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The quality-driven vehicle routing problem: Model and application to a case of cooperative logistics

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ABSTRACT

Inefficient road transportation causes unnecessary costs and emissions. This problem is even more severe in fresh food transportation, where temperature control is used to guarantee product quality. On a route with multiple stops, the quality of the transported products could be negatively influenced by the door openings and consequent temperature fluctuations. In this study, we quantify the effects of multi-stop transportation on food quality. To realistically model and quantify food quality, we develop a time-and temperature-dependent kinetic model for a vehicle routing problem. The proposed extensions of the vehicle routing problem enable quantification of quality decay on a route. The model is illustrated using a case study of cooperative routing, and our results show that longer, multi-stop routes can negatively influence food quality, especially for products delivered later in the route, and when the products are very temperature-sensitive and the outside temperature is high. Minimising quality loss results in multiple routes with fewer stops per route, whereas minimising costs or emissions results in longer routes. By adjusting driving speed, unloading rate, cooling rate, and by setting a quality threshold level, the negative quality consequences of multi-stop routes can be mitigated.

1. Introduction

The Vehicle Routing Problem (VRP) has been traditionally modelled for minimising distance or the costs of routing product flows to multiple locations. As a new variant of VRP, the green VRP has been developed to also account for emissions (Bektaş and Laporte, 2011). Different studies have focused on reducing the environmental impact of logistics and inventory management by testing the effect of different carbon reduction policies (Micheli and Mantella, 2018; Castellano et al., 2019; Daryanto et al., 2019). For fresh and frozen (food) supply chains, temperature control is needed, which causes extra costs and emissions due to the energy required for cooling. To address this, Stellingwerf et al. (2018a) have extended a model based on the VRP to account for the effects of temperature control on costs and emissions in fresh and frozen food logistics.

However, next to reducing emissions, to enhance the sustainability of food logistics it is also important to guarantee food quality, and hence, reduce food waste. In fresh food logistics the temperature fluctuations resulting from the increased number of stops on a route may further influence the quality of the products transported. Also, transporting multiple products with a different optimal temperature, can be challenging with substantial consequences for the product's quality. Therefore, temperature control is an essential factor in the distribution of food products (Akkerman et al., 2010). Keeping perishable foods cooled or frozen along the food supply chain is vital to guarantee food safety, manage food waste and ensure good quality of the final product. Therefore, it is necessary to consider the influence of temperature on food quality aspects in VRP modelling.

This study introduces a VRP that explicitly considers the quality decay in transportation planning, both in the constraints and in the objective function. Using the presented model, we compare several objectives including minimising costs, emissions, and quality loss. We then study the effect of transporting different products with different optimal temperatures in one vehicle on the resulting product quality. We also test the effect of other parameters.

We illustrate the model using the case of seven Dutch supermarket chains that cooperatively buy their products in order to obtain a lower

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price. The supermarket chains consider intensifying their cooperation by also transporting their products together, in order to save transportation costs and emissions. The partners wish to have a quantification of the potential risks and benefits related to quality decay, costs and emissions to decide whether it compensates for the information that they need to share with each other in a cooperative context. Logistics cooperation has been shown to be a feasible methodology to decrease both cost and emissions during transportation of food products (Cruijssen et al., 2007; Vanovermeire et al., 2014; Pérez-Bernabeu et al., 2015; Quintero-Araujo et al., 2017; Mittal et al., 2018; Stellingwerf et al., 2018b). Most of these studies found that cooperation can result in cost reductions (Cruijssen et al., 2007; Vanovermeire et al., 2014; Quintero-Araujo et al., 2017), and some have also identified reductions in emissions in addition to cost reductions (Pérez-Bernabeu et al., 2015; Mittal et al., 2018; Stellingwerf et al., 2018b). For a recent overview of the optimisation of different forms of cooperation, we refer to Defryn and Sörensen (2018). However, a cooperative route will result in an increased number of stops, which may negatively affect food quality. With our Quality Driven VRP (QDVRP), we can also assess the effect of logistics cooperation on food quality, costs, and emissions.

The remainder of the article is structured as follows. In Section 2 we discuss food quality and how it has been modelled, in Section 3 we mathematically formulate the problem, in Section 4 we show and discuss the results, and in Section 5 we conclude this article.

2. Modelling quality in food logistics planning

In the logistics literature, quality decay has been modelled using several approaches. We categorise these and discuss each of the categories in the following subsections.

2.1. Modelling quality considering product age and remaining shelf life

A common method to handle product quality in logistics modelling is to consider a fixed shelf life for perishable items. To approximate freshness, Amorim and Almada-Lobo (2014) have quantified the remaining shelf life as a percentage of the initial shelf life in a multi-objective VRP. They compared two objective functions: cost minimisation and maximisation of the an average shelf life. Stellingwerf et al. (2018b) proposed an inventory-routing problem (IRP) model that minimises costs, emissions, or a linear combination of both objectives, and applied it to a case of temperature-controlled food distribution. After finding the optimal routing and inventory plan, the resulting average product age upon leaving the distribution centres (DCs) was calculated in days. Likewise, Soysal et al. (2018) proposed a green IRP for perishable products. Each product was assumed to have a fixed shelf life, after which it would go to waste, incurring a penalty cost.

These studies provide a way of integrating shelf life or food quality into routing models, but they do not consider how external factors, such as temperature, affect the products during transportation. Modelling quality decay (which is dependent on external factors) instead of shelf life (which often is a predetermined date) should yield a more realistic way of modelling food quality.

2.2. Modelling quality with temperature-independent quality decay

To model quality decay, some studies have used a temperature-independent decay function. Thus Ambrosino and Sciomachen (2007) accounted for quality in their VRP by imposing a maximum number of stops on the routes of the vehicles if they carried frozen products. A binary variable was used to decide whether a certain vehicle would move only dry products or also frozen products. If frozen products were transported, a constraint to limit the maximum number of stops was activated.

Osvald and Stirn (2008) studied decay during transportation using a VRP with time windows and time-dependent travel times. They assumed that quality is linearly related to time and assigned a quality starting level that decreases over time for each load. They considered the effect of delays on quality and compared a standard cost-minimisation model with a cost-minimisation model including a penalty cost for product loss due to quality decay. Their study showed that by considering quality decay in the optimisation model, up to 40% of cost savings could be realised.

Chen et al. (2009) considered a quality decay function in their production scheduling and vehicle routing problem, where total profit was maximised. The study showed that a higher decay rate leads to a lower profit, and that deterioration could be reduced by using more vehicles. However, the latter also leads to an increase in transportation cost.

2.3. Modelling quality with temperature-dependent quality decay

Hsu et al. (2007) modelled the expected loss of inventory due to quality decay in a stochastic VRP with time windows. They considered decay to be stochastic: the higher the demand per stop, the longer the door-opening time, the higher the temperature in the vehicle, and the higher the chance of spoilage of the products transported. The goal of the model was to minimise cost, in which spoilage was part of the inventory cost. Aung and Chang (2014) used a similar model with a different objective function to determine the optimal temperature for a range of products.

