} \geqslant 1 \quad \forall i \in M \tag{70}$$

$$\sum_{i\in M} x_{0ikut} = 1 \quad \forall k, u, t \tag{71}$$

$$\sum_{i\in M} x_{i0kut} = 1 \quad \forall k, u, t \tag{72}$$

$$I_{iftm} = \sum_{m} I_{iftm} \quad \forall i \in M, f, t \tag{73}$$

$$i_m.p_{iftm} \leqslant I_{iftm} \leqslant i_{m+1}.p_{iftm} \quad \forall i \in M, f, t \tag{74}$$

$$\sum_{m} p_{iftm} = 1 \quad \forall i \in M, f, t \tag{75}$$

$$W \geqslant \left[\sum_{it} n_{it}/A\right] \tag{76}$$

$$W \geqslant \left[\sum_{i,k,u,t}\sum_{l=B}^{A} A.z_{ikut}/l\right] + \left[\sum_{it} n_{it}/B\right] - [A/B] \tag{77}$$

$$W \leqslant \sum_{i,t} n_{it}/B \tag{78}$$

$$W \leqslant \left[\sum_{i,k,u,t}\sum_{l=B}^{A} A.z_{ikut}/l\right] + \left[\sum_{it} n_{it}/A\right] - 1 \tag{79}$$

$$V \geqslant \left[\sum_{it} r_{it}/A\right] \tag{80}$$

$$V \geqslant \left[\sum_{i,k,u,t} \sum_{l=B}^{A} A.z_{ikut}/l \right] + \left[\sum_{it} r_{it}/B \right] - [A/B] \tag{81}$$

$$V \leqslant \sum_{i,t} r_{it}/B \tag{82}$$

$$V \leqslant \left[\sum_{i,k,u,t} \sum_{l=B}^{A} A.z_{ikut}/l \right] + \left[\sum_{it} r_{it}/A \right] - 1 \tag{83}$$

$$\sum_{i,k,u,t} z_{ikut} = \sum_{i,k,u,t} \sum_{l=B}^{A} l.z_{ikutl} \tag{84}$$

$$\sum_{l=B}^{A} z_{ikutl} = 1 \quad \forall i \in M, k, u, t \tag{85}$$

$$x_{ijkut}, n_{it}, r_{it}, z_{ikut}, C_{ift}, F_{ift}, p_{iftm}, z_{ikutl} \in \{0, 1\} \quad \forall (i,j) \in M, k, u, t, i \neq j \tag{86}$$

$$q_{ifkutt'}^{dd'}, I_{ift}, B_{ift}, EX_{ift}, y_{kut}, T_{ikut}, W, V, I_{iftm} \geqslant 0, Integer \quad \forall i \in M, f, k, u, d, d', t \tag{87}$$

4.2. Non-dominated sorting genetic algorithm II (NSGA-II)

In a single objective optimization, the objective is to find the best global minimum or maximum solution, whereas in the real world, managers require decisions based on various and occasionally conflicting objective functions. In such a case, there is not one feasible solution, while all the objective functions are simultaneously optimal. Instead of one optimal solution, there is a set of optimal solutions that proposes the minimum objective conflict. Such a set of solutions is called the optimal Pareto. There are various methods to address multi-objective problems. Some of these methods convert the multi-objective into a single objective model by using methods such as the objective weighting, the distance functions and the Min-Max formulation (Srinivas and Deb, 1994). With such methods, the results will be obtained in a single point solution while managers need to select a solution among the various alternatives during the decision process by making compromises. The other methods attempt to find a set of optimal solutions (optimal Pareto) that cannot be overridden by other solutions.

Deb et al. (2002) propose a meta-heuristic, referred to as the Non-dominated Sorting Genetic Algorithm II (NSGA-II), to solve multi-objective problems. This algorithm begins with an initial population that is randomly generated; in each iteration a new set of solutions is created from existing ones by applying specific crossover and mutation operators. In the crossover operator, two parents are selected, and then two new children are generated and obtained by integrating the parents' characteristics. In the mutation operator, one member is chosen and is changed in certain respects. Thereafter, the new solutions and current solutions are merged together in each iteration to make a new population.

The members of the new population are compared with each other by considering the rank and the crowding distance. To rank the members of a population, the concept of domination is used. Members of the population that are not dominated by other members belong to the front with a rank equal to 1. For instance, members that are dominated only by the individuals in the first front are assigned to the second front. Consequently, members of a same rank cannot dominate each other, leading to the conclusion that neither is better in all objective functions. In addition, the crowding distance determines the diversity in the population where a higher one is preferred. The distance measures the Euclidian distance between each member in a given front and its neighbors in the same front. The high value of this measure shows the wider diversity in the population. The value of the crowding distance for each member can be calculated using Eq. (88) where Z is the objective function, I_j is the value of the crowding distance for the jth outcome, $f_{j,n}$ presents the value of the jth outcome, the nth objective function, and finally, $f_{max,n}$ and $f_{min,n}$ show the value of the maximum and minimum of the nth objective function, respectively. Furthermore, the value of the crowding distance for boundary members (members with maximum and minimum values for the objective function) is infinite. This procedure continues until the stopping criterion is achieved (Niakan et al., 2015).

$$I_j = \sum_{n=1}^{Z} \frac{f_{j+1,n} - f_{j-1,n}}{f_{\max,n} - f_{\min}^{nn}} \tag{88}$$

5. Experimental results

In this section, we first show the applicability of our extended IRP framework from a numerical perspective. We then provide certain managerial insights resulting from a numerical analysis. Therefore, fifteen different instance problems (Table 2) are considered with different problem sizes (number of products and retailers), configuration types (vehicle types and technology) and horizon length (number of selling periods).

