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Quantifying the potential to improve on food waste, freshness and sales for perishables in supermarkets

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ABSTRACT

The focus of this paper is on improving the performance of fresh departments in supermarkets by reducing food waste, increasing freshness and/or increasing sales. First, two concepts will be introduced to quantify the improvement potential. Next, these concepts will be applied on empirical data for 3 product categories in 27 stores from 3 large retailers in Europe. The two concepts to quantify the improvement potential are called the Fresh Case Cover and the Efficient Frontier. The Fresh Case Cover is defined as the case pack size divided by the average demand during the store shelf life. A regression analysis shows that this single variable explains 42% of the variation in waste. The Efficient Frontier represents a lower bound on the waste needed in a store for any given On-Shelf Availability (OSA). It is demonstrated how the Efficient Frontier can be used to quantify the benefits from supply chain improvement projects and to evaluate fresh departments within a store. To quantify product freshness, an exact expression is derived and an approximation is developed and tested. To quantify waste an existing approximation is generalized. The results show that the improvement potential is very large. For example, increasing the store shelf life with just one day results in 43.1% less waste and 17% more freshness (or in 3.4% higher OSA) and unpacking in the DC results in 34.8% less waste and 1.6% more freshness (or in 2.0% higher OSA). Improving the store replenishment and execution is especially beneficial for medium and large stores.

1. Introduction

Consumers like to choose from a wide variety of high quality perishable products, which are preferably ultra-fresh. A survey among 10,000 consumers in the USA and Western-Europe revealed that access to the best quality fresh products is the most important consideration when choosing where to shop (Oliver Wyman, 2013). At the same time, one-third of all food produced for human consumption is lost or wasted with estimated associated costs equal to US\$ 990 billion every year (FAO, 2016). Since in developed countries most of the food waste occurs at the consumer level, increasing product freshness is also an important contributor to waste reduction.

Food suppliers and retailers are faced with the high costs and the social stigma of waste. Therefore they look for ways to reduce food waste and/or increase product freshness and sales. In 2015 the Consumer Goods Forum, a network of some 400 retailers and manufacturers from 70 countries with combined sales of 2.5 trillion euros, have promised to

halve the food they waste by 2025 (The Consumer Goods Forum, 2015). In 2014, The ECR Community Shrinkage and On-Shelf Availability Group started a project to find ways to increase sales and reduce waste. The objective of this 'Sell More, Waste Less' project was to combine scientific research and empirical data from three large European supermarket chains in order to quantify the potential to reduce food waste, to increase freshness to the consumer and/or increase sales. This paper extends the report of Broekmeulen and van Donselaar (2016) by introducing an exact expression for the freshness to the consumer, improving the used approximations, and analyzing the effects of improvement projects on freshness.

The research question in this paper is 'Which concepts can be used to quantify the improvement potential for perishable items in supermarkets and how large is this improvement potential?'. This paper is the first to develop and apply concepts to quantify the potential to reduce waste, increase freshness and/or increase sales for perishables by combining theoretical results with a large empirical dataset from multiple retailers.

The results show that the improvement potential for reducing waste and increasing sales and product freshness in practice is very large. Another finding is that a simple variable called the Fresh Case Cover, defined as the case pack size divided by the average demand during the shelf life, provides a good first indication for the percentage of waste. This simple variable enables people from different functional departments in the retail supply chain to discuss the implications for food waste from changes they intend to make in processes, technologies or assortments without needing a mathematical background. Another key concept used in this paper is the Efficient Frontier, which presents the numerical trade-off between product availability and food waste in retail stores. The Efficient Frontier is derived based on recently published approximation formulas for waste and On Shelf Availability (OSA) and can be used to quantify the potential food waste reduction or sales increase when key parameters like the shelf life and the case pack size are changed. It can also be used to quantify the performance of fresh departments in supermarkets. Finally this paper is the first to provide both an exact expression as well as an approximation for the product's freshness to the consumer. This approximation is first tested and later on used to quantify the impact of changes in key system parameters on freshness for the items in the empirical dataset.

In Section 2 the literature on food waste reduction in the retail supply chain will be reviewed. Section 3 will describe the research environment and the data provided by the supermarket chains. Section 4 will introduce two key concepts which will be used to quantify the improvement potential for fresh products. In Section 5 formulas are derived which express the waste fraction, OSA and the freshness as a function of the system parameters. In Section 6 the results from the analysis on the improvement potential for the three retailers will be presented. Finally, Section 7 will summarize the conclusions and discuss options for future research.

2. Literature review

The literature on measuring and improving the waste, freshness and/or OSA for perishables in the retail supply chain can be split in qualitative papers and quantitative papers.

The qualitative papers either provide frameworks to identify and evaluate improvement opportunities for perishable items, e.g. Dreyer et al. (2016), Balaji and Arshindera (2016), and Priefer et al. (2016) or provide improvement suggestions, like extending the product life (Lee et al., 2015), cooperating along the supply chain (Göbel et al., 2015) and improving supply chain planning and control (Chabada et al., 2014). A recent literature survey on fresh produce supply chain management is available in Shukla and Jharkharia (2013).

The quantitative papers can be split in three streams: papers which quantify the current performance level in the retail industry, papers which provide closed form mathematical expressions for performance indicators based on theoretical inventory models, and papers which quantify the performance indicators using for example simulation or Markov models.

The first stream of these papers, quantifying current performance levels, is strongly focused on measuring actual waste. These papers show that the waste at the retail level varies considerably, both between product categories and between countries. In the USA for example, waste (measured as a percentage of aggregated sales) varies between 11% for dairy products and 4% for meat products (Buzby et al., 2014). For Fruit & Vegetables for example, waste is reported to be 8–9% in the USA and in Switzerland, while studies in Sweden, Norway and Austria report waste in the range of 4%–5% (see Table 8 in Lebersorger and Schneider, 2014). All these papers show that waste at the retail level is significant. This paper differs from the papers above by focusing on the waste improvement potential rather than on the current waste levels and by also considering freshness and OSA. As will be explained later on, current waste levels are not the most suitable indicator for the potential to reduce food waste. Rather a comparison should be made between current waste

levels and minimal expected waste levels to achieve the current OSA. This paper contributes to the literature by providing a method to determine the minimal expected waste levels.

