RESEARCH PAPER

Energy-efficient frozen food transports: the Refrigerated Routing Problem

ARTICLE HISTORY
Compiled July 8, 2019

ABSTRACT
Given the growing importance of cold chains and the need to promote sustainable processes, energy efficiency in refrigerated transports is investigated at operational level. The Refrigerated Routing Problem is defined, involving multi-drop deliveries of palletised unit loads of frozen food from a central depot to clients. The objective is to select the route with minimum fuel consumption for both traction and refrigeration. The problem formulation considers speed variation due to traffic congestion phenomena, as well as decreasing load on board along the route as successive clients are visited. Transmission load for exposure of the vehicle to outdoor temperatures and infiltration load at door opening are modelled, taking into account outdoor conditions varying along the day and the year. The resulting multi-period problem is modelled and solved by means of Constraint Programming. Test scenarios come from a real local network for frozen bread dough distributed to supermarkets. Results show how fuel minimisation leads to the selection of different routes in comparison to the traditional total travel distance or time objectives. Energy savings are affected by demand distribution among the clients, departure time, number of visits per tour, seasonality and location of the delivery network.

KEYWORDS
Sustainability; Cold Chain; Frozen food; Refrigerated Routing Problem; Congestion; Constraint Programming

1. Introduction

With the shift towards the production and consumption of refrigeration-dependent food due to increasingly urbanisation and customer life style changes, cold chains have recorded an impressive growth (ITA, 2016). According to (Technavio, 2017) the global frozen food market, in particular, is expected to reach USD 311.9 billions by 2021, growing at a CAGR of more than 6%. Consumers, in facts, are much more tuned-in to the benefits of frozen food including waste reduction, convenience and health, and are discovering the breadth of choice in high-quality, on-trend products that are available to them with little preparation at home (FFE, 2018).

In the distribution of food products, temperature control is an essential factor, since it impacts on the level of product quality degradation, and on product safety, by limiting the growth of potentially harmful bacteria. To this end, three types of food supply chains (FSC) can be identified: frozen (below -18 °C), chilled, and ambient (Akkerman, Farahani, and Grunow, 2010). This classification reflects the main modes of handling products in terms of production and distribution technologies and to different ways of managing quality degradation, which in a frozen state may be almost stopped for some products. This reduces the complexity of the FSC design significantly and largely eliminates the need for quality change models (Van Der Vorst, Tromp, and Van Der Zee, 2009). As outlined by Soysal et al. (2012), in addition to the existing challenges, FSCs have been confronted with the increased attention for sustainable development. When embracing the sustainability concept, attention should be paid to energy efficiency along the cold chain (Meneghetti and Monti, 2015), since it has direct impact on both economic and environmental sides of the triple bottom line (Elkington, 1998). Purchase of energy, in facts, is one of the main indicators suggested by Yakovleva, Sarkis, and Sloan (2012) to evaluate the sustainability performance of supply chains.

Among the top 10 processes in the UK cold chain in terms of energy saving potential, transports have been recognised as the third one (James et al., 2009). As suggested by Zhu et al. (2018) detailed studies are needed on how to balance the goal of energy consumption, which is a foundation to guarantee food safety/quality, by controlling the temperature, emissions, as well as costs during storage, transportation and distribution of food products. Routing, in particular, has been included into the class of the most important additional decision in agri-food supply chain design, being present in the 10% of the models recently reviewed in (Esteso, Alemany, and Ortiz, 2018).

In this study, sustainability of the cold chain is pursued at the operational level by investigating energy efficient routing for palletised frozen food, typically serving a network of local supermarkets, e.g. for bread dough distribution. Modelling of fuel consumption for both refrigeration and traction is introduced, linking them to outdoor temperature and congestion in different time windows along the day and the season, leading to the definition of the Refrigerated Routing Problem (RRP). Comparisons with the solutions of traditional routing objectives of minimum travel distance and minimum time of the tour are provided. In addition, sensitivity analysis on typical tour attributes such as customers demand, network complexity, climate conditions of the region, as well as typical routing decisions (e.g. the starting time of the distribution tour) is performed.

The paper is structured as follows. In Section 2 a review of the recent literature on routing and food distribution is provided, while in Sections 3 and 4 the RRP is defined and modelled, respectively. Results of its application to an actual local distribution network is provided in Section 5 as the reference basic configuration, while sensitivity analysis is provided in Section 6. Finally, conclusions are summarised in Section 7.

2. The routing problem and refrigerated food distribution: a literature review

The routing problem has been studied in logistics literature since 1954, when the Traveling Salesman Problem was introduced by Dantzig, Fulkerson, and Johnson (1954), aiming at finding the shortest route for a salesman starting from a given city, visiting each of a specified group of locations, and then returning to the original point of departure. Many variations of increasing complexity have been introduced over the years, first of all the Vehicle Routing Problem (VRP), which consists of determining the optimal set of routes for a fleet of vehicles in order to satisfy the demands of a set of customers while respecting vehicle load capacity (see Toth and Vigo (2001) and Braekers, Ramaekers, and Van Nieuwenhuyse (2016) for a review on VRP). The objective function has been the travel distance minimisation, under the hypothesis of constant travel speed along the whole tour.

As life style has changed leading to increasing urbanisation with related traffic issues, congestion, neglected for decades in routing literature, couldn't be underestimated anymore. Therefore, models have been introduced with time-dependent travel speeds, assuming a constant speed value between two consecutive stops based on the departure time calculated considering a fixed unloading time for each stop (e.g. Eglese, Maden, and Slater (2006); Kuo, Wang, and Chuang (2009); Andres Figliozzi (2012); Kok, Hans, and Schutten (2012)). The objective function becomes travel time minimisation to be compared with the travel distance one, since lower tour durations sometimes correspond to longer routes, introducing also stochastic traffic conditions and path flexibility (Huang et al., 2017), and real time traffic data (Alvarez et al., 2018).

The growing attention to sustainability issues has led to the introduction of the Green Vehicle Routing Problem (GVRP), which deals with the optimisation of energy consumption during transportation (Lin et al., 2014), and the related Pollution Routing Problem (PRP) (Bektaş and Laporte, 2011; Koç et al., 2014), aiming at minimising greenhouse gas (GHG) emissions. As an extension of the PRP, Demir, Bektaş, and Laporte (2014b) studied the bi-objective PRP, where the fuel consumption and total traveling time are considered as conflicting objectives. The authors implemented an enhanced version of the Adaptive Large Neighbourhood Search algorithm introduced in by Demir, Bektaş, and Laporte (2012) to find a set of non-dominated solutions. In the multi-objective model presented by Molina et al. (2014), internal costs, CO_2 emissions and air pollutants emissions are simultaneously minimised. As a multi-objective optimisation method, they use the Weighted Tchebycheff procedure (Steuer and Choo, 1983), that allows to solve a unique optimisation problem, avoiding weakly non-dominated points. The above studies strongly rely on fuel consumption models. Demir, Bektaş, and Laporte (2014a) classify fuel consumption models into three main groups of increasing levels of complexity: (1) factor models, including simple methods; (2) macroscopic models, using average aggregate network parameters; (3) microscopic models, estimating the instantaneous vehicle fuel consumption and emission rates at a more detailed level. Xiao et al. (2012) propose a factor model for fuel consumption, depending on distance traveled and payload, obtained by linear regression on statistical data published by the Ministry of Land, Infrastructure, Transport, and Tourism of Japan. Most of the recent routing studies (see Demir, Bektaş, and Laporte, 2012; Franceschetti et al., 2013; Koç et al., 2014; Demir, Bektaş, and Laporte, 2014b; Franceschetti et al., 2017; Koç, 2018; Niu et al., 2018; Ehmke, Campbell, and Thomas, 2016, 2018) adopt microscopic models and in particular the Comprehensive Modal Emissions Modeling (CMEM) introduced by Barth, Scora, and Younglove (2004). In particular, Koç et al. (2014) adapt the comprehensive emissions model to account for the heterogeneous fleet case. However, Turkensteen (2017) has empirically determined that CMEM computations, when different but fixed speed values along each connection are assumed as in the above recent literature, lead to appropriate solutions only when traffic is free-flowing, so that acceleration/deceleration of real life driving can be neglected.

Literature specifically focused on transport along the cold chain is rather limited. Food transport refrigeration technologies have been investigated by Tassou, De-Lille, and Ge (2009) and more recently in (Rai and Tassou, 2017).

