Energy-efficient frozen food transports: the Refrigerated Routing Problem

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RESEARCH PAPER

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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

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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, relative distance, 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 (Bekta and Laporte, 2011), aiming at minimising greenhouse gas (GHG) emissions. Both of them strongly rely on fuel consumption models. Demir, Bekta, and Laporte (2014) 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. Most of the recent routing studies (see Demir, Bekta, and Laporte, 2012; Franceschetti et al., 2013, 2017; Koç, 2018; Niu et al., 2018; Ehmke, Campbell, and Thomas, 2016, 2018) adopt the latter and in particular the Comprehensive Modal Emissions Modeling (CMEM) introduced by Barth, Scora, and Younglove (2004),. 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 centers 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 centers, 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 modeling 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.

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.

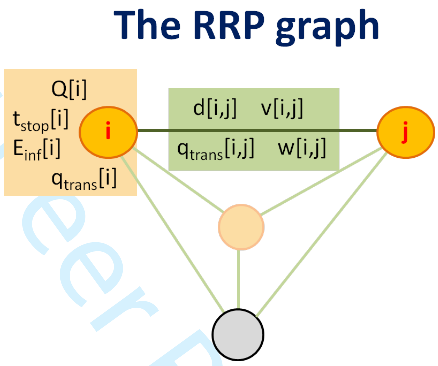


Figure 1. The RRP graph. Q[i] are the unit loads to be delivered at node i, $t_{stop}[i]$ is the stop time for unloading, $E_{inf}[i]$ the infiltration energy, $q_{trans}[i]$ the transmission load, $v[i,j]$ is the vehicle speed along arc (i,j), $w[i,j]$ is the load on board.

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 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 and indoor temperature (Owen, 2010), as in the following Eq. 1.

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

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:

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

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).

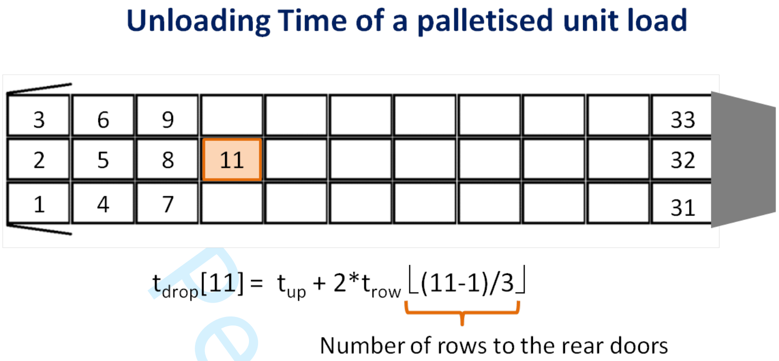


Figure 2. Time for unloading operation of palletised units

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:

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

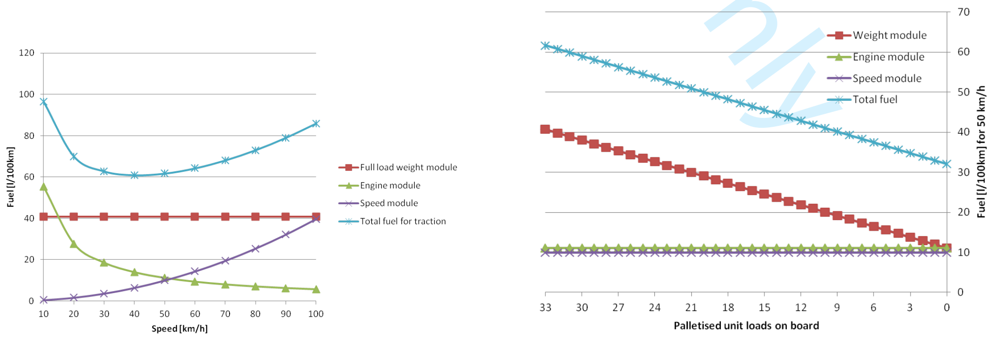
where λ is a function of the fuel-to-air mass ratio and the fuel heating value, γ

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, Bekta, 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]	2
t_{up}	Time to get up and down with a forklift	[s]	30
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 et al., 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:

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

The refrigeration fuel consumption $fuelR$ is related to the energy needed to counterbalance transmission and infiltration loads, 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 k of the multi-period model (see Table 2), the auxiliary binary variable $slot[i, k]$ is introduced and defined on the basis of the arrival time at the node, as in the following Eq. 7.

$$slot[i,k] = \begin{cases} 1 & \text{if} \quad \mathrm{start}[k] \le t_{arrival}[i] < \mathrm{end}[k] \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Each time slot k has a number of repetitions $\mathrm{h}[k]$ within the planning horizon; for example in a year the average temperature at a given time interval of the day in December should be repeated 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.