The fuzzy parameters need the definition of three values (most likely, pessimistic and optimistic). The most likely value, s^m, is first generated by using a uniform distribution (the uniform distributions illustrated in Table 3). Then, the method introduced by Lai and Hwang (1992) is used to generate the remaining optimistic and pessimistic values. Therefore, two random variables d_1 and d_2 are uniformly generated $(d_1, d_2) \sim Uniform\ (0.2.0.8)$, then the optimistic value s^o and the pessimistic one s^p are derived as follows:

$$s^o = (1 + d_1)s^m$$
$$s^p = (1 - d_2)s^m$$

Furthermore, the information associated with the fleet of vehicles (capacity, fixed cost, variable cost, speed in routes, unloading speed and GHG emissions) and the loading/unloading equipment (cost and GHG emissions) are provided in Tables 4 and 5, respectively. It is noteworthy that the GHG emissions of each vehicle is calculated according to the Greenhouse Gas (GHG) Protocol developed by the World Resources Institute and the World Business Council on Sustainable Development (WRI;WBCSD, 2001). The emissions for electricity produced from a renewable energy source, such as wind or solar, are set equal to zero.

Our IRP framework is coded using MATLAB 2014 on a personal computer Core i7, 2.27 GHZ with 12.0 GB RAM.

5.1. Parameter setting

It is obvious that selecting the value of NSGA-II parameters has a considerable impact on the performance of the resolution algorithm. The Taguchi method is applied to tune these parameters. The Taguchi method proposes two main categories of factors: controllable, and noise. The noise factors are out of control and their elimination is often impossible. The method attempts to find the optimal level of controllable factors by minimizing the effect of noise factors (Chatsirirungruang, 2009).

To use the Taguchi method in our case, the Spacing Metric (SM) is considered to evaluate the optimal results. The value of SM is calculated using Eq. (89) where d_i measures the Euclidian distance between consecutive solutions, $\bar{d}$ is the average of all d_i, and n denotes the number of members in the final solutions. It is noteworthy that a lower value of SM corresponds to a better performance of the algorithm.

Table 2
Size of instance problems.

Problem No.	Retailer	Product	Vehicle type	Vehicle technology	Loading/unloading equipment type	Period
1	2	2	3	2	2	2
2	3	1	3	2	2	3
3	5	2	3	2	2	2
4	10	7	3	2	2	3
5	13	6	3	2	2	4
6	15	4	3	2	2	3
7	15	5	3	2	2	4
8	16	12	3	2	2	7
9	18	8	3	2	2	5
10	19	7	3	2	2	5
11	20	10	3	2	2	6
12	22	9	3	2	2	5
13	22	15	3	2	2	7
14	25	12	3	2	2	7
15	25	15	3	2	2	8

Table 3
Random value of parameters.

Parameter	Uniform distribution to generate the Most Likely value	Parameter	Uniform distribution to generate the Most Likely value
I_{if0}	~U[0,3]	$\tilde{d}_{ift}$	~U[1,6]
IC_{if}	~U[1,2]× max{$\tilde{d}_{ift}$}	L_f (Period)	~U[0.05, 0.25]×|T|[b]
γ_{if} (€)	~U[10,20]	MA_f (kg)	~U[50,300]
O_{if} (€)	~U[40,60]	a_i	0
θ_f (€)	~U[5,30]	b_i (Hour)	~U[0.5,5]
R_{ft} (€)	~U[100,200]	GE (kg/unit)	3.7
c_{ij}[a] (km)	~U[5,35]		

[a] The distance between two points is calculated by "minimum length path".
[b] $|T|$ = Number of periods in studied horizon.

$$SM = \frac{\sum_{i=1}^{n-1}|\bar{d} - d_i|}{(n-1)\bar{d}} \quad (89)$$

In this paper, four critical parameters of the proposed resolution algorithm (*Npop*: number of population; *MaxIt*: maximum iteration; *CrR*: Crossover Rate; and *MuR*: Mutation Rate) are considered, and three levels for each factor are determined (Table 6). Additionally, Table 7 presents the combination of experiments and the answers obtained to tune the parameters. According to Fig. 1, the best levels of the parameters are selected as follows: second level of *Npop* (100), second level of *MaxIt* (120), third level of *CrR* (0.7), and first level of *MuR* (0.2). It is noteworthy that the Taguchi method is applied in the Minitab software.

5.2. Computational results

Different algorithms and techniques exist to check the feasibility of a multi-objective optimization problem such as the objective weighting, the distance functions and the Min-Max technique (Sazvar et al., 2014). To validate the feasibility of our proposed model, we use the weighted sum technique as a compromise programming method.

Table 4
Parameters of vehicle.

Vehicle type	Vehicle technology	Value of vehicle parameters					
		cap_{ku}	fc_{ku} (€)	$\tilde{v}_{ku}$ (€)	sp_{ku} (hour/unit)	$\tilde{s}_{ijku}$ (km/h)	GHG (kg/km)
Small	*Diesel*	75	30	~U[10,15]	0.03	~U[30,34]	0.374
	Electric		60	~U[15,20]	0.03	~U[35,38]	0
Medium	*Diesel*	150	80	~U[20,25]	0.03	~U[30,34]	0.603
	Electric		160	~U[30,35]	0.03	~U[35,38]	0
Large	*Diesel*	250	150	~U[30,35]	0.03	~U[30,34]	0.870
	Electric		300	~U[50,55]	0.03	~U[35,38]	0

Table 5
Parameters of loading/unloading equipment.

