The impact of dual sourcing on food supply chain networks: the case of Egyptian strawberries

Roberto Rossi,[1,2] Willem A. Rijpkema[2] and Jack G.A.J van der Vorst[2]

[1]University of Edinburgh Business School, UK
roberto.rossi@ed.ac.uk

[2]Logistics, Decision and Information Sciences, Wageningen University, the Netherlands
willem.rijpkema@wur.nl, jack.vandervorst@wur.nl

Abstract

Supply chain management for fresh produce differs significantly from that of other products. Similarly to other products, fresh produce quality plays a key role in consumer selection behavior. The key difference consists in the fact that, for fresh produce, quality varies over time and it is dramatically affected by storage conditions. Maintaining product quality along the distribution chain is therefore of utmost importance in these chains. Dual sourcing is a common practice adopted in supply chain management for enhancing sourcing flexibility and reducing transportation costs. This work investigates the impact of dual sourcing strategies on quality of fresh fruit traded in international food supply chains. By means of a discrete-event simulation model we investigate dual sourcing in the context of a prototype supply chain that mimics the structure and the operating conditions of a real supply chain.

Keywords: dual-sourcing, food supply chains, quality

1 Introduction

This work investigates the impact of dual sourcing strategies on quality of fresh fruit traded in international food supply chains. Dual sourcing is an established practice in supply chain management – see (Veeraraghavan and Scheller-Wolf, 2008; Schimpel, 2010; Klosterhalfen et al., 2011). When a company adopts dual sourcing, it typically ships a large volume of products via a cheap, but usually slow shipping mode, which we will call “regular”. However, the company also has the flexibility to ship more products when needed via an expedited shipping mode, which is more expensive. Companies therefore adopt dual sourcing to enhance flexibility of their sourcing strategy.

An issue that, to the best of our knowledge, has not been investigated yet in the literature, is the impact of dual sourcing on fresh produce quality. Existing literature on dual sourcing focuses on spare part management, car manufacturing, and on other similar fields (Schimpel, 2010). In these fields we typically find non-perishable products such as electronic components, engine parts etc. Clearly, a longer transportation time does not affect the quality of these products. However, little research exists on dual sourcing applied to fresh food produce. For fresh produce, a lean and fast chain is key to product quality on retail shelves. An interesting issue then is to study if dual sourcing, which is a common strategy among firms to reduce costs, may jeopardize product quality in food supply chains.

This research line stems from a discussion carried out with industrial partners involved in the context of a European project (Veg-i-trade) investigating safety and quality in international food supply chains. Our industrial partner currently adopts a dual sourcing strategy for shipping fresh strawberries from Egypt to Belgium. Based on the data provided by our partner and on existing literature on strawberry quality modeling, we designed a prototype chain network for the international trade of fresh strawberries. For this chain, we built a discrete event simulation model. Discrete-event simulation is a common modeling technique adopted in operations research (Riddals et al., 2000) and in food supply chain management (van der Vorst et al., 2000; van der Zee and van der Vorst, 2005). In discrete-event simulation, the operation of a system is represented as a chronological sequence of events. Each event occurs at an instant in time and marks a change of state in the system. The model we developed was then used to answer the following research questions:

- Does a dual sourcing inventory control policy, whilst reducing costs, guarantee a sufficient quality of strawberries at consumption and reasonable waste?
- How sensitive is a dual sourcing policy to variations of initial quality and temperatures along the chain?
- What is the impact of fuel cost variation on final product quality and on waste?

We next provide a detailed description of the case analyzed in this work.

2 Problem description

In this work we focus on a prototype chain network for the international trade of fresh strawberries; the structure of this chain has been derived from data collected in the context of several company interviews with an international fresh fruit distributor that operates in Belgium. We now summarize the structure and the core elements of this supply chain.

2.1 Logistic chain description

For confidentiality reasons, we will not disclose the name of the distributor for the case analyzed in this work. In what follows we will use generic terms such as "supplier" and "distributor" in place of the actual company names. Throughout the year, the distributor imports strawberries from different locations (see Table 1), both European (i.e. Spain and Netherlands) and non-European (i.e. Egypt).

Table 1: Import regions of strawberries for different seasons

Product	Availablilty												Country
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
Strawberry			■	■	■	■	■	■	■	■	■	■	Belgium
	■	■									■	■	Egypt
			■	■	■	■	■	■	■	■	■	■	Netherlands
	■	■	■	■	■							■	Spain

Each of these four chains – i.e. supply from Belgium, Spain, from the Netherlands and from Egypt – is different. In what follows we will focus on the chain that exposes the highest complexity and length: the one in which strawberries are sourced from Egypt.

A schematic depiction of the Egypt sourcing chain is given in Fig. 1.

In this chain strawberries are sourced from a single producer that owns large farms in the surroundings of El Cairo, Egypt. This producer serves a large number of customers, comprising the distributor discussed in this work. The distributor adopts a dual sourcing strategy. On a daily basis, it ships products by plane and, once per week, it ships a given amount by boat. Retail outlets order products daily from the distributor.