Most papers deal with food distribution at a supply chain management (SCM) level. In (Zhang, Habenicht, and Spieß, 2003), location and assignment of the central and distribution cold stores are obtained by minimising the total operating costs for warehousing and transportation, while maintaining the product quality. A penalty cost is introduced in order to consider the quality requirements, whose magnitude depends on the exceeded quality degradation over the maximum permitted. Van Der Vorst, Tromp, and Van Der Zee (2009) embed food quality models and sustainability indicators in discrete event simulation models, in order to facilitate an integrated approach towards logistic, sustainability and product quality analysis of the food supply chain. By introducing the new discrete event simulation tool ALADIN^{TM}, variations in product quality aspects (such as weight, colour and firmness) have been considered, in relation to the specific conditions the products are exposed to along the supply chain. Rong, Akkerman, and Grunow (2011) structure the whole supply network from production sites to distribution centres and retailers, minimising the logistic costs while satisfying the qualitative and demand requirements at the customers. The outputs of the model are the optimal temperature of refrigeration during both transportation and storage phases, quantity and time of shipment, and the optimal transport path. Zanoni and Zavanella (2012) introduce into a similar model the energy costs to cool the product depending on the batch size, a fixed cost for the specific cooling equipment, as well as fixed costs for receiving operations, holding costs, and the costs related to the quality degradation and loss in value of the product. In (Aiello, La Scalia, and Micale, 2012), the cold chain is modelled as a pipeline of stocking and transportation activities from the harvesting point to the final consumer, characterised by a deterministic temperature and a stochastic duration. The product deterioration level is introduced by a mathematical shelf-life model; duration distributions are assumed as normal random variables, determined by data-logs collected in a preliminary analysis. Soysal, Bloemhof-Ruwaard, and van der Vorst (2014) develop a multi-objective linear programming model for a generic multi-echelon beef logistics network problem involving third party logistics (3PL) firms, production regions, slaughterhouses, export departure and import arrival points at fixed locations. Road structure, vehicle and fuel type, loads, travelled distance, return hauls and product perishability are considered while pursuing two competing goals, such as minimising total logistics cost and minimising total CO_2 emissions from transportation operations. Validi, Bhattacharya, and Byrne (2014b) focus on the dairy industry, proposing a robust solution approach for the design of a capacitated distribution network for a two-layers supply chain for the distribution of milk in Ireland. The authors develop a green multi-objective optimisation model which minimises CO_2 emissions from transportation and total costs in the distribution chain (Validi, Bhattacharya, and Byrne, 2014a). A DoE-guided MOGA-II based solution method is proposed for locating a set of non-dominated solutions distributed along the Pareto frontier; realistic solutions, while considering different transportation scenarios, can so be identified (Validi, Bhattacharya, and Byrne, 2015). In (Accorsi, Gallo, and Manzini, 2017) perishable products storage and distribution operations are planned by minimising the overall costs for product packaging, refrigerated storage and delivery, and product spoilage, taking into account climate conditions influencing the food quality decay and the energy consumption of the cold chain. However, given the supply chain level, the above models consider a single-stop delivery, from the production sites to the distribution centres, or from the latter to the retailers.

Concerning operations, James, James, and Evans (2006) classify models for refrigerated transport into two macro categories: the ones based on heat and mass transfer and those focused on the microorganism growth in products during transportation. The first class is further divided into two groups: models focused on prediction of the product temperature and those analysing the environment of the refrigerated transport unit, while Censor and CoolVan are considered as combined models. The former models develop a 3-dimensional finite element analysis to predict the change in temperature at specific positions within the container when subjected to varying control regimes and ambient conditions. The second represents a more systematic and complete approach to simulate the temperature variation of food in multi-drop deliveries by means of an implicit finite difference method, proceeding from initial conditions to the end of the journey with variable time steps. Process capability indices (PCI) based on CoolVan simulations of thermal characteristic of potential journeys and product thermal properties are used in (Novaes et al., 2015), to calculate the route with the minimum travel distance, while respecting a minimum PCI value, by Simulating Annealing. Hsu, Hung, and Li (2007) include characteristics of perishable food delivery into VRP, by considering stochastic travel speed due to traffic congestion, loss of food related to the time the vehicle is open for unloading operations, energy consumed by storage equipment due to a fixed difference between indoor and outdoor temperature, and time-window constraints. Meneghetti, Da Rold, and Cortella (2018) detail refrigeration requirements for frozen palletised food transports considering both transmission and infiltration loads, relating them to the outdoor temperature varying daily and monthly and to the unit loads to be dropped-off at each client. The best route which minimises total fuel consumption for traction and refrigeration for a whole season/year is searched. The model considers a unique value of vehicle speed and doesn't account for fuel requirements due to load variation along the trip. The authors compare the traditional minimum travel distance solution with the minimum fuel one for frozen food deliveries to a local network of supermarkets, concluding that the optimal circuit remains unchanged, even if a preferred direction can be derived.

Given the growing importance of cold chains and refrigerated transports, a deeper analysis on the routing problem for frozen food is needed. In particular, congestion should be introduced, since it strongly impacts on fuel consumption for traction, as already demonstrated in the above literature. Moreover, it affects also refrigeration, because time during which products are exposed to thermal loads can vary and different outdoor temperatures can be faced during a trip. Furthermore, for palletised unit load deliveries, the weight of the vehicle can vary significantly from a stop to another and should be taken into account when fixing the best order to visit a given set of customers. In the following section, the new Refrigerated Routing Problem is proposed, which considers thermal loads depending on outdoor temperature varying along the day and the year, different stop times at each client depending on their demand, as well as different speed values and unit loads on board during each connection within the delivery tour.

3. The Refrigerated Routing Problem

The Refrigerated Routing Problem (RRP) can be defined as follows. Find the optimal route which minimises fuel consumption for a refrigerated vehicle, which departs from a production site/depot and delivers palletised unit loads of frozen products to a set of customers.

The vehicle is supposed to be at the proper indoor temperature fixed by the cold chain manager to preserve food quality and safety at the departure time of the tour. Therefore, only the refrigeration energy needed to balance thermal loads during transportation can affect routing decisions and should be taken into account. Refrigeration load can be ascribed to five components (Owen, 2010): the transmission load, the infiltration load, the product load, the internal load, and the equipment related load. Transmission load is the heat entering the refrigerated space through the walls of the vehicle, because of the temperature difference between indoor and outdoor environment, during both transport and drop-off operations at clients. The infiltration load mainly happens due to air density differences at door openings during unloading operations; it depends on both outdoor temperature and unloading time at each client. Product load represents the heat that must be removed to bring products to the maintaining temperature and the heat generated by products (e.g. respiration of fruits and vegetables) in the refrigerated space. In the RRP, already frozen food departing from a refrigerated warehouse is considered and therefore product load can be neglected. The internal load and the equipment load can be related to the devices and human operators entering the refrigeration space during unloading operations, and the heat generated by the devices that are permanently in the refrigeration environment, respectively. Internal and equipment loads, as they are typically modelled (see ASHRAE guidelines in Owen (2010)) can be considered as globally invariant with the route and so they are not taken into account. Therefore, the focus is on modelling transmission and infiltration loads during a delivery tour, which are detailed in Subsection 3.1.

To take into account variation of outdoor temperature along a day and among different months of the year, in a RRP the planning horizon is divided into time slots, similarly to models for district heating systems (e.g. Meneghetti and Nardin (2012)) or refrigerated facilities (Meneghetti and Monti, 2015; Meneghetti, Dal Magro, and Simeoni, 2018), leading to a multi-period model.

Moreover, a dynamic congestion as defined by Alvarez et al. (2018) is introduced, i.e. the proper traffic level is activated whenever the vehicle leaves a client. The speed is assumed constant along all the arc until the next stop; this assumption is coherent with last miles deliveries, where multiple stops are rather close, so that significant changes in traffic or in outdoor temperature when traversing a segment within the route can seldom happen. However, a limited waiting time is allowed at each stop after dropping the load if convenient, in order to respect the First In First Out property in the departing time from a client and fuel consumption because of outdoor temperature and speed slot discretisation. Vehicle slowdown, instead, is not allowed, since in real cases the drivers commonly adopt the maximum allowed speed to come back to the depot as soon as possible to start another trip or other activities. So, the intent is to select a route that intrinsically leads to fuel savings without affecting drivers' behaviour, who otherwise could undermine expected results. Waiting times of limited extension can be more naturally accepted by drivers than speed slowdowns, since they can be devolved to anticipate reporting or resting activities to be undertaken during a working day.

Given the classic notation of the Travelling Salesman Problem, the RRP can be described by a graph with nodes representing the central warehouse and the clients, each characterised by Q unit loads to be delivered (see Figure 1). The arc connecting every pair of nodes is associated with the travel distance $d[i, j]$ between them.

Differently from traditional TSP or VRP, however, the transmission power is added as an attribute of each edge, depending on the triggered time slot during which the vehicle departs from a client, characterised by a given outdoor temperature typical of the region. Similarly, any arc is associated with a vehicle speed value, depending on traffic congestion associated with the time slot of departure and road limits. Finally, each arc is associated also with a different load on board depending on the order clients are visited, which impacts on fuel consumption for traction, as described in Subsection 3.2.

Each node is characterised, together with transmission, also by the infiltration heat that should be removed due to door opening to drop off the unit loads demanded by each client. As described in the following subsection, beside indoor and outdoor temperature, infiltration is linked to unloading time and therefore to the quantity to be delivered to each client.

The delivery tour we are searching for is the circuit departing and returning from/to

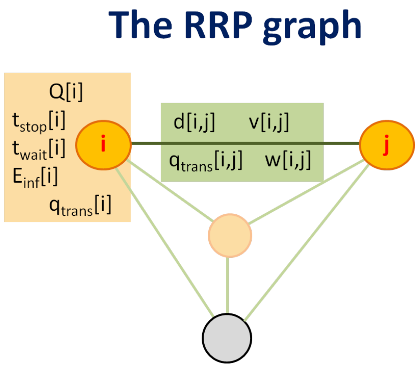


Figure 1. The RRP graph. Q[i] are the unit loads to be delivered at node i, $t_{stop}[i]$ is the stop time for unloading, $t_{wait}[i]$ is the waiting time at each stop if convenient, $E_{inf}[i]$ the infiltration energy, $q_{trans}[i]$ the transmission load, $v[i,j]$ is the vehicle speed along arc (i,j), $w[i,j]$ is the load on board.

the central warehouse (node 1) and visiting all clients, which corresponds to the minimum fuel consumption, involving both traction and refrigeration requirements.