Most papers with closed form expressions for the performance indicators as a function of system parameters are based on theoretical inventory models. Bakker et al. (2012) provide the most recent literature review on perishable inventory models. Since the exact analysis of perishable systems is extremely hard (Nahmias, 1982), most papers make strong simplifying assumptions like zero lead time or a case pack size equal to one. The advantage is that closed form expressions for performance indicators as a function of the system parameters are developed, which can be used to quantify the improvement potential. The disadvantage is that for application in practice, the quality of the expression depends on the number and type of assumptions made. Examples of papers with closed form expressions for performance indicators for perishables are Chiu (1995), Olsson and Tydesjö (2010), Van Donselaar and Broekmeulen (2012), Kouki et al. (2013, 2015). These papers on inventory models for perishable products with stochastic demand provide closed form expressions for waste and/or out-of-stocks as performance indicators but not for product freshness. Since waste at the consumer level is much higher than waste at the retail level and since access to the best quality fresh products is the most important consideration when choosing where to shop (Oliver Wyman, 2013), freshness to the consumer is also a very important performance indicator.

Recent papers which evaluate the quantitative effects of system parameters without deriving a closed form function for the performance indicators include the papers using simulation and/or a Markov model, e.g. Ferguson and Ketzenberg (2006), Ketzenberg and Ferguson (2008), Broekmeulen and van Donselaar (2009), Minner and Transchel (2010), and Haijema and Minner (2016). These papers typically use a full factorial design of experiments and consider all combinations of potential values for the system parameters, when evaluating the effect of these parameters. A drawback of this method is that all experiments are given the same weight, while in reality the system parameters may take on the median value more often than the low or the high value used in the full factorial design. A second drawback is that often the system parameters are assumed to be uncorrelated, while, as will become visible later on in this paper when analyzing the empirical data from the three retailers, many parameters are in fact correlated. A third drawback of this way of quantifying the effects of system parameters on system performance is the fact that the model always is a simplification of reality, based on assumptions.

Compared to the current literature as discussed above, this paper is the first to derive an exact as well as an approximate expression for product freshness in an inventory model for perishable items with stochastic demand. In addition, an existing approximation for waste is generalized. This paper is also the first paper to use empirical data from multiple retailers and multiple product categories for quantifying the improvement potential, rather than quantifying current performance levels. This improvement potential will be determined in two ways in this paper. First, a quantitative relationship between actual waste and one key indicator is demonstrated. Next, the potential to improve waste, freshness and OSA is quantified using empirical data, approximation formulae for waste and OSA and the new approximation for freshness. Since in both methods empirical data are used rather than a full factorial design of experiments, two drawbacks mentioned earlier (non-equal weights and correlated system parameters) are eliminated. The third drawback (model assumptions) is only eliminated in the first method, since the approximation in the second method is based on assumptions.

3. Research environment and data

In this paper empirical data are used to quantify the potential to improve on waste, freshness and OSA. These data are provided by three large supermarket chains in Europe, with the help of the ECR Community Shrinkage and On-Shelf Availability Group. This group is a platform for

FMCG manufacturers and retailers working on reduced shrinkage and improved On-Shelf Availability (OSA). The three participating supermarket chains all carry large assortments. Per supermarket chain nine stores were selected; three small, three medium and three large stores.

In this project three product categories were analyzed: fruits and vegetables, fresh meat and convenience products. These product categories generate a large part of the waste in a supermarket chain (Buzby et al., 2014). The retailers each have their own definition for the three product categories. Burgers for example are classified as fresh meat by one retailer and as convenience by another retailer. Since the assortments in the resulting database differ per product category per retailer and for reasons of confidentiality, the analyses in this paper are done for the total sample set rather than on subsets per retailer.

In this project only those items were considered having a price which does not vary for each individual consumer unit depending on the exact actual weight. These weight items were excluded to avoid data issues with the exact amount of products sold and delivered. To control the lead time to the stores and the average store shelf life of the product, only products are included which are supplied to the supermarket via the distribution center of the retailer.

The data provided by the retailers for every item-store combination in the sample include daily data on deliveries, sales and waste as well as data on the case pack size and the store shelf life. Stores order in integer multiples of the case pack size. The case pack size is often determined by the dimensions of the product and the plastic crate or box used to send the products to the store. The store shelf life is the average shelf life of the product when it enters the store. From each retailer data are available during at least one full year in the time-frame 2013–2015. In case a retailer only registered the minimum (= guaranteed) store shelf life, the average shelf life was set equal to this minimum store shelf life plus one day (based on observations at another retailer). The lead time and review period for the 27 stores are equal to 1 day.

The sample was further limited to item-store combinations having at least three weeks of sales during one year and three deliveries. This helps to reduce issues which arise when products are phasing-in or phasing-out of the assortment. The final sample used in this project contains 2474 items: 820 fruits and vegetables, 1044 convenience items, and 610 meat items. Large stores carry larger assortments than small stores. The total database for the 27 stores contains 17,093 item-store combinations.

The daily sales in the database is based on the regular sales, i.e. excluding any promotions. Promotions typically last one week. For stores which did not register the promotions separately, the promotions were determined by weeks having a price reduction of at least 15% and/or a lift factor equal to at least three (compared with sales in regular periods).

The top three rows in Table 1 show for each product category the median values of the daily sales, the case pack size and the store shelf life of all item-store combinations in the entire database which belong to the specific category. The last row shows the median value for the entire database.

In our sample, some retailers used discounting on the last day before expiration, either for all products in the assortment or for only a subset of the assortment. Another retailer did not use discounting at all, but decided to remove the products from the shelf one day ahead. Since we encountered different policies on waste and/or discounting, we decided to treat discounting the same as waste. Therefore, the daily waste in the database includes consumer units close to the expiration date which were discounted. Like daily sales and supply, waste is measured in consumer units. When a retailer registers the waste in sales value rather than in consumer units, the waste was estimated based on the waste in sales value and the average regular price three weeks before and after the time of waste registration. The actual waste percentage, i.e. the relative waste, in this project is defined as the waste divided by the sales, both in consumer units: %Waste = 100%·(Waste/Sales). The reason not to define waste relative to the supply, is the fact that significant mismatches were encountered between registered inflow and registered outflow per item-store combination. There are many potential explanations for these mismatches, e.g. errors in scanning and/or theft. Product freshness is defined as the average remaining shelf life for the consumer of the products sold.