Equipment	Equipment type	Value of loading/unloading equipment parameters	
		LC_d/UC'_d (€)	GHG (kg/1 kg)
Loading and Unloading	Electric	2.5	0
	Gas	2	0.003

Table 6
Parameter setting.

Factors	Proposed level		
	1	2	3
Npop	80	100	120
MaxIt	100	120	150
CrR	0.5	0.6	0.7
MuR	0.2	0.3	0.4

Table 7
Parameter configuration and values obtained in the Taguchi design experiments.

Experiments	Coded levels				Uncoded levels				Response
	Npop	MaxIt	CrR	MuR	Npop	MaxIt	CrR	MuR	
1	1	1	1	1	80	100	0.5	0.2	0.981
2	1	2	2	2	80	120	0.6	0.3	0.857
3	1	3	3	3	80	150	0.7	0.4	0.823
4	2	1	2	3	100	100	0.6	0.4	0.932
5	2	2	3	1	100	120	0.7	0.2	0.539
6	2	3	1	2	100	150	0.5	0.3	0.838
7	3	1	3	2	120	100	0.7	0.3	0.798
8	3	2	1	3	120	120	0.5	0.4	1.098
9	3	3	2	1	120	150	0.6	0.2	0.786

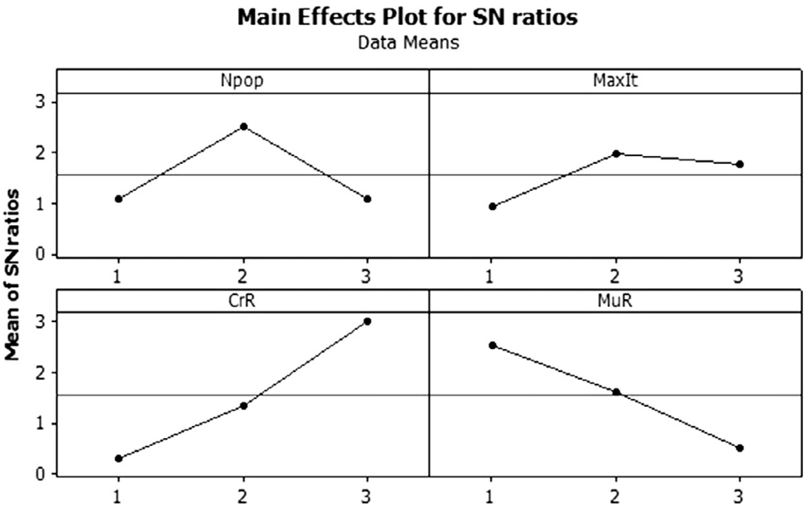


Fig. 1. Signal to noise ratio for each level of the parameters.

Being the most widely used technique, we use the weighted sum technique to check the feasibility of our optimization. We are aware of the main disadvantage of such a technique (optimal solutions in non-convex regions are not detected as reported in (Kim and de Weck, 2006)), but its use is only for feasibility checking and not for deriving optimal solutions.

With this technique, the problem is solved by considering each objective function separately in both the maximization and the minimization for finding extreme points of each objective function. Finally, a new single objective that strives to minimize the weighted sum over the normalized and non-dimensional objective function is solved. To solve such a problem, we use the "GAMS v22.2" optimization software using solver CPLEX v10.1.

To proof the applicability of our IRP, certain experiments are presented in the remainder of this section. The crisp model is solved by the NSGA-II algorithm, which is tuned for this problem. Consequently, a set of solutions referred to as the Pareto frontier is obtained. The Pareto set of this problem contains three important points or solutions with an optimum level for each objective function. We denote as solution A the optimum value associated with the profit objective (Z1), solution B as the optimum value of the service level (Z2), and solution C as the optimum value of the GHG emissions (Z3).

In the following, all the problem instances previously presented are solved; the uncertainty level α is set equal to 0.6, and the best solutions are reported in Table 8. It should be noted that, due to the normalization of the second objective function, the results of the latter are between zero and one.

In the following, we propose to detail the results associated with problems 3, 7, 11 and 15, which are representative of different sizes of the problem. The details for each type of solution is proposed in Table 9. The Pareto frontier of each problem is illustrated in Fig. 2. Please notice that we illustrate the service level in Fig. 2 as (1-Z2) since Z2 measures delays and backorders.

Table 8
The best value of each objective.

		The best value of each objective function		
Problem No.	Size of problem (i × f × t)	Profit	Service level	Green
1	2 × 2 × 2	829.00	1.00	4.01
2	3 × 1 × 3	1204.00	1.00	15.03
3	5 × 2 × 2	1618.50	1.00	7.51
4	10 × 7 × 3	5209.00	1.00	98.27
5	13 × 6 × 4	7341.00	1.00	201.42
6	15 × 4 × 3	8903.00	1.00	328.82
7	15 × 5 × 4	9346.00	1.00	338.40
8	16 × 12 × 7	17587.00	1.00	1279.39
9	18 × 8 × 5	15929.00	1.00	1005.98
10	19 × 7 × 5	16846.00	1.00	1205.05
11	20 × 10 × 6	32162.00	1.00	1980.93
12	22 × 9 × 5	41544.00	1.00	2079.92
13	22 × 15 × 7	77031.00	1.00	2890.11
14	25 × 12 × 7	94302.00	1.00	3307.32
15	25 × 15 × 8	103167.00	1.00	4530.53

We notice that providing the obtained optimal Pareto frontier to practitioners is a better means to increase their capability to select a solution among the Pareto set by considering their own managerial judgment on the preference and priority to accord for each objective function.