The studies just discussed show that shelf life and food quality have been considered in supply chain and logistics literature. However, they do not consider external factors such as temperature in the quality decay function.

2.4. Modelling quality with kinetics

Kinetic modelling is used to describe the direction and speed of different kind of reactions and it is often used to model changes in food products, for example as a function of temperature. This method is the basis for modelling quality in this paper; therefore, we now describe the main principles of kinetics modelling for quality decay of perishable products.

According to Van Boekel (2008) there exist four main types of reactions that can cause quality-related changes in food products: (i) chemical reactions, which often relate to oxidation reactions; (ii) microbial reactions; (iii) biochemical reactions, caused or catalysed by enzymes naturally present in foods; and (iv) physical reactions, such as coalescence, sedimentation and texture changes. These changes can be captured by mathematical models containing kinetic parameters. This is described in food quality modelling and mostly the Arrhenius equation is used for this purpose (Rong et al., 2011). The basics of kinetic modelling and the Arrhenius equation are presented in the Appendix and it is the basis for modelling quality in the next Section.

For reactions in food, zero and first order reactions are relevant. Zero order reactions happen at a constant speed, while in first order reactions, the speed changes linearly over time. In a zero order reaction, decay happens linearly over time. In a first order reaction, decay happens exponentially over time. This order type can be empirically derived, but in general degradation of quality attributes of fruits and vegetables follow a zero order reaction (Rong et al., 2011). Quality degradation that is mainly dependent on microbial growth (e.g. meat and fish) generally follow a first order reaction rate.

Rong et al. (2011) focused on integrating a food quality model in a logistics model. They used the Arrhenius equation to describe an *ad hoc* overall quality (not related to a specific real quality attribute), which they set at 100 at the beginning of the supply chain and then lowered as the product moved down the chain. They modelled food quality degradation through a mixed integer linear programming (MILP) model by combining existing food quality decay models and logistics models.

Table 1
Quality decay in food supply chains - a literature overview.

Reference	Topic	Time windows	Quality decay approach	Temperature-dependent	Number of commodities	Logistics cooperation
Ambrosino and Sciomachen (2007)	Food distribution VRP with split delivery	Yes	For frozen products, number of stops is limited	No	Multiple	No
Amorim and Almada-Lobo (2014)	Multi-objective VRP (costs and freshness)	Yes	Remaining shelf life as percentage of initial level	No	Multiple	No
Aung and Chang (2014)	Cold storage of multi-temperature commodities	No	Freshness gauge	Yes	Multiple	No
Chen et al. (2009)	Perishable products scheduling and routing	Yes	Continuous decay based on a product-specific decay rate	No	Multiple	No
Hsu et al. (2007)	VRPTW for perishable food delivery	Yes	Microbial growth based on cargo-hold openings	Yes	Single	No
Mishra et al. (2016)	Optimising storage temperatures for leafy greens	No	Arrhenius equation and microbial growth models	Yes	Multiple	No
Osvald and Stirn (2008)	VRP for perishable food distribution	Yes	Linear decay over time	No	Single	No
Rong et al. (2011)	MILP for production and distribution	No	Arrhenius equation	Yes	Single	No
Song and Ko (2016)	VRP for perishable food delivery	Yes	No	No	Multiple	No
Soysal et al. (2018)	IRP for perishable products	No	If the shelf life is exceeded, product becomes waste	No	Multiple	Yes
Stellingwerf et al. (2018b)	VMI in temperature-controlled chains	No	Product age is calculated in days	No	Single	Yes
Tsironi et al. (2017)	Predictive models for shelf life estimation	No	Arrhenius equation	Yes	Multiple	No
Zhang and Chen (2014)	Optimisation VRP in multi-product frozen food delivery	Yes	Damage during transport and service time	No	Multiple	No

In the model of Rong et al. (2011), products deteriorate by a given amount in each period such that the model can track the quality degradation over time. Each product starts with a given quality which decreases each period based on the time and temperature exposure. When the quality level is lower than the predetermined minimum, the product goes to waste.

Mishra et al. (2016) empirically estimated the parameters in the Arrhenius equation for the quality indicators appearance, wilting, browning, and off-odour for fresh-cut iceberg lettuce, fresh-cut romaine lettuce, and fresh-cut chicory. In their study, the decay was modelled as a percentage of initial quality lost.

Table 1 summarises the literature on modelling quality in food logistics, as described in this section.

3. Formal problem description and mathematical formulation

We now present the quality-driven vehicle routing problem. The model is an extension of the temperature-controlled load dependent VRP model of Stellingwerf et al. (2018a). We extend this model to account for quality decay at each stop and on each arc. We measure quality decay using explicit kinetic modelling based on Rong et al. (2011) and we make the service time demand-dependent based on the study of Hsu et al. (2007). We adjust it to account for multiple products, with different optimal temperature and their own Arrhenius parameters, based on Mishra et al. (2016). In addition, we use the total cost and total emissions calculations of Stellingwerf et al. (2018a).

The mixed integer linear programming problem under consideration is NP-hard since it encompasses the VRP which is known to be NP-hard. A summary of all notations (including the units of all variables and parameters) used is given Tables 11–13 in Appendix.

Let $G = (V, A)$ be a directed graph in which $V = \{0, 1, \dots, n\}$ is the set of nodes. The Central Distribution Centre (CDC) is located at vertex 0, $V' = V \backslash \{0\}$ is the set of DCs, and $A = \{(i, j) : i, j \in V, i \neq j\}$ is the set of arcs. With every arc (i, j) is associated a non-negative distance d_{ij}. We define p as an index for the set P of products with rate constant κ_0^p, activation energy EN_p^{act}, and optimal temperature T_p^{ref}.

There exists a set of K identical vehicles indexed by k of capacity L_k with a curb (empty) weight of L_k^0. The speed driven on arc (i, j) is denoted by v_{ij}. The demand of product p at each DC i is given by q_{ip}. The load inside every vehicle has a changing quality level denoted as Q_{ijkp}. At the starting CDC, all loads have an initial quality of Q_{0p}. We denote by t^{max} the maximum travelling time of one driver, and by σ_i the service time the vehicle spends at node i.

The following decision variables are used:

- x_{ijk} is a binary variable equal to 1 if and only if vehicle k drives from node i to node j
- y_{ijkp} is the total weight of product p carried, from node i to node j by vehicle k
- the binary decision variable z_{ijk} is used in a set of constraints to control the maximum cooling time on an arc
- D_{ijkp} is the total decay on an arc
- DV_{ijkp} is the decay during cooling time (at a variable temperature) on an arc
- DF_{ijkp} is the decay at a fixed temperature on an arc

- Q_{ijkp} is the quality level arriving at node j from node i of product p with vehicle k
- s_{ijk} is the cooling time of vehicle k on arc (i, j)
- $\bar{D}$ is a variable to minimise the maximum quality decay

3.1. Calculation of quality decay

Over time, fresh food products decay, which is temperature-dependent. When one type of fresh product is transported, the temperature in the vehicle is set to the optimum for that product. When there are more products, with different optimal temperatures in one vehicle, a temperature that is acceptable for all products is chosen. We assume that the outside temperature is higher than the temperature set in the vehicle, which means that the load needs to be cooled to reach the desired temperature. We also assume that the products need to be cooled but not frozen. After precooling, the temperature of the product inside transportation vehicles remains quite stable. However, temperatures quickly rise during operations such as loading and unloading the vehicle (Mercier et al., 2017). A cooled food product can be subjected to up to fifty door openings per transportation run (James et al., 2006). For (unfrozen) fresh food, the closer the product is to its optimal temperature, the slower it decays. In reality, when the temperature becomes lower than the optimum, freezing damage can occur. However, this freezing temperature is not considered in this model. When a vehicle visits a delivery point, the vehicle door opens, and consequently the temperature in the vehicle and that of the products in the vehicle will increase. When there are multiple stops, the products that are still in the vehicle after a delivery, are faced with this temperature increase. The cooling engine of the vehicle will start working to cool the vehicle again and return it to the set temperature.