Measuring the standard deviation of the daily sales for each item directly from the available empirical data has turned out to be not very robust due to distorting effects from promotions and products phasing-in and -out. To solve this, the suggestion proposed in Silver et al. (1998) is used. By taking a subset of items in the database which have no promotion and which are not phasing-in or phasing-out, a power function is estimated using regression. This results in the expression

$$\sigma_W = 0.7 \cdot \mu_W^{0.77} \tag{1}$$

with σ_W the standard deviation of the weekly sales and μ_W the average weekly sales. The adjusted R^2 is equal to 0.8944.

Many variables in the database turn out to be correlated. Correlations with the average daily sales are especially large. Table 2 shows the average value for the standard deviation of daily sales, case pack size and store shelf life for the 50% of the item-store combinations having the lowest average daily sales and the 50% having the highest. For reasons of confidentiality the data are normalized by setting the average value for the lowest 50% equal to one.

4. Two concepts to quantify the improvement potential

To answer the research question 'Which concepts can be used to quantify the potential to reduce food waste in supermarkets and how large is this potential?', first two concepts are introduced in this section: The Fresh Case Cover and the Efficient Frontier.

The **Fresh Case Cover (FCC)** is defined as the case pack size (Q) divided by the average daily sales (μ) during the store shelf life (m):

$$FCC = \frac{Q}{m \cdot \mu} \tag{2}$$

If demand were deterministic and constant, waste only occurs if the case pack size is not sold before the end of the shelf life, i.e. if $FCC > 1$. However, when demand is stochastic, waste will occur even when $FCC \leq 1$. In the results section it will be shown that FCC is a strong first indicator to predict the amount of waste and hence to predict the amount of waste reduction if any of the three parameters of the FCC are changed.

The **Efficient Frontier** is the graph which shows how the minimal expected waste percentage (i.e. the waste percentage which can be achieved in an' ideal' world) increases if the OSA increases. The OSA is defined here as the fill rate: the percentage of demand which can be fulfilled directly from inventory on the shelf. If a retailer wants to

Table 1
Data description for the entire dataset of 17,093 item-store combinations: median values for daily sales, case pack size, store shelf life and number of items.

Category	Daily sales μ	Case pack size Q	Store shelf life M	Number of items
Convenience	0.71	4	14	1044
Fresh meat	1.04	4	9	610
Fruits & Vegetables	2.18	6	7	820
All: median	1.07	4	8	2474

Table 2
Average values (normalized) for the standard deviation of daily sales, case pack size and store shelf life for the item-store combinations having the bottom 50% respectively the top 50% of average daily sales.

Average daily sales	StDev daily sales	Case pack size	Store shelf life
Lowest 50%	1	1	1
Highest 50%	6.30	1.47	0.60

increase their OSA level, they will have to increase their reorder level, which results in more inventory on the shelf and hence in more waste. The 'ideal' world referred to is a world in which customers buy First-In First-Out (FIFO) from the shelf and in which the EWA-replenishment logic (Broekmeulen and van Donselaar, 2009) is used. This logic is similar to the classical (R,s,nQ)-logic, where every R periods the inventory an order is placed if the inventory position is strictly below the reorder level (s) and the size of this order is an integer multiple (n) of a fixed case pack size (Q). The key difference with this (R,s,nQ)-logic is that the EWA (Estimated Withdrawal and Aging) logic subtracts the estimated amount of outdating from the inventory position before reordering. The EWA-logic outperforms the (R,s,nQ)-logic in most situations when items are perishable. It is important to note that in real life the world is less ideal and so more waste will be realised than the waste represented by the Efficient Frontier. As such, the Efficient Frontier can be interpreted as a lower bound for the waste percentage for any given OSA.

To determine the Efficient Frontier for any specific item-store combination, the reorder level is raised in steps of one consumer unit, starting with a reorder level equal to one. For every reorder level, the waste percentage and OSA are determined which can be achieved in the 'ideal' world using the approximations developed and described in the next Section. When applying these approximations, the consumer withdrawal behaviour is assumed to be FIFO and formula (1) to estimate the standard deviation of sales is used. Plotting all combinations of OSA and waste percentage in a graph will give the Efficient Frontier.

The Efficient Frontier can also be determined for a set of item-store combinations (e.g. all items in one store). Then the procedure is slightly different from the procedure described above. Rather than increasing the reorder level stepwise, now a target OSA level is increased stepwise (e.g. ranging from 80% to 99% in steps of 0.5%). For each target OSA level, for each item-store combination the reorder level is determined which achieves at least this target OSA level. For this reorder level both the expected OSA and the waste are determined. The formulas used to find the performance indicators for a given reorder level are discussed in the next Section. Note that since reorder levels are integer, the expected OSA which corresponds with the target OSA level will be higher than or equal to the target. Finally the waste percentage and the OSA for the entire set of item-store combinations is determined by taking the weighted waste percentage and the weighted OSA of all item-store combinations. Each target OSA level gives one data point in the Efficient Frontier for a set of item-store combinations.

The Efficient Frontiers described above can be used to quantify the potential to reduce the food waste in supermarkets when projects are initiated to improve the system parameters or when the performance of fresh departments in a store is evaluated. Below it is briefly explained how each of these two applications can be supported.

To quantify the improvement potential from changing system parameters like the store shelf life, basically two Efficient Frontiers need to be created: one based on the current and the other on the new parameter setting. By changing the parameter setting, the Efficient Frontier basically will shift, as illustrated in Fig. 1. The improvement can be used either to reduce waste or to increase sales (by increasing the OSA) or any mix of these two. The difference between the Efficient Frontiers (at the current performance level) measures how much can be gained by the change in parameter setting.

To evaluate the waste performance of a store and hence its improvement potential, retailers typically work with a budget or norm for waste per store which is identical for many stores within the retail chain, simply because the retailer has no model to differentiate these norms. Unfortunately, current waste percentages nor the difference between standard waste budgets and current waste levels are a good indicator for the improvement potential since stores differ on many dimensions. Using the store's Efficient Frontier allows for a more advanced and fairer performance evaluation, since the assortment carried by the store and the daily sales per item-store combination are explicitly taken into account when determining the best possible performance. The store performance is determined by measuring the distance between the current performance of the store and the performance according to the Efficient Frontier for that store (see Fig. 2). The closer to the Efficient Frontier, the better the store performs.