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

$$E_{trans}[i] = (t_{stop}[i] + t_{travel}[i]) \cdot \sum_{k} \left(slot[i,k] \cdot \mathrm{h}[k] \cdot \frac{\mathrm{SU}(\mathrm{To}[k] - \mathrm{Ti})}{\mathrm{COP}[k]} \right) \tag{8b}$$

$$E_{inf}[i] = \sum_{k} \left(slot[i,k] \cdot \mathrm{h}[k] \cdot \frac{\mathrm{AC}[k] + \mathrm{b}[k] \cdot (t_{stop}[i] - 40)}{\mathrm{COP}[k]} \right) \tag{8c}$$

Fuel for traction along the route $fuelT$ is calculated with CMEM (see Section 3.2) by the following Eq. 9 (see Table 1 and 2 for parameters).

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

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).

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

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

In order to associate each arc of the route with the congestion time slot j triggered at departure time from client i, the auxiliary binary variable slotV[i,j] is introduced by Eq. 11.

$$slotV[i,j] = \begin{cases} 1 & \text{if} \quad \mathrm{startV}[j] \leq t_{depart}[i] < \mathrm{endV}[j] \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

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.

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

$$v[i] = \sum_j slotV[i,j] \cdot \mathrm{V}[j] \qquad \forall i \tag{12b}$$

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

$$(load[1] = \mathrm{w} + \mathrm{m} \sum_i \mathrm{Q}[i]) \quad \wedge \quad (load[sort[i]] = load[sort[i-1]] - \mathrm{m} \cdot Q[sort[i]] \ \ \forall i \geq 2) \tag{12d}$$

The third group of constraints involves the variable attribute of each node in the route, such as arrival, stop 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.

$$t_{arrival}[1] = \text{begin} \ \wedge \ x[i] = h \Rightarrow t_{arrival}[h] = t_{depart}[i] + t_{travel}[i] \tag{13a}$$

$$t_{depart}[1] = \text{begin} \ \wedge \ t_{depart}[i] = t_{arrival}[i] + t_{stop}[i] \tag{13b}$$

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

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

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
$v[i]$	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
end[k]	End time of temperature time slot k
endV[j]	End time of congestion time slot j
h[k]	Number of repetition of temperature time slot k in the horizon
loss	Time loss factor for unloading operations
m	Palletised unit load [kg]
start[k]	Start time of temperature time slot k
startV[k]	Start time of congestion time slot k
t_fix	Fix time at client
To[k]	Outdoor temperature of time slot k
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. Several outdoor temperatures have been introduced for a total of 60 different time slots, corresponding to the average values of the 5 hours following the departure time (i.e. sufficient to cover any route) 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 0.39 and 0.70, coherently with the average yearly simulated and measured values provided by Bagheri, Fayazbakhsh, and Bahrami (2017). Congestion has been taken into account by 7 different time slots during a day (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. Speed time slots.

Time slot	**Speed [km/h]**
0 – 7	70
7 – 9	40
9 – 12	50
12 – 14	40
14 – 17	50
17 – 20	40
20 – 24	60

The model has been coded in MiniZinc (Nethercote et al., 2007), version 2.0.14, and solved using 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 500ms.

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 ($4 \rightarrow 3$ and $3 \rightarrow 1$) at higher speed. Indeed, the first two nodes fall in the speed time slot of 40 km/h whereas the last two in the one of 50 km/h.

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 ones

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 → 4 → 2 → 3 → 1	1 → 3 → 4 → 2 → 1	1 → 2 → 4 → 3 → 1
Total distance [km]	146	143	143
Total duration [min]	247	236	235
Weight module [l]	51.92	53.03	52.93
Engine module [l]	18.83	17.86	17.78
Speed module [l]	11.03	11.56	11.66
Traction [l]	81.78	82.45	82.37
Transmission [l]	4.60	4.34	4.28
Infiltration [l]	3.42	3.50	3.42
Refrigeration [l]	8.02	7.84	7.71
Total fuel consumption [l]	89.80	90.29	90.08

selected by the minimum distance and minimum duration circuit. In addition, the average speed per route is lower (42.5 km/h instead of 45 km/h), as a consequence also the consumption related to the speed module is reduced. However, the refrigeration consumption is larger due to higher transmission consumptions that are related to the longer travel time (247 minutes respect to 235 minutes) and therefore longer exposition of the vehicle to outdoor temperatures. As concerns the infiltration load, the related fuel consumption is higher for length minimisation with respect to both fuel and duration minimisation due to the different temperature slot triggered when arriving at the second client. Given the increasing outdoor temperature during the morning, the later visit at the second client of the route leads to greater AC and b values in Eq. 2.

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 60% 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 0.5% and the 0.3% 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 91% of the total fuel consumption, while the refrigeration only for the remaining 9%. 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
Total distance [km]	146	143	143	146
Total duration [min]	247	235	236	247
Traction [l]	81.78	80.74	80.71	79.81
Transmission [l]	4.60	4.35	4.33	4.6
Infiltration [l]	3.42	3.48	3.48	3.41
Refrigeration [l]	8.02	7.83	7.81	8.01
Total fuel consumption [l]	89.80	88.57	88.52	87.82

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 91% 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 minimisation, ranging from 0.5% for uniform demand, to 3.8% for $Q[i] = [0, 17, 8, 8]$ demand distribution, and to 6.3% for an even more skewed demand curve $Q[i] = [0, 21, 6, 6]$. Concerning the route duration minimisation, instead, in all the performed simulations with non uniform demand the same route of the fuel optimisation has been selected.