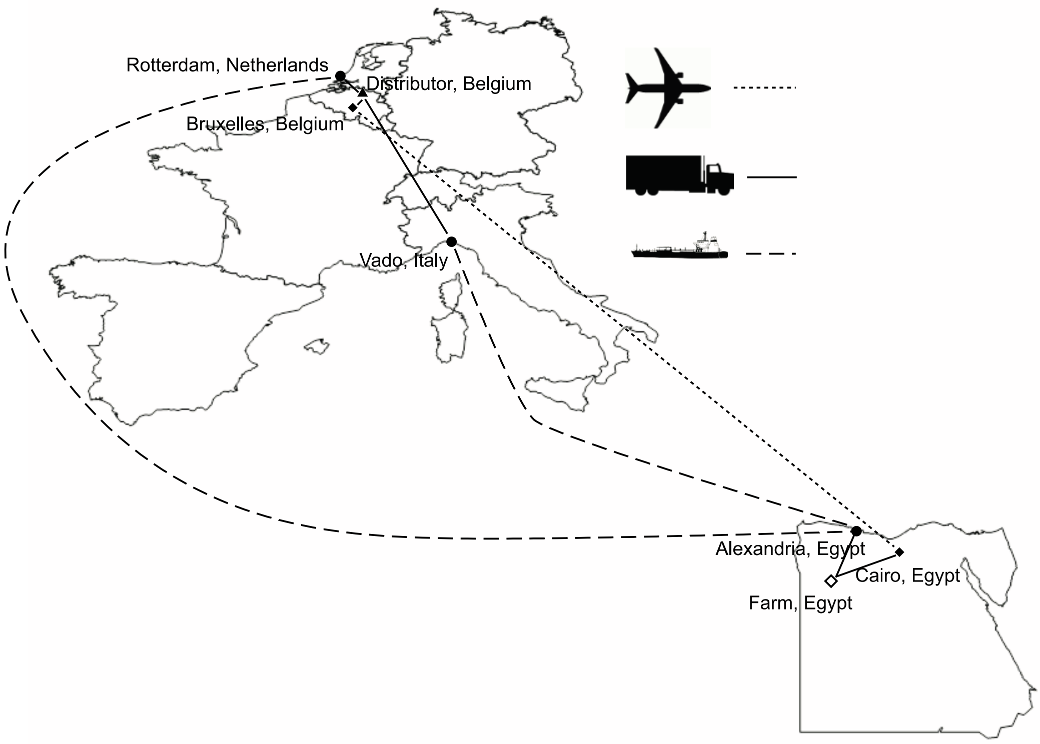

Figure 1: Supply network of fresh strawberries

Modeling the inventory control policy of a chain like the one in Fig. 1 poses a hard optimization challenge. When products do not expire, under a standard cost structure (i.e. convex fixed/variable ordering and proportional holding costs) comprising backordering costs at both producer and distributor and service level constraints (i.e. a prescribed daily non-stock out probability) at retailers, an optimal control strategy for the whole chain does not have a simple or well-known structure. This can be easily seen from the fact that even the optimal control strategy for a simple dual-sourcing chain such as the one in (Klosterhalfen et al., 2011) has a complex structure. Furthermore, as the authors remark in (Diks et al., 1996) the control of multi-echelon systems is often completely decentralized. In practice, the chain discussed in this work is also not centrally coordinated. The producer and the retail outlets are separate companies that do not share information on their stock levels, demand forecasts etc. Each actor within this chain therefore myopically optimizes its stocks to provide a given service level to the actors downstream. Furthermore, each actor carries out separate forecasting activities. In this work, we assume that actors have access to a probability distribution – for instance provided by the forecasting unit of the company – that describes the demand he/she is faced with.

Producer

Production runs on a daily basis from Monday to Friday to serve a normally distributed demand with expected value of 15 tons and standard deviation of 3.87 tons. These figures are representative for real volumes and random variations experienced by the producer. The producer implements a base-stock policy (Silver et al., 1998). In a base stock policy every day the producer sets the production quantity in order to target a given “order-up-to-level”. In our case, this is simply the expected demand (15 tons) plus some “safety stocks” to hedge against uncertainty. Safety stocks are computed by using the known “Newsboy” formula (Silver et al., 1998)

$$\text{safety stock} = \sigma G^{-1}(\alpha),$$

where σ is the standard deviation of the demand and $G^{-1}(\alpha)$ is the inverse cumulative distribution function of a standard normally distributed random variable computed at probability α. In what follows, we assume that the producer targets a service level $\alpha = 0.95$. If a stock out occurs at the producer, demand is backordered until the next production run.

Every morning, from Monday to Friday, production starts at 6.00am and lasts 6 hours. Employees pick strawberries from the field and pack them into punnets of approximately 250g each. These punnets are collected into crates that can contain 160 boxes. Crates are stacked into pallets (20 crates per pallet) in the field. A skilled employee takes around 30 seconds to fill a punnet, a pallet would be therefore completed in 24 hours if a single employee works on it. Clearly, this is not the case, since many employees work in parallel to fill crates. It is reasonable to assume that a pallet is completed in about half an hour, if 60 employees work together to fill crates. We can safely assume that each pallet remains on the field, at air temperature, for about 1 hour, while it is being filled and then transported to the cooling cell. The temperature in the field is normally distributed with mean 15 C and standard deviation 2 C[1]**.** Then the pallet is stored in a cooling cell in which the temperature is normally distributed with mean 1 C and standard deviation 0.25 C. Pallets remain in the cooling cell until an order arrives.

Transportation and lead-times
The distributor in Belgium places orders at noon and adopts two shipping modes, i.e. a dual-sourcing strategy.