To include quality in a VRP model, we model two decays in the chain; (1) the quality decay in the links and (2) quality decay in the nodes. Both decay processes are influenced by temperature variations. We define the quality decay of a product on a route as the sum of both types of decay:

$$D = \sum_{i \in V'} \sum_{k \in k} \sum_{p \in P} D_{ikp} + \sum_{i \in V'} \sum_{j \in V'} \sum_{k \in K} \sum_{p \in P} x_{ijk} D_{ijkp}, \tag{1}$$

where D is the summed quality decay, D_{ikp} is the quality decay of product p at node i in vehicle k, D_{ijkp} is the quality decay of product p at arc (i, j) in vehicle k.

The quality level Q_{ijkp} at an arc (i, j) is defined as the initial quality level when leaving the CDC, minus the decay that happened until reaching that arc. In order to guarantee a certain quality level for all partners a minimum quality level Q^{min} can be defined. The quality level and the initial quality level are described in constraints (39)–(42).

3.1.1. Quality decay at a node

The quality decay at a node is calculated using the Arrhenius equation assuming a zero order reaction for the products:

$$D_{ikp} = \kappa_0^p s_i \exp[\frac{-EN_p^{act}}{R}(\frac{1}{T_{ikp}} - \frac{1}{T_i^{ref}})], \tag{2}$$

where σ_i is the demand-dependent service time at node i, T_{ikp} is the temperature of the products in vehicle k at node i, EN_p^{act} is the activation energy of product p.

The service time at a node is calculated as follows:

$$s_i = \sum_{p \in P} q_{ip} \tau, \tag{3}$$

where q_i is the demand at node i, and τ is the unloading rate. We use an approximation based on the study of Tso et al. (2002) to calculate the temperature change of the products caused by the opening of the door during service time. The temperature change happens in a two-step process described in (4)–(6).

First, the air temperature of the vehicle is calculated:

$$T_{ik} = \min\{T^a; 0.5 s_i \phi (T^a - T_0) + T_0\} \quad i \in V', k \in K, \tag{4}$$

$$T_{0k} = T_0 \qquad k \in K, \tag{5}$$

where T_{ik} is the air temperature of vehicle k at the end of the service time at node i, T_{0k} is the air temperature of vehicle k when it leaves the CDC, T^a is the ambient temperature, ϕ is the speed of the temperature increase, which is assumed to be 0.0027 K/s based on the measurements of Tso et al. (2002), T_0 is the temperature that is set, which is called the *goal temperature* in the rest of the text. The factor of 0.5 is used to account for the first step of a two-step heating process.

Then, the product temperature is calculated:

$$T_{ikp} = \min\{T_{ik}; 0.5 s_i f (T_{ik} - T_0) + T_0\}, \tag{6}$$

where T_{ikp} is the temperature of the products in vehicle k at the end of the service time at node i. The factor of 0.5 is used to account for the second step of a two-step heating process. For the CDC, we assume no unloading time, and consequently, the air and product temperature will be equal to the goal temperature.

3.1.2. Quality decay on an arc

After visiting a node, the vehicle closes and the engine starts cooling the load. When the goal temperature is reached, the engine keeps the temperature at the goal temperature. The quality decay on an arc can thus be divided into two parts: first, there is decay while the temperature decreases from the after-opening temperature, and then there is decay during the rest of the arc traverse, at a fixed temperature:

$$D_{ijkp} = DV_{ijkp} + DF_{ijkp}, \tag{7}$$

where D_{ijkp} is the decay on an arc, DV_{ijkp} is the decay during cooling time on an arc (v for variable temperature), and DF_{ijkp} is the decay during the rest of the arc crossing time (f for fixed temperature). The decay is dimensionless.

The decay of product p during cooling time at the arc is calculated as

$$DV_{ijkp} = \kappa_0^p s_{ijk} \exp[\frac{-EN_p^{act}}{R}(\frac{1}{0.5(T_i^k + T_0)} - \frac{1}{T_p^{ref}})], \tag{8}$$

where s_{ijk} is the cooling time of vehicle k on arc (i, j), T_p^{ref} is the reference (optimal) temperature of product p. Since the cooling time is dependent on the weight of the load, which is a decision variable, its calculation is given together with the other constraints (see (46)–(48)).

When the vehicle temperature is down to its optimal level, the rest of the arc is crossed at a stable temperature, i.e. the goal or optimal temperature. The decay at the arc when the temperature is stable is calculated as

$$DF_{ijkp} = \kappa_0^p (\frac{x_{ijk} d_{ij}}{v_{ij}} - s_{ijk}) \exp[\frac{-EN_p^{act}}{R}(\frac{1}{T_0} - \frac{1}{T_p^{ref}})], \tag{9}$$

where κ_0 is the rate constant, $\frac{x_{ij} d_{ij}}{v_{ij}}$ is used to calculate the time spent on arc (i, j), and T_{ij} is the temperature of the vehicle when it moves from node i to node j.

3.1.3. Minimising the maximum decay

For a single company delivering food to multiple outlets, it makes sense to minimise total decay. However, in a cooperative mode, the different partners might find it more important that there is not too much difference between the quality they receive.

Therefore, we also calculate the maximum decay $\bar{D}$ as

$$\sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \sum_{p \in P} \hat{D}_{ijkp} = Q_{0p} - \frac{Q_{ijkp}}{Q_{0p}}, \tag{10}$$

$$\hat{D}_{ijkp} \leq \bar{D} \qquad , \tag{11}$$

where $\hat{D}_{ijkp}$ is the relative decay of a product p on arc (i, j) in vehicle k. In constraint (11) $\bar{D}$ is defined as the maximum level of decay of all products arriving at all nodes. Objective (27) minimises the maximum decay $\bar{D}$.