The analysis of the two best solutions A (Z1) and B (Z2) associated with problem No.11 shows that the manager can achieve the highest service level but the impact on the economic performance would be a profit decrease of 53%. Such a result permits the measurement of the impact of exogenously targeting a given service level without coordinating with the logistics component, i.e., the inventory and transportation costs. Indeed, target service levels are, in general, a corporate strategy or a marketing decision; when they are exogenously chosen, the impact on the logistics cost could be important.

Our framework enables practitioners to link the profit with the achieved service level and to help them to judgmentally select the best tradeoff. Such an analysis is common in Inventory Management but was never developed with IRPs to the best of our knowledge. For instance, we analyze the Pareto frontier of problem No. 11 obtained to deduce the set of solutions where a small variation of the profit has a significant impact on the service level. Table 10 illustrates the profit loss as a function of the service level improvement for problem No. 11. According to table 10, in the set of solutions 7, 8, 15, 16, 24 and 25, the service level can be improved by approximately 25–27% with less than a 7% decrease in the profit. This set of solutions is valuable for companies that are under pressure in a competitive marketplace where the achieved service level is an important customer satisfaction criterion. We refer to this set of solutions as the "solutions with a high priority".

In contrast to this set of solutions, there is another set where a small improvement of the service level needs a significant impact on the profit. This set of solutions needs to be avoided. According to Table 10, in solutions 10, 11, 13 and 14 the service level can be improved by less than 3%, while the profit needs to be reduced by approximately 15–20%. We refer to these solutions as the "solutions with low priority". Fig. 3 shows the optimal Pareto frontier for problem No. 11, considering the high and low priority of solutions.

Please notice that the above analysis assumes that the demand distribution is independent of the achieved service level. In the long-term, it is obvious that improving the service level may also increase the demand and improve the revenue component of the profit function. The above solution could also be used to analyze the impact of the service level improvement or decease the green footprint of the IRP solution.

As previously noted, three important solutions, corresponding to the extreme solutions optimizing each objective function, could be considered by the decision maker. In addition to these three solutions, one could consider a fourth one referred to as the compromise solution. Therefore, we need to define the ideal solution, which is at the interface between the three extreme solutions and that provides the best values for Z1, Z2 and Z3 (Fig. 4). The compromise solution may be interesting for managers who attempt to find the solution, which is closer to the ideal point. The latter cannot be achieved in practice (Marler and Arora, 2004).

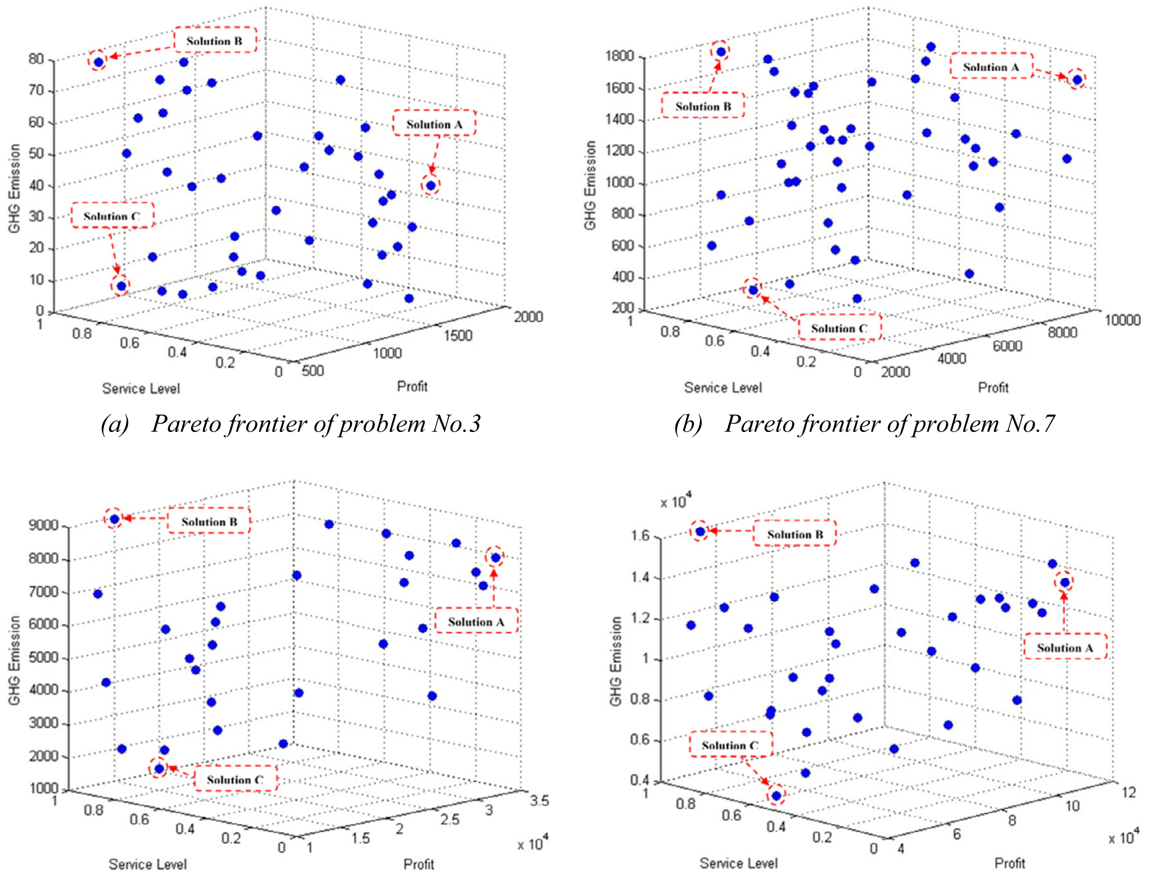
To find the compromise solution, we first need to normalize the objective functions and to convert their values to a number between 0 and 1. Such a normalization is needed because the objective functions are expressed with different units. Then, as a second step, the Euclidean Distance (ED) between each solution and the ideal point is calculated using Eq. (90). Finally, the solution leading to the lower Euclidean Distance from the ideal point is selected as the compromise solution.