Daily, it sources a certain number of pallets by plane from the farm in Egypt. This is the most expensive and the fastest way to receive pallets in Belgium from Egypt. Pallets are shipped from the farm to El Cairo airport in cooled trucks. Temperature in all cooled trucks used along the chain is Normally distributed with mean 2 C and standard deviation 0.35 C. The distance of the farm from El Cairo international airport is 160 km, which a typical truck used for transporting strawberry pallets covers in about 2 hours. Then pallets undergo customs operations for about 4 hours, during this time they are typically stored at open-air temperature. Finally, they are loaded on the plane. The trip by plane takes 6 hours, this time comprises loading and unloading operations. The temperature in the plane is normally distributed with mean 1 C and standard deviation 0.25 C. Finally, pallets undergo custom operations at the destination airport in Belgium and they are transported via cooled trucks to the distribution center (3 hours trip) where they are stored at a temperature that is normally distributed with mean 1 C and standard deviation 0.25 C, until the next replenishment order from retail shops arrives.

Alternatively, instead of shipping pallets by plane, the distributor every Monday may ship a certain volume by boat. The distance from Alexandria harbor is 320 km, which a typical truck used for transporting strawberry pallets covers in about 4 hours. Customs operations in Egypt and the Netherlands are comparable to those discussed above. There are two possible destination harbors for shipping pallets. They can be shipped either to Vado in Italy and then transported by truck to Belgium, or they can be shipped to Rotterdam and the transported by truck to Belgium. In this work we assume that all the pallets are shipped to Rotterdam. The temperature in the boat is Normally distributed with mean 1 C and standard deviation 0.25 C.

[1] Temperature in El Cairo varies between 10 and 20 degreed between November and February, see http://en.wikipedia.org/wiki/Cairo#Climate.

The boat trip to Rotterdam takes 6 days, in contrast to the 6 hours for the plane trip. Under this assumption, we have effectively two possible sourcing modes: expedited and regular.

Dual sourcing is an active area of research in inventory control. As shown in (Veeraraghavan and Scheller-Wolf, 2008) computing an optimal dual sourcing policy for the situation depicted above is a complex matter. For this reason, the authors proposed a simpler **"dual-index policy"** that provides good performances and that is easier to implement and optimize. In a dual-index policy we have two "order-up-to-levels", one for the expedite orders (S_e) and one for the regular orders (S_r), where $S_e < S_r$. Inventory is first raised to S_e via an expedite order, if it is lower than this level; then it is further raised to S_r via a regular order. In (Klosterhalfen et al., 2011) the authors proposed an alternative, and simpler, **"constant-order policy"** that operates in a similar fashion, but in which the regular order is always of a fixed size Q, and thus we don't have an order-up-to-level for regular orders. The authors showed that none of these policies dominates the other from a cost perspective and that both these policy provide satisfactory performances when compared to the optimal one. We will investigate next how these policies impact product quality in the supply chain here analyzed.

Retail outlet

The distributor serves a number of retail outlets. If a stock-out occurs at the distributor, demand is backordered until the next replenishment arrives. In our model we included 10 retail outlets to simulate a realistic chain. Each retail outlet places a replenishment order every day around midday. The exact time of each order is randomized (i.e noon +/- 5 minutes, uniformly distributed) and the producer serves orders on a first come first serve basis. Before midday, shop assistants out-of-date products. We assume that the management of each retail outlet has correctly estimated the rate parameter λ of the Poisson distribution of its customer demand, and that this information is used for inventory control purposes. Inventory control at the retail outlet is performed by employing a base stock policy targeting a service level $\alpha = 0.95$. The discussion on how to compute the daily order-up-to-level is analogous to the one presented for the producer. If a stock out occurs at a retailer, demand is backordered until the next replenishment arrives. At a retail outlet, products are stored at a temperature that is Normally distributed with mean 3 C and standard deviation 0.5 C.

Consumer demand

For each retail shop, customers purchase products from 8am to 8pm, a total of 12 hours shopping time. Purchases follow a Poisson distribution with rate $\lambda = 600$ units/day at each of the 10 retail shops; this corresponds to 0.150 tons of expected demand per shop, and to a total expected demand of 1.5 tons. Consumers are grouped in two categories. 40% of them selects the freshest product based on the packing date, since strawberries do not have a use-by date, 60% selects the product in front of the shelf. Products are regularly ordered on the shelves, so that the oldest appear in front.

Household consumption

Once a product has been purchased, we assume the product is transported at home by car. The transport time is assumed to be distributed according to a $\gamma(\frac{5.25}{2}, 8.17)$ distribution, i.e. we consider an average transport time of about 21 minutes. The distribution $\gamma(5.25,8.17)$ was derived by using data taken from (Evans et al., 1999) and it is representative for distances in the south of England. To account for the shorter distances in the Netherlands we divide the above distribution by two, thus yielding $\gamma(\frac{5.25}{2}, 8.17)$. The storage temperature is distributed according to $4 + 21\beta(\frac{15}{7}, \frac{27}{7})$, the resulting mean is 11.5 °C and the standard deviation is 3.8 °C, this is taken from (Evans, 1992).

Consumer store their products in a refrigerator whose temperature is assumed to be normally distributed with mean 5.99 °C and standard deviation 1.83 °C. The time to consumption is distributed according to a negative exponential distribution with expected value of 4h. The choice of a negative exponential distribution is based on (Nauta et al., 2003) and reflects the fact that typically a product is consumed well before it expires, while other products remain for long time in the refrigerator and then they are typically trashed. In our study, products that are not consumed before the quality drops to the acceptance level are thrown away.

2.2 Sensor quality

Spoilage of strawberries can have several different causes. One of the factors that play a key role in the spoilage process is the mold Botrytis cinerea. We adopt the model in (Hertog et al., 1999) for modeling spoilage of strawberries packed under modified atmosphere. As shown in Fig. 2 spoilage follows a sigmoid pattern.

