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Mehmet Soysal, Jacqueline M. Bloemhof-Ruwaard, Rene Haijema, Jack G.A.J. van der Vorst

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Abstract

The transition to sustainable food supply chain management has brought new key logistical aims such as reducing food waste and environmental impacts of operations in the supply chain besides the traditional cost minimization objective. Traditional assumptions of constant distribution costs between nodes, unlimited product shelf life and deterministic demand used in the Inventory Routing Problem (IRP) literature restrict the usage of the proposed models in current food logistics systems. From this point of view, our interest in this study is to enhance the traditional models for the IRP to make them more useful for the decision makers in food logistics management. Therefore, we present a multi-period IRP model that includes truck load dependent (and thus route dependent) distribution costs for a comprehensive evaluation of CO_2 emission and fuel consumption, perishability, and a service level constraint for meeting uncertain demand. A case study on the fresh tomato distribution operations of a supermarket chain shows the applicability of the model to a real-life problem. Several variations of the model, each differing with respect to the considered aspects, are employed to present the benefits of including perishability and explicit fuel consumption concerns in the model. The results suggest that the proposed integrated model can achieve significant savings in total cost while satisfying the service level requirements and thus offers better support to decision makers.

Keywords: Inventory routing, Greenhouse gas emissions, Energy consumption, Perishability, Chance-constrained programming

1. Introduction

Ensuring collaborative relationships throughout a supply chain is an effective strategy to gain competitive advantage. Vendor Managed Inventory (VMI) refers to a collaboration between a vendor and its customers in which the vendor takes on the responsibility of managing inventories at customers (Hvattum and Løkketangen, 2009). The vendor decides on quantity and time of the shipments to the customers, but has to bear the responsibility that the customers do not run out of stock (Andersson et al., 2010). The VMI policy is often regarded as a win-win arrangement: suppliers can better coordinate deliveries to customers, since the vehicle routes can be based on the inventory levels observed at the customers rather than the replenishment orders coming from the customers, and customers do not have to dedicate resources to inventory management (Coelho et al., 2012a; Campbell et al., 1998; Raa and Aghezzaf, 2009). Due to such benefits, and the increase in availability of monitoring technologies facilitating the share of accurate and timely information among the chain partners, the VMI policy has received much attention in recent years. However, execution of the VMI policy in an effective way is not a simple task, since under this policy the vendor has to deal with an integrated problem consisting of its own vehicle routing decisions and inventory decisions of customers (Campbell and Savelsbergh, 2004; Raa and Aghezzaf, 2009). This integrated problem, especially arising in VMI systems (Yu et al., 2008), is known in literature as the Inventory Routing Problem (IRP).

The IRP addresses the coordination of two components of the supply chain: the inventory management and the vehicle routing (Jemai et al., 2013). A generic representation of the IRP is illustrated in Figure 1. The traditional objective is to minimize total distribution and inventory costs during the planning horizon without causing stock-outs at any of the customers (Aghezzaf et al., 2006). The supplier has to make three simultaneous decisions: (1) when to deliver to each customer, (2) how much to deliver to each customer each time it is served, and (3) how to combine customers into vehicle routes (Bertazzi et al., 2008; Coelho et al., 2012b). In the traditional Vehicle Routing Problems (VRPs), the supplier aims to satisfy the orders given by the customers so as to minimize total distribution cost. On the contrary, in the IRP, orders are determined by the supplier based on input on customers usage (demand). Moreover, in the IRP, the supplier aims to manage inventory of customers such that they do not experience a stock-out, whereas traditional VRPs do not have such a concern. The presence of the inventory component in the IRP adds a time dimension to the related routing problem (Bertazzi et al., 2008). The IRP is thus regarded as a medium-term problem, whereas the VRP is a short term one (Moin and Salhi, 2007). Applications of the IRP arise in a large variety of industries, including the distribution of liquified natural gas, raw material to the paper industry, food distribution to supermarket chains, automobile components, perishable items, groceries, cement, fuel, blood, and waste organic oil (see respective references in Coelho and Laporte (2013); Coelho et al. (2012b)).

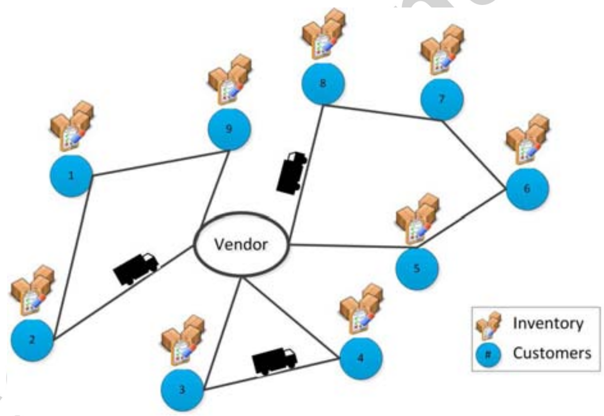

Figure 1: A generic representation of the Inventory Routing Problem

In the last two decades, food supply chain management has evolved due to various reasons such as demand for safe and high quality food products, increasing health consciousness of consumers, growth of world population, climate change, limited natural resources and escalating sustainability awareness. More specific, food logistics systems have seen the transition from a focus on traditional supply chain management to food supply chain management, and successively, to sustainable food supply chain management (Soysal et al., 2012). This transition has brought new key logistical aims besides the cost minimization objective: (i) the ability to control product quality in the supply chain and deliver high quality food products in various forms to final consumers by incorporating product quality information in logistics decision making, (ii) the ability to collaborate in the supply chain network to reduce food waste and (iii) the ability to reduce environmental and societal impacts of operations (Soysal et al., 2012). The aforementioned developments have stimulated companies and researchers to consider multiple Key Performance Indicators (KPIs) such as cost, food waste and transportation emissions in food logistics management projects (e.g., Zanoni and Zavanella (2012) and Soysal et al. (2014)).

Some traditional assumptions in the IRP literature restrict the usage of the proposed models in current food logistics systems. These assumptions, which can be regarded as doubtful from the practical point of view, are summarized as follows. First, IRP models often assume that distribution costs between nodes are known in advance and are constant (e.g., Vidović et al. (2013) and Qin et al. (2014)). However, fuel consumption and therefore cost can change based on vehicle load which is dependent on the visiting order of the customers (Kara et al., 2007; Kuo and Wang, 2011). The literature for a number of VRPs shows that an explicit consideration of fuel consumption in logistics operations can help to reduce relevant operational costs and environmental externalities (e.g., Bektaş and Laporte (2011) and Franceschetti et al. (2013)). Second, a common assumption of an unlimited product shelf life in the IRP models is restrictive in that it does not allow for the consideration of quality decay of products. This is one of the main obstacles for the application of the basic IRP models in food logistics management. Third, a widespread tendency is to assume that customer usages are known in advance in the beginning of the planning horizon, which is clearly not the case in reality. These are the main weaknesses of the basic IRP models to be improved.

From this point of view, our interest in this study is to enhance the traditional models for the IRP to make them more useful for the decision makers in food logistics management. In order to achieve that improvement, we do not rely on all common assumptions of the basic IRP models. Therefore, in our problem setting, distribution costs between nodes are not known in advance and can change according to the routing schedule employed, the product is subject to quality decay because of the perishability nature and customer usage is not known a priori. Moreover, we estimate fuel consumption and emissions based on a comprehensive emissions model that allows to incorporate transportation cost and emissions more accurately and explicitly. Consequently, we develop a comprehensive chance-constrained programming model for the multi-period IRP that accounts for perishability, explicit fuel consumption and demand uncertainty. The proposed model manages relevant KPIs of total energy use (emissions), total driving time, total routing cost, total inventory cost, total waste cost, and total cost, simultaneously. To the best of our knowledge, such an attempt has not yet been made for the IRP.

The rest of the paper is structured as follows. Section 2 presents a review of the relevant literature on the IRP and clarifies the contribution of our work. Section 3 defines the problem and presents the optimization model. Section 4 presents three different variations of the proposed model, which are employed to show the benefits of including perishability and explicit fuel consumption considerations in the model. Section 5 presents a simulation for the problem to evaluate the solutions of the optimization models. Section 6 presents computational results on a real life distribution problem. The last section presents conclusions and future research directions.

2. Related literature review

The traditional IRP without perishability and sustainability concerns has been extensively studied in the literature. The interested reader is referred to the reviews by Moin and Salhi (2007), Andersson et al. (2010) and Coelho et al. (2012b) on the topic. Our focus here is on attempts aimed to incorporate additional KPIs to the IRP. Relatively few studies on the IRP have bothered to introduce new KPIs to the proposed models. We can subdivide the related literature in two groups: (i) studies with perishability considerations, (ii) studies with environmental or societal considerations.

First, we review the studies on IRP with perishability considerations. Federgruen et al. (1986) study the IRP for a perishable product with a fixed lifetime during which it can be used and after which it must be discarded, e.g., human blood, food and medical drugs. They distinguish two age classes, fresh and old, based on the product remaining lifetime and discard the product that reaches the maximum age in inventory. Le et al. (2013) and Al Shamsi et al. (2014) study the IRP for a perishable product with a fixed lifetime as well. Both studies restrict the total amount of time that products can be stored in facilities and do not allow product wastes. Coelho and Laporte (2014) integrate an age tracking approach to the IRP of a perishable product with a fixed shelf life. The age tracking approach ensures to distinguish products according to their shelf lives and has also been used in literature for other logistics problems such as inventory problems (Haijema, 2013), and production and distribution problems (Rong et al., 2011; Van Elzakker et al., 2014). Jia et al. (2014) incorporate quality time windows (shelf life limit) to the IRP of a perishable product with the same objective as the age tracking approach: controlling deteriorating item's quality which has a fixed shelf life. We note that both Coelho and Laporte (2014) and Jia et al. (2014) allow product wastes in the IRP. A number of studies on inventory management deal with products which have limited shelf life as well (e.g., Minner and Transchel (2010) and Rossi et al. (2010)). However, these studies do not take routing decisions into account. The reviews of Nahmias (1982), Amorim et al. (2011), Karaesmen et al. (2011) and Bakker et al. (2012) can be consulted for more information about research on supply chain management of products that are perishable.

Second, we review the studies on IRP with environmental or societal considerations. Treitl et al. (2012) and Al Shamsi et al. (2014) incorporate emissions to the IRP through estimating fuel consumption. Both studies employ the same approach as in Bektaş and Laporte (2011) for estimating fuel consumption and emissions that is based on the comprehensive emissions model of Barth et al. (2005) and Barth and Boriboonsomsin (2009). Al-e hashem and Rekik (2013) and Alkawaleet et al. (2014) incorporate emissions to the IRP as well. However, both studies employ a distance-based emission calculation approach, i.e. emissions produced by vehicle type per unit distance, that does not consider the other factors such as vehicle load and vehicle speed. There exist other studies on a similar problem class, VRPs, with an explicit consideration of environmental issues, such as fuel consumption or emissions (e.g., Bektaş and Laporte (2011) and Franceschetti et al. (2013)). Note that these studies have interest in routing schedules and do not consider inventory decisions. The interested reader is referred to the reviews by Demir et al. (2014) and Lin et al. (2014) on this topic.