$$ED_i = \sqrt{\left(f_1^i - f_1^{ideal}\right)^2 + \left(f_2^i - f_2^{ideal}\right)^2 + \left(f_3^i - f_3^{ideal}\right)^2} \tag{90}$$

Fig. 4 illustrates the compromise solution in the Pareto frontier associated with problem No. 11. As reported in Table 11, solution number 17 is the compromise. This solution shows a profit of 16061.00, a service level of 0.71, and an environmental criterion of 5092.12. This solution corresponds to the closest solution to the ideal point and could be chosen by the manager. The comparison between the compromise and the best solutions shows that the values of profit, service level and GHG emissions are decreased by 50%, 29% and 61%, respectively, when compared with the best values.

Table 9
The best value of each objective in final Pareto.

Problem No.	OF	The best solutions Solution A	Solution B	Solution C	CPU time (s)
3	Z_1	**1618.50**	815.00	758.00	28.54
	Z_2	0.09	**1.00**	0.87	
	Z_3	41.53	76.03	**7.51**	
7	Z_1	**9346.00**	4727.00	3814.00	309.31
	Z_2	0.00	**1.00**	0.75	
	Z_3	1687.50	1730.40	**338.40**	
11	Z_1	**32162.00**	15107.00	12114.00	947.02
	Z_2	0.00	**1.00**	0.69	
	Z_3	8244.46	8987.22	**1980.93**	
15	Z_1	**103167.00**	54325.00	43406.00	1962.73
	Z_2	0.00	**1.00**	0.53	
	Z_3	14377.22	15852.25	**4530.53**	



(a) Pareto frontier of problem No.3 *(b) Pareto frontier of problem No.7*

(c) Pareto frontier of problem No.11 *(d) Pareto frontier of problem No.15*

Fig. 2. Optimum Pareto solutions of four problems instances.

Table 10
Evolution of the Profit Loss with the service level improvement (Problem No.11).

No. solution	%lost profit	%service level improvement	No. solution	%lost profit	%service level improvement
1 (Solution A)	10.94	11.00	15	6.54	25.49
2			16		
3			17	17.66	7.82
4			18		
5			19 (Solution B)		
6			20		
7	1.97	26.54	21		
8			22		
9	6.82	4.21	23		
10	15.74	3.11	24	2.61	26.36
11			25		
12	2.04	1.94	26	5.01	4.61
13	20.02	2.62	27		
14			28 (Solution C)		

As noted in Section 3.1, the step wise holding cost is used to model the products' non-freshness if they are transferred from one period to another; this is equivalent to a situation with a fixed holding cost where non-fresh products are offered at a discount selling price. In the following analysis, we investigate the impact of the product non-freshness on the optimal solution. Therefore, we consider a particular case of the holding function presented in Eq. (1). The unit holding cost for each product is assumed to be equal to the fixed component, h_{if}^{fix}, plus a second component that we hereafter call the "variable holding cost" written as a percentage, λ_{if}, of the unit revenue:

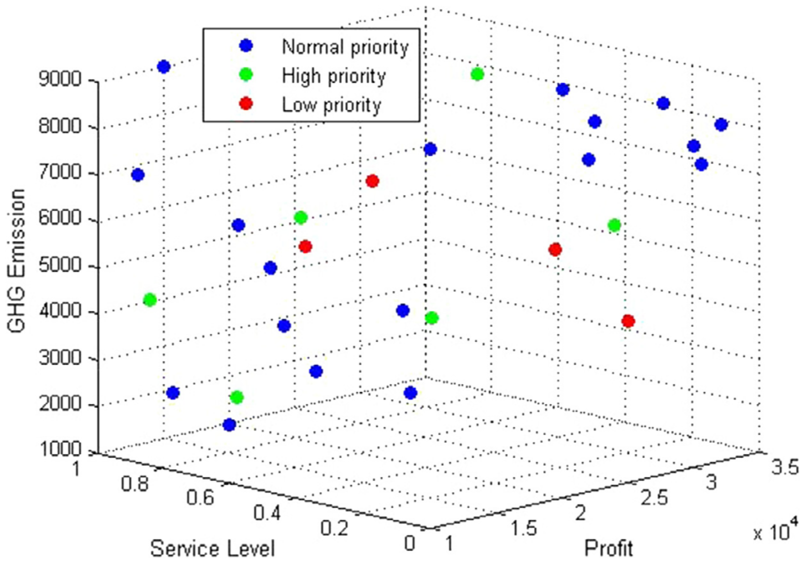


Fig. 3. Classification of solutions (Problem No.11).