3.2. Fuel and emissions calculation in ambient transportation

Studies have shown that the fuel use in ambient transport is linearly related to the motive power requirement (Barth and Boriboonsomsin, 2009; Bektaş and Laporte, 2011). The latter depends on the weight carried, the slope of the road, the distance travelled and the vehicle speed. The motive power MP_{ij} on arc (i,j) can be approximated as

$$MP_{ij} = \alpha_{ij}(y_{ijkp} + L_k^0)d_{ij} + \beta v_{ij}^2 d_{ij}, \tag{12}$$

where α_{ij} is the arc-specific constant, and β is the vehicle-specific constant. Eqs. (13) and (14) show how these constants are calculated:

$$\alpha_{ij} = a + g\sin\theta_{ij} + gRR\cos\theta_{ij}, \tag{13}$$

where a is the acceleration of the vehicle (m/s^2), g is the gravitational constant (m/s^2), θ_{ij} refers to the average slope on arc (i,j) (degrees), RR is the rolling resistance (dimensionless). The vehicle-specific constant is calculated as

$$\beta_k = 0.5\ COD\ B\rho, \tag{14}$$

where COD is the drag coefficient B is the frontal area of the vehicle and ρ is the air density.

In (15) fuel use for ambient transport (f^a) is calculated by summing up the power requirements for all routes and converting those into fuel use. This is achieved by dividing the power by 3.6×10^6 to convert a Joule (J) into a kilowatt-hour (kWh), by the chemical to motive energy conversion efficiency (η^m), and by the energy content of the fuel (ECF):

$$\begin{aligned} f^a = (&\sum_{i\in V}\sum_{j\in V}\sum_{k\in K}\sum_{p\in P}\alpha(y_{ijkp} + L_k^0)d_{ij} \\ &+ \sum_{i\in V}\sum_{j\in V}\sum_{k\in K}\beta d_{ij}x_{ijkt}v_{ij}^2)\frac{1}{3.6\times 10^6\ ECF\ \eta^m}. \end{aligned} \tag{15}$$

where y_{ijkp} is the weight of product p carried from node i to j with vehicle k, and L_k^0 is the curb weight of vehicle k.

The emissions from ambient transport are linearly related to fuel use:

$$E^a = f^a e^f, \tag{16}$$

where e^f is the emissions factor which converts fuel use into CO_2 emissions, and E^a are the CO_2 emissions of ambient transport.

3.3. Fuel and emissions calculation in refrigerated transportation

Stellingwerf et al. (2018a) have approximated the cost, the fuel consumption and the emissions of refrigerated transport, so that the impact of temperature controlled transport can be estimated in route optimisation models. In refrigerated transport, fuel is used both for motive power and for keeping the temperature of the load at the right level. The energy used for temperature control depends on the heat that enters through the vehicle wall while it drives, and on the heat that enters the vehicle when the door opens. The heat entering through the wall is calculated as

$$HW = \frac{\sum_{i\in V'}\sum_{j\in V'}\sum_{k\in K}x_{ijk}d_{ij}US_k\Delta T}{3.6\times 10^6 v_{ij}}, \tag{17}$$

where $x_{ijk}d_{ij}/v_{ij}$ is used to calculate the total driving time, U is the heat transfer coefficient, S_k is the surface area of vehicle k, and ΔT is the difference in temperature between the inside and the outside of the vehicle. The heat entering when the door opens is calculated as

$$HS = \sum_{i\in V}\sum_{j\in V'}\sum_{k\in K}x_{ijk}H_i, \tag{18}$$

where H_i is the heat entering during service time at stop i, which is calculated as

$$H_i = \frac{V_k HCA(T_{ik} - T_0)}{3.6\times 10^6}, \tag{19}$$

where V_k is the volume of vehicle k, HCA is the volumetric heat capacity of air, and the factor 3.6×10^6 is used to convert J to kWh.

The total fuel used for refrigeration of the load can then be calculated as

$$f^r = \frac{HW + HS}{\eta^e COP\ ECF}, \tag{20}$$

where f^r refers to the fuel used for refrigeration of the load of the vehicle, η^e is the efficiency by which the chemical energy from the fuel is converted to electricity to drive the refrigeration system, and COP is the coefficient of performance, which measures how much thermal energy can be removed with a certain amount of electrical energy (Tassou et al., 2009).

The emissions related to refrigerated transport are a function of fuel used for motion, of fuel used for refrigeration, and of refrigerant leakage. Refrigerant leakage emissions can be approximated by multiplying the emissions needed for refrigeration by a given factor. Eq. (21) shows the calculation of emissions caused by refrigeration of the load and Eq. (22) gives the total emissions for refrigerated transport:

$$E^r = f^r e^f e^r, \tag{21}$$

where E^r are the emissions of refrigerated transport, and e^r is the emissions factor that converts emissions caused by fuel use into emissions caused by both fuel use and refrigerant leakage. The total emissions associated with temperature controlled transportation are then

$$\begin{aligned} E &= E^a + E^r \\ &= f^a e^f + f^r e^f e^r \\ &= \frac{\sum_{i\in V}\sum_{j\in V}\sum_{k\in K}\alpha y_{ijkp}d_{ij} + \sum_{i\in V}\sum_{j\in V}\sum_{k\in K}\beta d_{ij}x_{ijk}v^2}{3.6\times 10^6\ ECF\ \eta^m}e^f \\ &+ \frac{\sum_{i\in V'}\sum_{j\in V'}\sum_{k\in K}x_{ijk}d_{ij}US_k\Delta T}{3.6\times 10^6 v_{ij}\eta^e COP\ ECF}e^f e^r \\ &+ \frac{\sum_{i\in V}\sum_{j\in V'}\sum_{k\in K}x_{ijk}H_i}{\eta^e COP\ ECF}e^f e^r. \end{aligned} \tag{22}$$

3.4. Cost calculation

The total transportation cost can be calculated as follows by adding wage cost and fuel cost:

$$C = \sum_{i\in V}\sum_{j\in V}\sum_{k\in K}\frac{c^w d_{ij}x_{ijk}}{v_{ij}} + \sum_{i\in V'}\sum_{j\in V}\sum_{k\in K}c^w x_{ijk}\sigma_i + (f^a + f^r)c^f, \tag{23}$$

where C refers to the costs, c^w is the driver wage per time unit, c^f is the unit fuel cost, c^w is the unit wage cost, and σ_i is the service time at node i. Note that fuel is used both for driving (f^a, see Eq. (15)) and for temperature control (f^r, see Eq. (20)).