5. The Key Performance Indicators

To be able to analyze the improvement potential for the three supply chains and to apply the concept of the Efficient Frontier, expressions are needed for three Key Performance Indicators: the On-Shelf Availability (β), the waste fraction (z) and the freshness to the consumer (φ). These expressions are derived below. Since the Efficient Frontier is based on the
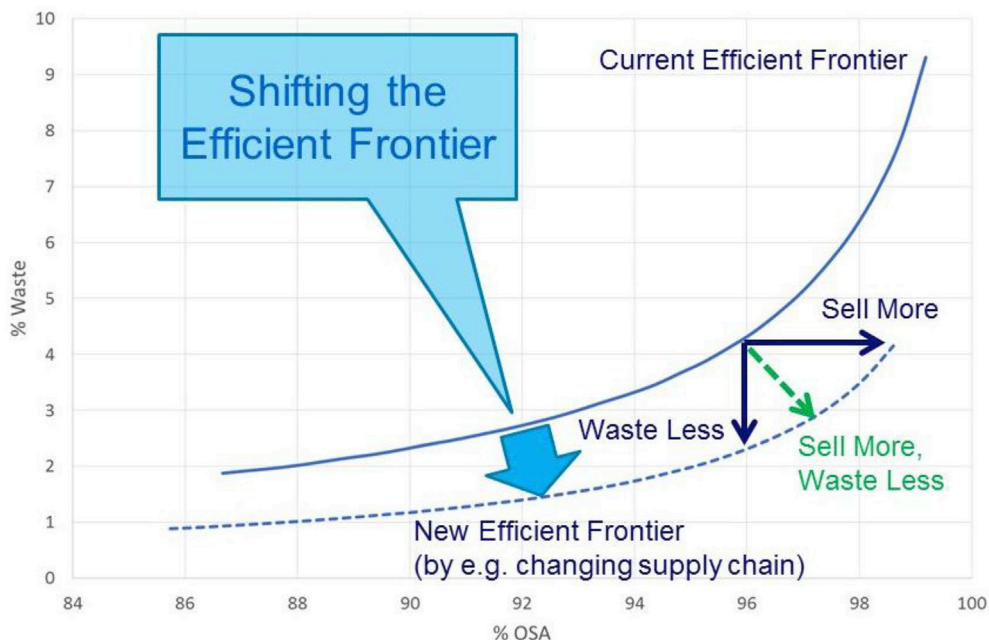

Fig. 1. Shifting the Efficient Frontier due to a change in parameter setting.
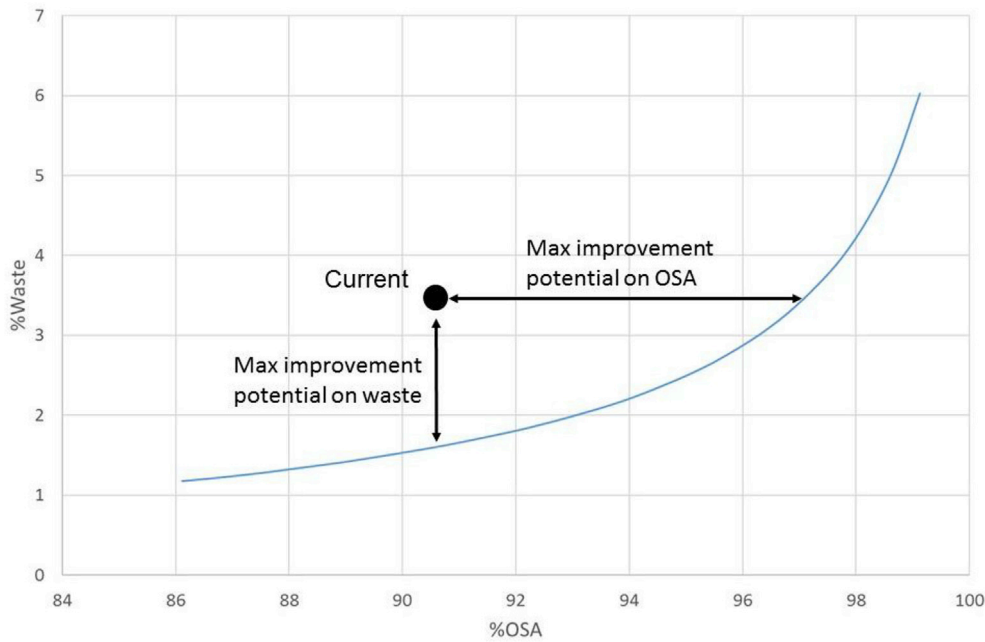
Fig. 2. Evaluating the store performance by using the Efficient Frontier.

assumptions of FIFO withdrawal and the EWA replenishment logic, the approximations for β and z in Van Donselaar and Broekmeulen (2012) are used as a starting point. In this paper their approximation for the waste fraction is modified in three ways:

1. Their first approximation for the waste fraction, called z_A, is modified by taking into account the discrete nature of inventories in a retail environment: hence the term $s - \lfloor L + m + \rho \rfloor \cdot \mu$ in z_A is replaced with the associated rounded number $\|s - \lfloor L + m - \rho \rfloor \cdot \mu\|$.
2. Their intermediate approximation for the waste fraction, called z_{regr}, is a linear function of 7 constructs of variables including the construct $(1 - \beta)$. As mentioned in their paper, this construct has little added value relative to the other constructs. To simplify the approximation this construct is omitted from z_{regr} and new regression coefficients are determined using the same logic as in their paper.
3. Their approximations were derived and tested for environments with up to 30% waste. Since in the empirical dataset in this paper more than 10% of the item-store combinations have more than 30% waste, their approximation is generalized. Based on the observation that their approximation z_A performs very well when the waste fraction is high, the weighted combination of z_A and z_{regr} is used rather than just z_{regr}. This gives:

$$z'_{regr} = \frac{z_{regr} + z_A^{k+1}}{1 + z_A^k} \qquad (3)$$

After testing this approximation for several integer values of k, the best results were obtained with the value $k = 3$.

The resulting approximations for β and z are denoted by $\widehat{\beta}$ and $\widehat{z}$.