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 and 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.

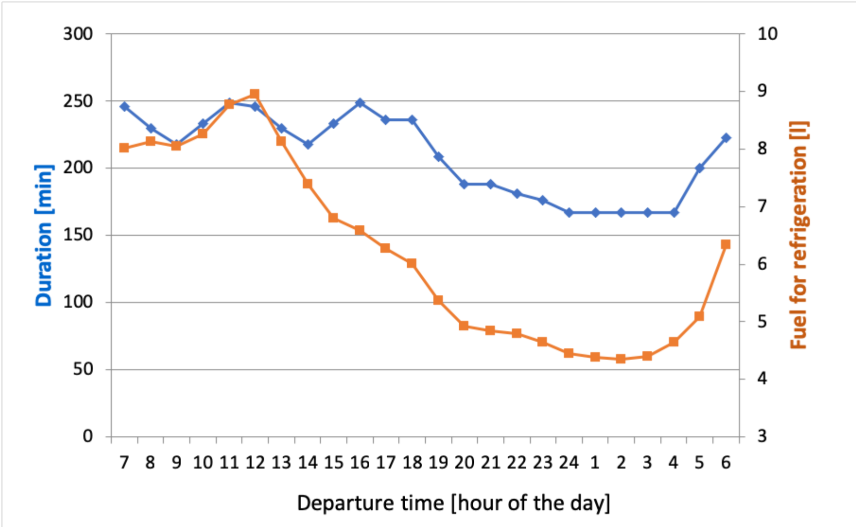


Figure 5. Travel time per route (left axis, diamond blue dot) and refrigeration fuel consumption (right axis, square orange dot) for different departure times.

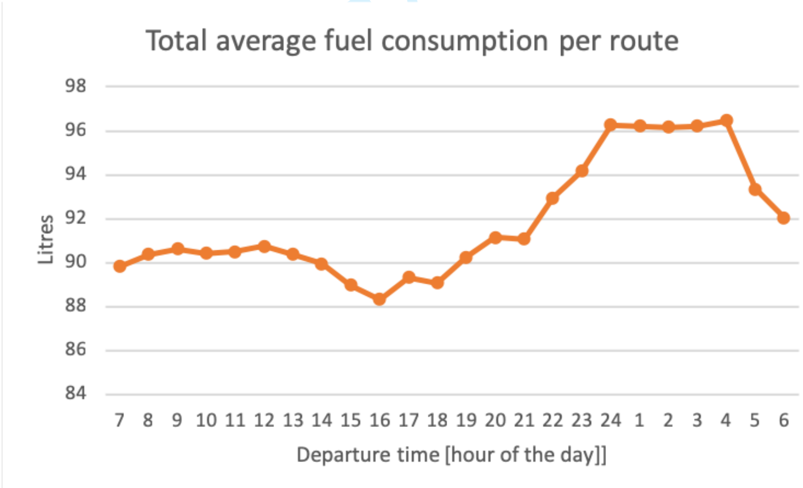


Figure 6. Total consumption per route averaged on the whole yearly planning horizon for different departure times.

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). Thus, given the 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 7 % with respect to the basic configuration (departure time at 7 a.m.).

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.

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]	247	247	247	247
Traction [l]	81.78	81.78	81.78	81.78
Transmission [l]	4.60	2.52	4.02	6.57
Infiltration [l]	3.42	1.93	3.06	4.81
Refrigeration [l]	8.02	4.45	7.08	11.38
Total fuel consumption [l]	89.8	86.23	88.86	93.16

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 5% in winter, to 8% in the mid-season and 12% 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 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 consumptios and on the performance of the adopted solver are described.

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.

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]
Total distance [km]	69	123	148
Total duration [min]	139	216	269
Traction [l]	36.32	66.31	83.03
Refrigeration [l]	4.68	7.62	12.79
Total consumption [l]	41.00	73.93	95.82

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).

In addition, the computational time is strongly dependent on the number of clients, varying from 300ms for the case of only 2 clients to 12 minutes for the one with 8 clients.

6.5. *Localities*

In the final simulation, we selected four 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]	81.8	81.8	81.8	81.8	81.8
Transmission [l]	2.57	2.98	4.6	4.76	6.74
Infiltration [l]	1.83	2.19	3.42	3.45	4.78
Refrigeration [l]	4.39	5.17	8.02	8.21	11.52
Total fuel consumption [l]	86.19	86.97	89.82	90.01	93.32
Refrigeration/Total fuel cons[%]	5.09	5.94	8.93	9.12	12.34
Refrigeration/Refr[Udine] [%]	-45.26	-35.54	0.00	2.37	43.64

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 12.34 % 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 -45% to +43%, confirming how different climate conditions strongly affect refrigeration requirements, which therefore can play a different role on pursuing energy efficiency.

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.

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, 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.

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