3.1. *Refrigeration requirements modelling*

Refrigeration load along the delivery tour has to be counterbalanced so as to avoid temperature increase of the product above the right indoor temperature identified by SCM models. The two main components, as describe above, are the transmission load and the infiltration load.

The transmission load q_{trans} is the heat entering the refrigerated space through the walls of the vehicle during both traveling and stops, and can be calculated as the product of the exchange surface S, the global heat transfer coefficient U depending on insulation provided by the vehicle walls (see Table 1 for a typical value for semitrailer), and the difference between outdoor temperature (T_o) and indoor temperature (T_i) (Owen, 2010), as in the following Eq. 1.

$$q_{trans} = S \cdot U \cdot (T_o - T_i) \qquad [\text{kW}] \tag{1}$$

The transmission energy in each arc of the route can then be calculated by multiplying the transmission load and the related travel time, while transmission energy in a node can be evaluated by considering the related stop time.

Infiltration load due to air exchange is more complex to evaluate. While infiltration through the vehicle body and closed doors is normally taken into account in the $S \cdot U$ value of Eq. 1 (Owen, 2002), infiltration during unloading operations requires more attention. Literature on infiltration load has mainly been focused on estimating heat gain through doorways in refrigerated facilities (Owen, 2010), where doors remain open for very short times at forklift passage. Infiltration load when doors remain open for longer periods as during unloading operations of refrigerated vehicles has received poor attention in literature.

According to the recent research on the topic by Lafaye De Micheaux et al. (2015), the infiltration power during unloading operations is time and temperature dependent. The infiltration power is initially bell-shaped, but it stabilises to a value b_{T_i,T_o}, around

40s after the doors opening. Therefore, the infiltration energy E_{inf} to be removed, when doors remain open for more than 40s, can be calculated as in the following Eq. 2:

$$E_{inf} = AC_{T_i,T_o} + b_{T_i,T_o}(t_{stop} - 40) \qquad [\text{kJ}] \tag{2}$$

where AC_{T_i,T_o} is the area under the bell curve during approximately the first 40 s, and t_{stop} is the total elapsed time for unloading operations, with open doors.

Both AC and b depend on the outdoor temperature T_o and the indoor temperature T_i. Lafaye De Micheaux et al. (2015) provide experimental data and patterns just for few combinations of indoor-outdoor temperatures, so the quadratic interpolations proposed in (Meneghetti, Da Rold, and Cortella, 2018) are adopted to link infiltration parameters to the outdoor temperature of each time slot of the multi-period RRP.

To estimate t_{stop} in Eq. 2, actual unloading times for deliveries of palletised frozen food to a local network of supermarkets have been measured on the field and used to derive Equation 3 and data in Table 1. Time for unloading operations depends on the position of each palletised unit within the refrigerated vehicle. Considering one level only (i.e. stacking is not allowed), palletised unit loads are commonly organised by rows moving from the rear doors towards the traction unit. Referring to Figure 2, technical time to drop off a unit load u, when pallets are numbered consecutively from the rear (the first to be dropped off) to the front of the semitrailer, can be evaluated as:

$$t_{drop}[u] = t_{up} + 2 \cdot t_{row} \left\lfloor \frac{u-1}{p_{row}} \right\rfloor \tag{3}$$

where t_{up} is the time for a picker to get in and out the trailer with the forklift, t_{row} is the time to move or return from one row to another (approximately equal to standard pallet length or width basing on pallet orientation), and p_{row} is the number of palletised unit loads per row (see Table 1 for typical values). The final value of t_{stop} is evaluated by summing up t_{drop} for all the unit loads to be delivered to a given client, which depends on both quantity and position of the units on board.

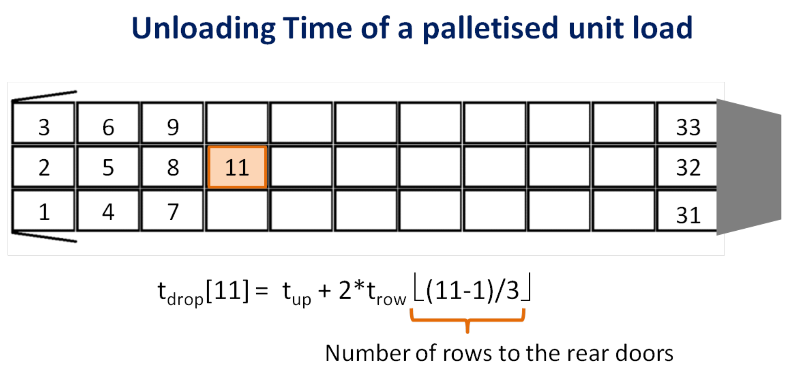


Figure 2. Time for unloading operation of palletised units

3.2. *Traction fuel requirements modelling*

To estimate fuel consumption for traction, the CMEM approach (Barth, Scora, and Younglove, 2004) is adopted, since it allows us to explicitly consider the main factors expected to impact on the RRP, such as the speed connected to congestion, the travel time related to both distance and speed, and the vehicle weight varying during the trip as unit loads are dropped-off at clients. Moreover, given the type of deliveries involved in the RRP, traffic can be considered as free-flowing as suggested by Turkensteen (2017).

The CMEM-based fuel consumption F [l] for traction related to a distance d [m] covered with constant speed v [m/s] by a vehicle with curb weight w [kg] and a transport load l [kg], can be reformulated, as suggested by Franceschetti et al. (2017), as in the following Eq. 4:

$$F(d, v, l) = A \cdot (w + l)d + B \cdot d/v + C \cdot d \cdot v^2 \tag{4}$$

A, B and C are non negative constants calculated as in Eqs. 5:

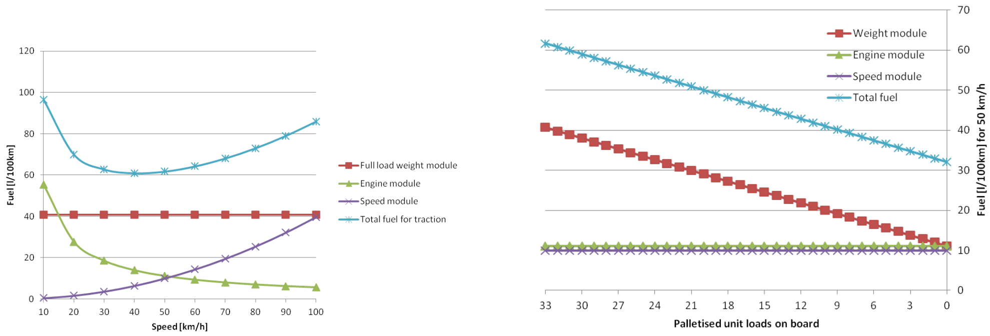
$$\begin{aligned} A &= \lambda\gamma\alpha && [\mathrm{l/(kg\ m)}] \\ B &= \lambda k N_e V && [\mathrm{l/s}] \\ C &= \lambda\gamma\beta && [\mathrm{l\ s^2/m^3}] \end{aligned} \tag{5}$$

where λ is a function of the fuel-to-air mass ratio and the fuel heating value, γ depends on diesel engine efficiency and the vehicle drive train efficiency, α takes into account the road angle and the rolling resistance coefficient, k is the engine friction factor, N_e the engine speed, V the engine displacement, while β depends on the aerodynamics drag coefficient and the frontal surface area of the vehicle (refer to Barth, Scora, and Younglove (2004) for a complete description). To calculate Eq. 4, we refer to the typical data used in (Demir, Bektaş, and Laporte, 2012; Franceschetti et al., 2013; Ehmke, Campbell, and Thomas, 2018; Koç, 2018; Niu et al., 2018; Soysal et al., 2018) and to specific vehicle characteristics for semitrailers adopted in refrigerated transports taken from commercial catalogues, as reported in Table 1.

The first term in Eq. 4 is known as the weight module, since it takes into account the impact of carb weight and payload on fuel consumption; the second term is known as the engine module and it is linear on travel time; the third term is the speed module, growing with the square of vehicle speed. Figure 3(a) shows the impact of speed (and thus of congestion phenomena) on fuel consumption of the refrigerated semitrailer considered in Table 1, for a 100 km travel distance and a full product load of 19800 kg. In Figure 3(b), the impact of load on fuel consumption is reported, considering the drop-off of palletised unit loads of 600 kg (as for frozen bread dough) for a maximum vehicle capacity of 33 unit loads an and a given constant speed. Load variation affects fuel consumption significantly. Therefore, the change on load after each stop along a delivery tour should be properly introduced in energy efficient routing, especially when clients have different demand and therefore their order of visit can impact on total fuel consumption.