The freshness to the consumer, denoted by φ, is equal to the average age of the products actually sold to the consumer:

$$\varphi = \frac{\sum_{i=1}^{m} i \cdot s_i}{\sum_{i=1}^{m} s_i} \qquad (4)$$

with s_i the number of consumer units sold with remaining age i days, measured at the moment the consumer actually buys the product. According to Little's law (Little and Graves, 2008) the average time a product spends in the system is equal to the average number of products

in the system divided by the average daily supply. For a perishable inventory system with outdating at discrete moments the number of products in the system is equal to the expected inventory on hand just before outdating, denoted with I. So the average remaining shelf life is equal to the shelf life when the product enters the store (m) minus the average time spent in the system. With z the relative outdating (as a fraction of average daily demand) and β the fill rate, the average remaining shelf life can be expressed as:

$$\frac{\sum_{i=0}^{m} i \cdot s_i}{\sum_{i=0}^{m} s_i} = m - \frac{I}{[z + \beta]} \cdot \frac{1}{\mu} \qquad (5)$$

Note that the average remaining shelf life also takes into account products which are outdated and not sold to the consumers, which is reflected by the fact that the summations in (5) now also include $i = 0$. Combining (4) and (5) gives an exact expression for the freshness to the consumer:

$$\varphi = \left(m - \frac{I}{[z + \beta]} \cdot \frac{1}{\mu} \right) \left(1 + \frac{z}{\beta} \right) \qquad (6)$$

While equation (6) is exact, the literature provides no closed form expressions for I, z and β. Therefore the freshness is approximated by using $\widehat{z}$ and $\widehat{\beta}$ as well as an approximation for I. The variable I is approximated by using the exact expressions for the expected inventory on hand in an inventory system for non-perishable items with back-ordering (see Van Donselaar and Broekmeulen, 2013). Then, for a lost sales system with perishable items, discrete demand, a lead time equal to L days and a review period equal to R days, (R integer), and the EWA replenishment logic, the approximation $\widehat{I}$ for the expected inventory on hand at the end of any day just before outdating can be written as:

$$\widehat{I} = \frac{1}{R} \sum_{i=1}^{R} \sum_{j=0}^{Q-1} \sum_{d=0}^{s+i-1} (s + j - d) \cdot P[D_{L+i} = d] \qquad (7)$$

with D_t the demand during t days.

By using the observation that the freshness to the consumer is always at least equal to $(R + 1)/2$ days and at most equal to $m - (R - 1)/2$ days, the final approximation used for φ is equal to:

$$\varphi = \min\left[m - \frac{R-1}{2}, \max\left(\frac{R+1}{2}, \left(m - \frac{\hat{I}}{[\hat{z} + \hat{\beta}]} \cdot \frac{1}{\mu}\right)\left(1 + \frac{\hat{z}}{\hat{\beta}}\right)\right)\right] \quad (8)$$

The quality of the approximations for z and φ derived above are tested with simulation using a full factorial design with lead time and review period equal to one day, FIFO withdrawal behavior, EWA replenishment logic and the other parameters the same as in the full factorial design in Van Donselaar and Broekmeulen (2012). The approximations turn out to be accurate. While the average simulated value for z in this test set is equal to 0.2695 (i.e. 26.95% of demand is wasted), the approximation error for z $(= z - \hat{z})$ is on average equal to 0.0007 with standard deviation equal to 0.00278. The average simulated value for the freshness φ in this test set is equal to 4.2635 days, the approximation error for φ is on average equal to 0.0106 days with standard deviation equal to 0.2096 days.

6. Results

To show how the Fresh Case Cover can be used to quantify the waste reduction potential for the participating retailers, first the relationship between the Fresh Case Cover and the actual waste percentage is examined. To this purpose, the item-store combinations are grouped in subsets having similar *FCC*-values: the i-th subset with $i = 1, \dots, 20$, only contains the item-store combinations having a Fresh Case Cover in the range $(i-1) \cdot 0.05 \le FCC < i \cdot 0.05$. Item-store combinations with *FCC > 1* were left out of this analysis due to the relative low number of observations per subset. For each subset the average weighted actual waste percentage is calculated with average daily sales as weight factors. This results in 20 data points which are shown in Fig. 3. This analysis shows that the waste percentage can be approximated by a linear function of the Fresh Case Cover. When applying linear regression on the entire dataset, the resulting adjusted R^2 is equal to 0.42, implying that 42% of the variation in the waste percentage is explained by the *FCC* score. These observations in combination with the fact that the *FCC* is extremely easy to calculate and to explain to people without mathematical background, makes the *FCC* a good first indicator for the waste percentage.

While retailers can have good reasons to carry a small percentage of items with a large waste percentage in the assortment, e.g. when introducing new products, it is also essential to monitor whether these items do not keep generating too much waste. If after negotiations with the supplier the case pack size and the shelf life are given, then the main factor determining the waste level is the average demand. Retailers can use the relationship between the waste percentage and the FCC as illustrated in Fig. 3 together with the profit margin for the new item to set targets for the minimum average demand for any new item and from there on monitor whether this minimum demand is reached within a prescribed time frame.

When applying the FCC as a first indicator, it should be noted that each observation in Fig. 3 represents the average waste for a large subset, potentially containing thousands of item-store combinations; the value for the waste percentage for a specific item-store combination can vary much more than suggested by the graph in Fig. 3. This is due to the fact that the waste percentage depends also on the OSA level and on the exact combination of values for the case pack size, the shelf life and the daily sales and due to the fact that the actual waste percentage measured is based on a limited number of observations from a random variable. This implies that while the FCC is a very strong first indicator for waste when applied to a large set of item-store combinations, the actual waste for one specific item-store combination will show more variation than suggested by Fig. 3. If a more advanced indicator is needed, it is suggested to use the Efficient Frontier logic.

The Efficient Frontier, which shows how the waste percentage depends on the OSA in an ideal world, for the set with all 17,093 item-store combinations is shown in Fig. 4, together with the freshness.

Fig. 4 shows that indeed waste increases exponentially if OSA increases, especially if OSA is close to 100%. This is in line with the observation that retailers set OSA targets lower for perishables than for non-perishables. Fig. 4 also shows that freshness is strongly correlated with waste and decreases substantially if OSA increases.

The Efficient Frontiers are different for the three product categories as can be observed in Fig. 5. A potential explanation for the fact that the Efficient Frontier for Fruit and Vegetables is more efficient than for the product categories Fresh Meat and Convenience products is the fact that the median sales per item-store combination is substantially larger for the Fruit and Vegetables (see Table 1).