Table 1: Studies on IRPs that have perishability or fuel consumption (emissions) considerations

	Perishability		Fuel or emissions considerations			Demand uncertainty
	Shelf life	Waste	Traveled distance	Vehicle load	Vehicle speed	
Federgruen et al. (1986)	✓	✓	-	-	-	✓
Treitl et al. (2012)	-	-	✓	✓	✓	-
Al-e hashem and Rekik (2013)	-	-	✓	-	-	-
Le et al. (2013)	✓	-	-	-	-	-
Alkawaleet et al. (2014)	-	-	✓	-	-	-
Al Shamsi et al. (2014)	✓	-	✓	✓	✓	-
Coelho and Laporte (2014)	✓	✓	-	-	-	-
Jia et al. (2014)	✓	✓	-	-	-	-
This study	✓	✓	✓	✓	✓	✓

Our brief review shows that none of the above mentioned studies presented in Table 1, except Al Shamsi et al. (2014), has addressed an IRP with both perishability and sustainability concerns simultaneously. The study of Al Shamsi et al. (2014), however, does not take potential product wastes and demand uncertainty into account. Note that product wastes can be inevitable when the demand is not known in advance. The other given studies, except Federgruen et al. (1986) that take demand uncertainty into account, rely on a completely deterministic environment as well. This diminishes the chance to obtain robust solutions for real-world problems where the actual demand is not known in advance, which is often the case in practice. Some of the studies (e.g., Bertazzi et al. (2013), Hemmelmayr et al. (2010), Huang and Lin (2010) and Yu et al. (2012)) consider demand uncertainty on IRP, however these studies stick to traditional approaches that focus only on a single KPI: cost.

A convenient way to capture the risk associated with uncertain demand is to use a chance-constrained programming approach. Therefore, we formulate the IRP as a chance-constrained programming model. It is first introduced by Charnes and Cooper (1959) and further studied by many authors during the last years, such as Yu et al. (2012) and Rahim et al. (2014) on IRP, and Hendrix et al. (2012), Rossi et al. (2008) and Pauls-Worm et al. (2014) on inventory problems.

To conclude, our study adds to the literature on IRP by: (1) developing a comprehensive chance-constrained programming model with demand uncertainty for a multi-period generic IRP that accounts for the KPIs of total energy use (emissions), total driving time, total routing cost, total inventory cost, total waste cost, and total cost, (2) presenting the applicability of the model on the fresh tomato distribution operations of a supermarket chain operating in Turkey based on mostly real data.

3. Problem description

The problem in this study is defined on a complete graph $G = \{V, A\}$, where $V = \{0, ..., |V|\}$ is the set of nodes and $A = \{(i, j) : i, j \in V, i \neq j\}$ is the set of arcs. Node 0 represents the vendor and the remaining nodes $V^{'} = V \backslash \{0\}$ represent customers. The set of vehicles is given as $K = \{1, 2..., |K|\}$, each with capacity c and located at the vendor. Freight is delivered to customers from the vendor through these vehicles that start and end at the vendor's location. Each vehicle can perform at most one route per time period. Each customer can be served by more than one vehicle, hence the total freight assigned to each customer can be split into two or more vehicles. It is assumed that the demand $d_{i,t}$ in each period $t \in T = \{1, ..., |T|\}$ is distributed normally with mean $\mu_{i,t}$ and standard deviation $\sigma_{i,t}$, $\forall i \in V^{'}, t \in T$. For each customer, an inventory holding cost h_i,$\forall i \in V^{'}$ occurs at each period. However, the product has a fixed shelf life of $m \geq 2$ periods. Therefore, if a product stays in inventory more than m periods, it becomes spoiled and cost of waste p occurs. The demand of all customers in each period must be satisfied with a probability of at least α. The demand that cannot be fulfilled in one period is backlogged in the next period.

The aim of the problem in this study is to determine the routes and quantity of shipments in each period such that the total cost comprising routing, inventory and waste costs is minimized. Routing cost consists of driver and fuel consumption cost for each arc in the network. Let r denote the wage for the drivers and l denote the fuel price per liter. The driver of each vehicle is paid from the beginning of the time horizon until the time he returns to the starting point. Fuel consumption is mainly dependent on traveled distance, vehicle load and vehicle speed. The following section presents the fuel consumption calculation in greater detail.

3.1. Fuel consumption and emissions

We employ the same approach as in Bektaş and Laporte (2011), Demir et al. (2012) and Franceschetti et al. (2013) for estimating fuel consumption that is based on the comprehensive emissions model of Barth et al. (2005). According to this model, the total amount of fuel used, EC (in liters), for traversing a distance a (m) at constant speed f (m/s) with load F (kg) is calculated as follows:

$$EC = \lambda\Big(y(a/f) + \gamma\beta a f^2 + \gamma s(\mu + F)a\Big)$$

where $\lambda = \xi/(\kappa\psi)$, $y = k_e N_e V_e$, $\gamma = 1/(1000\varepsilon\varpi)$, $\beta = 0.5 C_d A_e \rho$, and $s = g\sin\phi + gC_r\cos\phi$. Furthermore, k_e is the engine friction factor (kJ/rev/liter), N_e is the engine speed (rev/s), V_e is the engine displacement (liter), μ is the vehicle curb weight (kg), g is the gravitational constant (9.81 m/s^2), ϕ is the road angle, C_d and C_r are the coefficient of aerodynamic drag and rolling resistance, A_e is the frontal surface area (m^2), ρ is the air density (kg/m^3), ε is the vehicle drive train efficiency and ϖ is an efficiency parameter for diesel engines, ξ is the fuel-to-air mass ratio, κ is the heating value of a typical diesel fuel (kJ/g), ψ is a conversion factor from grams to liters from (g/s) to (liter/s). For further details on these parameters, the reader is referred to Demir et al. (2011). After estimating fuel consumption amounts, we estimate related emission (CO_2) levels by using a fuel conversion factor u (kg/l) for transport activities.

3.2. Chance-constrained programming model with demand uncertainty

This section presents a mathematical formulation for the studied problem. Table 2 presents the notation for the model.

We now present the formulation, starting with the objective function.

$$\begin{aligned}
&Minimise \sum_{i\in V'}\sum_{t\in T} I^+_{i,t} h_i && \text{(1.i)}\\
&+\sum_{i\in V'}\sum_{t\in\{T|t\geq m\}} E[W_{i,t}]p && \text{(1.ii)}\\
&+\sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}\lambda\Big(y(a_{ij}/f)X_{i,j,k,t} + \gamma\beta a_{ij} f^2 X_{i,j,k,t} + \gamma s(\mu X_{i,j,k,t} + F_{i,j,k,t})a_{ij}\Big)l && \text{(1.iii)}\\
&+\sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}(a_{ij}/f)X_{i,j,k,t}r. && \text{(1.iv)}
\end{aligned}$$

$$\tag{1}$$

The objective function (1) comprises four parts: (1.i) expected inventory cost, (note that $I^+_{i,t}$ is derived from $E[I_{i,t}]$ through constraints (3)), (1.ii) expected waste cost, (1.iii) fuel cost from transportation operations and (1.iv) driver cost.

Table 2: Parameters and decision variables

Symbol	Meaning
$E[.]$	expectation operator
V	set of all nodes including the vendor 0, $V = \{0, 1, 2..., \|V\|\}$
$V^{'}$	set of customers, $V^{'} = V \backslash \{0\}$
A	set of all arcs, $A = \{(i, j) : i, j \in V, i \neq j\}$
T	set of time periods, $T = \{1, 2..., \|T\|\}$
K	set of vehicle, $K = \{1, 2..., \|K\|\}$
m	fixed maximum shelf life, $m \geq 2$, in periods,
$d_{i,t}$	demand of customer $i \in V^{'}$ in time period $t \in T$, normal random variable with mean $\mu_{i,t}$, standard deviation $\sigma_{i,t}$, in kg,
α	pre-defined satisfaction level of probabilistic inventory constraint,
c	capacity of a vehicle, in kg,
$a_{i,j}$	distance between node i and j, $(i, j) \in A$, in m,
f	vehicle speed, (m/s),
λ	technical parameter, $\xi/\kappa\psi$, see section 3.1,
y	technical parameter, $k_e N_e V_e$, see section 3.1,
γ	technical parameter, $1/(1000\varepsilon\varpi)$, see section 3.1,
β	technical parameter, $0.5 C_d A_e \rho$, see section 3.1,
s	technical parameter, $g \sin\phi + g C_r \cos\phi$, see section 3.1,
μ	curb-weight of vehicle, in kg,
l	fuel price per liter, €/l,
p	penalty cost for the wasted product, €/kg,
r	wage rate for the drivers of the vehicles, €/s,
h_i	holding cost per period at customer $i \in V^{'}$, €/kg,
$I_{i,t}$	the amount of inventory at customer $i \in V^{'}$ at the end of period $t \in T \cup \{0\}$, in kg, where $I_{i,0} = 0, \forall i \in V^{'}$,
$I^{+}_{i,t}$	derived decision variable to calculate positive inventory levels, in kg,
$Q_{i,k,t}$	the amount of product delivered by vehicle $k \in K$ to customer $i \in V^{'}$ in the beginning of period $t \in T$, in kg,
$X_{i,j,k,t}$	binary variable equal to 1 if vehicle $k \in K$ goes from $i \in V$ to $j \in V$ in period $t \in T$, and 0 otherwise,
$F_{i,j,k,t}$	the load on vehicle $k \in K$ which goes from $i \in V$ to $j \in V$ in period $t \in T$, in kg,
$W_{i,t}$	the amount of waste at customer $i \in V^{'}$ at the end of period $t \in T$, in kg.

$$E[I_{i,t}] = \sum_{s=1}^{t} \sum_{k \in K} Q_{i,k,s} - \sum_{s=1}^{t} (E[d_{i,s}] + E[W_{i,s}]), \qquad \forall i \in V^{'}, t \in T \tag{2}$$

$$I^{+}_{i,t} \geq E[I_{i,t}], \qquad \forall i \in V^{'}, t \in T \tag{3}$$

$$E[W_{i,t}] \geq E[I_{i,t-m+1}] - \sum_{a=t-m+2}^{t} E[d_{i,a}] - \sum_{a=t-m+2}^{t-1} E[W_{i,a}], \qquad \forall i \in V^{'}, t \in \{T|t \geq m\} \tag{4}$$

$$E[W_{i,t}] = 0, \qquad \forall i \in V^{'}, t \in \{T|t < m\} \tag{5}$$

$$Pr\Big(I_{i,t} \geq 0\Big) \geq \alpha, \qquad \forall i \in V^{'}, t \in T. \tag{6}$$

Constraints (2) to (6) relate to the inventory decisions. In particular, constraints (2) calculate expected inventory levels for each customer per period by taking the amounts of total product delivered, expected demand and expected waste into account. Hereby, we assume $I_{i,0} = 0, \forall i \in V^{'}$. Constraints (3) define variables which are used for the calculation of inventory costs in the objective function. Constraints (4) and (5) calculate expected waste at each customer per period. Constraints

(6) are the service-level constraints on the probability of a stock-out at the end of each period.