3.5. Formulation of objectives and constraints

For the QDVRP model, we consider the three objective functions of minimising product decay D (24), minimising CO_2 emissions (25), minimising cost (26), and minimising the maximum decay (27), which have been defined in terms of the model parameters and variables in Eqs. (1), (22) and (23) and in constraint (11):

Minimise D (24)

Minimise E (25)

Minimise C (26)

Minimise $\bar{D}$ (27)

subject to

$$\sum_{i\in V'}\sum_{k\in K}x_{0ik} \le |K| \tag{28}$$

$$\sum_{j\in V}\sum_{k\in K}y_{jikp} - \sum_{j\in V}\sum_{k\in K}y_{ijkp} = q_{ip} \qquad i\in V', p\in Pi \ne j \tag{29}$$

$$y_{i0kp} = 0 \qquad i \in V', k \in K, p \in P \tag{30}$$

$$y_{ijkp} \leq (L_k - q_{ip})x_{ijk} \qquad i \in V, j \in V, k \in K, p \in P, i \neq j \tag{31}$$

$$y_{0jkp} \leq L_k x_{0jk} \qquad j \in V, k \in K, p \in P \tag{32}$$

$$y_{ijkp} \geq q_{jp} x_{ijk} \qquad i \in V, j \in V, k \in K, p \in P, i \neq j \tag{33}$$

$$\sum_{i \in V} \sum_{j \in V'} \frac{d_{ij} x_{ijk}}{v_{ij}} + \sum_{i \in V} \sum_{j \in V'} x_{ijk} s_i \leq t^{max} \qquad k \in K \tag{34}$$

$$\sum_{i \in V} \sum_{j \in V} \sum_{k \in K} x_{ijk} = 0 \qquad i = j \tag{35}$$

$$\sum_{i \in V} x_{ijk} = \sum_{j \in V} x_{jik} \qquad j \in V, k \in K \tag{36}$$

$$\sum_{i \in V} \sum_{k \in K} x_{i0k} = \sum_{i \in V'} \sum_{k \in K} x_{0ik} \tag{37}$$

$$\sum_{j \in V} x_{0jk} \leq 1 \qquad k \in K \tag{38}$$

$$Q_{0ikp} = Q_{0p} x_{0ik} \qquad i \in V', p \in P, k \in K \tag{39}$$

$$\sum_{j \in V} Q_{jikp} - \sum_{j \in V} Q_{ijkp} = D_{ikp} + \sum_{j \in V} D_{ijkp} \qquad i \in V', p \in P, k \in K \tag{40}$$

$$Q_{ijkp} \leq Q_0 x_{ijkp} \qquad i \in V', j \in I, p \in P, k \in K \tag{41}$$

$$Q_{ijkp} \geq Q^{min} \qquad i \in V, j \in I, p \in P, k \in K \tag{42}$$

$$x_{ijk} \in \{0, 1\} \qquad i \in V, j \in V, k \in K \tag{43}$$

$$s_{ijk} \leq \frac{x_{ijk} d_{ij}}{v_{ij}} + M z_{ijk} \qquad i \in V', j \in V, k \in K \tag{44}$$

$$-s_{ijk} \leq -\frac{x_{ijk} d_{ij}}{v_{ij}} + M z_{ijk} \qquad i \in V', j \in V, k \in K \tag{45}$$

$$s_{ijk} \leq \sum_{p \in P} y_{ijkp} \frac{d_{ij} x_{ijk}}{v_{ij}} \left(\frac{T_i - T_0 + 0.001}{T^a - T_0}\right) + M z_{ijk} \qquad i \in V', j \in V, k \in K \tag{46}$$

$$-s_{ijk} \leq -\sum_{p \in P} y_{ijkp} \frac{d_{ij} x_{ijk}}{v_{ij}} \left(\frac{T_i - T_0 + 0.001}{T^a - T_0}\right) + M z_{ijk} \qquad i \in V', j \in V, k \in K \tag{47}$$

$$z_{ijk} \in \{0, 1\} \qquad i \in V', j \in V, k \in K, \tag{48}$$

where M is a very large number. Constraints (28) specify that no more than $|K|$ vehicles available leave the CDC. Constraints (29) are balance constraints; after a node is visited, the load of the vehicle diminishes with the demand delivered to that node. Constraints (30) force the vehicle to return to the CDC empty. Constraints (31)–(33) set boundaries on the minimum and maximum weight transported over an edge and connect decision variables x_{ijk} and y_{ijkp} such that the emission-minimising objective function can remain linear. Constraints (34) limit the maximum working time per driver. Constraints (35) forbid routes between the same location. Constraints (36) enforce that if a node is entered by a vehicle, it should leave from the same node. Constraints (37) state that the number of vehicles leaving the CDC should be equal to the number returning. Constraints (38) force the model to use a new vehicle when a new route from the CDC is started. Constraints (39) set the initial quality level. Constraints (40) are the quality balance constraints. Constraints (41) ensure that the quality cannot exceed the initial quality. Constraints (42) define the minimum quality level. Constraints (43) are binary constraints. Constraints (44)–(48) define the cooling time. They ensure that the cooling time is either equal to a function of the load, the cooling speed, and the difference in temperature of the vehicle, and the goal temperature, or equal to the total arc crossing time.

Fig. 1 visually summarises the model for the Quality Driven Vehicle Routing Problem.

4. Computational results and discussion

In the computational experiments, we first test the effect of using different objective functions (minimising cost, emissions, total decay, and maximum decay) on a number of key performance indicators: decay, emissions, cost, distance, travelling time and computation time. In terms of quality decay, we measure *total decay*, which is the sum of the decays of the different products at the different locations; *average quality*, which is the quality that the partners receive on average; and *maximum decay*, which is the highest decay received by (one of the) partners. Note that the maximum decay is the complement of the minimum quality level. Dependent on the context, we show the one that is more relevant. We also show how quality changes along a delivery route. Then, in our sensitivity analyses we test the effects of different parameters in the QDVRP on the KPIs when decay is minimised. We test the effects of using a quality threshold level, different unloading rates, outside temperature, driving speed, cooling rate, and different optimal product temperatures.

The model was coded and solved exactly using Fico Xpress Mosel version 8.0 on a PC with Intel Core i5 processor (2.6 GHz) and eight GB of memory.

Table 2
Distances (in km) between the DCs of the supermarket chains (denoted by 1–7) and the CDC (denoted by 0).

	0	1	2	3	4	5	6	7
0	0	91	6	134	82	117	74	192
1	91	0	91	75	134	43	20	155
2	6	91	0	134	84	117	75	194
3	134	75	134	0	168	46	94	90
4	82	134	84	168	0	158	140	180
5	117	43	117	46	158	0	59	117
6	74	20	75	94	140	59	0	174
7	192	155	194	90	180	117	174	0

Table 3
Kinetic parameters and demand (kg) of each product for all DCs.

Kinetic parameter	Product 1	Product 2	Product 3
k_0 (s^{-1})	3.08×10^{-6}	3.84×10^{-6}	1.96×10^{-6}
EN^{act} (J/mol)	77 900	76 304	88 521
DC			
1	432	432	216
2	2160	648	648
3	648	216	432
4	792	403	432
5	1080	432	648
6	979	86	259
7	864	432	432

4.1. Data and assumptions

Our case study is based on data obtained from seven supermarket chains that cooperatively purchase their products in order to obtain a lower unit price. The cooperatively bought products arrive at the cooperative's central distribution centre (CDC), and then each supermarket chain individually transports their part of the order to their Distribution Centre (DC), from which they are further distributed towards the supermarket shops. The supermarket chains consider to also cooperate on the transportation from the CDC to the DCs to save costs and CO_2 emissions, but they are worried that cooperative routing might affect food quality. We base our study on demand data of three types of vegetables for the different supermarket chains. Of those products, the optimal temperatures, and parameters that describe the degradation rate for different quality attributes have been studied (Tsironi et al., 2017). The distances between the cooperative's central distribution centre (CDC) and the distribution centres (DC) of each supermarket chain are given in Table 2.