The Efficient Frontier is also used to quantify the improvement potential from several interventions. This is done both for a retailer having the objective to increase sales (Table 3) and for a retailer having the
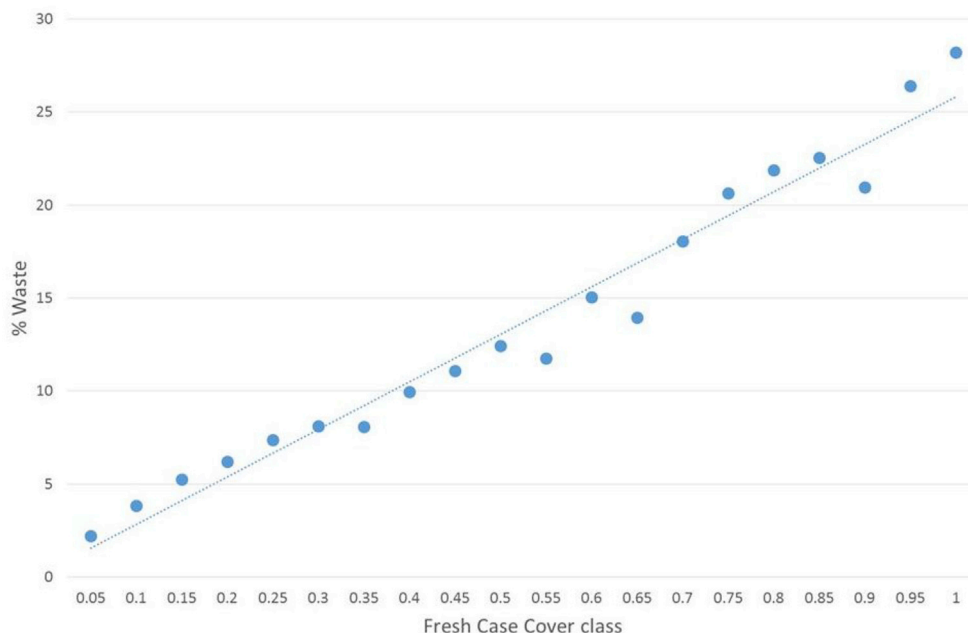

Fig. 3. The relationship between the actual waste percentage and the Fresh Case Cover.
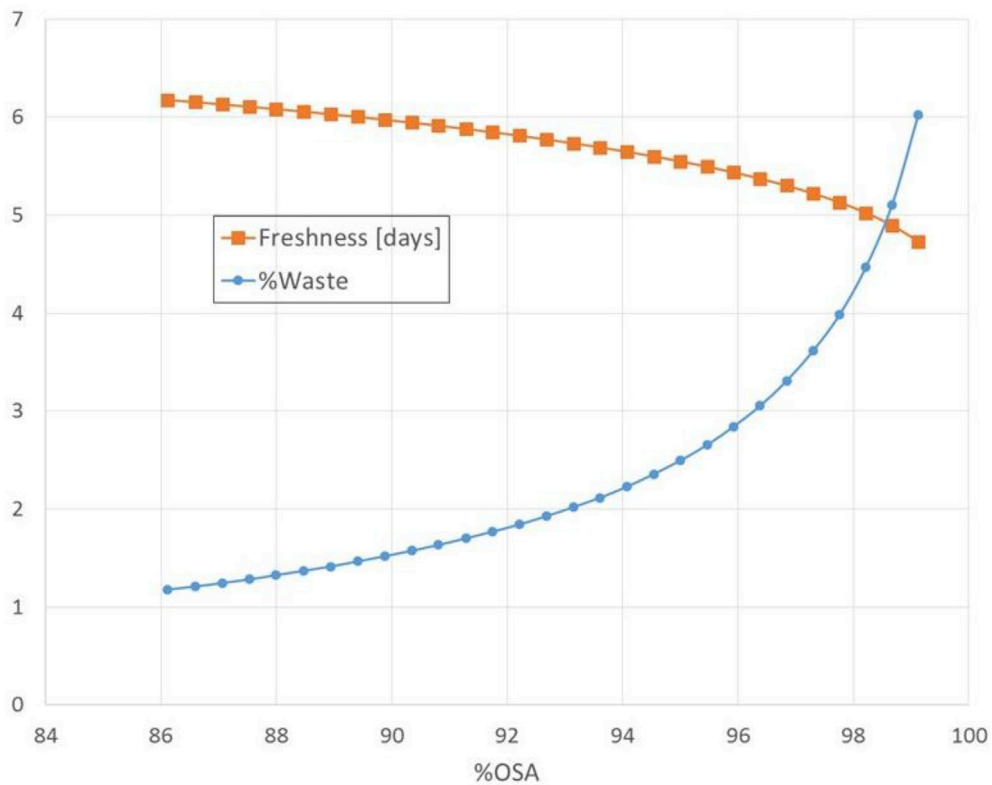
Fig. 4. The Efficient Frontier for the set with all 17,093 item-store combinations.
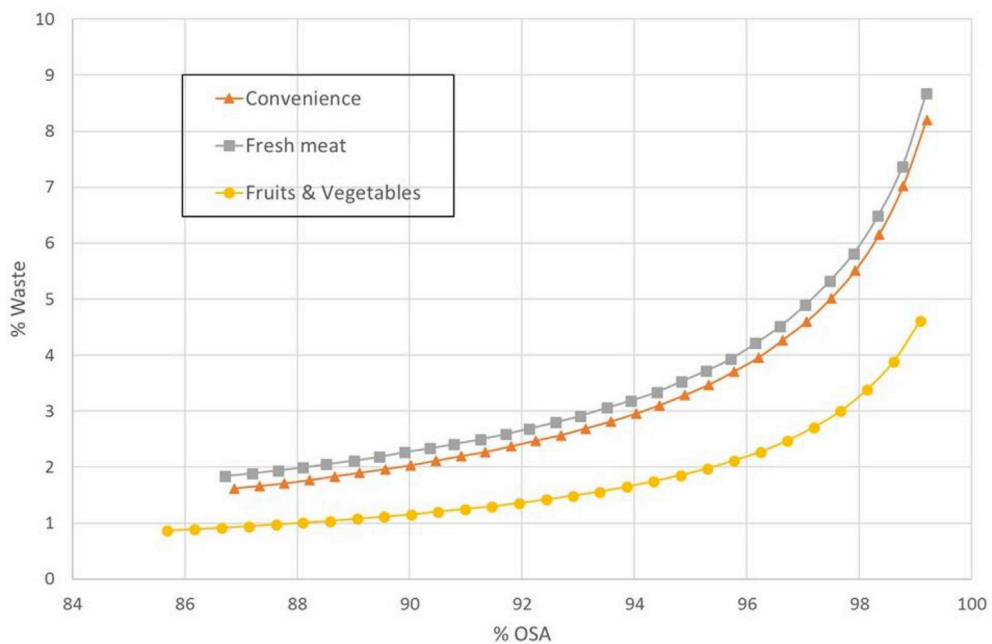

Fig. 5. The Efficient Frontiers for the three product categories.

objective to reduce waste and to increase freshness (Table 4).