Table 1. Refrigerated vehicle specifications

Symbol	Description	Units	Value
A	CMEM weight module constant	[l/(kg km)]	14.94E-6
B	CMEM engine module constant	[l/h]	5.54
C	CMEM speed module constant	[l h^2/km^3]	39.62E-6
S	Exchange surface	[m^2]	150
U	Global heat transfer coefficient	[W/(m^2 K)]	0.44
p_{row}	Number of unit loads per row	[unit loads]	3
sc	Specific fuel consumption	[l/kWh]	0.30
t_{doors}	Time to open/close the rear doors	[s]	12
t_{row}	Time to move from one u.l. row to another	[s]	3
t_{up}	Time to get up and down with a forklift	[s]	36
w	Carb weight	[kg]	7450



(a) Speed (b) Load on board

Figure 3. CMEM based fuel consumption of a semitrailer for a 100 km distance with: varying speed (a); varying load on board (600 kg per palletised unit load) at 50 km/h (b).

4. The RRP model equations

The RRP has been modelled and solved by Constraint Programming (CP), since it allows the modeller to focus on the desire properties of the solution, by introducing objective functions and constraints among variables of any complex structure, without limitation to linearity (Rossi, van Beek, and Walsh, 2006). Furthermore, CP requires minimum parameter tuning to be adapted to different contexts with respect to meta-heuristics methods (e.g. genetic algorithms, simulated annealing, or tabu search). It can rely also on advanced solvers embedding the most advanced search strategies elaborated by the CP scientific community and a rich language with several abstractions.

Departing from the proposed RRP definition, index i is used in the following equations to identify a client, including the depot ($i = 1$, initial and final node of the route), as well as the arc departing from it. For sake of clarity, variables are written in Italics and reported in Table 2, while input parameters in normal text (see Tables 1 and 2). We are searching the ordered circuit which visits all N clients with minimum fuel consumption over the whole horizon, as in the following Eq. 6:

$$\min \quad \sum_{i=1}^{N} (\mathit{fuelR}[i] + \mathit{fuelT}[i]) \tag{6}$$

The refrigeration fuel consumption $\mathit{fuelR}[i]$ is related to the energy needed to counterbalance transmission and infiltration loads at node i, as well as transmission load along the arc departing from the same node, as explained in Section 3.1. In order to associated each node i, as well as the arc departing from it, with the proper parameters based on the outdoor temperature of each time slot of the day of the multi-period model (see Table 2), the auxiliary integer variable $slotT[i]$ is introduced and defined on the basis of the arrival time at the node and the temperature time slot duration, as in the following Eq. 7, where $\underline{div}$ is the integer division operator.

$$slotT[i] = t_{arrival}[i] \;\; \underline{div} \;\; \mathrm{durationT} \tag{7}$$

The above variable is used as the index in the following element constraints to access the proper parameter table, where data for each temperature time slot have been recorded (e.g. To, COP, AC, b, Days). If 24 hourly time slots per day (h = 24) and 12 monthly periods are considered (K = 12), then a 288 rows table should be generated to record parameters for a yearly planning horizon. Each temperature time slot of the day for every period has a number of repetitions (Days, see Parameter Table 2) within the planning horizon, so the average temperature at a given hour of the day in December should be counted for all the days of that month (i.e. 31). Therefore, fuel consumption for refrigeration in the whole horizon can be calculated by the following Eqs. 8.

$$fuelR[i] = (E_{trans}[i] + E_{inf}[i])/\mathrm{sc} \tag{8a}$$

$$E_{trans}[i] = P_{trans}[i] \cdot (t_{stop}[i] + t_{waiting}[i] + t_{travel}[i]) \tag{8b}$$

$$P_{trans}[i] = \sum_{j=1}^{K} \left(\mathrm{Days}[slotT[i] + \mathrm{h}(j-1)] \frac{\mathrm{SU} \cdot (\mathrm{To}[slotT[i] + \mathrm{h}(j-1)] - \mathrm{Ti})}{\mathrm{COP}[slotT[i] + \mathrm{h}(j-1)]} \right) \tag{8c}$$

$$E_{inf}[i] = \sum_{j=1}^{K} \left(\mathrm{Days}[slotT[i] + \mathrm{h}(j-1)] \frac{\mathrm{AC}[slotT[i] + \mathrm{h}(j-1)] + \mathrm{b}[slotT[i] + \mathrm{h}(j-1)](t_{stop}[i] - 40)}{\mathrm{COP}[slotT[i] + \mathrm{h}(j-1)]} \right) \tag{8d}$$

Fuel for traction along the route $fuelT$ is calculated with CMEM (see Section 3.2) by the following Eq. 9, where numTour represents the total number of delivery tours to be performed in the whole planning horizon (see Tables 1 and 2 for parameters).

$$fuelT[i] = \mathrm{numTour} \cdot (\mathrm{A} \cdot (\mathrm{w} + \mathrm{m} \cdot load[i]) \cdot d[i] + \mathrm{B} \cdot t_{travel}[i] + \mathrm{C} \cdot d[i] \cdot v[i]^2) \tag{9}$$

The first group of constraints (see Eqs. 10) is added to the model in order to properly set the circuit departing from and returning to the depot while visiting all the clients. In particular, Eq. 10a defines the decision variables array $x[i]$ of the direct successors of each node, involving all the nodes in a Hamiltonian circuit, similarly to traditional

TSP. The primitives *alldifferent* and *circuit* provided by most CP solvers are invoked to this end. Eq. 10b defines the ordered route from decision variables $x[i]$, recursively (node 1 is the depot).

$$\textit{alldifferent}(x) \wedge \textit{circuit}(x) \tag{10a}$$

$$sort[1] = 1 \quad \wedge \quad sort[i] = x[sort[i-1]] \quad \forall i \geq 2 \tag{10b}$$

In order to associate each arc of the route with the proper speed value triggered at departure time from client i, the following element constraint is introduced by Eq. 11 to access the speed parameter of the congestion slot.

$$v[i] = \mathrm{V}[t_{depart}[i] \;\; \underline{div} \;\; \mathrm{durationV}] \tag{11}$$

The second group of constraints (see Eqs. 12) sets the variable attributes of each arc departing from node i in the RRP, such as distances, speeds, travel times and load on board.

$$d[i] = \mathrm{D}[i, x[i]] \qquad \forall i \tag{12a}$$

$$t_{travel}[i] = d[i]/v[i] \qquad \forall i \tag{12b}$$

$$(load[1] = \sum_i \mathrm{Q}[i]) \quad \wedge \quad (load[sort[i]] = load[sort[i-1]] - Q[sort[i]] \;\; \forall i \geq 2) \tag{12c}$$

The third group of constraints involves the variable attributes of each node in the route, such as arrival, stop, waiting and departure times, as shown in Eqs. 13. In particular, to calculate the stop time in each node coherently with the proposed Eq. 3 in Section 3.1, the actual position within the vehicle of the first palletised unit load to be dropped off at client i is considered in Eq. 13d.

$$(t_{arrival}[1] = \mathrm{begin}) \quad \wedge \quad (t_{arrival}[x[i]] = t_{depart}[i] + t_{travel}[i]) \tag{13a}$$

$$(t_{depart}[1] = \mathrm{begin}) \quad \wedge \quad (t_{depart}[i] = t_{arrival}[i] + t_{stop}[i] + t_{waiting}[i]) \tag{13b}$$

$$(t_{stop}[1] = 0) \quad \wedge \quad (t_{stop}[i] = \mathrm{t\_fix} + 2 \cdot t_{doors} + \sum_{k=0}^{\mathrm{Q}[i]-1} t_{drop}[pallet[i] + k])) \tag{13c}$$

$$(pallet[sort[2]] = 1) \wedge (pallet[sort[i+1]] = pallet[sort[i]] + \mathrm{Q}[sort[i]] \;\; \forall i > 2) \tag{13d}$$

Table 2. Model Main Variables (in Italics) and Parameters

Symbol	Description
$d[i]$	Distance from client i to the next client in the route
$load[i]$	Load on board in the arc departing from client i
$sort[j]$	j^{th} client visited during the delivery tour
$t_{arrival}[i]$	Arrival time at client i
$t_{depart}[i]$	Departure time from client i
$t_{stop}[i]$	Stop time at client i for unloading operations
$t_{travel}[i]$	Travel time to cover the distance from client i to the next in the route
$t_{waiting}[i]$	Waiting time at client i before departure
$v[i]$	Speed during the arc departing from client i
$x[i]$	Successor of node i in the route
AC[k]	Infiltration energy in the first 40 s of open doors in time slot k
b[k]	Infiltration power after 40 s in temperature time slot k
begin	Start time of the delivery tour
COP[k]	Coefficient of performance for temperature time slot k
D[i, j]	Distance on the map from node i to node j
Days[k]	Number of repetition of temperature time slot k per period in the horizon
durationT	Duration of each time slot per period for outdoor temperature [h]
durationV	Duration of each time slot for congestion [h]
h	Number of temperature time slots per day
m	Palletised unit load [kg]
t_fix	Fix stop time at each client
To[k]	Outdoor temperature of time slot k
numTour	Number of delivery tours in the whole planning horizon
V[j]	Speed value for congestion time slot j

5. Results: the reference case study

A network of 3 supermarkets served from a production plant and located in a semi-urban region near Udine city in North-Eastern Italy has been taken as the reference case (see Fig. 4). Deliveries involve palletised unit loads of 600 kg frozen dough, i.e. bread whose cooking is completed directly at sell points, at -20 °C indoor temperature. The vehicle capacity is set to 33 unit loads on standard Europallet with no stacking, as typical for refrigerated semitrailers (see Fig. 2). Each client has the same demand equal to 11 unit loads.