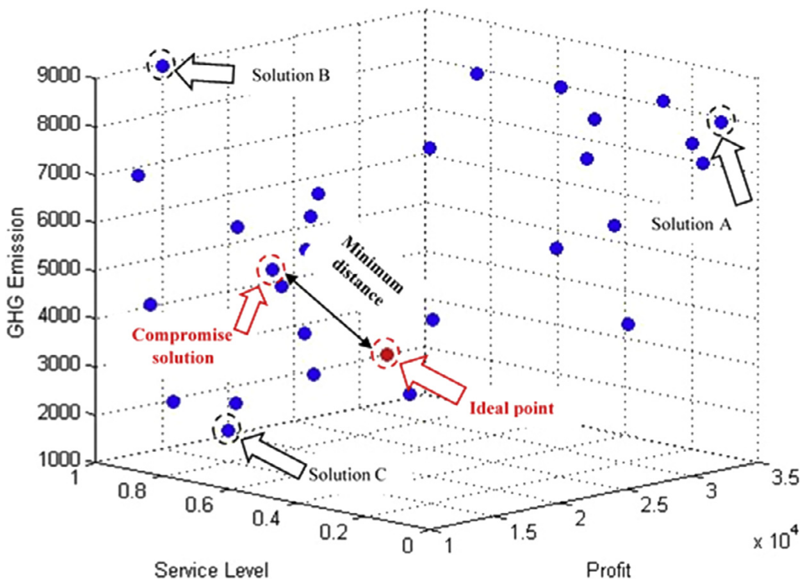


Fig. 4. Compromise and ideal point (Problem No.11).

Table 11
Compromise solution against the best solutions in the final Pareto.

Problem No.	OF	Compromise solution (No.17)	The best solutions		
			Solution A	Solution B	Solution C
11	Z_1	16061.00	**32162.00**	15107.00	12114.00
	Z_2	0.71	0.00	**1.00**	0.69
	Z_3	5092.12	8244.46	8987.22	**1980.93**

$$h_{if} = h_{if}^{fix} + (\lambda_{if}.R_{ft})$$

Thus, the problem is equivalent to a situation where only the fixed h_{if}^{fix} is charged for each item remaining in the stock but where these items are offered a discount λ_{if} on the unit revenue when transferred and consumed in the next period. As

Table 12
The best value of each objective in different value of λ_{if}.

Value of λ_{if}	The best value of each objective function					
	Profit				Service level	Green
	Revenue	Cost[a]	Variable holding cost	Profit[b]		
0.0	187305.00	150544.00	0.00	36761.00	0.89	1910.84
0.01	187492.00	150618.00	140.00	36734.00	0.89	1923.29
0.02	187508.00	150.734.00	190.00	36584.00	0.90	1934.05
0.03	187574.00	144006.00	7222.00	36319.00	0.90	1938.40
0.04	187672.00	144126.00	7542.00	36004.00	0.90	1956.19
0.05	187703.00	144180.00	7606.00	35917.00	0.91	1959.32
0.2	188854.00	144858.00	8587.00	35409.00	0.93	2002.96
0.4	188959.00	146021.00	10048.00	32890.00	0.97	2105.92
0.6	192608.00	150306.00	12305.00	29997.00	1.00	2281.07

[a] Total cost where the variable holding cost are excluded.
[b] Profit = (Revenue-Cost-Variable holding cost).

Table 13
Value of fix holding cost and revenue.

Situation	Uniform distribution Unit fixed holding cost	Unit revenue
Situation 1	~U[5,10]	~U[100,200]
Situation 2	~U[10,15]	~U[50,100]

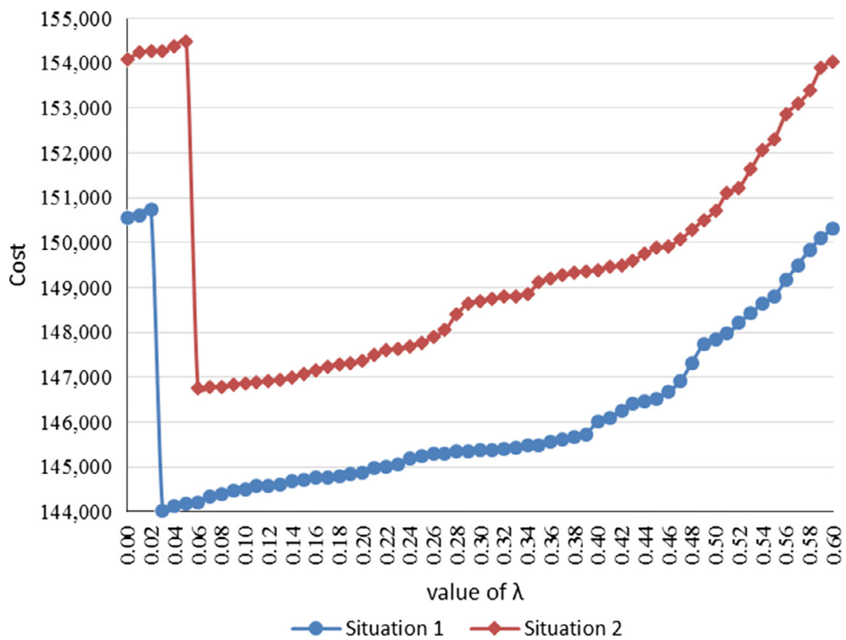


Fig. 5. Variation of the cost (exclusive of the variable holding cost) with λ (Problem No.11).

encouraged in Section 3.1, the product non-freshness could be included in the system as an additional holding cost, because the remaining items should be inspected before being transferred to the next period. The non-freshness could also be included as a discount price leading to a lower unit revenue of the non-fresh products. That is, the revenue for non-fresh product is not R_{ft} but is replaced by $(1-\lambda_{if})R_{ft}$.