The kinetic parameters of the three products and demands of the three products for the DCs can be found in Table 3. The following assumptions are also made for the base case: For all products, the

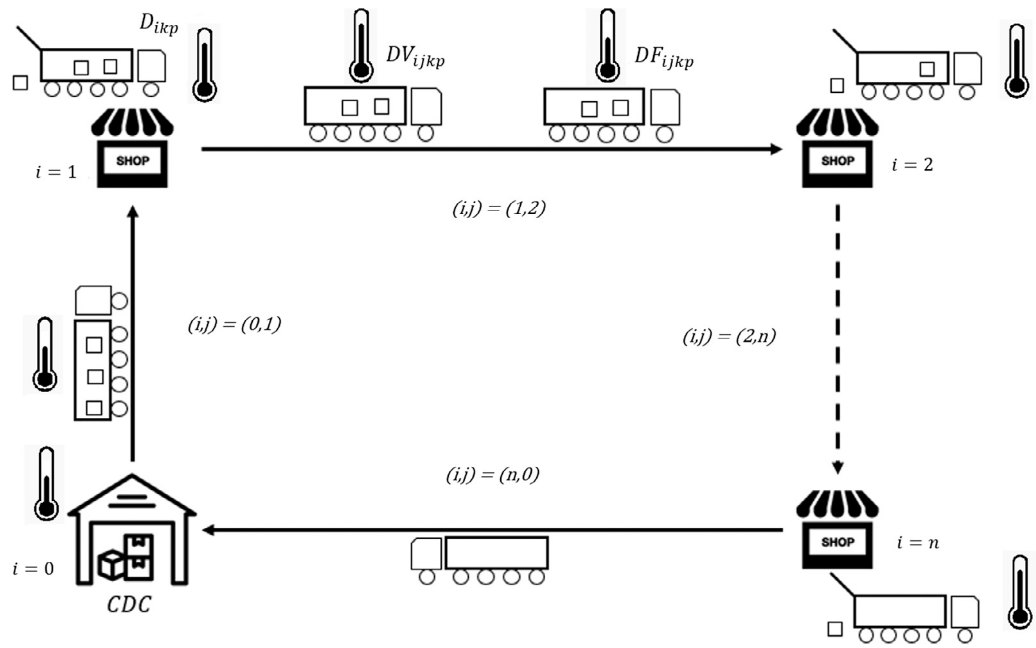

Fig. 1. Graphical representation of the QDVRP model.

Table 4
KPIs resulting from minimising the different objectives for different numbers of vehicles.

		Minimisation objective											
	Indiv.	Cost			Decay			Emission			Maximum decay		
Available vehicles	7	2	3	4	2	3	4	2	3	4	2	3	4
Total decay	4.7	4.53	4.47	4.47	4.53	4.47	4.43	4.53	4.53	4.53	4.53	4.47	4.43
- Maximum decay (%)	15	42	42	42	42	42	29	42	42	42	42	42	29
- Average quality (%)	92	81	83	83	81	83	88	81	81	81	81	83	88
Emissions (kg CO_2)	1695	886	888	888	886	888	1074	886	886	886	886	888	1074
Cost (€)	1074	570	562	562	570	562	676	570	570	570	570	562	676
Distance (km)	1393	639	644	644	639	644	808	639	639	639	639	644	808
Travel time (h)	13.4	10.0	8.7	8.7	10.0	8.7	9.4	10.0	10.0	10.0	10.0	8.7	9.4
Used vehicles	7	2	3	3	2	3	4	2	2	2	2	3	4
Computation time (s)	3	7	30	574	27	480	1231	11	24	24	32	310	408

optimal temperature is 275 K (2 °C), and the vehicle's goal temperature is 275 K (2 °C) as well. The ambient temperature is 293 K. The unloading time is 0.8 s per kg of load. The cooling time is 0.4 s per kg of load in the vehicle. Since the products in the case are fresh cut vegetables it was assumed that the order reaction of the Arrhenius equation was a zero order reaction (Tsironi et al., 2017). There is a three-vehicle fleet available. Each vehicle has an empty weight of 10 000 kg and a capacity of 30 000 kg.

4.2. Base case: comparing different objective functions

We run the model with different objectives to better understand how food quality changes in a cooperative route. When one objective function is used, the others turn into indicators rather than objectives. Also, we test how different numbers of allowed vehicles affect the outcomes by changing constraint (28). The number of vehicles that is actually used by the model is calculated ex-post by summing x_{ijk}. We also show the results of the model for individual routing to compare cooperative and individual route planning. The results are summarised in Table 4. In this Table, the total decay is the (dimensionless) sum of the decays of all products of all customers, while the minimum and the average decay are percentages of the original quality that the customers receive.

Table 4 shows that cooperation results in lower total decay, emissions, costs, distance, travel time, and vehicle use. However, in the non-cooperative scenario, the average quality is higher and the maximum decay is lower. We compare different objectives and different numbers of allowed vehicles, and Table 4 shows that the number of used vehicles differs per objective function. For minimisation of emissions, it is optimal to use two vehicles; for cost minimisation, it is optimal to use three vehicles, and for maximum and total decay minimisation, it is optimal to use four vehicles. Allowing for only one vehicle results in infeasibility because of the driving time constraint. Allowing for more than four vehicles does not lead to new solutions. In the sensitivity analyses we further explore the effects of the different parameters on quality decay, as well as on the other performance indicators.

4.3. Sensitivity analyses

In this section we test the effect of setting a threshold value for a minimum quality level, unloading rate, outside temperature, driving speed, cooling rate, and optimal temperature on the results of the quality decay minimisation model.

4.3.1. Threshold for minimum quality level

Since total decay minimisation can result in some customers receiving a rather low product quality (reflected in the minimum product quality in Table 4), we test the effect of quality thresholds (Table 5).

Table 5
Effect of quality threshold on average quality delivered based on order in a route, and on the other KPIs.

Threshold	Vehicles	Order visited					Total decay	Emissions	Cost	Travelling time	Computation time
		1	2	3	4	5					
80	4	91	85				4.6	1268	801	12.4	120
≤71	4	91	87	75			4.4	1074	676	9.4	132
0	3	92	89	80	73	64	4.5	888	562	8.7	480
0	2	91	85	80	73	64	4.5	886	570	10.0	27

Table 6
Effect unloading rate on KPIs and routes.

Rate (s/kg)	0.4	0.8	1.2
Total decay (–)	2.7	4.5	6.3
– Minimum quality (%)	74	58	61
– Average quality (%)	90	83	80
Emissions (kg CO_2)	888	888	1071
Cost (€)	553	562	696
Distance (km)	644	644	803
Travelling time (h)	7.7	8.7	12.2
Computation time (s)	120	480	542

Table 7
Effect outside temperature on KPIs and routes.