$$\sum_{i\in V, i\neq j} X_{i,j,k,t} = \sum_{i\in V, i\neq j} X_{j,i,k,t}, \qquad \forall j \in V^{'}, k\in K, t\in T \tag{7}$$

$$\sum_{j\in V, i\neq j} X_{i,j,k,t} \leq 1, \qquad \forall i \in V, k\in K, t\in T \tag{8}$$

$$\sum_{j\in V, i\neq j} F_{i,j,k,t} = \sum_{j\in V, i\neq j} F_{j,i,k,t} - Q_{i,k,t}, \qquad \forall i \in V^{'}, k\in K, t\in T \tag{9}$$

$$F_{i,j,k,t} \leq cX_{i,j,k,t}, \qquad \forall (i,j) \in A, k\in K, t\in T. \tag{10}$$

Constraints (7) to (10) relate to the routing decisions. In particular, constraints (7) ensure flow conservation for each vehicle at each node in each period. Constraints (8) ensure that each vehicle can perform at most one route per time period. Constraints (9) and (10) model the flow on each arc and ensure that vehicle capacities are respected in each period. Constraints (9) provide also the benefit of eliminating subtours that do not include the vendor, since the load on each vehicle is monotonically decreasing as customers are visited (Bard and Nananukul, 2009; Treitl et al., 2012).

$$X_{i,j,k,t} \in \{0,1\}, \qquad \forall (i,j) \in A, k\in K, t\in T \tag{11}$$

$$F_{i,j,k,t} \geq 0, \qquad \forall (i,j) \in A, k\in K, t\in T \tag{12}$$

$$-\infty < I_{i,t} < +\infty, \qquad \forall i \in V^{'}, t\in T \tag{13}$$

$$I^{+}_{i,t}, W_{i,t} \geq 0, \qquad \forall i \in V^{'}, t\in T \tag{14}$$

$$Q_{i,k,t} \geq 0, \qquad \forall i \in V^{'}, k\in K, t\in T. \tag{15}$$

Constraints (11) to (15) represent the restrictions imposed on the decision variables.

3.3. Deterministic approximation of the chance-constrained programming model with demand uncertainty

Solving the above chance constrained model is complicated as the product have a fixed expiration date. In line with Pauls-Worm et al. (2014), we therefore consider a deterministic approximation. The deterministic constraints for the stochastic chance constraints (6) are rewritten as follows.

Constraints (6) ensure the inventory level at the end of every period to be nonnegative with a probability of service level α. Therefore, starting inventory level of every period should be higher than the demand of that period, with a probability higher than the service level. These constraints now can be rewritten as,

$$Pr\Big(I_{i,t-1} + \sum_{k\in K} Q_{i,k,t} \geq d_{i,t}\Big) \geq \alpha, \qquad \forall i \in V^{'}, t\in T. \tag{16}$$

Applying constraints (2) to constraints (16), we have

$$Pr\Big(\underbrace{\sum_{s=1}^{t-1}\sum_{k\in K} Q_{i,k,s} - \sum_{s=1}^{t-1}(d_{i,s} + E[W_{i,s}])}_{I_{i,t-1}} + \sum_{k\in K} Q_{i,k,t} \geq d_{i,t}\Big) \geq \alpha, \qquad \forall i \in V^{'}, t\in T. \tag{17}$$

Rearranging the constraints (17) yields

$$Pr\Big(\sum_{s=1}^{t}\sum_{k\in K} Q_{i,k,s} - \sum_{s=1}^{t-1} E[W_{i,s}] \geq \sum_{s=1}^{t} d_{i,s}\Big) \geq \alpha, \qquad \forall i \in V^{'}, t\in T. \tag{18}$$

If $G_{d_{i,1}+d_{i,2}+...+d_{i,t}}(y)$ is the cumulative distribution function of $D_i(t) = d_{i,1} + d_{i,2} + ... + d_{i,t}$, then

$$\sum_{s=1}^{t}\sum_{k\in K} Q_{i,k,s} - \sum_{s=1}^{t-1} E[W_{i,s}] \geq G^{-1}_{D_i(t)}(\alpha), \qquad \forall i \in V^{'}, t \in T. \tag{19}$$

$D_i(t) = \sum_{s=1}^{t} d_{i,s}, \quad \forall i \in V^{'}$ will be normally distributed if the $\{d_{i,s}\}, \forall i \in V^{'}, s \in T$ with mean $\mu_{i,s}$ and standard deviation $\sigma_{i,s}$ are each normally distributed, and pairwise uncorrelated (Bookbinder and Tan, 1988). Therefore,

$$G^{-1}_{D_i(t)}(\alpha) = \sum_{s=1}^{t} \mu_{i,s} + \sqrt{(\sum_{s=1}^{t}(\mu_{i,s})^2)}CZ_\alpha, \qquad \forall i \in V^{'}, t \in T. \tag{20}$$

where C is the coefficient of variation which is assumed to be constant and Z_α is a standard normal random variate with cumulative probability of α. Therefore,

$$\sum_{s=1}^{t}\sum_{k\in K} Q_{i,k,s} - \sum_{s=1}^{t-1} E[W_{i,s}] \geq \sum_{s=1}^{t} \mu_{i,s} + \sqrt{(\sum_{s=1}^{t}(\mu_{i,s})^2)}CZ_\alpha, \qquad \forall i \in V^{'}, t \in T. \tag{21}$$

As a result, the model is simplified through transforming the stochastic terms by replacing constraints (6) with constraints (21). Then, the resulting deterministic linear formulation, which is the approximation of the chance-constrained programming model with demand uncertainty, is: (1)–(5), (7)–(15) and (21). This integrated model that takes perishability, explicit fuel consumption and demand uncertainty into account is denoted by M_{PF}.

4. Variations of the integrated model M_{PF}

In this section, we derive from model M_{PF}, three models (M, M_F and M_P) to present the benefits of including perishability and explicit fuel consumption considerations in the model. Table 3 presents the considered aspects in the model variations.

Table 3: Considered aspects in the model variations

	Perishability		Fuel or emissions considerations				Demand uncertainty
	Shelf life	Waste	Traveled distance	Vehicle load	Vehicle speed	Vehicle characteristics	
M	-	-	✓	-	-	-	✓
M_F	-	-	✓	✓	✓	✓	✓
M_P	✓	✓	✓	-	-	-	✓
M_{PF}	✓	✓	✓	✓	✓	✓	✓

Model M does not take perishability into account. Fuel consumption is calculated based on only traveled distance in M, therefore it does not have explicit fuel consumption concern as well. Model M_F also disregards perishability. However, it calculates fuel consumption explicitly through taking traveled distance, vehicle load, vehicle speed and vehicle characteristics into account. Model M_P has perishability concern. However, it considers only traveled distance while calculating fuel consumption, and therefore does not have explicit fuel consumption concern. The integrated model, M_{PF}, presented in the previous section has both perishability and explicit fuel consumption concerns. Lastly, note that all models take demand uncertainty into account. The following subsections present models M, M_F and M_P.

4.1. Model without perishability and without explicit fuel consumption concerns (M)

We adapt M_{PF} by making some changes so that the new model, M, ignores perishability and explicit fuel consumption, as shown in Table 3. Initially, the fuel cost component (1.iii) in the objective function (1) is replaced with the following fuel cost calculation equation based on only traveled distance:

$$\sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}(a_{ij}/1000)X_{i,j,k,t}bl. \tag{22}$$

where a new introduced parameter, b, refers to fuel consumption per km. The other components (1.i, 1.ii and 1.iv) in the objective function (1) are not changed. Afterwards, the maximum shelf life parameter, m, needs to be set a number which is larger than the length of the planning horizon $|T|$. Model M thus determines an IRP plan as if the products are non-perishable. In reality the product is perishable with a maximum shelf life of say $m^{'} < m$. To evaluate within the MILP what the resulting inventory and waste costs would be if the plan for non-perishables is applied to a perishable product with a shelf life of $m^{'}$ periods, constraints (23)–(30) are added to the formulation. These constraints do not influence the solution of M, as the constraints are not used in the objective function.

$$E[I^{'}_{i,t}] = \sum_{s=1}^{t}\sum_{k\in K} Q_{i,k,s} - \sum_{s=1}^{t}(E[d_{i,s}] + E[W^{'}_{i,s}]), \qquad \forall i \in V^{'}, t \in T \tag{23}$$

$$E[W^{'}_{i,t}] = max\big(E[I^{'}_{i,t-m^{'}+1}] - \sum_{a=t-m^{'}+2}^{t} E[d_{i,a}] - \sum_{a=t-m^{'}+2}^{t-1} E[W^{'}_{i,a}], 0\big), \qquad \forall i \in V^{'}, t \in \{T|t \geq m^{'}\} \tag{24}$$

$$E[W^{'}_{i,t}] = 0, \qquad \forall i \in V^{'}, t \in \{T|t < m^{'}\} \tag{25}$$

$$Waste = \sum_{i\in V^{'}}\sum_{t\in\{T|t\geq m^{'}\}} E[W^{'}_{i,t}]p, \tag{26}$$

$$Inv = \sum_{i\in V^{'}}\sum_{t\in T} max\big(I^{'}_{i,t}, 0\big)h_i, \tag{27}$$

$$-\infty < I^{'}_{i,t} < +\infty, \qquad \forall i \in V^{'}, t \in T \tag{28}$$

$$W^{'}_{i,t} \geq 0, \qquad \forall i \in V^{'}, t \in T \tag{29}$$

$$Waste, Inv \geq 0. \tag{30}$$

where $m^{'}$ refers to the maximum shelf life. Furthermore, $Waste$ and Inv auxiliary variables refer to the total waste and total inventory costs calculated using the inventory and waste tracking auxiliary variables $I^{'}_{i,t}$ and $W^{'}_{i,t}$, $\forall i \in V^{'}, t \in T$. In particular, constraints (23) calculate expected inventory levels, and constraints (26) and (27) calculate expected waste at each customer per period. Constraints (26) and (27) calculate respectively total waste and inventory costs. Constraints (28)–(30) represent the restrictions imposed on the decision variables.

Apart from these constraints, to calculate total fuel cost explicitly for the comparison purposes with the other types, constraints (31)–(33) are added to the formulation.

$$\sum_{j \in V'} F_{j,0,k,t} \leq 0, \qquad \forall k \in K, t \in T \tag{31}$$

$$Fuel = \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \Big(y(a_{ij}/f) X_{i,j,k,t} + \gamma \beta a_{ij} f^2 X_{i,j,k,t} + \gamma s (\mu X_{i,j,k,t} + F_{i,j,k,t}) a_{ij} \Big) l, \tag{32}$$

$$Fuel \geq 0. \tag{33}$$

where $Fuel$ auxiliary variable refers to total fuel consumption cost calculated based on the explicit fuel consumption model that considers traveled distance, vehicle load and vehicle speed. In particular, constraints (31) ensure that vehicles do not carry load which is more than the total amount delivered to the customers. Note that M_{PF} penalizes carrying more than enough load through explicit fuel consumption cost component existing in its objective function (1). Constraint (32) does not affect solutions and is used to estimate total fuel consumption cost. Constraint (33) represents the restriction imposed on the decision variable. As a result, the resulting constraints for M are (2)–(15), (21), and (23)–(33).