Figure 4. The graph of the reference case.

The delivery tour starts from the depot (node 1) at 7:00 a.m. and covers actual travel distances as taken from Google Maps. A maximum waiting time of 30 min is allowed at each stop, discretised by intervals of 5 min. Several outdoor temperatures have been introduced for a total of 288 different time slots, corresponding to the average hourly values per each month of the year, as provided by the local meteorological agency ARPAfvg-OSMER. COP varies over the different temperature slots of the year between 0.32 and 0.75, coherently with the average yearly simulated and measured values provided by Bagheri, Fayazbakhsh, and Bahrami (2017). Congestion has been taken into account by 24 hourly time slots during a day as summarised in Table 3, ranging between a minimum speed of 40 km/h for peak hours to a maximum of 70 km/h (night hours).

Table 3. Daily speed time slots.

Time slot	Speed [km/h]
0 – 6	70
6 – 7	60
7 – 8	40
8 – 9	45
9 – 11	50
11 – 12	45
12 – 13	40
13 – 14	45
14 – 15	50
15 – 16	55
16 – 17	50
17 – 18	45
18 – 19	40
19 – 20	50
20 – 24	60

The model has been coded in MiniZinc (Nethercote et al., 2007), version 2.0.14, and run under the Gecode solver. All experiments ran on a Windows 8.1 Pro machine with 8 GB of RAM memory and Intel ® Core i5-4200U (1.60GHz) processor. The computational time for the reference case has been 0.38 s.

Table 4. Results of the basic simulation. The fuel consumption values are averaged on the whole yearly horizon.

	Objective		
	Fuel consumption	**Length**	**Duration**
Route	$1 \to 4 \to 2 \to 3 \to 1$	$1 \to 3 \to 4 \to 2 \to 1$	$1 \to 2 \to 4 \to 3 \to 1$
Waiting times [min]	[0, 0, 0, 0]	[0, 0, 0, 0]	[0, 0, 0, 0]
Total distance [km]	146	143	143
Total duration [min]	239	234	233
Weight module [l]	35.67	37.12	37.01
Engine module [l]	17.99	17.51	17.49
Speed module [l]	11.96	11.95	11.99
Traction [l]	65.62	66.58	66.49
Transmission [l]	4.43	4.23	4.26
Infiltration [l]	3.54	3.54	3.54
Refrigeration [l]	7.97	7.77	7.8
Total fuel consumption [l]	73.59	74.35	74.29

Table 4 reports the results obtained on the basic simulation scenario for different objectives, that are the minimisation of the total fuel consumption, as well as the more traditional total distance travelled and the total duration of the route.

Different optimal routes are selected depending on the objective to minimise. In detail, for the minimum length and duration the optimal circuit is the same but with opposite direction: this happens because for the minimum duration it is preferred to visit later nodes 4 and 3 in order to travel longer arcs ($4 \to 3$ and $3 \to 1$) at higher speed. Indeed, the first two nodes fall in the speed time slot of 40 km/h and 45 km/h respectively, whereas the last two in the one of 50 km/h. In all the routes waiting times at nodes are not convenient.

The route identified with the minimum fuel consumption objective gets savings mainly from the traction consumption: the vehicle travels lower distances with a bigger load (weight module) because the first two nodes visited are closer respect to the minimum distance or duration circuits. However, the refrigeration consumption is larger due to higher transmission consumptions that are related to the longer travel time (239 minutes respect to 233–234 minutes) and therefore longer exposition of the vehicle to outdoor temperatures. Infiltration load remains unchanged since the same quantities are delivered at each stop and globally the same temperature slots are activated at door openings along a route.

Results highlight how including congestion into routing optimisation models leads to additional information on route covering for the traditional objectives of total travel distance and travel time minimisation. Even when the selected circuit and therefore the total distance are the same as in this basic case, however knowing the optimal direction can lead to time and energy savings.

Furthermore, neglecting load on board variations along the route due to drop-off operations as common in literature, can lead to misleading information about fuel consumption, especially with palletised unit loads of significant weight such as for frozen food deliveries. As shown in Table 4, the weight module of CMEM model (see Section 3.2) accounts for more than 50% of the traction fuel requirements and thus strongly affects route selection in a RRP.

However, fuel savings of this basic scenario are rather limited, i.e. the 1.03% and the 0.95% relative increase for distance and duration minimisation with respect to the minimum fuel consumption objective of the RRP (see Table 4). The traction requirements account for the 89% of the total fuel consumption, while the refrigeration only for the remaining 11%. It follows that for such a simple network optimising travel distance or duration, which affect the modules of the CMEM model (see Section 3.2) for traction requirements, leads also to effectively lower fuel consumption and a limited amount can be further reduced by introducing the more complex model proposed for the RRP. Nevertheless, several parameters are involved in a RRP, which can affect route selection and related fuel consumption. Therefore, a sensitivity analysis is required in order to get more insights from a sustainable perspective, as provided in the following section.

6. Sensitivity analysis

Departing from the basic configuration of the reference case and adopting the fuel minimisation objective of a typical RRP, a sensitivity analysis is performed on the main input parameters, which can potentially affect route selection.

6.1. *Delivery quantities*

Simulations are performed in order to assess the impact of a different demand distribution among the clients, which in the basic scenario have equal delivery quantities. In particular, we analyse the case in which one client presents a demand almost double with respect to the others (i.e. 17 unit loads versus 8).

Table 5. Fuel consumption for different delivery quantities.

Quantities Q[i]	**[0, 11, 11, 11]**	**[0, 17, 8, 8]**	**[0, 8, 17, 8]**	**[0, 8, 8, 17]**
Route	1→4→2→3→1	1→2→4→3→1	1→3→4→2→1	1→4→2→3→1
Waiting times [min]	[0, 0, 0, 0]	[0, 0, 0, 0]	[0, 0, 0, 0]	[0, 0, 0, 0]
Total distance [km]	146	143	143	146
Total duration [min]	239	233	233	239
Traction [l]	65.62	66.49	66.57	65.62
Transmission [l]	4.43	4.25	4.23	4.42
Infiltration [l]	3.54	3.53	3.53	3.53
Refrigeration [l]	7.97	7.78	7.76	7.95
Total fuel consumption [l]	73.59	74.27	74.33	73.57

From Table 5 it can be noticed that the client with the largest delivery quantity is always the first one to be visited. The explanation is that the traction consumption, which constitutes the 89% of the total consumption, is dominated by the weight module, which is proportional to the load on board along any arc and decreases as drop-off operations are performed at successive clients. Moreover, even the refrigeration requirements is reduced since most of the unit loads are transported and dropped off at the best outdoor temperature conditions, i.e. early in the morning. Thus, serving firstly the client with the largest demand leads to fuel savings.

Compared to the basic simulation with equal quantity deliveries, a non uniform demand leads to select different routes basing on the most important client and consequently gain different energy savings. To this regard, the fuel optimisation perspective gains a relative fuel decrease with respect to the traditional distance and travel time minimisation, ranging from 1.03% for uniform demand, to 4.6% for $Q[i] = [0, 8, 17, 8]$ demand distribution, and to 8% for an even more skewed demand curve $Q[i] = [0, 6, 21, 6]$.

6.2. *Start time*

The departure time from the production plant/depot represents a crucial parameter for the RRP. Different portions of the day involved by the delivery tour correspond, in facts, to different outdoor temperatures as well as different travel speeds due to congestion phenomena. Therefore, we can investigate about the most convenient departure time for the delivery tour from a fuel minimisation perspective.

Simulations related to different departure times corresponding to each hour of the day have been performed and reported in Figures 5 - 6, under the hypothesis that the driver always adopts the maximum speed allowed by traffic and semi-urban driving limits (see Table 3). This assumption is coherent with the actual behaviour of drivers and also with personnel cost reduction, as confirmed by local shipping companies.

When waiting times are not allowed, the duration of the delivery route (see Fig. 5) resembles the speed pattern reported in Table 3. Minimum times are recorded during the night when speed grows up to 70 km/h, while during the day the duration is strictly dependent on traffic peak hours involved in the delivery tour. Refrigeration requirements (see Fig. 5) increase during the warm portions of the day as expected and reach their minimum during the night when the lowest temperatures are recorded. However, due to the main impact of traction on fuel consumption, final energy requirements are more affected by allowed speed than outdoor temperatures (see Figure 6). When no waiting times are allowed (see the orange bullet line in Fig. 6), given the

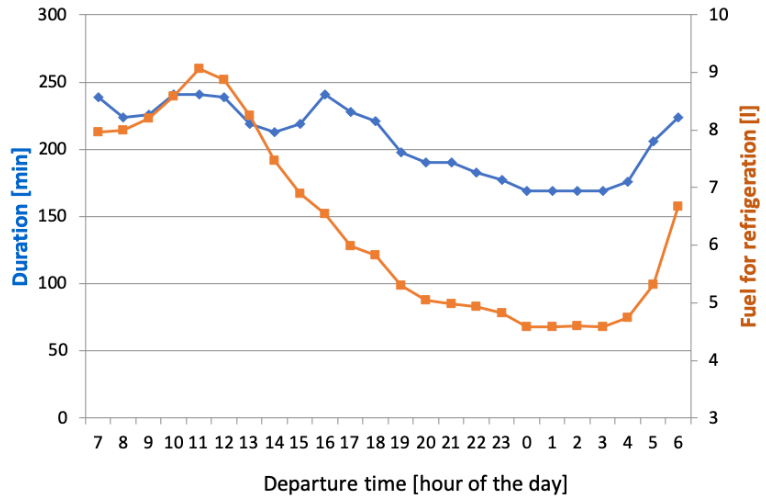


Figure 5. Travel time per route (left axis, diamond blue dot) and refrigeration fuel consumption (right axis, square orange dot) for different departure times and no waiting times allowed at each stop.

significantly higher speed values adoptable during night hours, fuel consumption grows due to the speed module of CMEM model (see Section 3.2) to a maximum of 8.9 % with respect to the basic configuration (departure time at 7 a.m.). If waiting times are allowed, the model triggers additional stop times at clients to slow down the vehicle by accessing time slots with lower speed values, in order to reduce the speed module and thus fuel consumption for traction. However, the maximum fuel saving is only 2.6% for a duration increase of 45.4% (e.g. for a start time of 4:00, the total travel time changed from 176 to 256 minutes).