Outside temperature (°C)	2	10	20	30
Total decay (–)	1.0	1.8	4.5	11.9
– Minimum quality (%)	92	84	58	18
– Average quality (%)	96	93	83	62
Emissions (kg CO_2)	729	801	888	1164
Cost (€)	501	524	562	724
Distance (km)	639	644	644	803
Travelling time (h)	10.0	8.7	8.7	10.7
Computation time (s)	3	27	42	883

Table 5 shows the average product quality received based on the order at which a customer is visited, as well as the total decay, emissions, cost, travelling time and computation time. Since we expected quality thresholds to result in shorter routes, we allow for four vehicles instead of three. Allowing for more than four vehicles gives the same results as allowing for four vehicles, so those results are not shown. As a comparison, also the three- and two-vehicle results without threshold level are shown. Testing a threshold of 85% or higher results in infeasible solutions since at some individual routes there is already 15% quality loss for some products, and a threshold level of lower than 71% results in the same solution as having no threshold since the minimum quality level when there is no threshold is 71%. Table 5 shows that a higher quality threshold results shorter routes; in the 80% threshold route, only two customers are visited per route. Also, it shows that using four vehicles instead of three results in a lower total quality decay as it allows for shorter routes. However, the highest threshold (80%) causes an increase in decay, as well as in cost and emissions.

4.3.2. Unloading rate

In the model, an unloading rate is assumed based on communication with practise. We test different unloading rate to test how influential it is in terms of quality decay (Table 6).

Table 6 shows that the door opening time is higher and the temperature increase at a stop is higher when the unloading rate is lower. When unloading happens twice as fast (which can be caused by automation in loading/unloading), total decay can reduce with 40% and the minimum received quality and the average quality increase with 16 and 7 percentage points, respectively. When increasing unloading rate, costs and emissions stay the same, or improve.

4.3.3. Outside temperature

Table 7 shows the effect of the outside temperature on the KPIs when decay is minimised.

As the results imply, the outside temperature is an important factor in quality decay. When we combine this with the effect of unloading rate, we can see that in warmer countries, it is especially important to unload quickly. Also, at a temperature of 30 °C, the minimum quality reaches a level (18%) that will probably be unacceptable for most customers.

4.3.4. Driving speed

We varied the speed matrix to test different average driving speeds (Table 8). The base case (scenario 1.0) has an average driving speed of 55 km/h, and the other scenarios (denoted 0.6 – 1.4) define by which number the speed matrix is multiplied to obtain the new speed matrix. The base case speed matrix can be found in Table 14 (Appendix).

Table 8 shows that a higher driving speed can reduce total quality decay, while for emissions and cost, the intermediate driving speeds give better results. However, in terms of minimum and average decay level, a lower driving speed (up to 0.8 times the base case speed matrix) results in better solutions. This is because the lower driving speeds result in two two-destination routes and one three-destination route, while the faster scenarios (0.9 times the base case speed and up) result in two one-destination routes and one five-destination route. In terms of emissions and costs, a speed close to the base case results in the best performance.

4.3.5. Cooling rate

Different cooling rates were tested and the results are presented in Table 9.

Table 9 shows that only a very fast cooling rate changes the optimal route and consequently, the cost and emissions. However, the effect of cooling rate is much smaller compared with the effect of unloading rate. As a consequence of the different route at the fastest cooling rate, the minimum quality level does improve significantly.

4.3.6. Optimal temperature

So far, we have assumed that all products had the same optimal temperature (275 K, 2 °C). Here, we test the effect of different optimal temperatures, while minimising quality decay.

Table 10 shows that a higher average optimal temperature significantly decreases decay. This implies that considering quality decay is very important for temperature-sensitive products with a low optimal temperature, especially if they are transported in a warm environment. In the scenario with three different optimal temperatures, the products are transported at the average optimal temperature. This causes product 1 to be transported above its optimal temperature, but still, the average and minimum decay are better than in the scenario where all products need a low temperature.

4.4. General discussion

Compared with cost and emissions minimisation, decay minimisation results in using more vehicles and driving sorter routes. When driving longer routes, the product quality arriving at locations visited later in the route is lower. This difference in quality level could be corrected by setting a threshold quality level for all locations. This, however, yields higher costs and emissions. In our case study, we also tried to minimise the maximum decay to reduce the quality difference between locations but this did not produce other solutions. However,

Table 8
Effect of driving speed on KPIs and routes.

Scenario	0.6	0.7	0.8	0.9	1.0	1.1	1.2	1.3	1.4
Route 1	(0, 2, 4, 0)	(0, 2, 4, 0)		(0, 2, 0)					
Route 2	(0, 3, 7, 0)	(0, 5, 3, 7, 0)		(0, 4, 0)					
Route 3	(0, 6, 1, 5, 0)	(0, 6, 1, 0)		(0, 6, 1, 5, 3, 7, 0)					
Total decay (–)	5.0	4.8	4.7	4.6	4.5	4.4	4.3	4.3	4.3
– Minimum quality (%)	74	69	70	57	58	59	59	60	60
– Average quality (%)	86	85	86	83	83	83	84	84	84
Emissions (kg CO_2)	1024	1003	1020	867	888	913	941	972	1006
Cost (€)	744	694	684	561	562	567	575	585	598
Distance (km)	844	803	803	644	644	644	644	644	644
Travelling time (h)	16.3	14.0	12.6	9.5	8.7	8.1	7.6	7.2	6.9
Computation time (s)	198	120	39	325	480	685	976	577	1314

Table 9
Effect of cooling rate on KPIs and routes.

Scenario	Fast	Base	Slow	Slowest
Cooling rate (s/kg)	0.2	0.4	0.6	0.8
Total decay (–)	4.4	4.5	4.6	4.6
– Minimum quality (%)	73	58	57	56
– Average quality (%)	83	83	83	83
Emissions (kg CO_2)	1073	888	888	888
Cost (€)	684	562	562	562
Distance (km)	802	644	644	644
Travel time (h)	10.5	8.7	8.7	8.7
Computation time (s)	28	480	1699	7656

Table 10
Effect of the optimal product temperature on KPIs and routes. T_0 is the goal temperature in the vehicle. T_1–T_3 are the optimal temperatures of product 1 to 3.

T_0 (K)	275	280	280
T_1 (K)	275	280	275
T_2 (K)	275	280	280
T_3 (K)	275	280	285
Total decay (–)	4.5	1.4	2.3
– Minimum quality (%)	58	76	62
– Average quality (%)	83	90	89
Emissions (kg CO_2)	888	845	845
Cost (€)	562	543	543
Distance (km)	644	644	644
Travelling time (h)	8.7	8.7	8.7
Computation time (s)	480	405	326

in a setting with more alternative routes, this approach may yield different solutions. In literature focusing on emissions reduction in logistics, recent papers have combined transportation and inventory management (Micheli and Mantella, 2018; Stellingwerf et al., 2018b; Castellano et al., 2019; Daryanto et al., 2019). This study has focused on how to implement quality modelling in routing literature but future research could extend this study to a wider supply chain context by, for example, also considering quality loss during storage.