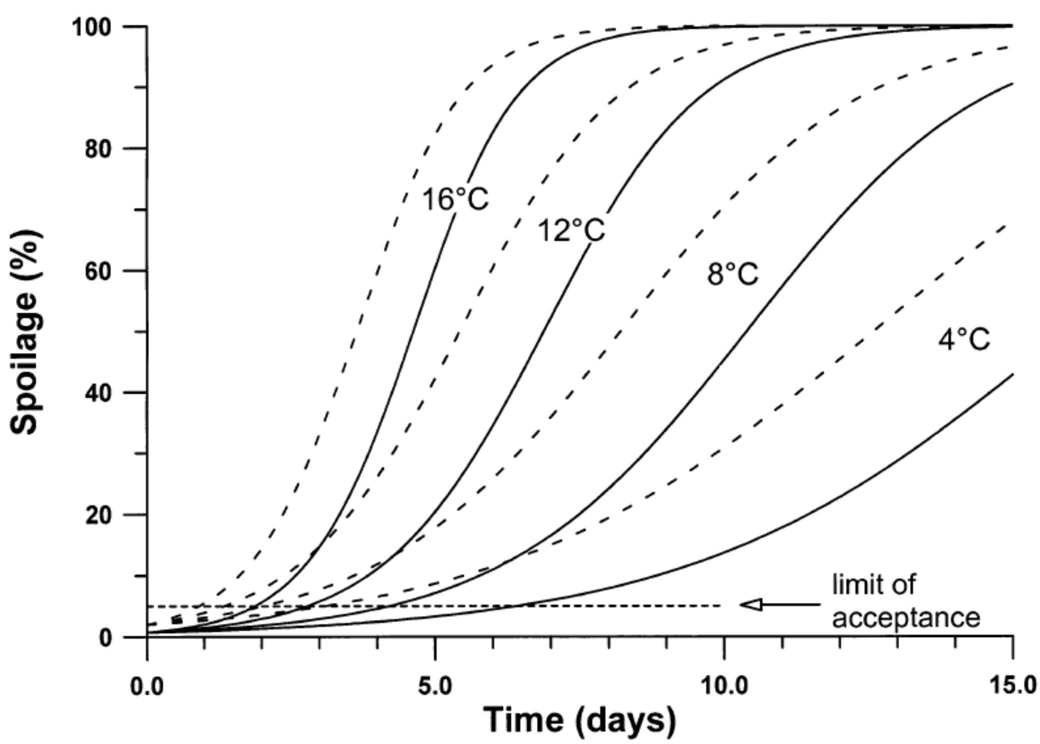

Figure 2: Strawberry spoilage (variety Elsanta) caused by Botrytis cinerea (Hertog et al., 1999)

The differential equation that describes the spoilage process is

$$\frac{dN}{dt} = Rel_{MR} \cdot k_s \cdot N \cdot \left(\frac{N_{max}-N}{N_{max}}\right),$$

where N denotes the percentage of strawberries affected. We denote the initial percentage of strawberries affected as N_0. k_s denotes the spoilage rate constant. Rel_{MR} is the relative metabolic rate; this term introduces the effect of the storage atmospheres in the rate of spoilage. In the case of strawberries packaged in air, as it is the case in our study, this term of the equation can be ignored, i.e. its value can be set to 1.

The temperature dependence of k_s is described by the following Arrhenius relationship

$$k_s = k_s^{\mathrm{ref}} e^{\frac{E_a^s}{R_g}\left(\frac{1}{T_{\mathrm{ref}}^s}-\frac{1}{T}\right)}$$

where $k_s^{\mathrm{ref}} = 6.9 \cdot 10^{-6} \frac{1}{sec}$ is the maximum quality change rate, $E_a^s = 7.0108 \cdot 10^4 \frac{\mathrm{J}}{\mathrm{mol}}$ is the activation energy, R_g is the universal gas constant, and $T_{\mathrm{ref}}^S = 284.15$ K is the temperature at which the maximum quality change rate applies. The initial quality N_0 of a batch at $t = 0$ is uniformly distributed in 0.798 ± 0.709. The limit of acceptance, that determines when a package becomes waste, is set to 5% of strawberries affected. All these values are fixed according to (Hertog et al., 1999) and (Schouten et al., 2002).

3 Software implementation

Our system was implemented by using the Stochastic Simulation in Java (SSJ) library[2]. SSJ is an object-oriented simulation library. This library provides facilities for modeling hybrid discrete/continuous simulation systems and it is therefore particularly suitable for the problem discussed in this work. The library features both, “Event” objects, which represent atomic events that occur at a certain point in time – for instance the purchase of a packet of salad – and “Continuous” objects, which instead represent items for which we aim to track a property that changes over time – for instance the quality of a punnet of strawberries. For each continuous object in the system, we simply provide the associated differential equation and the initial condition. During simulation, SSJ performs the required integration and updates the dynamic property by using one of the many available strategies, for instance Runge-Kutta integration method (Butcher 2008). If an object moves through the supply chain during simulation and enters a particular storage location that is associated with a specific temperature distribution, the integration procedure will generate, at each integration step, a new random temperature value that will be used to carry out the integration step. By using this facility, we were able to model customer demand flowing through the system by using discrete event simulation, while product quality decay was modeled by using the Runge-Kutta integration method made available in SSJ. The integration step was fixed to one hour, since a finer granularity did not prove to be beneficial.