4.2. Model with explicit fuel consumption concern (M_F)

We adapt M_{PF} by making some changes so that the new model, M_F, ignores perishability, as shown in Table 3. Same as we do for M, first, the maximum shelf life parameter, m, needs to be set a number which is larger than the length of the planning horizon $|T|$ to ignore the possibility of waste during the whole planning horizon. Afterwards, constraints (23)–(30) are employed to calculate total inventory and total waste costs for the comparison purposes with the other types. Then, the resulting constraints for M_F are (2)–(15), (21), and (23)–(30). Note that no changes occur in the objective function (1).

4.3. Model with perishability concern (M_P)

We adapt M_{PF} by making some changes so that the new model, M_P, does not take fuel consumption explicitly into account, as shown in Table 3. Same as we do for M, first, fuel cost from transportation operations component (1.iii) in the objective function (1) is replaced with the equation (22). The other components (1.i, 1.ii and 1.iv) in the objective function (1) are not changed. Apart from that, constraints (31)–(33) are employed to calculate total fuel cost for the comparison purposes with the other types. Then, the resulting constraints for M_P are (2)–(15), (21), and (31)–(33).

So far in this section, we present optimization models that differ in terms of considered aspects. In the next section, we present a simulation model which is used for a performance evaluation of the model solutions.

5. Performance evaluation by simulation

As it is already mentioned, the optimization models M, M_F, M_P and M_{PF} are the deterministic approximations of the related stochastic models. Therefore, solutions of the formulations can be readily obtained with a commercial MILP solver. In this section, we have proposed a simulation model to evaluate the solutions of these models in terms of inventory and waste performances, and to check whether these solutions are feasible.

The simulation model obtains the delivery schedules from the optimization models and calculates achieved average service level for each customer per period, and average total inventory and waste costs according to the realized demand and maximum shelf life of the product. Due to the fact that the delivery schedules are obtained from the optimization models, we do not calculate emissions, driving time and routing cost amounts by the simulation model to prevent double calculation. The pseudocode of the simulation model is presented in Algorithm 1.

Algorithm 1: Simulation model algorithm

```
Data: Delivery schedule from the optimization model, Q_{i,k,t} in kg, ∀i ∈ V', k ∈ K, t ∈ T ;
Fixed maximum shelf life parameter, m ≥ 2;
Demand mean μ_{i,t} and standard deviation σ_{i,t} in kg, ∀i ∈ V', t ∈ T;
Penalty cost for the wasted product, p (€/kg) and holding cost per period at customers, h (€/kg);
Result: Average total inventory cost, Average total waste cost, Average service level;
Initialization: set all arrays ← 0;
for sim = 1 to S (simulation number) do
    for i = 1 to |V'| do
        for t = 1 to |T| do
            Generate random demand, d_{i,t} ~ N(μ_{i,t}, σ_{i,t});
            Compute inventory-I (waste not included), IB_{i,t} = Σ_{s=1}^{t} Σ_{k∈K} Q_{i,k,s} − Σ_{s=1}^{t} d_{i,s};
            if t < m then
                Set inventory-II (waste included), I_{i,t} ← IB_{i,t};
            else
                Compute waste, W_{i,t} = I_{i,t−m+1} − Σ_{a=t−m+2}^{t} d_{i,a} − Σ_{a=t−m+2}^{t−1} max(W_{i,a}, 0);
                Compute inventory-II (waste included), I_{i,t} = IB_{i,t} − Σ_{s=1}^{t} max(W_{i,s}, 0);
            if I_{i,t} > 0 then
                Keep track of total inventory for computing inventory costs, SI+ = I_{i,t};
            if I_{i,t−1} + Σ_{k∈K} Q_{i,k,t} < d_{i,t} then
                Keep track of # of stock outs for computing achieved average service levels, SA_{i,t} ++;
            if W_{i,t} > 0 then
                Keep track of total waste for computing waste costs, SW+ = W_{i,t};
Compute achieved average service level for customer i in period t, AAS_{i,t} = (SA_{i,t}/S);
Compute average total inventory cost, TI = (SI/S)h;
Compute average total waste cost, TW = (SW/S)p.
```

6. Case study

This section presents an implementation of the proposed model, M_{PF}, and its above described variations, M, M_F and M_P, on the fresh tomato distribution operations of a supermarket chain operating in Turkey. We first describe the data used, then present the results.

6.1. Description and Data

The underlying transportation network includes one distribution center (DC) and 11 supermarkets (customers) as presented in Figure 2. The DC is responsible for providing fresh tomatoes to the supermarkets. We note that in some places there exist multiple supermarkets which are relatively close to each other (e.g., Izmir, Kusadasi and Didim). In these circumstances, we aggregate customers and select one supermarket according to size and/or location. The planning horizon length is four weeks.

We assume that homogeneous vehicles are used for the deliveries, each with a capacity of 10 tonnes. The parameters used to calculate the total fuel consumption cost are taken from Demir et al. (2012) and are given in Table 4. The fuel consumption per km parameter, b, which is

Figure 2: Representation of the logistics network

required for M and M_P, is calculated as 0.21 l/km with the fuel consumption calculation model introduced previously based on the assumption that vehicle is assumed as half-loaded. Note that M and M_P disregard the effect of vehicle load on fuel consumption and take only traveled distance into account as a parameter while estimating related fuel consumption amounts. We use 2.63 kg/l as a fuel conversion factor to estimate CO_2 emissions from transportation operations (Defra, 2007). Distances between nodes (see Table 10 in the appendix) are calculated using Google Maps[1]. Vehicles travel at a fixed speed of 80 km/h.

Table 4: Setting of vehicle and emission parameters

Notation*	Description	Value
ξ	Fuel-to-air mass ratio	1
κ	Heating value of a typical diesel fuel (kJ/g)	44
ψ	Conversion factor (g/liter)	737
k_e	Engine friction factor (kJ/rev/liter)	0.2
N_e	Engine speed (rev/s)	33
V_e	Engine displacement (liter)	5
ρ	Air density (kg/m^3)	1.2041
A_e	Frontal surface area (m^2)	3.912
μ	Curb-weight (kg)	6350
g	Gravitational constant (m/s^2)	9.81
ϕ	Road angle	0
C_d	Coefficient of aerodynamic drag	0.7
C_r	Coefficient of rolling resistance	0.01
ε	Vehicle drive train efficiency	0.4
ϖ	Efficiency parameter for diesel engines	0.9
l	Fuel price per liter (€)	1.7
r	Driver wage (€/s)	0.003

Source: Demir et al. (2012)
* See section 3.1 for the description of the notation.

[1]http://maps.google.nl/,Onlineaccessed:February2014

Demand means (see Table 11) are generated randomly for purposes of sensitivity analysis as will be shown in the following section. The coefficient of variation for the demand is assumed to be constant and equal to 0.1 for all supermarkets in each week. The demand for each supermarket in each week must be satisfied with a probability of at least 95%. Holding cost at supermarkets is taken as 10% of the average marketplace selling price of tomatoes[2] in that region of Turkey, and is equal to 0.06 €/kg-week. Shelf life of fresh tomatoes is nearly two weeks (Aguayo et al., 2004). Therefore, if a fresh tomato stays in inventory more than two weeks, it becomes spoiled and cost of waste occurs. The cost of waste is estimated as 0.6 €/kg based on the average marketplace selling price of tomatoes. The aim of the problem is to determine the routes and quantity of shipments in each week such that the total cost is minimized.

6.2. Analysis and Discussion

The ILOG-OPL development studio and CPLEX 12.6 optimization package has been used to develop and solve the presented formulations for the case study. The resulting integrated model, M_{PF}, has 1321 continuous and 1056 binary variables, and 1548 constraints. Optimal solutions were obtained on a computer of Pentium(R) i5 2.4GHz CPU with 3GB memory. Our experimentation shows that it takes on average nearly one and half hour to get optimal solutions. The simulation model is implemented in Visual C++ programming language. The simulation number (S) is set to 1000000.

We focus on six KPIs: (i) total emissions, (ii) total driving time, (iii) total routing cost comprised of fuel and wage cost, (iv) total inventory cost, (v) total waste cost, and (vi) total cost. Optimization models M, M_F, M_P and M_{PF} are assessed with respect to these KPIs.

6.2.1. Base case solution

Table 5 presents performance of the models with respect to all KPIs. According to the results, M and M_F, which neglect perishability, provide relatively lower total emissions, driving time and routing cost than M_P and M_{PF}. As it is shown in Table 7, M and M_F solutions propose different routes for the deliveries, i.e., resulting routes for the first period are different. However, total quantity of shipments to each supermarket in each period is the same that leads to the same inventory, waste and service level performances for the two models (see Table 6). In our problem, the demand for each customer in each week has to be satisfied with a probability of at least 95%. The achieved average service levels obtained from the simulation analysis show that M and M_F cannot always meet the desired service level, i.e., service level falls below 95% for supermarkets 1, 3, 9 and 10 in the last period (see Table 6). Therefore, optimal solutions obtained from M and M_F do not guarantee feasible solutions for our problem. These two models perform poor in terms of service level as they plan delivery amounts as if there is no chance of product wastes at customers. In the simulation analysis, waste occurrences nevertheless cause to encounter such cases where inventory falls below zero. Both optimization and simulation results presented in Table 5 confirm as well that the perishability ignorance in M and M_F leads to poor waste cost performance compared to the other two models, M_P and M_{PF}, which consider perishability of products. For instance, according to the simulation results, this ignorance causes more than five-fold increase in waste cost. To conclude, M and M_F outperforms M_P and M_{PF} in some KPIs, however, the simulation analysis show that M and M_F fail to generate a feasible plan for our problem.

[2] `http://halfiyatlari.org/izmir.html,Onlineaccessed:February2014`

Table 5: Summary results for base case

	KPIs	M	M_F	M_P	M_{PF}
Optimization Results	Average vehicle load (kg\km)	3506.0	3222.1	3493.3	2618.6
	# of vehicles used	7	7	8	8
	Total emissions (kg)	1449.0	1436.5	1898.4	1862.5
	Total driving time (h)	35.6	35.8	46.7	47.6
	Total fuel cost (€)	936.6	928.6	1227.1	1203.9
	Total wage cost (€)	385.0	386.7	504.0	514.5
	Total routing cost (€)	1321.6	1315.3	1731.1	1718.4
	Total inventory cost (€)	904.9	904.9	805.2	792.9
	Total waste cost (€)	1208.8	1208.8	61.4	61.4
	Total cost (€)	3435.3	3429.0	2597.6	2572.7
Simulation Results	Average total inventory cost (€)	895.8	895.8	790.6	774.5
	Average total waste cost (€)	1276.7	1276.7	198.9	198.9
	Average total cost (€)	3494.1	3487.8	2720.6	2691.8
	Achieved average service levels are presented in Table 6.				

Table 7 shows that M_P and M_{PF} solutions propose different routes for the deliveries. However, except for two supermarkets, 8 and 9, total quantity of shipments to the supermarkets in each period is the same, as shown in Table 6. M_P and M_{PF} meet the service level targets for all supermarkets in each period, since both of them account for product waste. These two models' solutions still cannot completely avoid waste occurrences due to the service level constraints. The service level constraints require to keep a certain amount of inventory at customers in all periods according to the demand means and coefficient of variation to satisfy the desired service level targets. In some circumstances, such as at supermarket 4 in period four, the desired service level requirement causes product wastes as a result of too much inventory. In particular, the vendor, who is responsible for the inventories at customers in our problem, bears waste risk to satisfy demand with a probability of at least 95%. It is a crucial task to balance product waste and out-of-stock in practice as well.