5. Conclusions

We have introduced, modelled and solved the Quality Driven Vehicle Routing Problem (QDVRP), which is an extension of the traditional VRP, that explicitly considers the quality aspects of food and perishable transportation. Our model was applied to a cooperative setting to study the effects of multi-stop routing on food quality, but also on cost and emissions. Our sensitivity analyses showed that faster unloading (e.g., by automation in loading/unloading process) or faster cooling (i.e. equipping the vehicles with better cooling engines) can reduce total quality decay. Also, technical improvements to prevent heat from entering the vehicles when unloading could reduce decay. The outside temperature is also very influential on the decay rate. However, this is hard to influence, but one could choose to transport food products very early in the morning or at night to benefit from a lower outside temperature, and to avoid traffic jams. Also, faster driving can decrease total decay. However, in our case study, a lower speed resulted in a higher minimum and average quality. Moreover, an intermediate speed results in better costs and emissions.

The QDVRP model has scientific impact because it extends VRP literature in order to also account for quality decay on a multi-stop route, and the model can be used to explore the relation between economic, environmental and quality objectives. In practise, the model can be used to gain insight in possible quality losses during transportation, and cooperative partners can use this model to measure the impacts of food logistics cooperation on costs, emissions and quality decay. Moreover, the model can be used to test the effect of technological improvements to reduce quality decay during road transportation.

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Appendix

Food quality models

The general equation to describe quality decay (Rong et al., 2011) is as follows:

$$\frac{dq}{dt} = \kappa q^n, \tag{49}$$

where dq is the change in quality (dimensionless), dt is the change in time (days), κ is the degradation rate (days^{-1}), which was approximated using the Arrhenius equation (Eq. (50)), and n indicates the order or the reaction (1 for a first order reaction, and 0 for a zero order reaction).

For temperature-dependent reaction kinetics, the Arrhenius law (Van Boekel, 2008) is very often used to predict the rate constant κ of a reaction based on absolute temperature T:

$$\kappa = \kappa_0 \exp(\frac{-EN^{act}}{RT}), \tag{50}$$

where κ is the rate constant (s^{-1} for a first order reaction and mol/L/s for a zero order reaction), κ_0 is the pre-exponential factor (s^{-1} for

Table 11
Sets and indices used in the models.

Set	Definition and index
A	Set of arcs (i, j)
I	Set of nodes i
K	Set of vehicles k
P	Set of products p

Table 12
Variables used in the models.

Variable	Unit	Definition
C	€	Total cost
D	–	Summed decay
$\bar{D}$	–	Variable to minimise maximum quality decay
$\hat{D}_{ijkp}$	–	The relative decay of a product p on arc (i,j) in vehicle k
D_{ijkp}	–	Decay on arc (i,j) for product p transported with vehicle k
DV_{ijkp}	–	Decay during cooling time (at a variable temperature) on arc (i,j) for product p transported with vehicle k
DF_{ijkp}	–	Decay at a fixed temperature on arc (i,j) for product p transported with vehicle k
E	kg	Total CO_2 emissions
Q_{ijkp}	–	Quality level arriving at node j from node i of product p with vehicle k
s_{ijk}	s	Cooling time of vehicle k on arc (i,j)
x_{ijk}	–	Binary: 1 if arc (i,j) is crossed with vehicle k, 0 otherwise
y_{ijkp}	kg	Weight of product p transported by vehicle k from node i to node j
z_{ijk}	–	Binary for big M method

Table 13
Parameters used in the models.

Parameter	Unit	Definition
α_{ij}	m/s^2	Arc-specific constant
β	kg/m	Vehicle-specific constant
ΔT	K	Difference in temperature inside an outside vehicle
η^e	–	Chemical to refrigeration energy conversion efficiency
η^m	–	Motive energy conversion efficiency
ϕ	K/s	Speed of the temperature increase
κ	mol/(Ls)	Rate constant
κ^0	mol/(Ls)	Pre-exponential factor
ρ	kg/m^3	Air density
σ_i	s	Service time at stop i
θ_{ij}	°	Slope of the road on arc (i,j)
τ	s/kg	Unloading rate
a	m/s^2	Acceleration of the vehicle
B	m^2	Frontal area of the vehicle
COD	–	Coefficient of drag
COP	–	Coefficient of performance
d_{ij}	m	Distance of arc (i,j)
c^f	€/L	Unit fuel cost
c^w	€/s	Unit wage cost
EN_p^{act}	J/mol	Activation energy of product p
ECF	kWh/L	Energy content of the fuel
E^a	kg CO_2	Emissions of ambient transport
e^f	kg/L	Fuel to CO_2 emissions factor
E^r	kg CO_2	Emissions of refrigerated transport
e^r	kg/kg	Emissions factor refrigerated transport
f^a	L	Fuel use for ambient transport
f^r	L	Fuel use for refrigerated transport
g	m/s^2	Gravitational constant
H_i	kWh	Heat entering during service time at stop on node i
HS	kWh	Heat entering during service time
HW	kWh	Heat entering through the wall
HCA	$J/(m^3\ K)$	Volumetric heat capacity of air at constant pressure
L_k	kg	Capacity of vehicle k
L_k^0	kg	Curb weight of vehicle k
M	–	A very large number
MP_{ij}	kWh	Motive power on arc (i,j)
q_{ip}	–	Demand node i of product p
Q_{0p}	–	Initial quality product p
Q^{min}	–	Minimum quality level
R	J/(mol K)	Gas constant
RR	–	Rolling resistance
S_k	m^2	The surface area of vehicle k
t^{max}	s	Maximum travelling time for one driver
T	K	Temperature
T_0	K	Goal temperature (temperature at i = 0)
T_{0k}	K	Air temperature in vehicle k when it leaves the CDC
T^a	K	Ambient temperature
T_{ik}	K	Air temperature of vehicle k at the end of the service time at node i
T_{ikp}	K	Product temperature in vehicle k at the end of the service time at node i
T_p^{ref}	K	Reference (optimal) temperature of product p
U	$W/m^2/K$	Heat transfer coefficient
v_{ij}	m/s	Speed driven on arc (i,j)
V_k	m^3	Volume of vehicle k

Table 14
Base case speed matrix (km/h).

	0	1	2	3	4	5	6	7
0		45.9	50.7	51.4	63.4	65.9	50.5	46.7
1	59.1		42.9	48.1	60.2	65.3	44.5	46.9
2	64.2	60.3		60.2	66.4	63.6	59.1	50.5
3	61.0	64.7	44.2		67.9	58.9	51.3	52.3
4	41.8	49.7	50.0	50.4		65.5	48.2	48.1
5	50.7	52.1	46.8	47.8	42.3		42.5	50.2
6	62.5	63.1	44.9	65.3	65.2	61.1		50.7
7	62.8	56.8	59.7	59.8	59.3	59.2	60.9	

a first order reaction and mol/L/s for a zero order reaction), EN^{act} is the activation energy (Joule/mol), R is the gas constant (8.3145 Joule/mol/K), and T is the temperature in degrees Kelvin (K). Different quality attributes at different temperatures for a certain type of food can be empirically estimated for the Arrhenius equation.

Notations

Table 11 describes the sets and indices used in the models, Table 12 summarises all decision variables used, and Table 13 gives an overview of all parameters.

Speed matrix

Table 14 shows the base case speed matrix.

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