Near-optimal policy parameters for the dual-index policy and for the constant order policy were obtained by using genetic algorithms (GA); for a comprehensive review on metaheuristic techniques in optimization see (Blum and Roli, 2008). Genetic algorithms are a meta-heuristic method for computing near-optimal solutions to complex optimization problems. They typically proceed by iteratively improving a solution for a certain number of steps or until some “quality indicator” reaches a satisfactory value. A solution is usually encoded as a “chromosome”, that is an array of integer or real values whose elements represent an assignment for the decision variables of the problem. Via a number of “operators” such as mutation, recombination etc, GA tries to move from one chromosome to another to improve an objective function, such as the cost or the profit of a plan. More specifically we employed an open source library in java (JGAP[3]) to compute, for the dual-index policy 5 different S_e, one for each expedite order placed from Monday to Friday, and 1 S_r for the regular order placed on Monday – therefore our chromosome comprises 6 values; for the constant-order policy, 5 different S_e, one for each expedite order placed from Monday to Friday, and the constant order quantity Q for the regular order placed on Monday – also in this case we have a chromosome with 6 values. The objective function that is minimized is

[2] http://www.iro.umontreal.ca/~simardr/ssj/indexe.html

[3] http://jgap.sourceforge.net/

the expected total cost at the distributor. This cost comprises fixed ordering costs for expedite and regular orders – where the cost of an expedite order is higher than that of a regular order – proportional holding cost, incurred for holding one unit of inventory in stock, and penalty cost, incurred when a unit of demand from a retailer cannot be met from available inventory. To compute near-optimal constant-order policy parameters we ran a JGAP optimization with a population size of 1000 units and 100 evolutions. The configuration used for the GA is the one in the `DefaultConfiguration` class provided with the library. We ran 5 optimization cycles and take the best solution among those produced.

4 Scenario analysis

In this section we discuss how the constant-order policy (COP) and the dual-index policy (DIP) impact product quality and age at consumption, as well as waste at producer, distributor and retailer.

4.1 Scenarios

We now introduce the scenarios considered in our analysis.

Scenario 1 (base case COP): This scenario constitutes the base case of our simulation analysis under a constant-order policy. Chain parameters are set as discussed in Section 2. The holding cost is set to 10 cents per punnet per day, the backordering cost is 50 cents per punnet per day, the cost of shipping 1 punnet by boat is 10 cents, the cost for shipping 1 punnet by plane is 30 cents. The solution obtained with GA sets the constant order quantity to $Q = 24410$, and the order-up-to-levels for the expedite orders placed from Monday to Friday to $S_e = [4065, 36471, 24434, 36626, 36632, 6800]$, respectively. This policy, when implemented at the distributor, has an expected total cost of 1405$ per day.

Scenario 2 (base case DIP): This scenario constitutes the base case of our simulation analysis under a dual-index policy. Chain parameters are set as discussed in Section 2. The holding cost is set to 10 cents per punnet per day, the backordering cost is 50 cents per punnet per day, the cost of shipping 1 punnet by boat is 10 cents, the cost for shipping 1 punnet by plane is 30 cents. The solution obtained with GA sets the order-up-to-level for the regular order on Monday to $S_r = 49625$, and the order-up-to-levels for the expedite orders placed from Monday to Friday to $S_e = [24661, 17009, 25976, 36985, 36964, 17252]$, respectively. This policy, when implemented at the distributor, has an expected total cost of 1421.3$ per day.

Scenario 3 (climate change COP) & Scenario 4 (climate change DIP): In these scenarios we assume that open-air temperature at the producer is impacted by climate change. We therefore consider an open-air temperature that is normally distributed with mean 16 C and standard deviation of 3 C. Scenario 3 implements a constant order policy, while scenario 4 implements a dual-index policy under these modified temperature conditions.

Scenario 5 (repacking COP) & Scenario 6 (repacking DIP): In these scenarios we assume that repacking activities impact mean and standard deviation of storage temperature at the distributor. Repacking is carried out at a temperature of 10 C. We therefore consider an overall storage temperature at the distributor that is Normally distributed with mean 3 C and standard deviation of 0.75 C. This modified temperature distribution accounts for the additional variation introduced by repacking activities. Scenario 5 implements a constant order policy, while scenario 6 implements a dual-index policy under these modified temperature conditions.

Scenario 7 (higher quality punnets COP) & Scenario 8 (higher quality punnets DIP): In these scenarios we assume that the initial quality of a batch at $t = 0$ is uniformly distributed in 0.3 ± 0.250. That is we consider punnets in which 0.05 up to 0.55 percent of the strawberries are affected by Botrytis cinerea. We aim to assess the impact of higher quality products that enter the chain. Scenario 7 implements a constant order policy, while scenario 8 implements a dual-index policy under these modified initial quality conditions.

Scenario 9 (higher fuel costs COP) & Scenario 10 (higher fuel costs DIP): In these scenarios, we assume that the expedite shipping cost per punnet rises to 50 cents, while the cost for regular transport is not affected. Scenario 9 implements a constant order policy, while scenario 10 implements a dual-index policy under these modified shipping costs.

4.2 Results

The ten scenarios discussed in the previous section are simulated for a period of 60 days. We adopt the common random number strategy (Sloan and Unwin, 1990) for conducting our simulations; therefore the system employs a single random number generator that is always initialized with the same seed, so that all the runs are comparable. The results of our simulation runs are shown in Table 2. Shaded rows contains statistics for scenarios implementing a constant order policy, white rows contains statistics for scenarios implementing a dual-index policy. For each scenario, we report mean (μ) and standard deviation (σ) of the product quality and product age observed when a consumer takes the product out of the fridge to consume it. Note that, according to the given acceptance criterion, only products with quality less or equal to 5 are acceptable for consumption. We also report mean and standard deviation of the retailer waste at the end of each day. The retailer also adopts the aforementioned acceptance criterion.