Vehicle load is dependent on the visiting order of the customers. We track the average vehicle load (kg\km) to investigate the effect of vehicle load size on the defined KPIs. M_F and M_{PF} take explicit fuel consumption concern into account and therefore account for vehicle load in addition to traveled distance while estimating fuel consumption amounts. According to the results presented in Table 5, M and M_F solutions propose to use seven vehicles for deliveries. Although M_F has worse total driving time or distance performance, it performs better than M in terms of total emissions due to the fact that M_F has less average vehicle load (see Table 5). M_P and M_{PF} solutions propose to use eight vehicles for deliveries. Similarly, less total driving time of M_P cannot guarantee less total emissions compared to M_{PF} due to the fact that M_P has higher average vehicle load. Explicit fuel consumption consideration in M_F and M_{PF} affects not only total emissions, but also the other KPIs, and routing and delivery decisions as shown in Tables 5, 6 and 7. In summary, results show that vehicle load affects fuel consumption and emissions and therefore it needs to be considered while making decisions in logistics. The effect of vehicle load on fuel consumption has also been shown in, e.g., Bektaş and Laporte (2011) and Demir et al. (2012), and our results confirm that the previous findings also hold in our problem.

Both optimization and simulation results reveal that M_{PF} including perishability and explicit fuel consumption concerns performs better than the other models in terms of total cost. M_F neglecting perishability concern has slightly better total cost performance than M neglecting perishability and explicit fuel consumption concerns. Resulting total cost of the M_{PF} solution is better

Table 6: Delivery, inventory, waste quantities and achieved average service levels for supermarkets during the whole planning horizon

Models	Cust. #	Delivery (kg) Weeks 1	2	3	4	Inventory (kg) Weeks 1	2	3	4	Waste (kg) Weeks 1	2	3	4	Achieved Service (%) Weeks 1	2	3	4
$M\&M_F$	1	1462	-	1689	-	562	-	689	-	-	162	-	89	100.0	95.0	100.0	77.1
	2	1630	1273	1817	1237	230	303	421	457	-	-	-	-	95.0	95.0	95.3	95.0
	3	1116	-	1990	-	616	-	740	-	-	116	-	140	100.0	95.0	100.0	84.1
	4	1281	2768	912	-	181	449	861	-	-	-	-	461	95.0	95.0	99.9	95.0
	5	1223	955	1608	1146	173	227	336	381	-	-	-	-	95.0	95.0	95.0	95.0
	6	1397	516	410	1497	197	214	224	321	-	-	-	-	94.9	94.9	94.9	94.9
	7	932	743	1035	-	132	175	710	-	-	-	-	210	95.0	95.0	100.0	95.0
	8	2213	407	304	1364	313	319	304	368	-		19	-	95.0	95.0	95.0	94.9
	9	932	1155	-	1397	132	887	-	97	-	-	187	-	95.0	100.0	95.0	76.6
	10	1281	2449	-	-	181	1030	-	-300	-	-	630	-	95.0	100.0	99.9	0.0
	11	3028	3451	2615	3359	428	678	793	952	-	-	-	-	95.0	95.0	95.0	95.0
$M_P\&M_{PF}$	1	1048	414	1069	620	148	162	231	251	-	-	-	-	95.0	95.0	95.0	95.0
	2	1630	1273	1809	1245	230	303	413	457	-	-	-	-	95.0	95.0	95.0	95.0
	3	582	534	1370	620	82	116	236	256	-	-	-	-	94.9	95.0	95.0	95.0
	4	1281	2768	507	405	181	449	457	405	-	-	-	57	95.0	95.0	95.0	95.0
	5	1223	955	1608	1146	173	228	336	381	-	-	-	-	95.0	95.0	95.0	95.0
	6	1397	516	410	1497	197	214	224	321	-	-	-	-	94.9	94.9	94.9	94.9
	7	932	743	518	517	132	175	193	210	-	-	-	-	95.0	95.0	95.0	95.0
	10	1281	1738	407	304	181	319	326	304	-	-	-	26	95.0	95.0	95.0	95.0
	11	3028	3451	2615	3359	428	678	793	952	-	-	-	-	95.0	95.0	95.0	95.0
M_P	8	2213	407	323	1364	313	300	323	388	-	19	-	-	95.0	95.0	96.0	95.7
	9	932	416	944	1193	132	147	391	284	-	-	-	-	95.0	95.1	100.0	95.1
M_{PF}	8	2213	407	304	1384	313	319	304	388	-	-	19	-	95.0	95.0	95.0	95.8
	9	932	416	740	1397	132	147	187	284	-	-	-	-	95.0	95.1	95.1	95.1

than that of M and M_F on average 33.4% according to the optimization results and on average 29.7% according to the simulation results. Additionally, as it is discussed before, M and M_F do not guarantee feasible solution for our problem. On one hand, M_P solutions meet service levels that show the benefit of perishability incorporation to the model. On the other hand, it performs nearly 1.1% worse than M_{PF} in terms of total cost in both optimization and simulation analysis that shows the cost of not incorporating explicit fuel consumption to the model. To conclude, results present the importance of perishability and explicit fuel consumption issues on the studied problem.

Our analysis on the base case show the consequences of perishability and/or explicit fuel consumption ignorance. M_{PF} takes these two aspects into account simultaneously. The models M, M_F

Table 7: Resulting routes from the models

Models	Routes	Weeks 1	2	3	4
M	1^{st}	0-7-6-5-2-3-4-0	0-11-10-9-8-7-6-5-0	0-4-3-2-0	0-11-8-9-6-5-2-0
	2^{nd}	0-1-8-9-10-11-0	0-4-2-0	0-1-11-8-7-6-5-0	-
M_F	1^{st}	0-11-7-6-5-2-3-4-0	0-11-10-9-8-7-6-5-0	0-4-3-2-0	0-11-8-9-6-5-2-0
	2^{nd}	0-1-8-9-10-11-0	0-4-2-0	0-1-11-8-7-6-5-0	-
M_P	1^{st}	0-7-6-5-2-3-4-0	0-1-11-10-9-8-7-6-5-0	0-4-3-2-0	0-4-3-2-0
	2^{nd}	0-1-8-9-10-11-0	0-4-3-2-0	0-1-11-10-9-8-7-6-5-0	0-1-11-10-9-8-7-6-5-0
M_{PF}*	1^{st}	0-11-7-6-5-2-3-4-0	0-11-10-9-6-5-7-8-1-0	0-4-3-2-0	0-1-8-9-10-0
	2^{nd}	0-1-8-9-10-11-0	0-4-3-2-0	0-1-11-10-9-8-7-6-5-0	0-11-7-6-5-2-3-4-0

* Resulting routes from M_{PF} are also visualised in the Figure 3.

Figure 3: Representation of the resulting routes from M_{PF} for each period

and M_P that account for none of the aspects or only a single aspect provide optimal plans for our problem that are higher in cost compared to M_{PF}. Moreover, M and M_F that disregard quality decay cannot meet the desired service level. The managerial implication of these results is that use of the proposed integrated model, M_{PF}, can provide least cost solutions for the studied problem while satisfying the service level requirements. In the coming section, we carry out further analysis to observe the performances of these models under different scenarios.

6.2.2. Sensitivity analysis

This section presents sensitivity analysis for the models with respect to changes in the demand means, coefficient of variation, maximum shelf life, holding cost, service level, fuel price and vehicle speed. In particular, 17 scenarios have been formulated for the sensitivity analysis. In each scenario, different model parameters (demand means, $d_{i,t}$: Demand 1,2, coefficient of variations: $C = 0.05, 0.15, 0.2$, fixed shelf lives, weeks,: $m = 3, 4$, holding costs per period,€/kg,: $h = 0.03, 0.09, 0.12$, service levels, %, : $\alpha = 90, 92.5, 97.5$, fuel price,€/l,: $l = 1.2, 2.2$ and vehicle speed, km/h,: $f = 40, 120$) are employed to observe the effects of changes in the related parameters on the defined KPIs. Results of the optimization sensitivity analysis are presented in Table 8.

• *Comparison among models in terms of total cost:*

In all scenarios, M_{PF} performs better than M in terms of total cost. Average total cost gap between the two model solutions is 24.3% according to the optimization results and 21.7% according to the simulation results. The results do not indicate a systematic total cost gap change between M and M_{PF} as l or f changes, whereas the total cost gap between the two model solutions increases as C or α increases. The C or α increase leads to waste cost increase in both model solutions. However, the waste cost increase in M solution is more than that in M_{PF} solution. For instance, the waste cost of M solution is €689 more than that of M_{PF} solution when $C = 0.05$, whereas this cost difference increases to €1807 when $C = 0.2$. Similarly, the waste cost of M solution is €975 more than that of M_{PF} solution when $\alpha = 90\%$, whereas this cost difference increases to €1253