We explore the latter scenario in the following numerical analysis where we rewrite the profit as the revenue (including the discount offered for non-fresh products) minus the logistics IRP cost (where only the fixed holding cost is represented).

The results of Problem No. 11 for different values of the revenue discount percentage λ_{if} are presented in Table 12:

It is apparent that discounting non-fresh products is a means to increase the service level; however, the profitability of the system is negatively impacted. We recall that discounting is a penalty for holding non-fresh product. Discounting is a means to eliminate these non-fresh products that are not generating extra demand. If the discount percentage is higher, the system avoids having non-fresh products; consequently, lower quantities are delivered, and vehicle tours are performed more often. Therefore, the stockout probability could be lower (the service level is consequently higher), and the green footprint is higher.

It is important to notice in Table 12 that the Cost (exclusive of the variable holding cost) as well as the (Revenue-the variable holding cost) are non-monotonous with the revenue discount percentage λ_{if}.

We investigate the latter issue by considering two situations with different values of the unit fixed cost h_{if}^{fix} and the unit revenue R_{ft} (cf. Table 13):

The evolution of the cost (exclusive of the variable holding component) illustrated in Fig. 5 and the evolution of the revenue (inclusive of the non-freshness cost, i.e., inclusive of the variable holding component) illustrated in Fig. 6 show a threshold value of the discount percentage.

The logistics IRP cost is superior on the right side after the threshold. From a logistic perspective, if non-fresh products have no logistics cost, the discount option is welcome, because it permits better management of the joint inventory and dis-

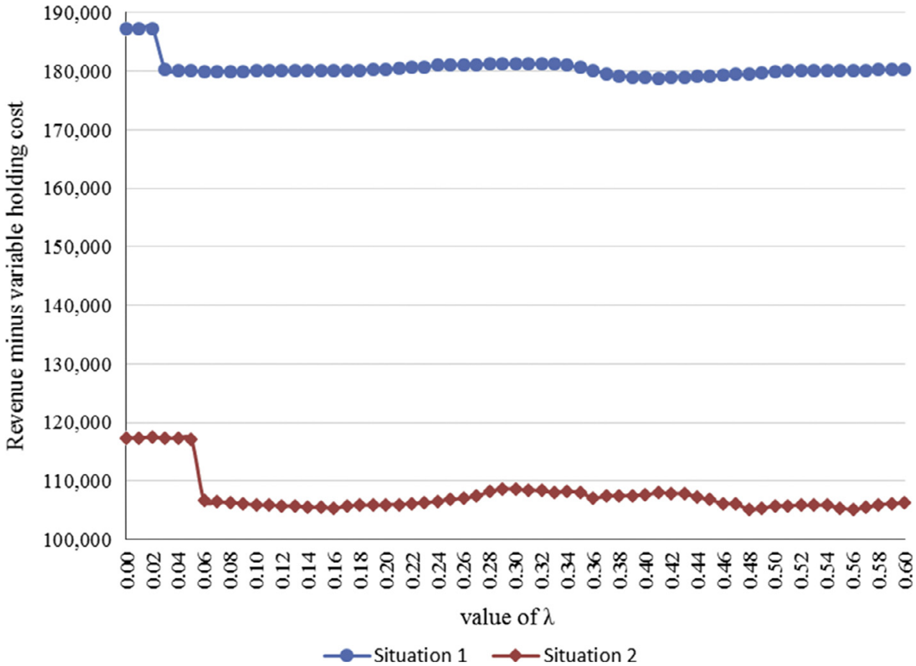


Fig. 6. Variation of "discounted" revenue (Revenue – variable holding cost) with λ (Problem No.11).

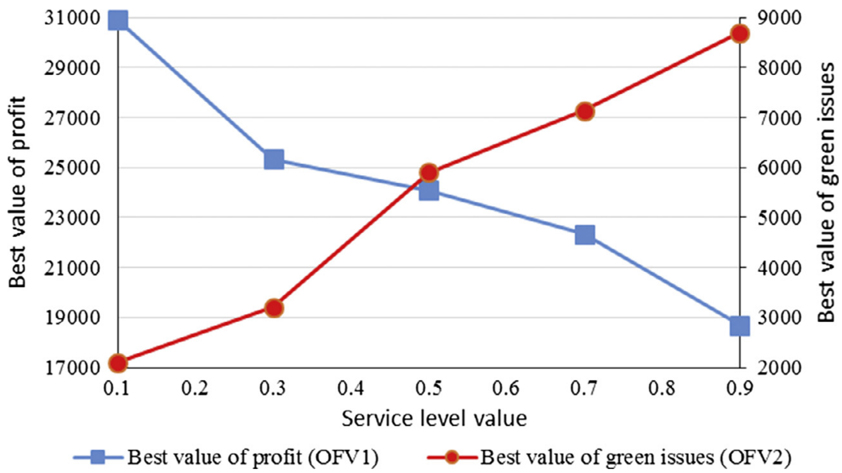


Fig. 7. Variation of best value of profit and green issues against the variation of the fixed value of service level (Problem No.11).