Table 2: Simulation results

	Quality at consumption		Age at consumption (hrs)		Retailer waste (punnets)	
Scenario	μ	σ	μ	σ	μ	σ
1	11.8	14.7	238	131	1477	861
2	16.9	21.4	276	166	1685	863
3	11.8	14.7	238	131	1478	863
4	16.8	21.4	276	166	1683	867
5	13.0	15.9	236	131	1577	901
6	18.3	22.2	275	166	1765	891
7	6.38	10.2	252	133	869	603
8	10.2	17.1	289	169	1102	698
9	26.2	27.2	353	196	2154	945
10	28.1	28.0	366	202	2220	963

Unfortunately, due to the heavy tailed behavior of the system the figures in Table 2 are not very representative. This behavior is clearly seen in Fig. 3-7 for both product quality and product age at consumption. These empirical distributions also show that a dual-index policy, employed in scenario 2, exhibits fatter tails than a constant order policy.

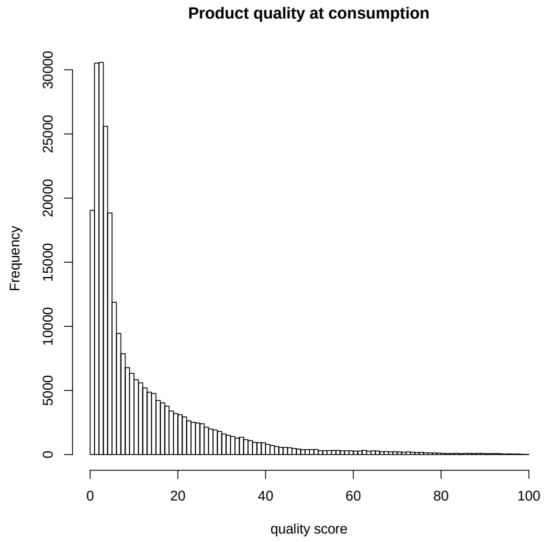

Figure 3: Scenario 1

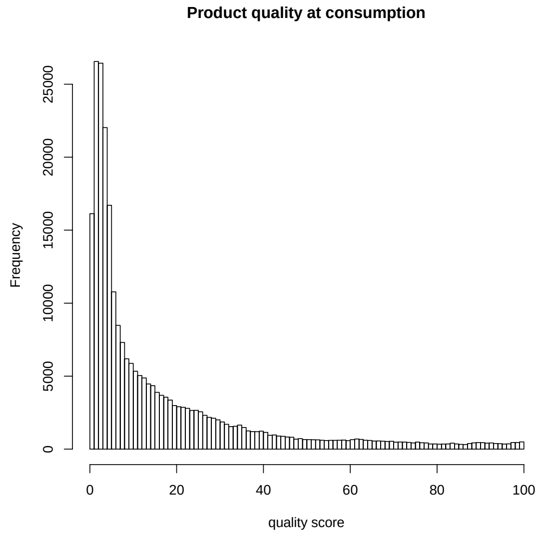

Figure 5: Scenario 2

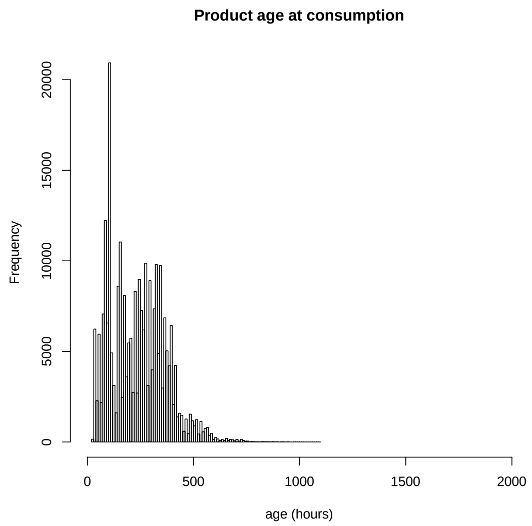

Figure 4: Scenario 1

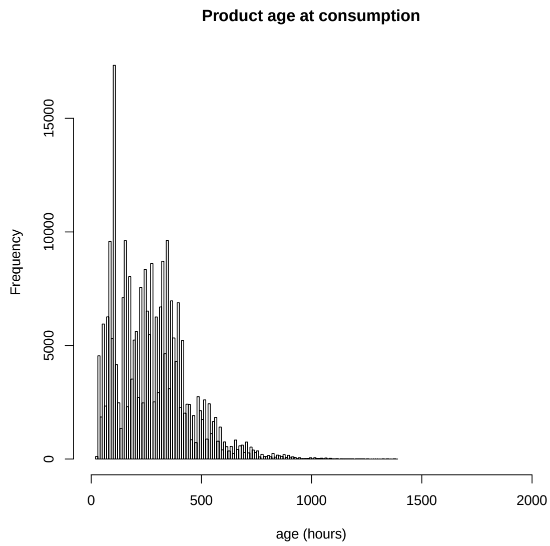

Figure 6: Scenario 2

In Fig. 7-9 we also report boxplots[4] – see (Hartwig and Dearing 1979) and (Mcgill, Tukey et al. 1978) – for the empirical distribution of the quality and of the age at consumption, as well as of the retailer waste distribution for each scenario. In the boxplot of the quality at consumption a red line marks the acceptance threshold. Only punnets with a quality factor lower than 5 – i.e. with less than 5% of strawberries affected by Botrytis – are consumed.