Table 8: Results of optimization sensitivity analysis

Scenarios	Models	Total emissions (kg)	Total driving time (h)	Total fuel cost (€)	Total wage cost (€)	Total routing cost (€)	Total inventory cost (€)	Total waste cost (€)	Total cost (€)
Base case	M	1449.0	35.6	936.6	385.0	1321.6	904.9	1208.8	3435.3
	M_F	1436.5	35.8	928.6	386.7	1315.3	904.9	1208.8	3429.0
	M_P	1898.4	46.7	1227.1	504.0	1731.1	805.2	61.4	2597.6
	M_{PF}	1862.5	47.6	1203.9	514.5	1718.4	792.9	61.4	2572.7
Demand 1*	M	1585.7	39.1	1025.0	421.9	1446.9	769.9	915.2	3132.0
	M_F	1552.5	39.5	1003.5	426.8	1430.3	769.9	915.2	3115.4
	M_P	1909.5	46.7	1234.3	503.9	1738.2	767.5	107.5	2613.2
	M_{PF}	1856.0	47.5	1199.7	513.1	1712.8	767.5	107.5	2587.8
Demand 2*	M	1653.7	39.6	1069.0	427.9	1496.8	895.5	495.9	2888.3
	M_F	1685.1	41.4	1089.2	446.7	1535.9	861.4	495.9	2893.3
	M_P	1914.6	46.7	1237.6	503.9	1741.5	842.5	0.0	2584.0
	M_{PF}	1891.6	46.9	1222.7	506.7	1729.4	842.5	0.0	2571.9
$C = 0.05$	M	1439.6	35.6	930.5	385.0	1315.5	585.4	688.6	2589.5
	M_F	1422.0	35.8	919.2	386.2	1305.3	585.4	688.6	2579.3
	M_P	1886.9	46.7	1219.6	504.0	1723.6	399.5	0.0	2123.1
	M_{PF}	1846.9	47.3	1193.8	511.2	1705.0	399.5	0.0	2104.5
$C = 0.15$	M	1458.3	35.6	942.6	385.0	1327.6	1207.8	1813.2	4348.6
	M_F	1506.0	37.8	973.5	408.8	1382.2	1179.4	1380.0	3941.6
	M_P	1942.4	47.0	1255.5	507.5	1763.0	1159.4	392.0	3314.5
	M_{PF}	1874.5	47.7	1211.7	515.4	1727.1	1159.4	392.0	3278.5
$C = 0.2$	M	1487.7	36.1	961.6	389.6	1351.2	1469.8	2546.6	5367.6
	M_F	1559.7	39.2	1008.2	422.9	1431.1	1447.3	1752.1	4630.5
	M_P	1950.7	47.0	1260.9	507.6	1768.5	1524.2	739.4	4032.0
	M_{PF}	1882.2	48.0	1216.6	518.3	1734.9	1524.2	739.4	3998.4
$m = 3$ weeks	M	1449.0	35.6	936.6	385.0	1321.6	1071.5	197.9	2591.0
	M_F	1436.5	35.8	928.6	386.7	1315.3	1071.5	197.9	2584.7
	M_P	1515.2	37.2	979.4	402.0	1381.4	1056.7	0.0	2438.1
	M_{PF}	1538.8	39.0	994.7	421.1	1415.8	997.5	15.7	2429.0
$m = 4$ weeks	M	1449.0	35.6	936.6	385.0	1321.6	1091.3	0.0	2412.9
	M_F	1436.5	35.8	928.6	386.7	1315.3	1091.3	0.0	2406.6
	M_P	1449.1	35.6	936.7	385.0	1321.6	1091.3	0.0	2413.0
	M_{PF}	1436.5	35.8	928.6	386.7	1315.3	1091.3	0.0	2406.6
$h = 0.03$ €/kg	M	1264.4	30.5	817.3	329.4	1146.8	538.9	1899.8	3585.4
	M_F	1304.6	32.2	843.2	347.6	1190.9	518.1	1533.7	3242.7
	M_P	1898.3	46.7	1227.0	504.0	1731.0	402.6	61.4	2194.9
	M_{PF}	1855.6	47.4	1199.4	511.7	1711.1	402.6	61.4	2175.1
$h = 0.09$ €/kg	M	1746.9	43.2	1129.2	466.6	1595.7	1197.8	410.6	3204.1
	M_F	1765.7	44.8	1141.3	484.1	1625.4	1181.1	340.8	3147.3
	M_P	1927.1	47.0	1245.7	507.5	1753.2	1189.4	61.4	3003.9
	M_{PF}	1862.4	47.6	1203.9	514.5	1718.3	1189.4	61.4	2969.1
$h = 0.12$ €/kg	M	1850.6	45.7	1196.2	493.4	1689.6	1583.5	243.6	3516.7
	M_F	1818.4	46.2	1175.4	498.9	1674.3	1583.5	243.6	3501.4
	M_P	1927.3	47.0	1245.8	507.5	1753.3	1585.8	61.4	3400.4
	M_{PF}	1862.4	47.6	1203.9	514.5	1718.3	1585.8	61.4	3365.5

Scenarios	Models	Total emissions (kg)	Total driving time (h)	Total fuel cost (€)	Total wage cost (€)	Total routing cost (€)	Total inventory cost (€)	Total waste cost (€)	Total cost (€)
$\alpha = 90\%$	M	1444.9	35.6	934.0	385.0	1319.0	766.1	974.6	3059.6
	M_F	1430.4	35.8	924.6	386.7	1311.3	766.1	974.6	3052.0
	M_P	1893.2	46.7	1223.7	504.0	1727.7	629.8	0.0	2357.5
	M_{PF}	1850.6	47.3	1196.2	511.2	1707.4	629.8	0.0	2337.2
$\alpha = 92.5\%$	M	1446.7	35.6	935.1	385.0	1320.1	826.6	1070.4	3217.1
	M_F	1433.1	35.8	926.3	386.7	1313.1	826.6	1070.4	3210.1
	M_P	1895.3	46.7	1225.1	504.0	1729.1	707.9	0.0	2437.0
	M_{PF}	1858.0	47.6	1201.0	513.9	1714.9	699.5	0.0	2414.4
$\alpha = 97.5\%$	M	1452.9	35.6	939.1	385.0	1324.1	1024.3	1440.3	3788.7
	M_F	1501.3	37.8	970.4	408.8	1379.2	1001.8	1046.8	3427.8
	M_P	1932.1	47.0	1248.9	507.5	1756.4	933.3	188.0	2877.7
	M_{PF}	1868.4	47.6	1207.7	514.5	1722.2	933.3	188.0	2843.4
$l = 1.2$ €/l	M	1560.8	38.6	712.1	416.5	1128.6	868.0	657.8	2654.4
	M_F	1587.4	40.3	724.3	435.4	1159.7	839.2	573.9	2572.8
	M_P	1927.1	47.0	879.3	507.5	1386.8	792.9	61.4	2241.1
	M_{PF}	1866.4	47.4	851.6	512.2	1363.8	792.9	61.4	2218.1
$l = 2.2$ €/l	M	1449.0	35.6	1212.1	385.0	1597.1	904.9	1208.8	3710.8
	M_F	1436.6	35.8	1201.7	386.7	1588.4	904.9	1208.8	3702.1
	M_P	1898.4	46.7	1588.0	504.0	2092.0	805.2	61.4	2958.5
	M_{PF}	1862.4	47.6	1557.9	514.5	2072.4	792.9	61.4	2926.6
$f = 40$ km/h	M	1401.6	71.3	906.0	770.0	1675.9	904.9	1208.8	3789.6
	M_F	1388.9	71.6	897.8	773.4	1671.2	904.9	1208.8	3784.9
	M_P	1836.2	93.3	1186.9	1007.9	2194.8	805.2	61.4	3061.3
	M_{PF}	1803.4	94.9	1165.7	1024.4	2190.1	792.9	61.4	3044.4
$f = 120$ km/h	M	1973.6	23.8	1275.7	256.7	1532.4	904.9	1208.8	3646.0
	M_F	1963.5	23.9	1269.2	257.8	1527.0	904.9	1208.8	3640.7
	M_P	2585.0	31.1	1670.9	336.0	2006.9	805.2	61.4	2873.4
	M_{PF}	2564.3	31.6	1657.5	341.5	1999.0	792.9	61.4	2853.2

C: Coefficient of variation, m: fixed maximum shelf life, h: holding cost, α: service level.
* Demand mean set is presented in Table 11.

when $\alpha = 97.5\%$. The differences in waste cost changes thus mainly causes extension of the total cost gap between these two models as C or α increases.

In a similar, but reverse way, the total cost gap between M_{PF} and M solutions decreases as m or h increases. The reason is that the waste cost decrease in M solution due to the m or h increase is more than that in M_{PF} solution. For instance, the waste cost of M solution is €1147 more than that of M_{PF} solution when $m = 2$, whereas this cost difference decreases to €0 when $m = 4$. Similarly, the waste cost of M solution is €1838 more than that of M_{PF} solution when $h = 0.03$, whereas this cost difference decreases to €182 when $h = 0.12$. The differences in waste cost changes thus mainly causes reduction of the total cost gap between these two models as m or h increases.

M_F and M_{PF} provide the same solutions in scenario $m = 4$ where fixed shelf life is equal to the planning horizon length. In this scenario, these models have thus the same total cost performances, whereas M_{PF} has better cost performance than M_F in the rest of the scenarios. Average total cost gap between the two model solutions is 20.5% according to the optimization results and 18.2% according to the simulation results. The results do not indicate a systematic total cost gap change between M_F and M_{PF} as C, α, l or f changes. However, similar with the case between M and M_{PF}, the total cost gap between M_F and M_{PF} solutions decreases as m or h increases. This is mainly due to the fact that the waste cost decrease in M_F solution is more than that in M_{PF} solution.

In all scenarios, M_{PF} performs better than M_P in terms of total cost. However, the total cost gaps, on average 0.9% according to the optimization results and 0.8% according to the simulation results, are relatively smaller than those observed between M_{PF} and M or M_F. The results do not indicate a systematic total cost gap change between M_{PF} and M_P as C, h or f changes. However, the total cost gap between M_{PF} and M_P solutions slightly increases as α or l increases and the gap slightly decreases as m increases without a systematic waste cost change as it has been observed in the previous analysis.

The simulation analysis indicate parallel results with the optimization results except a case in the scenario $m = 3$. According to the optimization results, M_{PF} performs 0.4% better than M_P in terms of total cost, whereas simulation results indicate that total cost performance of M_P is 1.1% better than M_{PF}. This is mainly due to the difference in waste cost performances. According to the optimization results, waste cost of M_{PF} solution is €15.7 more than that of M_P solution, whereas the realized difference observed from the simulation analysis is €55. This waste cost increase causes M_{PF} to perform worse than M_P. Therefore, if only optimization results are considered, a decision maker may disregard M_P solution that shows better performance in the simulation analysis. This case reveals the benefit of conducting simulation analysis on the delivery schedules obtained from the optimization models, which are the approximations of the stochastic problems.

So far in this subsection relative total cost performances of the models are presented. We now present the effects of changes in the C, m, h, α, l and f to the total costs of models as follows: (i) Total costs of all model solutions increase as C increases. The main drivers of the increase in total costs are growths in inventory and waste amounts. (ii) Total costs of all model solutions decrease as m increases. The main drivers of the decrease in total costs are reductions in routing and waste costs. (iii) Total costs of M_P and M_{PF} solutions increase as h increases. The main contribution to these growths comes from increasing inventory costs. However, the results do not indicate a systematic total cost change for M and M_F as h changes. (iv) Total costs of all model solutions except M_F increase as α increases. The main contribution to these growths comes from increasing inventory costs. (v) Total costs of all model solutions increase as l increases. The main contribution to these growths comes from increasing routing costs. (vi) The results do not indicate a systematic total cost change for all models as f changes.

- *Comparison among models in terms of other KPIs:*

In all except three scenarios ($m = 3, 4$ and $h = 0.12$), M and M_F cannot meet the service level requirements for each customer and period, and thus do not guarantee feasible solutions for the studied problem. Note that the resulting waste costs of M and M_F solutions in the scenarios $m = 3, 4$ and $h = 0.12$ are relatively lower than that obtained in the other scenarios, where these two models do not provide feasible solutions. This shows that the stock-out risk increases when the product waste increases. On the contrary, M_P and M_{PF} achieve to satisfy the service targets in all scenarios, since these two models take perishability and therefore waste into account.

In all except one scenario ($m = 4$), M and M_F show relatively better performance with respect to total emissions, total driving time and total routing cost compared to M_P and M_{PF}. However, note that except the three scenarios ($m = 3, 4$ and $h = 0.12$), M and M_F provide infeasible solutions for the studied problem.

In all except one scenario ($m = 3$), routing and delivery plans obtained from M_{PF} provide less emissions compared to that from M_P. We note that M_{PF} does guarantee less total cost but not less total emissions, since it aims to minimize cost.

• *A general overview:*

The results show that the basic model, M, which does not account for perishability and explicit fuel consumption, has poor cost performance largely due to the higher waste costs compared to the other models. Moreover, M often cannot provide feasible solutions for the problem. Extending M through incorporating explicit fuel consumption has usually slightly improved the total cost performance, but still cannot ensure to have feasible solutions. On the contrary, extension of M through incorporating perishability has significantly improved the total cost performance in all except one scenario ($m = 4$), where perishability is not a crucial issue anymore. Additionally, the new ability of the model to account for product wastes has enabled to have feasible solutions for the problem in all scenarios. Finally, the integrated model, M_{PF}, which is the extended version of M in terms of perishability and explicit fuel consumption, has provided the least cost and feasible solutions in all scenarios. The main managerial implication of the results is that perishability and explicit consideration of fuel consumption are important aspects in the IRP and the proposed integrated model, M_{PF}, which accounts for the both aspects, offers better support to decision makers.