Table 14
Sensitivity analysis based on α-uncertain level (Problem No.11).

α-level	OF	The best solutions			CPU time (s)
		Solution A	Solution B	Solution C	
0.6	Z_1	**32162.00**	15107.00	12114.00	947.02
	Z_2	0.00	**1.00**	0.69	
	Z_3	8244.46	8987.22	**1980.93**	
0.7	Z_1	**31383.00**	14672.00	13464.00	1037.29
	Z_2	0.00	**1.00**	0.73	
	Z_3	8360.39	8361.40	**2164.03**	
0.8	Z_1	**30124.00**	15993.00	13874.00	982.13
	Z_2	0.00	**1.00**	0.67	
	Z_3	8203.07	9026.91	**2245.96**	
0.9	Z_1	**29765.00**	15346.00	11392.00	910.21
	Z_2	0.00	**1.00**	0.54	
	Z_3	8037.61	8875.26	**2182.41**	
1	Z_1	**29291.00**	13809.00	14387.00	936.72
	Z_2	0.00	**1.00**	0.59	
	Z_3	7628.92	9077.82	**2491.18**	

tribution decisions. However, for increasing λ_{if}, the system will avoid holding non-fresh products to avoid penalizing the profitability. Therefore, the logistics need to deliver lower quantities and make tours more often; this, in turn, increases the IRP logistics costs. The revenue (inclusive of the non-freshness cost) is superior on the left side of the threshold; the margin optimization avoids offering the discount option for non-fresh products, which increases the sales revenue. However, on the other side, the logistics costs increase considerably.

With regard to the linkage between the profit, service level and the green IRP footprint, the following figure illustrate the evolution of the best ''profit'' and ''green'' solutions with different values of the service level (Fig. 7).

As intuitively expected, the higher the service level is, the lower the profit is. This result is mainly due to the increase of the logistics and inventory costs; in addition, the higher GHG emissions is due to the need to perform more tours and more loading and unloading tasks.

In the following, we end our numerical analysis by studying the impact of the uncertainty degree on the three IRP objective functions. Therefore, we increase the value of the uncertainty level α and investigate the impact on the results on Problem No.11. (cf. Table 14). The profit is decreasing with α, while the GHG emissions are increasing with it. When the system is subject to more uncertainty, more inventory is needed; consequently more trips are made, and more products may need to be recycled. We note that the invariant service level in Solution B is due not to the invariance of the service level with uncertainty but to the normalization of the service level measure that assigns the value 1 for the best solution.

6. Conclusions

This research presents a new study of the Inventory Routing Problem by considering the service level and the GHG emissions in the distribution of perishable products. We proposed a new multi-objective mathematical model in which the first objective function maximizes the profit function. The second objective function maximizes the service level by minimizing the rate of delays and the rate of the number and frequency of backorders. The third objective function minimizes the GHG emissions produced by vehicles, loading/unloading equipment, and expired products. In this framework, we considered perishable products by defining a specific expiration date and investigated the impact of using electric vehicles and loading/unloading equipment in urban transportation. Moreover, to increase the effectiveness of the proposed model in addressing uncertainty, certain parameters such as demand, variable transportation costs and vehicle speed were modeled as uncertain parameters. A fuzzy possibilistic approach was adopted to convert the original model to an equivalent auxiliary crisp model, and NSGA-II as a multi-objective evolutionary algorithm was designed and tuned to obtain the optimal Pareto frontier. Finally, analyses were conducted to demonstrate the strength of the proposed algorithm, and certain managerial insights were described. In particular:

- We showed the ease of application of the proposed framework and the manner in which the results could be used to derive the best tradeoff between the three objective functions. Indeed, the results could be interpreted differently, based on the judgmental weight that the decision maker could assign to each objective.
- We explored the linkage between the profit/service level and the green footprint under an IRP framework. Such a linkage was recently explored in the inventory context, but none of the IRP investigations considered it to the best of our knowledge. In companies, target service levels are generally a corporate strategy or marketing matter. Inventory holding and distribution costs are logistics matters. These two matters are, in some firms, decided separately. The green footprint

is an ethical/sustainability/legislation (in some countries) matter. Our proposal permits us to first model an IRP with these conflicting objectives and to propose tradeoff mechanisms. For managers, it is possible to check the impact of x% increase of the service level on the logistics costs as well as the green footprint.

- In an internally nonintegrated company, the framework permits us to analyze the penalty of not coordinating service level choices with logistics operations. The results provided in Table 10 are an excellent illustration of the managerial implications with regard to the link between service levels and logistics costs in the IRP.
- We explored the cost of product non-freshness and its impact on the performance. The product non-freshness could either be paid by the logistics side as an additional holding cost motivated by the need to inspect products before transferring them to the next period. The non-freshness could also be modeled as a lower margin for non-fresh items enabled by a price discount offered for these products.

Our future research in this area will consider other more practical issues to be added in the IRP modeling, including the dynamic IRP modeling enabled by the use of real time data such as the traffic status and the real time point of sale data. Such data allow the decision maker to dynamically adapt routes and delivery decisions based on the updates received. Among our future developments, we also foresee the introduction of more sustainable criteria in the IRP modeling, in addition to GHG emissions. These criteria could apply to the accident rate or risk for each route.

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