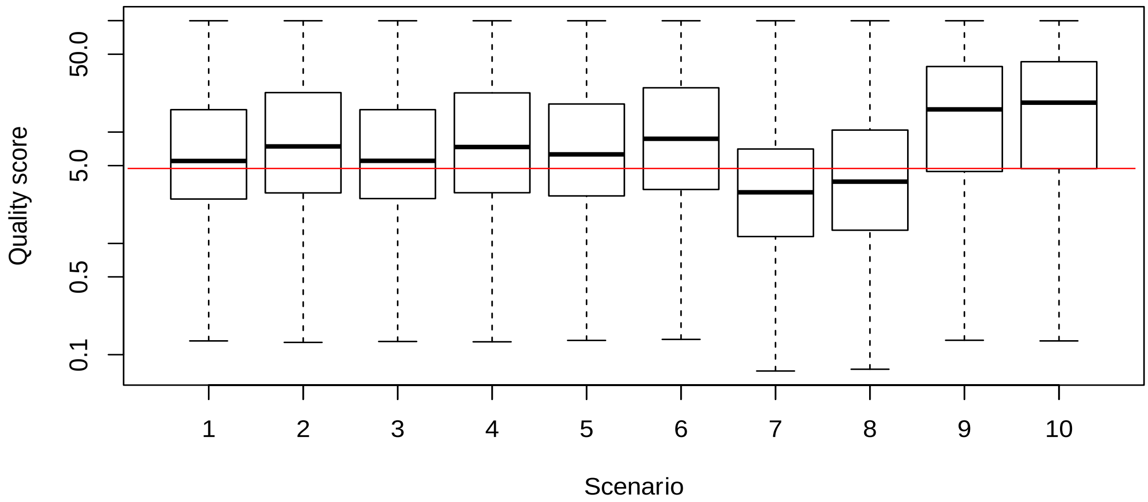

Figure 7: Quality at consumption

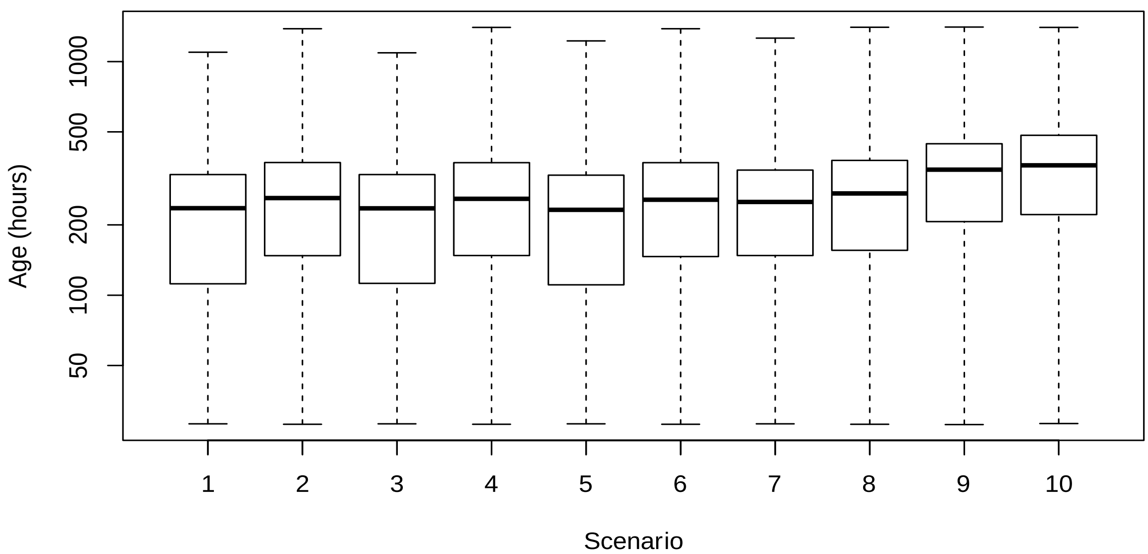

Figure 8: Age at consumption

[4] A boxplot (also known as a box-and-whisker diagram or plot) is a convenient way of graphically depicting groups of numerical data through their five-number summaries: the smallest observation (sample minimum), lower quartile (Q1), median (Q2), upper quartile (Q3), and largest observation (sample maximum).