The above results show how the departure time can be an effective decision variable to reduce time or energy requirements of a given delivery tour, thus providing managers with the chance of optimising the desired performance in accordance with clients working shifts, and also with final customer behaviours in the case of palletised frozen food delivery to supermarkets.

6.3. *Seasonality*

Simulations have been performed to analyse how seasonality can affect route selection and fuel requirements. Therefore, the planning horizon has been changed from the whole year to a single season, namely winter (from December to March), summer (from May to September) and mid season (April, October November). Results are reported in Table 6.

While traction requirements remain unchanged over different seasons, refrigeration requirements grows moving from winter to summer, as expected. The optimal route remains unchanged, but the impact of refrigeration on total fuel requirements moves from 6% in winter, to 13% in the mid-season and 20% in summer. It should be underlined how another kind of seasonality can occur, affecting speed distribution and limits along the day and therefore traction requirements. Traffic congestion, in facts, can change due to tourism in the region in summer or winter and also school closure in the summer. In these cases, also the optimal circuit is likely to change from one season to another. Therefore, modifying the planning horizon and consequently adopting a

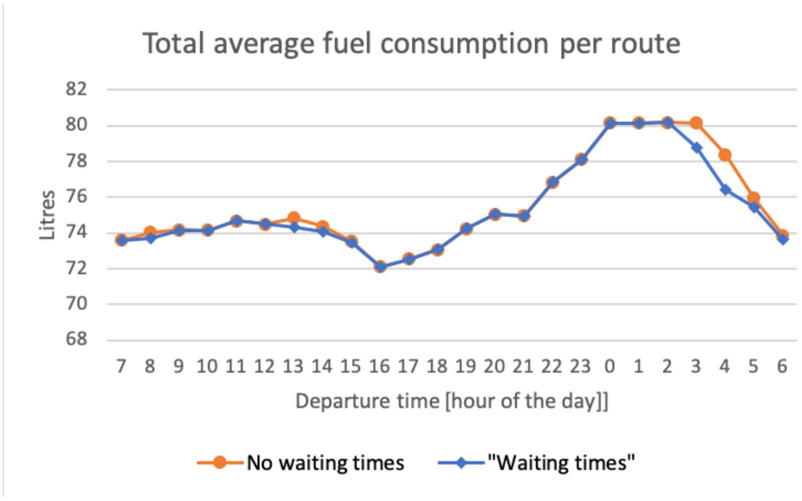


Figure 6. Total consumption per route averaged on the whole yearly planning horizon for different departure times with no waiting times (bullet orange dot line) and maximum 30 min waiting times allowed (diamond blue dot line)

Table 6. Comparison of fuel consumption on different seasons.

	1 year	winter	mid season	summer
Route	[1, 4, 2, 3]	[1, 4, 2, 3]	[1, 4, 2, 3]	[1, 4, 2, 3]
Total distance [km]	146	146	146	146
Total duration [min]	239	239	239	239
Traction [l]	65.62	65.62	65.62	65.62
Transmission [l]	4.43	2.43	3.14	4.99
Infiltration [l]	3.54	2.01	7.02	11.32
Refrigeration [l]	7.97	4.44	10.16	16.31
Total fuel consumption [l]	73.59	70.06	75.78	81.93

different route per season can be an effective way to foster sustainability of frozen food deliveries.

6.4. *Network complexity*

In this section, experiments about the impact of the network complexity on fuel consumption and on the performance of the adopted solver are described.

Table 7. Results for scenarios with 2, 4 and 8 clients.

Number of clients	**2**	**4**	**8**
Quantities Q[i]	[0, 16, 16]	[0, 8, 8, 8, 8]	[0, 4, 4, 4, 4, 4, 4, 4, 4]
Route	[1, 3, 2]	[1, 2, 3, 4, 5]	[1, 6, 2, 5, 4, 3, 9, 8, 7]
Waiting times [min]	[0, 0, 0]	[0, 0, 0]	[0, 0, 0, 0, 0, 0, 25, 0, 0]
Total distance [km]	89	123	141
Total duration [min]	163	212	281
Traction [l]	37.11	52.67	57.88
Refrigeration [l]	5.16	7.64	11.8
Total fuel consumption [l]	42.27	60.31	69.68

In order to compare the results with a different number of nodes, we developed three scenarios with a number of clients equal to 2, 4 and 8. Indeed, for this particular type of transportation that involves palletised unit loads of frozen food delivered to supermarkets, the number of clients visited in a single route seldom exceeds the maximum value here experimented. On each scenario, the total load is kept unchanged (32 pallets) and it is spanned among the clients in a homogeneous way. The clients are located in the same regional area individuated by a square with side equal to 60 km. Maximum waiting times of 30 minutes per stop are allowed.

As expected, the outcome is that increasing the network complexity leads to higher fuel consumption, due to both refrigeration and traction components. As a matter of fact, a more complex route requires a larger total distance and longer travel times, which directly affect traction and refrigeration requirements. Concerning the latter, it should be underlined how the infiltration load grows proportionally to the number of stops due to the bell shaped contribution to thermal load encountered at each doors opening (see Eq. 2).

6.5. *Localities*

In the final simulation, we selected five different localities that are characterised by a diverse climate, in order to establish how fuel consumption changes depending on outdoor temperature values and distribution along the year. We identified Helsinki for the humid continental climate, Hamburg for the oceanic climate, Udine for the subtropical climate, Siracusa for a mediterranean climate, and finally Singapore for the tropical climate.

Table 8. Fuel consumption on different localities.

	Helsinki	Hamburg	Udine	Siracusa	Singapore
Traction [l]	65.62	65.62	65.62	65.62	65.62
Transmission [l]	2.52	2.88	4.43	4.59	6.64
Infiltration [l]	1.93	2.26	3.54	3.53	5.02
Refrigeration [l]	4.45	5.14	7.97	8.12	11.66
Total fuel consumption [l]	70.07	70.76	73.59	73.74	77.28
Refrigeration/Total fuel cons[%]	6.35%	7.26%	10.83%	11.01%	15.09%
Refrigeration/Refr[Udine] [%]	-44.17%	-35.51%	0.00%	1.88%	46.30%

For all the localities, the same route and traction consumption are obtained given that distances, speed time slots and load requirements are the same as the basic scenario. On the contrary, refrigeration consumption changes consistently moving from Helsinki, where the average daily temperature is about 6 °C (decreasing to -2.5 °C in winter) to Singapore, where there is no seasonality and the temperatures are uniform, ranging from a minimum of 25 °C to a maximum of 30 °C during all the year. It can be noticed that also the relative impact of the refrigeration on the total fuel consumption grows with the outdoor temperature, arriving up to the 15% for Singapore. In the last line of Table 8, we report the refrigeration consumption on the different localities respect to the basic scenario (Udine). The value obtained exhibits a variation from -44% to +46%, confirming how different climate conditions strongly affect refrigeration requirements, which therefore can play a different role on pursuing energy efficiency.

6.6. *Computational performance*

The computational performance of the proposed CP approach when problem size increases is related to both the number of clients to be served within a route and to the waiting time slots allowed.

We compared a brute force solver developed in C++ language with the CP approach implemented in Minizinc and run under the Gecode solver on the same machine (Windows 8.1 Pro, 8 GB of RAM memory and Intel ® Core i5-4200U (1.60GHz) processor).

For 8 clients (i.e. 9 nodes) experiments with waiting time slots ranging from 0 to 6 possible intervals of 5 minutes each (i.e. maximum 30 minutes) were considered. The number of solutions to be evaluated by the brute force technique is therefore $8! \times (k+1)^8$ where k is the number of waiting time slots considered at each stop. The CP approach has proven to scale better than the brute force technique as waiting time intervals grow, as shown in Table 9.

Table 9. Comparison of runtimes between CP and a brute force approach.