6.2.3. Environmental impact minimization

In our problem, total emissions and total waste are the environmental condition indicators that reflect the state of the physical environment affected by the logistics operations. M_{PF} quantifies the total environmental impact in terms of cost through fuel and waste cost components in the objective function (1). In this section, the objective function is adapted so that the model can provide an optimal solution which has the lowest total environmental impact cost. In particular, the expected inventory (1.i) and driver (1.iv) cost components are removed from the objective function (1), and the formulation is minimized over an environmental objective function that comprises only expected waste (1.ii) and fuel (1.iii) costs. This change ensures to obtain the most environmentally-friendly solution in terms of total emissions and waste. The new variation of M_{PF} that has emphasis only on reducing fuel and waste costs is denoted as M'_{PF}. Figure 4 presents the performance of M'_{PF} compared to M_{PF}.

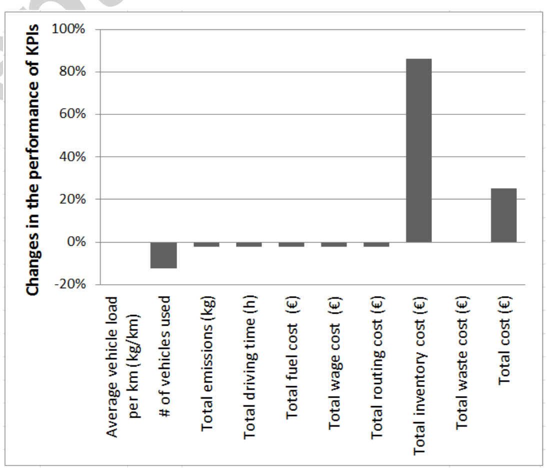

Figure 4: The performance of M'_{PF} compared to the M_{PF} for the base case.

The results show that M'_{PF} slightly outperforms M_{PF} in terms of number of vehicles used, total emissions, total driving time, and total fuel, wage and routing costs. M'_{PF} solution ensures to have nearly 2% reductions in total emissions (39.6kg), total driving time (one hour), and total fuel (€25.6), wage (€10.6) and routing costs (€36.2) with one less vehicle in total compared to M_{PF} solution. However, M_{PF} performs 86.2% better in terms of total inventory cost (€683.6) and 25.2% in terms of total cost (€647.4) compared to M'_{PF}. Both model solutions have the same total waste costs. This means that nearly 2% total emissions reduction through the use of environmental objective comes at a cost increase of 25.2%. Therefore, additional cost of having a more environmentally-friendly solution is significant for the studied problem. In summary, M_{PF} provides the least cost solution, however, there can be still room to reduce the total environmental impact comprised of emissions and waste by means of M'_{PF}.

6.2.4. Modified larger case study

In order to show the performances of the models in a larger problem, we have modified the network. In the new modified setting, nine artificial customers are added (see Figure 5) and three vehicles (one more compared to the base case) are employed for the deliveries. Distances between the nodes and customer demands are shown in Tables 10 and 12. The resulting integrated model, M_{PF}, has 5521 continuous and 5040 binary variables, and 6092 constraints for the new relatively large case study.

Figure 5: Representation of the modified logistics network

Table 9 presents the results obtained from the models with a solver cut-off time of five hours. The lower bound gap reported in the table shows the percentage gap from the best-known lower bound provided by the solver. In contrast to the base case, where optimal solutions for the integrated model M_{PF} are obtained within nearly one and half hour, for the larger problem, either optimal solutions for the models have not been obtained yet or optimality of the solutions have not been

Table 9: Summary results for the large case

Models	Total emissions (kg)	Total driving time (h)	Total fuel cost (€)	Total wage cost (€)	Total routing cost (€)	Total inventory cost (€)	Total waste cost (€)	Total cost (€)	Lower bound gap (%)
M	2380.0	54.0	1538.4	583.0	2121.4	1319.6	574.9	4015.9	1.34
M_F	2362.2	57.5	1526.9	620.6	2147.5	1308.8	549.8	4006.2	4.14
M_P	2489.1	57.7	1608.9	623.1	2232.0	1348.9	114.3	3695.2	2.58
M_{PF}	2362.8	59.3	1527.3	640.4	2167.7	1327.2	114.3	3609.3	2.48

proved yet within five hours. This shows the increasing complexity of the problem as the case size increases.

Regarding performances of the models in terms of the defined KPIs, similar results are obtained with the base case. Results for the larger case confirm the benefit of taking perishability and explicit fuel consumption into account as well. According to the optimization results, integrated model M_{PF} has achieved total cost savings by 11.3% compared to M, 11% compared to M_F and 2.4% compared to M_P. Additionally, simulation results show that M and M_F cannot meet the desired service levels, whereas M_P and M_{PF} satisfy the service levels.

7. Conclusions

In this paper, we have modeled and analyzed the IRP to account for perishability, explicit fuel consumption and demand uncertainty. To the best of our knowledge, the model is unique in using a comprehensive emission function and in modeling waste and service level constraints as a result of uncertain demand. The proposed model can be used to aid food logistics decision-making process in coordinating inventory and transportation decisions in VMI systems.

We have showed the added value of the proposed model M_{PF} based on case study data and a broad set of experiments. To present the benefits of considering perishability and explicit fuel consumption in the model, the following model variations are employed: (i) M which ignores the perishability of products and explicit fuel consumption, (ii) M_F which ignores the perishability of products and (iii) M_P which ignores explicit fuel consumption. M and M_F cannot meet the desired service levels in all scenarios due to the perishability ignorance which results in relatively higher product wastes. On the contrary, accounting for the perishability allows M_P and M_{PF} to satisfy the service levels in all scenarios. M_{PF} outperforms the other variations of the model in terms of total cost. According to the optimization results, M_{PF} can achieve average savings in total cost by 24.3% compared to M, 20.5% compared to M_F and 0.9% compared to M_P. In the experiments, we have changed the values of the following problem parameters: the demand means, coefficient of variations, fixed shelf lives, holding costs service levels, fuel price and vehicle speed. It appears that the added value of M_{PF} compared to the other model variations in terms of total cost changes according to the parameter values. For instance, the total cost gap between M and M_{PF} solutions increases as C or α increases and decreases as m or h increases. Additionally, the use of more environmentally-friendly objective function (in model M'_{PF}) shows that 2% decrease in total emissions can be obtained in return for a 25.2% significant total cost increase.

The results support the view that the improvement of the IRP model through perishability and explicit fuel consumption incorporation makes it more useful than a basic model that disregards both aspects for the decision makers in food logistics management. One possible extension of the paper is to develop a heuristic algorithm for the studied problem, which will enable to handle instances that are larger in size. The model proposed in this paper can be used to validate and verify the potential of such heuristic algorithms. The other possible extension is to consider a generic logistics network that has many-to-many (multiple suppliers and customers) distribution structure.

APPENDIX

In this section, we present the distance and demand data used for the models.

Table 10: Distances between nodes, in kms

	DC	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
DC	-	67	89.2	126	78.1	70.6	106	66.3	64.4	156	151	35.5	139	118	37	49	116	155	52	97	93
1	73.2	-	154	191	143	144	141	101	74.3	166	176	61.5	165	144	110	123	181	221	52	123	119
2	70.8	136	-	65.9	62.9	113	158	118	126	218	212	97.2	201	180	81	66	101	96	51	159	155
3	126	192	69.5	-	98.9	171	233	193	182	274	268	153	259	238	142	129	139	68	119	216	213
4	78.4	144	63.2	99.7	-	123	185	145	134	226	220	105	208	187	91	79	38	95	98	166	162
5	70.9	144	105	163	115	-	50.2	58.4	120	155	220	105	196	114	36	38	106	193	113	167	163
6	106	131	161	222	175	50.9	-	41.6	75.3	105	199	84.4	149	66	87	89	157	264	148	144	135
7	66.5	91.2	121	182	135	58.2	40.1	-	35.3	117	159	44.4	111	78	44	60	169	209	108	104	95
8	67.4	74.9	149	185	137	92.7	74.4	34.5	-	92.1	120	34.8	78	54	78	117	175	215	99	71	62
9	158	166	239	276	228	155	106	116	92.4	-	69.6	126	43	39	160	176	266	306	190	123	89
10	150	176	232	268	220	221	192	152	119	70	-	119	30	109	187	200	258	298	182	95	61
11	35	60.3	116	153	105	106	83.6	43.7	30.6	123	118	-	107	84	72	84	143	182	66	65	61
12	139	165	220	257	209	196	149	110	79	44	30	108	-	83	176	189	247	287	171	84	50
13	120	145	201	238	190	113	66	78	54	40	109	87	83	-	122	133	228	267	151	123	114
14	37	110	84	140	92	36	86	44	77	154	180	71	175	120	-	20	130	170	92	132	129
15	50	127	69	127	79	38	83	60	117	205	198	88	192	171	21	-	117	156	77	150	146
16	115	181	100	137	39	106	222	182	171	258	251	142	245	224	128	116	-	77	135	203	199
17	157	222	95	68	95	201	263	223	212	300	292	183	287	265	170	157	77	-	146	244	240
18	56	52	54	117	99	124	149	109	98	185	178	69	172	151	92	76	137	146	-	130	126
19	96	122	177	214	166	167	143	103	70	123	89	65	83	122	133	146	204	244	128	-	36
20	93	118	174	210	163	163	134	94	61	89	55	61	50	114	129	142	201	240	124	37	-

Table 11: Demand means (kg) for the supermarkets in each week in different scenarios

	Base case demand set				Demand set 1				Demand set 2			
	Weeks				Weeks				Weeks			
Supermarkets	1	2	3	4	1	2	3	4	1	2	3	4
1	900	400	1000	600	500	1400	1300	300	1500	1000	2600	2000
2	1400	1200	1700	1200	800	1100	1500	1800	2000	500	1200	800
3	500	500	1250	600	1300	600	1000	1900	300	750	900	600
4	1100	2500	500	400	1600	2200	800	600	3000	1150	700	2100
5	1050	900	1500	1100	800	700	900	900	800	550	800	400
6	1200	500	400	1400	2000	800	200	1200	500	3000	1500	1800
7	800	700	500	500	700	300	2500	800	200	1000	400	400
8	1900	400	300	1300	600	1200	1300	1100	1600	600	300	600
9	800	400	700	1300	250	1100	600	600	2200	400	2300	2200
10	1100	1600	400	300	900	300	1100	400	900	900	600	300
11	2600	3200	2500	3200	1800	2200	2500	3400	1400	1100	400	1000
Total	13350	12300	10750	11900	11250	11900	13700	13000	14400	10950	11700	12200

Table 12: Demand means (kg) for the supermarkets in each week for the large case

	Weeks			
Supermarkets	1	2	3	4
1	900	400	1000	600
2	1400	1200	1700	1200
3	500	500	1250	600
4	1100	2500	500	400
5	1050	900	1500	1100
6	1200	500	400	1400
7	800	700	500	500
8	1900	400	300	1300
9	800	400	700	1300
10	1100	1600	400	300
11	2600	3200	2500	3200
12	700	400	800	600
13	1200	1200	1900	800
14	600	500	1250	600
15	1300	2600	600	400
16	1050	700	1400	900
17	1300	500	400	1400
18	700	800	600	500
19	1500	400	300	1200
20	800	400	1100	600
Total	22500	19800	19100	18900

References

Aghezzaf, E.H., Raa, B., Van Landeghem, H., 2006. Modeling inventory routing problems in supply chains of high consumption products. European Journal of Operational Research 169, 1048–1063.