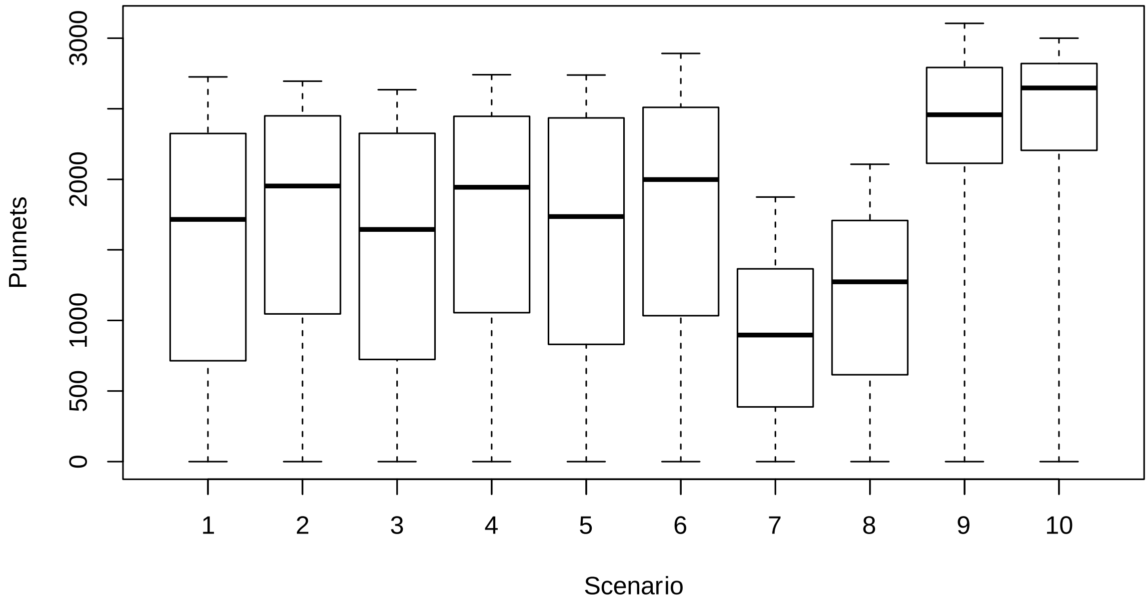

Figure 9: Retailer waste

5 Discussion

From the data reported for scenario 1 and 2 we immediately see that a dual-index policy performs poorly compared to a constant order policy. The authors in (Klosterhalfen et al., 2011) already showed that none of these policies dominate the other from a cost perspective. Further to this, our results show that the more constant inflow of fresh products ensured by a constant order policy guarantees higher quality at consumption and reduces waste at retailers. However, both the policies perform poorly with respect to the given acceptance criterion, since the average quality at consumption is on average, well above the acceptable limit: 5% of affected strawberries in a box. This answers our first research question.

From scenario 3 and 4 we observe that an increase of the mean and of the standard deviation of the open-air temperature at the producer has only a marginal effect on the metrics considered in this work. Therefore, from a temperature perspective, climate change will not impact significantly the quality of the products. Clearly, a higher temperature may ease the development of diseases or other factors that may impact quality. Therefore the conclusion drawn here holds only for the impact on quality caused by the mold Botrytis.

Repacking activities do impact product quality at consumption and retailer waste as demonstrated in scenario 5 and 6. Because of higher waste at the retailer, the product age at consumption slightly decreases. The take-home message is to avoid repacking as much as possible. Repacking is an activity that creates value. However, since repacking is carried out at temperatures significantly higher than the nominal ones employed for storing products in the warehouse, mold growth accelerates. The management should carefully consider if the added value from repacking exceed the associated loss of quality value. Scenario 7 and 8 demonstrate that a marginal improvement of the contamination at the sourcing farm has the potential to dramatically reduce growth of the mold along the chain, and thus to improve quality at consumption and reduce waste. This answers our second research question.

An increased fuel cost for expedited transport necessarily means that, in scenario 9 and 10, new policy parameters must be computed for both the constant order and the dual-index policy. The solution obtained with GA for the constant order policy sets the constant order quantity to $Q = 34575$, and the order-up-to-levels for the expedite orders placed from Monday to Friday to $S_e = [34307, 4979, 39961, 20707, 46790, 593]$, respectively. This policy, when implemented at the distributor, has an expected total cost of 1800$ per day. The solution obtained with GA for the dual-index policy sets the order-up-to-level for the regular order on Monday to $S_r = 72334$, and the order-up-to-levels for the expedite orders placed from Monday to Friday to $S_e = [35944{,}55219{,}16009{,}54319{,}1954{,}34571]$, respectively. This policy, when implemented at the distributor, has an expected total cost of 1842.8$ per day. Clearly, from the results presented, an increase in transportation costs for expedited shipments has a detrimental effect on quality and waste. The management should be aware that in such a situation, a mere optimization of the expected total cost of running the chain represents a poor strategy. Any optimization model employed should carefully strike a balance between cost reduction and quality loss due to the increase of products shipped via regular orders. This answers our last research question.

6 Future works

This work has several limitations. Firstly, the impact of controlled atmosphere in the warehouse is not taken into account. Products are typically stored under modified CO2 concentrations that tend to reduce or even stop mold growth. Advanced model for strawberry quality include the effect of CO2 concentration. In this sense, results presented may be seen as worst-case scenarios, since in a modified atmosphere, mold growth will be significantly slower. Secondly, the optimization algorithms adopted for computing near-optimal inventory control policy parameters are heuristics. Future works may investigate difference observed when an optimal control policy is implemented. Further to this, a challenging area for further research is the development of dual sourcing optimization models that include service level constraints involving product quality. Finally, a thorough validation of the results here presented should be carried out to validate the model and to calibrate its parameters against the actual operating conditions of the chain.

7 Conclusions

We investigated the impact of two well-known dual sourcing strategies, the constant order policy and the dual-index policy, on the quality of fresh strawberries traded in international food supply chains. As quality metric, we modeled the growth of Botrytis cinerea; a widespread mold that attacks strawberries. We demonstrated that a constant order policy provides better and more stable quality than a dual-index policy. Both these policies are not impacted by potential temperature changes due to climate change at the sourcing farms, while variations in temperature conditions along the chains, due for instance to repacking activities, significantly impact end product quality and waste at retail locations. We observed that a slight improvement of the contamination at the sourcing farm has the potential to dramatically reduce growth of the mold along the chain, and thus improve quality at consumption and reduce waste. Finally, we showed that a mere optimization of the operating costs of the chain may lead to poor solutions from a product quality perspective; future research should therefore investigate advanced optimization models able to optimize operating costs subject to service level constraints on stochastic product quality.

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