The five interventions reported here are:

1. Increase shelf life for the store with 1 day,
2. Unpack all items in the retailer's DC (case pack size store is 1),
3. Lower OSA with 2% for all item-store combinations,

4. Differentiate service levels, i.e. lower the OSA with 3% for slow movers (80% of assortment) and increase with 3% for fast movers, and
5. Delist the bottom 10% slow movers from the assortment.

The third and fifth intervention are only quantified when the aim of the retailer is to reduce waste. In both Tables it is assumed that each

Table 3
Improvement potential when the main objective is to increase OSA.

Project	% Waste reduction	% OSA increase
Increase shelf life with 1 day	4.6	**3.4**
Unpack all items in DC	8.5	**2.0**
Increase shelf life with 1 day and unpack all items in DC	11.2	**4.4**
Differentiate service levels	0.9	**1.3**

Table 4
Improvement potential when the main objective is to reduce waste and increase freshness.

Project	% Waste reduction	% Freshness increase	% OSA increase
Increase shelf life with 1 day	**43.1**	17.0	0.0
Unpack all items in DC	**34.8**	1.6	0.0
Increase shelf life with 1 day and unpack all items in DC	**68.2**	18.8	0.0
Lower OSA with 2%	**18.2**	3.1	−2.0
Differentiate service levels	**13.3**	−0.4	0.3
Delist 10% from the assortment	**7.9**	−0.9	0.0

intervention is applied for the items in the three product categories for all 27 stores. The improvement potential is measured by comparing the performance before (Base) and after (Project) the intervention:

$$\%Waste_{Reduction} = 100\% \cdot \frac{Waste_{Base} - Waste_{Project}}{Waste_{Base}} \tag{9a}$$

$$\%OSA_{Increase} = 100\% \cdot \frac{OSA_{Project} - OSA_{Base}}{OSA_{Base}} \tag{9b}$$

$$\%Freshness_{Increase} = 100\% \cdot \frac{Freshness_{Project} - Freshness_{Base}}{Freshness_{Base}} \tag{9c}$$

The results show that increasing the shelf life with one day has the biggest potential, independent of the management objective: 3.4% increase in OSA or 43.1% waste reduction and 17% more freshness. Note that if the current OSA would be 95%, a 3.4% increase in OSA implies that the percentage of unfulfilled demand drops with 68%: from 5% to 1.6%. The second best improvement project is unpacking at the DC, i.e. delivering in the most flexible way to the stores without any restriction on the minimal order quantity. This leads to a 2.0% increase in OSA or 34.8% waste reduction and 1.6% more freshness. The fact that the increase in freshness is relatively small in this scenario is due to the fact that in many cases a reduction in case pack size implies an increase in the reorder level in the store to ensure the OSA is not reduced. While reduced case pack sizes have a positive effect on freshness, higher reorder levels have a negative effect on freshness. The third row in both Tables shows the effect when these two best interventions are combined. According to Table 4, when the OSA is reduced with 2%, waste can be reduced with 18.2% and freshness increased 3.1%. Whether this is a feasible intervention for any retailer depends on the costs of waste and the willingness of customers to substitute in case an item is out-of-stock. Although differentiating service levels (3% lower for slow movers and 3% higher for fast movers) is not the intervention with the highest benefit, it is relatively easy to implement. With the final intervention, delisting 10% of the assortment with the lowest average daily sales, the total waste will be reduced with 7.9% at the expense of de decrease in freshness equal to 0.9% and an overall decrease of OSA equal to 0.6% if the customers would not be willing to substitute.

When implementing these interventions, often some other costs (e.g. investment costs) or qualitative arguments have to be included in the final decision process.

Measuring the actual waste from the 27 stores relative to the waste according to their Efficient Frontier reveals to what extent waste can be reduced through better store replenishment and execution (given case pack sizes, shelf lives and average daily demand). The relative distance to the Efficient Frontier is equal to 49.7% on average, with standard deviation equal to 19.1%.

While the average improvement potential is 49.7%, this improvement potential is the maximum achievable, since it is based on comparison with the performance in an ideal world. Since in most stores for example not all consumers will have FIFO withdrawal behaviour, the actual improvement potential for the stores will be smaller. Furthermore, small stores typically show a smaller potential to reduce waste through improved store replenishment and execution, which can be explained by the fact that the majority of their waste is caused by the system parameters (e.g. the case pack size), which are out of their control.

Many stores have a more or less comparable FCC value, but still show a large variation in their improvement potential. For the stores having the biggest improvement potential within this group, a more in-depth analysis is recommended at the item-store combination level. By studying for some of the item-store combinations, having the biggest gap between the actual waste and the waste according to the Efficient Frontier, the time series of deliveries, sales and waste, potential explanations for this gap may be revealed. For example for a high-priced item a department manager stopped ordering the item when waste occurred and then resumed ordering again 1 or 2 weeks later. A topic of further research is to study the effects of these types of ordering behaviour on consumer demand and waste.

7. Conclusions and future research

In this paper an exact expression and an approximation for freshness to the consumer are derived. In addition a modified and generalised approximation for the waste percentage is derived. These results together with two methods for quantifying the improvement potential at the retail level for perishable products are presented and applied using empirical data. The Fresh Case Cover turns out to be a simple and powerful first indicator for the amount of food waste. It is especially useful for a large set of item-store combinations or as a communication tool between people from different departments to get a first impression on how the design of their supply chain affects the amount of waste. The Efficient Frontier is a more advanced indicator which also explicitly takes into account the impact of the On-Shelf Availability (OSA) on the waste percentage. The Efficient Frontier for the total dataset of 17,093 item-store combinations shows that waste increases exponentially with the OSA level. Product Freshness is shown to be strongly negatively correlated with waste. The Efficient Frontier can be used to quantify the potential of different improvement projects like reducing the minimum order quantity for the stores or increasing the store shelf life. Another application of the Efficient Frontier is to evaluate the performance of a store or of a fresh department.