Aguayo, E., Escalona, V., Artés, F., 2004. Quality of fresh-cut tomato as affected by type of cut, packaging, temperature and storage time. European Food Research and Technology 219, 492–499.

Al Shamsi, A., Al Raisi, A., Aftab, M., 2014. Pollution-inventory routing problem with perishable goods, in: Golinska, P. (Ed.), Logistics Operations, Supply Chain Management and Sustainability. Springer International Publishing. EcoProduction, pp. 585–596.

Alkawaleet, N., Hsieh, Y.F., Wang, Y., 2014. Inventory routing problem with CO_2 emissions consideration, in: Golinska, P. (Ed.), Logistics Operations, Supply Chain Management and Sustainability. Springer International Publishing. EcoProduction, pp. 611–619.

Amorim, P., Meyr, H., Almeder, C., Almada-Lobo, B., 2011. Managing perishability in production-distribution planning: a discussion and review. Flexible Services and Manufacturing Journal , 1–25.

Andersson, H., Hoff, A., Christiansen, M., Hasle, G., Løkketangen, A., 2010. Industrial aspects and literature survey: Combined inventory management and routing. Computers & Operations Research 37, 1515–1536.

Bakker, M., Riezebos, J., Teunter, R.H., 2012. Review of inventory systems with deterioration since 2001. European Journal of Operational Research 221, 275–284.

Bard, J.F., Nananukul, N., 2009. Heuristics for a multiperiod inventory routing problem with production decisions. Computers & Industrial Engineering 57, 713–723.

Barth, M., Boriboonsomsin, K., 2009. Energy and emissions impacts of a freeway-based dynamic eco-driving system. Transportation Research Part D 14, 400–410.

Barth, M., Younglove, T., Scora, G., 2005. Development of a Heavy-Duty Diesel Modal Emissions and Fuel Consumption Model. Technical Report. California Path Program Intitute of Transportation Studies, University of California, Berkeley.

Bektaş, T., Laporte, G., 2011. The Pollution-Routing problem. Transportation Research Part B 45, 1232–1250.

Bertazzi, L., Bosco, A., Guerriero, F., Lagana, D., 2013. A stochastic inventory routing problem with stock-out. Transportation Research Part C: Emerging Technologies 27, 89–107.

Bertazzi, L., Savelsbergh, M., Speranza, M.G., 2008. Inventory routing, in: The vehicle routing problem: latest advances and new challenges. Springer, pp. 49–72.

Bookbinder, J.H., Tan, J.Y., 1988. Strategies for the probabilistic lot-sizing problem with service-level constraints. Management Science 34, 1096–1108.

Campbell, A., Clarke, L., Kleywegt, A., Savelsbergh, M., 1998. The inventory routing problem, in: Fleet management and logistics, pp. 95–113.

Campbell, A.M., Savelsbergh, M.W.P., 2004. A decomposition approach for the inventory-routing problem. Transportation Science 38, 488–502.

Charnes, A., Cooper, W.W., 1959. Chance-constrained programming. Management science 6, 73–79.

Coelho, L.C., Cordeau, J.F., Laporte, G., 2012a. The inventory-routing problem with transshipment. Computers & Operations Research 39, 2537–2548.

Coelho, L.C., Cordeau, J.F., Laporte, G., 2012b. Thirty years of inventory-routing. Technical Report. CIRRELT-2012-52, CIRRELT, Montreal, Canada.

Coelho, L.C., Laporte, G., 2013. The exact solution of several classes of inventory-routing problems. Computers & Operations Research 40, 558–565.

Coelho, L.C., Laporte, G., 2014. Optimal joint replenishment, delivery and inventory management policies for perishable products. Computers & Operations Research , –.

Defra, 2007. Guidelines to Defra's GHG conversion factors for company reporting - Annexes updated June 2007. Technical Report. Department for Environment, Food and Rural Affairs.

Demir, E., Bektaş, T., Laporte, G., 2011. A comparative analysis of several vehicle emission models for road freight transportation. Transportation Research Part D: Transport and Environment 16, 347–357.

Demir, E., Bektaş, T., Laporte, G., 2012. An adaptive large neighborhood search heuristic for the Pollution-Routing problem. European Journal of Operational Research 223, 346–359.

Demir, E., Bektaş, T., Laporte, G., 2014. A review of recent research on green road freight transportation. European Journal of Operational Research 237, 775–793.

Federgruen, A., Prastacos, G., Zipkin, P.H., 1986. An allocation and distribution model for perishable products. Operations Research 34, 75–82.

Franceschetti, A., Honhon, D., Van Woensel, T., Bektaş, T., Laporte, G., 2013. The time-dependent Pollution-Routing problem. Transportation Research Part B Methodological 56, 265–293.

Haijema, R., 2013. A new class of stock-level dependent ordering policies for perishables with a short maximum shelf life. International Journal of Production Economics 143, 434–439.

Al-e hashem, S.M.J.M., Rekik, Y., 2013. Multi-product multi-period inventory routing problem with a transshipment option: A green approach. International Journal of Production Economics , –.

Hemmelmayr, V., Doerner, K.F., Hartl, R.F., Savelsbergh, M.W., 2010. Vendor managed inventory for environments with stochastic product usage. European Journal of Operational Research 202, 686–695.

Hendrix, E.M.T., Haijema, R., Rossi, R., Pauls-Worm, K.G.J., 2012. On solving a stochastic programming model for perishable inventory control, in: Murgante, B., Gervasi, O., Misra, S., Nedjah, N., Rocha, A.A.C., Taniar, D., Apduhan, B.O. (Eds.), Computational Science and Its Applications ICCSA 2012. Springer Berlin Heidelberg. volume 7335 of *Lecture Notes in Computer Science*, pp. 45–56.

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

Hvattum, L.M., Løkketangen, A., 2009. Using scenario trees and progressive hedging for stochastic inventory routing problems. Journal of Heuristics 15, 527–557.

Jemai, Z., Rekik, Y., Kalai, R., 2013. Inventory routing problems in a context of vendor-managed inventory system with consignment stock and transshipment. Production Planning & Control 24, 671–683.

Jia, T., Li, X., Wang, N., Li, R., 2014. Integrated inventory routing problem with quality time windows and loading cost for deteriorating items under discrete time. Mathematical Problems in Engineering , 1–14.

Kara, I., Kara, B.Y., Yetis, M.K., 2007. Energy minimizing vehicle routing problem, in: Dress, A., Xu, Y., Zhu, B. (Eds.), Combinatorial Optimization and Applications. Springer Berlin Heidelberg. volume 4616 of *Lecture Notes in Computer Science*, pp. 62–71.

Karaesmen, I.Z., SchellerWolf, A., Deniz, B., 2011. Managing perishable and aging inventories: Review and future research directions, in: Kempf, K.G., Keskinocak, P., Uzsoy, R. (Eds.), Planning Production and Inventories in the Extended Enterprise. Springer US. volume 151 of *International Series in Operations Research & Management Science*, pp. 393–436.

Kuo, Y., Wang, C., 2011. Optimizing the VRP by minimizing fuel consumption. Management of Environmental Quality: An International Journal 22, 440–450.

Le, T., Diabat, A., Richard, J.P., Yih, Y., 2013. A column generation-based heuristic algorithm for an inventory routing problem with perishable goods. Optimization Letters 7, 1481–1502.

Lin, C., Choy, K.L., Ho, G.T.S., Chung, S.H., Lam, H.Y., 2014. Survey of Green Vehicle Routing Problem: Past and future trends. Expert Systems with Applications 41, 1118–1138.

Minner, S., Transchel, S., 2010. Periodic review inventory-control for perishable products under service-level constraints. OR spectrum 32, 979–996.

Moin, N.H., Salhi, S., 2007. Inventory routing problems: A logistical overview. The Journal of the Operational Research Society 58, 1185–1194.

Nahmias, S., 1982. Perishable inventory theory: A review. Operations Research 30, 680–708.

Pauls-Worm, K.G.J., Hendrix, E.M.T., Haijema, R., van der Vorst, J.G.A.J., 2014. An MILP approximation for ordering perishable products with non-stationary demand and service level constraints. International Journal of Production Economics 157, 133–146.

Qin, L., Miao, L., Ruan, Q., Zhang, Y., 2014. A local search method for periodic inventory routing problem. Expert Systems with Applications 41, 765–778.

Raa, B., Aghezzaf, E.H., 2009. A practical solution approach for the cyclic inventory routing problem. European Journal of Operational Research 192, 429–441.

Rahim, M.K.I.A., Zhong, Y., Aghezzaf, E., Aouam, T., 2014. Modelling and solving the multiperiod inventory-routing problem with stochastic stationary demand rates. International Journal of Production Research , 1–13.

Rong, A.Y., Akkerman, R., Grunow, M., 2011. An optimization approach for managing fresh food quality throughout the supply chain. International Journal of Production Economics 131, 421–429.

Rossi, R., Tarim, S.A., Hnich, B., Prestwich, S., 2008. A global chance-constraint for stochastic inventory systems under service level constraints. Constraints 13, 490–517.

Rossi, R., Tarim, S.A., Hnich, B., Prestwich, S.D., 2010. Computing replenishment cycle policy parameters for a perishable item. Proceedings of the 24th MEC-EurOPT-2010, Izmir, Turkey , 241–247.

Soysal, M., Bloemhof, J.M., Meuwissen, M.P.M., Van der Vorst, J.G.A.J., 2012. A review on quantitative models for sustainable food logistics management. International Journal on Food System Dynamics 3, 136–155.

Soysal, M., Bloemhof, J.M., Van der Vorst, J.G.A.J., 2014. Modeling food logistics networks with emission considerations: The case of an international beef supply chain. International Journal of Production Economics 152, 57–70.

Treitl, S., Nolz, P.C., Jammernegg, W., 2012. Incorporating environmental aspects in an inventory routing problem. a case study from the petrochemical industry. Flexible Services and Manufacturing Journal , 1–27.

Van Elzakker, M.A.H., Zondervan, E., Raikar, N.B., Hoogland, H., Grossmann, I.E., 2014. Optimizing the tactical planning in the fast moving consumer goods industry considering shelf-life restrictions. Computers & Chemical Engineering , –.

Vidović, M., Popović, D., Ratković, B., 2013. Mixed integer and heuristics model for the inventory routing problem in fuel delivery. International Journal of Production Economics .

Yu, Y., Chen, H., Chu, F., 2008. A new model and hybrid approach for large scale inventory routing problems. European Journal of Operational Research 189, 1022–1040.

Yu, Y., Chu, C., Chen, H., Chu, F., 2012. Large scale stochastic inventory routing problems with split delivery and service level constraints. Annals of Operations Research 197, 135–158.

Zanoni, S., Zavanella, L., 2012. Chilled or frozen? decision strategies for sustainable food supply chains. International Journal of Production Economics 140, 731–736.