Number of clients	8	8	8	8	8	8
Waiting time slots	[0..1]	[0..2]	[0..3]	[0..4]	[0..5]	[0..6]
Route	[1,6,2,5,4,3,9,8,7]	[1,6,2,5,4,3,9,8,7]	[1,6,2,5,4,3,9,8,7]	[1,6,2,5,4,3,9,8,7]	[1,6,2,5,4,3,9,8,7]	[1,6,2,5,4,3,9,8,7]
Waiting times [min]	[0,0,0,0,0,0,0,0,0]	[0,0,0,0,0,0,0,0,0]	[0,0,0,0,0,0,0,0,0]	[0,5,0,0,0,0,20,0,0]	[0,0,0,0,0,0,25,0,0]	[0,0,0,0,0,0,25,0,0]
Tour duration [min]	252	252	252	281	281	281
Fuel consumption [l]	69.86	69.86	69.86	69.79	69.68	69.68
Runtimes:						
CP	33s	1m55s	2h20m	10h27m	9h38m	144h49m
Brute force	64s	27m20s	4h33m	27h38m	116h38m	400h20m

Moreover, the CP approach allows to more easily insert new constraints to adapt the model to particular conditions and exploit the circuit constraint to cut the research tree, e.g. when a non complete graph should be considered. However, it is clear that the complexity of the objective function makes hard the task of tree pruning by the CP solver.

Future research should be addressed to use more sophisticated CP solvers already applied to industrial problems (e.g. CP Optimizer, Laborie et al. (2018)) or explore other solution methods, for example by hybridising CP with local search techniques (see Cipriano, Di Gaspero, and Dovier (2013); Dekker et al. (2018)), in order to strongly reduce the solving times, whenever suboptimal solutions are acceptable.

7. Conclusions

Nowadays, cold chains have gained increasing attention due to the growing demand of frozen food by a more and more urbanised world. Refrigerated transports, where temperature control is essential, represent a crucial process to enhance the sustainability of the whole supply chain. Therefore, related optimisation models to support typical decisions such as route selection should be developed.

This study introduces the Refrigerated Routing Problem (RRP), aimed at selecting the route with minimum fuel consumption in a sustainability perspective for multi-drop deliveries of frozen palletised unit loads from a central depot to clients, e.g. from a production plant towards regional supermarkets. In comparison to typical routing problems in literature, requirements for both traction and refrigeration, which is strictly related to outdoor temperature conditions, are considered and modelled. The former includes the consideration of congestion phenomena in traffic peak hours, as well as the variation of load on board due to deliveries of unit loads of significant weight at each client. To this end, an instantaneous vehicle fuel consumption model has been adopted. Concerning the latter, the most recent literature results on infiltration load at door openings have been taken into account, besides the more consolidated transmission load calculation. To properly consider temperature variation along the day and the year, a multi-period model has been developed. Waiting times are allowed at each stop to access the more favourable conditions in terms of both speed and outdoor temperature.

Results on a case study of a local network for frozen bread dough deliveries to supermarkets have shown how traction requirements overcome refrigeration ones and are most related to load variation, which has been often ignored in multi-drop delivery modelling. This suggests how a greater potential to enhance energy efficiency and thus sustainability of transports within the cold chain lies on reducing traction consumption rather than on improving refrigeration systems.

Different routes are selected when considering total fuel minimisation in comparison to the more traditional optimisation of total travel distance or tour duration. Even if for the basic scenario energy savings gained with fuel minimisation are rather limited, however the sensitivity analysis has underlined how different problem conditions can alter route selection and related energy savings. Therefore, different operational practices can be suggested. In particular, a non uniform demand leads to serve the most important client as the first in the delivery tour, in order to benefit both from the reduced load on board for the remaining part of the circuit and from favourable outdoor temperatures when delivering in the early morning. Otherwise, selecting the route basing on travel distance leads to higher fuel consumption, which significantly increases with the quantity delivered to the major clients. The departure time impacts on energy savings since different outdoor temperatures and allowed speed values due to traffic congestion are triggered. Similarly, refrigeration consumption per route grows from winter to summer since a greater thermal load has to be counterbalanced to maintain the refrigerated space at the temperature required to preserve food quality and safety. The location where the delivery tour takes place impacts also on fuel consumption, but not on route selection that remains unchanged among different climatic conditions. However, the impact of refrigeration with respect to traction grows significantly from cold to tropical climates, thus playing a different role for pursuing energy efficiency. Finally, the complexity of the network, i.e. the number of clients to be visited given the same vehicle capacity, impacts on both traction requirements and the refrigeration ones, due to the longer total distance and tour duration to cover all the stops. In particular, infiltration load, depending on the number of door openings, grows proportionally to the number of visits, while transmission load increases with the time that the vehicle is exposed to outdoor temperature.

The RRP has been defined for a single refrigerated vehicle, since shipping operations in last miles deliveries of frozen food are often taken by very small enterprises with a very limited fleet. However, a possible extension of the study is the development of RRP into R-VRP, i.e. considering the assignment of the proper routes to a whole fleet of vehicles. Furthermore, given the complexity of the RRP and the consequent exponential increase of solving times, as proven by simulations on network configuration and allowed waiting times, future research should be addressed to the development of more sophisticated modelling and solving techniques, in order to limit computational times while preserving the accuracy of solutions.

References

Accorsi, R., A. Gallo, and R. Manzini. 2017. "A climate driven decision-support model for the distribution of perishable products." *Journal of Cleaner Production* 165: 917–929.

Aiello, G., G. La Scalia, and R. Micale. 2012. "Simulation analysis of cold chain performance based on time-temperature data." *Production Planning and Control* 23 (6): 468–476.

Akkerman, R., P. Farahani, and M. Grunow. 2010. "Quality, safety and sustainability in food distribution: A review of quantitative operations management approaches and challenges." *OR Spectrum* 32 (4): 863–904.

Alvarez, P., I. Lerga, A. Serrano-Hernandez, and J. Faulin. 2018. "The impact of traffic congestion when optimising delivery routes in real time. A case study in Spain." *International Journal of Logistics Research and Applications* 21 (5): 529–541.

Andres Figliozzi, M. 2012. "The time dependent vehicle routing problem with time windows: Benchmark problems, an efficient solution algorithm, and solution characteristics." *Transportation Research Part E: Logistics and Transportation Review* 48 (3): 616–636.

Bagheri, F., M.A. Fayazbakhsh, and M. Bahrami. 2017. "Real-time performance evaluation and potential GHG reduction in refrigerated trailers [valuation des performances en temps rel et de la rduction potentielle des GES dans les remorques frigorifiques]." *International Journal of Refrigeration* 73: 24–38.

Barth, M., G. Scora, and T. Younglove. 2004. "Modal emissions model for heavy-duty diesel vehicles." *Transportation Research Record* 1 (1880): 10–20.

Bektaş, T., and G. Laporte. 2011. "The Pollution-Routing Problem." *Transportation Research Part B: Methodological* 45 (8): 1232–1250.

Braekers, K., K. Ramaekers, and I. Van Nieuwenhuyse. 2016. "The vehicle routing problem: State of the art classification and review." *Computers and Industrial Engineering* 99: 300–313.

Cipriano, Raffaele, Luca Di Gaspero, and Agostino Dovier. 2013. "A Multi-paradigm Tool for Large Neighborhood Search." In *Hybrid Metaheuristics*, Vol. 434 of *Studies in Computational Intelligence*, 389–414. Springer.

Dantzig, G., R. Fulkerson, and S. Johnson. 1954. "Solution of a Large-Scale Traveling-Salesman Problem." *Journal of the Operations Research Society of America* November 01: 393–410.

Dekker, Jip J., Maria Garcia de la Banda, Andreas Schutt, Peter J. Stuckey, and Guido Tack. 2018. "Solver-Independent Large Neighbourhood Search." In *Principles and Practice of Constraint Programming*, Vol. 11008 of *Lecture Notes in Computer Science*, 81–98. Springer.

Demir, E., T. Bektaş, and G. Laporte. 2012. "An adaptive large neighborhood search heuristic for the Pollution-Routing Problem." *European Journal of Operational Research* 223 (2): 346–359.

Demir, E., T. Bektaş, and G. Laporte. 2014a. "A review of recent research on green road freight transportation." *European Journal of Operational Research* 237 (3): 775–793.

Demir, Emrah, Tolga Bektaş, and Gilbert Laporte. 2014b. "The bi-objective Pollution-Routing Problem." *European Journal of Operational Research* 232 (3): 464 – 478.

Eglese, R., W. Maden, and A. Slater. 2006. "A Road Timetable to aid vehicle routing and scheduling." *Computers and Operations Research* 33 (12): 3508–3519.

Ehmke, J.F., A.M. Campbell, and B.W. Thomas. 2016. "Vehicle routing to minimize time-dependent emissions in urban areas." *European Journal of Operational Research* 251 (2): 478–494.

Ehmke, J.F., A.M. Campbell, and B.W. Thomas. 2018. "Optimizing for total costs in vehicle routing in urban areas." *Transportation Research Part E: Logistics and Transportation Review* 116: 242–265.

Elkington, J. 1998. *Cannibals with Forks: The Triple Bottom Line of the 21st Century.* Stoney Creek, CT: New Society Publishers.

Esteso, A., M.M.E. Alemany, and A. Ortiz. 2018. "Conceptual framework for designing agri-food supply chains under uncertainty by mathematical programming models." *International Journal of Production Research* 56 (13): 4418–4446.

FFE. 2018. "Frozen Food Retail Growth Accelerates." *Frozen Food Europe* January 4.

Franceschetti, A., E. Demir, D. Honhon, T. Van Woensel, G. Laporte, and M. Stobbe. 2017. "A metaheuristic for the time-dependent pollution-routing problem." *European Journal of Operational Research* 259 (3): 972–991.