Applying the Efficient Frontier on the 17,093 item-store combinations has revealed a very large improvement potential. For example, increasing the shelf lives with one day will result in 43.1% waste reduction and 17% fresher products (or 3.4% increase in OSA). Evaluating the store performance relative to the Efficient Frontier has shown that many large and medium sized stores can benefit from improved store replenishment and execution, but that smaller stores benefit more from reduced minimum order quantities and larger shelf lives. Retailers are recommended to apply the techniques developed in this paper using their own data. For example, the slope and intercept of the relationship between actual waste and the Fresh Case Cover will be different for different retailers if they pursue different OSA targets.

Options for future research include quantifying the effect of the customer withdrawal behaviour and the week pattern on the waste level, generalising the waste approximations (e.g. for situations with long lead times and review periods), comparing the effects of (no) discounting strategies (when the products near their expiration date) on the demand and the waste level, studying the impact of different ordering behaviours

on the consumer behaviour and the waste, and finally using regression analysis on empirical data to find out to what extend the waste percentage not only depends on the case pack size, the shelf life and the average demand but also on factors like the store, the product category etc.

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References

Bakker, M., Riezebos, J., Teunter, R.H., 2012. Review of inventory systems with deterioration since 2001. Eur. J. Operat. Res. 221, 275–284.

Balaji, M., Arshindera, K., 2016. Modeling the causes of food wastage in Indian perishable food supply chain. Resour. Conserv. Recycl. 114, 153–167.

Broekmeulen, R.A.C.M., van Donselaar, K.H., 2009. A heuristic to manage perishable inventory with batch ordering, positive lead-times and time-varying demand. Comput. Operat. Res. 36 (11), 3013–3018.

Broekmeulen, R.A.C.M., van Donselaar, K.H., 2016. Sell More, Waste Less: Increasing Sales and Reducing Waste in the Fresh Supply Chain. ECR Community, Brussels, Belgium.

Buzby, J.C., Wells, H.F., Hyman, J., 2014. The estimated amount, value, and calories of postharvest food losses at the retail and consumer levels in the United States, USDA economic research service. Econ. Inf. Bull. 121.

Chabada, L., Damgaard, C.M., Dreyer, H.C., Hvolby, H., Dukovska-Popovska, I., 2014. Logistical causes of food waste: a case study of a Norwegian distribution chain of chilled food products. In: Grabot, et al. (Eds.), APMS 2014, Part I, IFIP AICT, vol. 438, pp. 273–280.

Chiu, H.N., 1995. A heuristic (R,T) periodic review perishable inventory model with lead times. Int. J. Prod. Econ. 42, 1–15.

Dreyer, H.C., Strandhagen, J.O., Hvolby, H., Romsdal, A., Alfnes, E., 2016. Supply chain strategies for speciality foods: a Norwegian case study. Prod. Plan. Control 27 (11), 878–893.

FAO, 2016. Website Food and Agriculture Organization of the United Nations (FAO). Key facts on food loss and waste you should know. http://www.fao.org/save-food/resources/keyfindings/en/.

Ferguson, M., Ketzenberg, M.E., 2006. Information sharing to improve retail product freshness of perishables. Prod. Operat. Manag. 15 (1), 57–73.

Göbel, C., Langen, N., Blumenthal, A., Teitscheid, P., Ritter, G., 2015. Cutting food waste through cooperation along the food supply chain. Sustainability 7, 1429–1445.

Haijema, R., Minner, S., 2016. Stock-level dependent ordering of perishables: a comparison of hybrid base-stock and constant order policies. Int. J. Prod. Econ. 181, 215–225.

Ketzenberg, M.E., Ferguson, M., 2008. Managing slow-moving perishables in the grocery industry. Prod. Operat. Manag. 17 (5), 513–521.

Kouki, C., Jemaï, Z., Minner, S., 2015. A lost sales (r, Q) inventory control model for perishables with fixed lifetime and lead time. Int. J. Prod. Econ. 168, 143–157.

Kouki, C., Sahin, E., Jemai, Z., Dallery, Y., 2013. Assessing the impact of perishability and the use of time temperature technologies on inventory management. Int. J. Prod. Econ. 143 (1), 72–85.

Lee, P., Osborn, S., Whitehead, P., 2015. Reducing food waste by extending product life. http://www.wrap.org.uk/sites/files/wrap/Product%20Life%20Report%20Final_0. pdf.

Lebersorger, S., Schneider, F., 2014. Food loss rates at the food retail, influencing factors and reasons as a basis for waste prevention measures. Waste Manag. 34, 1911–1919.

Little, J.D.C., Graves, S.C., 2008. Little's Law. In: Chhajed, D., Lowe, T.J. (Eds.), Building Intuition: Insights from Basic Operations Management Models and Principles. Springer Science+Business Media LLC, New York, pp. 81–100 (Chapter 5).

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

Nahmias, S., 1982. Perishable inventory theory: a review. Operat. Res. 30, 680–708.

Oliver Wyman, 2013. Getting fresh: lessons from the global leaders in fresh food. http://www.oliverwyman.com/content/dam/oliver-wyman/europe/germany/de/insights/publications/2015/jan/OW_POV_Getting%20Fresh.pdf.

Olsson, F., Tydesjö, P., 2010. Inventory problems with perishable items: fixed lifetimes and backlogging. Eur. J. Operat. Res. 202, 131–137.

Priefer, C., Jörissen, J., Bräutigam, K., 2016. Food waste prevention in Europe – a cause-driven approach to identify the most relevant leverage points for action. Resour. Conserv. Recycl. 109, 155–165.

Shukla, M., Jharkharia, S., 2013. Agri-fresh produce supply chain management: a state-of-the-art literature review. Int. J. Operat. Prod. Manag. 33 (2), 114–158.

Silver, E.A., van Pyke, D.F., Peterson, R., 1998. Inventory Management and Production Planning and Scheduling, third ed. Wiley, Chichester.

The Consumer Goods Forum, 2015. Consumer goods industry commits to food waste reduction. http://www.theconsumergoodsforum.com/consumer-goods-industry-commits-to-food-waste-reduction.

Van Donselaar, K.H., Broekmeulen, R.A.C.M., 2012. Approximations for the relative outdating of perishable products by combining stochastic modeling, simulation and regression modeling. Int. J. Prod. Econ. 40 (2), 660–669.

Van Donselaar, K.H., Broekmeulen, R.A.C.M., 2013. Determination of safety stocks in a lost sales inventory system with periodic review, positive lead-time, lot-sizing and a target fill rate. Int. J. Prod. Econ. 143 (2), 440–448.