Franceschetti, A., D. Honhon, T. Van Woensel, T. Bektaş, and G. Laporte. 2013. "The time-dependent pollution-routing problem." *Transportation Research Part B: Methodological* 56: 265–293.

Hsu, C.-I., S.-F. Hung, and H.-C. Li. 2007. "Vehicle routing problem with time-windows for perishable food delivery." *Journal of Food Engineering* 80 (2): 465–475.

Huang, Y., L. Zhao, T. Van Woensel, and J.-P. Gross. 2017. "Time-dependent vehicle routing problem with path flexibility." *Transportation Research Part B: Methodological* 95: 169–195.

ITA. 2016. *Top Markets Report: Cold Chain.* Technical Report. https://www.trade.gov/topmarkets/pdf/Cold_Chain_Executive_Summary.pdf: International Trade Administration U.S.

James, S. J., M. J. Swain, T. Brown, J. A. Evans, S. A. Tassou, Y. T. Ge, I. Eames, J. Missenden, G. Maidment, and D. Baglee. 2009. *Improving the Energy Efficiency of Food Refrigeration Operations.* Technical Report. The Institute of Refrigeration.

James, S.J., C. James, and J.A. Evans. 2006. "Modelling of food transportation systems - a review." *International Journal of Refrigeration* 29 (6): 947–957.

Koç, Çağri. 2018. "Analysis of vehicle emissions in location-routing problem." *Flexible Services and Manufacturing Journal* First online 27 July.

Koç, Çağri, Tolga Bektaş, Ola Jabali, and Gilbert Laporte. 2014. "The fleet size and mix pollution-routing problem." *Transportation Research Part B: Methodological* 70: 239 – 254.

Kok, A.L., E.W. Hans, and J.M.J. Schutten. 2012. "Vehicle routing under time-dependent travel times: The impact of congestion avoidance." *Computers and Operations Research* 39 (5): 910–918.

Kuo, Y., C.-C. Wang, and P.-Y. Chuang. 2009. "Optimizing goods assignment and the vehicle routing problem with time-dependent travel speeds." *Computers and Industrial Engineering* 57 (4): 1385–1392.

Laborie, Philippe, Jérôme Rogerie, Paul Shaw, and Petr Vilím. 2018. "IBM ILOG CP Optimizer for Scheduling." *Constraints* 23 (2): 210–250.

Lafaye De Micheaux, T., M. Ducoulombier, J. Moureh, V. Sartre, and J. Bonjour. 2015. "Experimental and numerical investigation of the infiltration heat load during the opening of a refrigerated truck body." *International Journal of Refrigeration* 54: 170–189.

Lin, C., K.L. Choy, G.T.S. Ho, S.H. Chung, and H.Y. Lam. 2014. "Survey of Green Vehicle Routing Problem: Past and future trends." *Expert Systems with Applications* 41 (4 PART 1): 1118–1138.

Meneghetti, A., G. Da Rold, and G. Cortella. 2018. “Sustainable refrigerated food transport: searching energy efficient routes.” *IFAC-PapersOnLine* 51 (11): 618–623.

Meneghetti, A., F. Dal Magro, and P. Simeoni. 2018. “Fostering renewables into the cold chain: How photovoltaics affect design and performance of refrigerated automated warehouses.” *Energies* 11 (5).

Meneghetti, A., and L. Monti. 2015. “Greening the food supply chain: An optimisation model for sustainable design of refrigerated automated warehouses.” *International Journal of Production Research* 53 (21): 6567–6587.

Meneghetti, Antonella, and Gioacchino Nardin. 2012. “Enabling industrial symbiosis by a facilities management optimization approach.” *Journal of Cleaner Production* 35: 263–273.

Molina, Jose Carlos, Ignacio Eguia, Jesus Racero, and Fernando Guerrero. 2014. “Multi-objective Vehicle Routing Problem with Cost and Emission Functions.” *Procedia - Social and Behavioral Sciences* 160: 254 – 263.

Nethercote, Nicholas, Peter J Stuckey, Ralph Becket, Sebastian Brand, Gregory J Duck, and Guido Tack. 2007. “MiniZinc: Towards A Standard CP Modelling Language.” In *Principles and Practice of Constraint Programming (CP 2007)*, 529–543.

Niu, Y., Z. Yang, P. Chen, and J. Xiao. 2018. “Optimizing the green open vehicle routing problem with time windows by minimizing comprehensive routing cost.” *Journal of Cleaner Production* 171: 962–971.

Novaes, A.G.N., Jr. Lima, O.F., C.C. De Carvalho, and E.T. Bez. 2015. “Thermal performance of refrigerated vehicles in the distribution of perishable food.” *Pesquisa Operacional* 35 (2): 251–284.

Owen, Mark S., ed. 2002. *2002 ASHRAE Handbook - Refrigeration*, Chap. 29 Cargo containers, railcars, trailers and trucks, 29.1-11. Atlanta GA: ASHRAE.

Owen, Mark S., ed. 2010. *2010 ASHRAE Handbook - Refrigeration*, Chap. 24 - Refrigerated-Facility Loads, 24.1-7. Atlanta GA: ASHRAE.

Rai, A., and S.A. Tassou. 2017. “Environmental impacts of vapour compression and cryogenic transport refrigeration technologies for temperature controlled food distribution.” *Energy Conversion and Management* 150: 914–923.

Rong, A., R. Akkerman, and M. Grunow. 2011. “An optimization approach for managing fresh food quality throughout the supply chain.” *International Journal of Production Economics* 131 (1): 421–429.

Rossi, Francesca, Peter van Beek, and Toby Walsh. 2006. *Handbook of Constraint Programming.* Elsevier Science Inc., New York.

Soysal, M., J.M. Bloemhof-Ruwaard, R. Haijema, and J.G.A.J. van der Vorst. 2018. “Modeling a green inventory routing problem for perishable products with horizontal collaboration.” *Computers and Operations Research* 89: 168–182.

Soysal, M., J.M. Bloemhof-Ruwaard, M.P.M. Meuwissen, and J.G.A.J. van der Vorst. 2012. “A Review on Quantitative Models for Sustainable Food Logistics Management.” *Int. J. Food System Dynamics* 3 (2): 136–155.

Soysal, M., J.M. Bloemhof-Ruwaard, and J.G.A.J. van der Vorst. 2014. “Modelling food logistics networks with emission considerations: The case of an international beef supply chain.” *International Journal of Production Economics* 152 (0): 57 – 70.

Steuer, Ralph E., and Eng-Ung Choo. 1983. “An interactive weighted Tchebycheff procedure for multiple objective programming.” *Mathematical Programming* 26 (3): 326–344.

Tassou, S.A., G. De-Lille, and Y.T. Ge. 2009. “Food transport refrigeration - Approaches to reduce energy consumption and environmental impacts of road transport." *Applied Thermal Engineering* 29 (8-9): 1467–1477.

Technavio. 2017. *Global Frozen Food Market 2017-2021*. Technical Report. https://www.technavio.com/report: Technavio Research.

Toth, Paolo, and Daniele Vigo, eds. 2001. *The Vehicle Routing Problem*. Philadelphia, PA, USA: Society for Industrial and Applied Mathematics.

Turkensteen, M. 2017. "The accuracy of carbon emission and fuel consumption computations in green vehicle routing." *European Journal of Operational Research* 262 (2): 647–659.

Validi, S., A. Bhattacharya, and P.J. Byrne. 2014a. "Integrated low-carbon distribution system for the demand side of a product distribution supply chain: A DoE-guided MOPSO optimiser-based solution approach." *International Journal of Production Research* 52 (10): 3074–3096.

Validi, Sahar, Arijit Bhattacharya, and P.J. Byrne. 2014b. "A case analysis of a sustainable food supply chain distribution system: A multi-objective approach." *International Journal of Production Economics* 152 (152): 71 – 87.

Validi, Sahar, Arijit Bhattacharya, and P.J. Byrne. 2015. "A solution method for a two-layer sustainable supply chain distribution model." *Computers & Operations Research* 54: 204 – 217.

Van Der Vorst, J.G.A.J., S. Tromp, and D. Van Der Zee. 2009. "Simulation modelling for food supply chain redesign; Integrated decision making on product quality, sustainability and logistics." *International Journal of Production Research* 47 (23): 6611–6631.

Xiao, Yiyong, Qiuhong Zhao, Ikou Kaku, and Yuchun Xu. 2012. "Development of a fuel consumption optimization model for the capacitated vehicle routing problem." *Computers & Operations Research* 39 (7): 1419 – 1431.

Yakovleva, Natalia, Joseph Sarkis, and Thomas Sloan. 2012. "Sustainable benchmarking of supply chains: the case of the food industry." *International Journal of Production Research* 50 (5): 1297–1317.

Zanoni, Simone, and Lucio Zavanella. 2012. "Chilled or frozen? Decision strategies for sustainable food supply chains." *International Journal of Production Economics* 140 (2): 731–736.

Zhang, G., W. Habenicht, and W.E.L. Spieß. 2003. "Improving the structure of deep frozen and chilled food chain with tabu search procedure." *Journal of Food Engineering* 60 (1): 67–79.

Zhu, Z., F. Chu, A. Dolgui, C. Chu, W. Zhou, and S. Piramuthu. 2018. "Recent advances and opportunities in sustainable food supply chain: a model-oriented review." *International Journal of Production Research* 56 (17): 5700–5722.