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Discounting and dynamic shelf life to reduce fresh food waste at retailers

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ABSTRACT

Approximately 89 million of tonnes of food is wasted every year in the EU along the whole food supply chain. The reasons for food waste by retailers include inappropriate quality control, overstocking and inaccurate forecasting. This study shows that food wasted by retailers can be reduced by discounting old products or by applying a dynamically adjustable expiration date (in other words dynamic shelf life (DSL)). We developed a simulation based optimization model to optimize the replenishment and discounting policy of a retailer who sells meat products. DSL outperforms a fixed shelf life (FSL) in terms of profit, waste, shortages and food safety. Furthermore, replenishment quantities can be higher. The benefits of DSL are greater when demand is low or when the shelf life of products is short. Discounting is a successful strategy to reduce food waste for both FSL and DSL. DSL without discounting is more effective than FSL with discounting. Combining DSL and discounting, allows for a further reduction of food waste.

1. Introduction

Food waste is a major problem for society. Approximately 89 million of tonnes is wasted in the EU every year (Monier et al., 2011). The most common causes of perishable food waste at a retailer are overstocking, consumer behaviour, inappropriate quality control and product handling (Wang and Li, 2012; Whitehead et al., 2011). Therefore, an inventory management strategy and more focus on consumer behaviour are needed at the retailer. Products close to the use-by date are perceived as products with lower quality by consumers and are therefore less favourable to purchase (Tsiros and Heilman, 2005). Discounting is a well-known technique to convince consumers to buy less favourable products and to reduce food waste.

Another way to reduce food waste is to better predict product quality and according adjust the shelf life (or use-by date) dynamically. Products with a maximal shelf life of less than 2 weeks are considered to be perishable products. For most of these products (e.g. meat, fish, dairy) it is obligatory to determine a use-by date and print it on the product packaging. The time between production and the use-by date is called shelf life. For highly perishable products, the shelf life is determined by producers and is often set rather conservatively to ensure food safety (Soethoudt et al., 2012). Conservative shelf life setting can cause unnecessary waste at retailers and increases when consumers are selective about the use-by dates or if demand varies a lot. It is expected that a DSL can reduce the amount of unnecessary waste. DSL is defined as a shelf life that can be adjusted to the actual quality of the product, either by adjusting the date or by indicating the quality of a product with a different technique, such as Time-Temperature Indicators (TTI). The latter has already proven to be beneficial in stochastic environments (Herbon et al., 2012). An extra advantage of a DSL is that the products that are sold are safer. The conventional approach of setting a FSL allows products to spoil before they reach the use-by date. This research evaluates the benefits of DSL for fresh meat products because fresh meat is highly perishable. Meat products are spoiled when bacterial counts are too high, and therefore food safety can be at stake when products pass their use-by date (Bruckner, 2010). To reduce food waste and ensure safe products we will study the effect of DSL and discounting on profit, waste, shortage and the replenishment quantity for a perishable product at a retailer.

The effect of discounting on a retailer's performance is well studied, e.g. see (Elmaghraby and Keskinocak, 2003; Lin et al., 2016; Transchel and Minner, 2009; Zhao and Zheng, 2000). However, some researchers make assumptions which do not hold for supermarkets (see Bakker et al. (2012); Chung and Lin (2001)). On the other hand, the effect of DSL on a retailer's performance is hardly studied, nor is the combined effect of DSL and discounting. Both have an effect on the retailer performances however it is not yet known which of the two options is the most effective or how effective the combination of the two is.

In addition, we will study the effect of discounting and DSL on the optimal replenishment quantities. Existing studies on DSL do not study

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the effect on the replenishment strategy. The effect of discounting on the replenishment strategy is only studied in the context of FSL (Farughi et al., 2014; Lin et al., 2016; Liu et al., 2008; Qin et al., 2014). It is unknown how the replenishment strategy of a retailer will be affected when DSL or the combination of DSL and discounting is applied.

In this study we will fill these research gaps by evaluating the effect of discounting and DSL on the replenishment of a retailer and on its performance in terms of waste, profit, shortages and product quality. Discounting and DSL will be studied separately as well as combined. To study the effect of discounting and DSL on the replenishment, discount levels and replenishment quantities are optimized integrally.

In section 2 relevant literature on discounting and DSL is discussed. Section 3 presents the models used in this research. In section 4 we numerically investigate the effectiveness of DSL, discounting and their combination for a variety of experiments. Section 5 closes the paper with conclusions and discussions.

2. Literature

To position this paper, we discuss the literature related to discounting and DSL. We limited ourselves to articles published since 2008, in order to present an overview of recent developments. In Table 1 the most relevant articles are listed, which are obtained using search keywords: *perishables* AND [*dynamic pricing* OR *discount* OR *dynamic shelf life*]. Articles are assessed on several criteria; first if they include dynamic pricing or discounting and if prices are based on quality. Then how shelf life is set, fixed or dynamic and if demand is modelled deterministic or stochastic. When optimization is included, the focus of optimization is given. The last columns in the table explain which part of the supply chain (SC) is taken into account and if simulation is used. In 2.1 research on dynamic pricing is described in more detail and in 2.2 the literature about DSL. The other columns of the table are incorporated in those paragraphs. As indicated in the last row of Table 1, this paper differentiates itself from most existing literature by including a DSL instead of a FSL. The few articles found that do include DSL, do not include the optimization of discount levels and replenishment quantities as we have.

2.1. Discounting and dynamic pricing

Discounting or determining an optimal price is a topic well studied in literature. Several good reviews are available such as Elmaghraby and Keskinocak (2003) and Bakker et al. (2012).

As Table 1 indicates, most of the reviewed articles include dynamic pricing or discounting. Profit is maximized by determining the optimal price and/or optimal replenishment (policy) (Farughi et al., 2014; Rabbani et al., 2016; Zhang et al., 2015). Price determination by product quality is done by Avinadav et al. (2013); Chew et al. (2014); Qin et al. (2014) and Lin et al. (2016). Most researchers that focus on discounting/dynamic pricing developed an optimization model to evaluate a single, deteriorating product with a price dependent and deterministic demand. Berk et al. (2009) did not include replenishment policies in their research but investigated the effect of costs that come with adapting the price. Next to that, they are one of the few who incorporated stochastic demand. In order to solve the optimization problem they developed a heuristic. Liu et al. (2008) developed an optimization model to determine optimal price and ordering decision. They first developed the model for deterministic demand and later extend it to stochastic demand. Demand is price and quality dependent, and they apply an RFID tag to indicate food quality. Chew et al. (2014) also used stochastic demand. They evaluated a product with a multi-period life-time and allowed substitution between products of different age categories. For a life-time of 2 periods they show that an optimal price can be obtained analytically. For life-times higher than 2 periods a heuristic is developed to find the optimal solution. The results show that profit increases when price and order quantity for both products are determined together. Avinadav et al. (2013) developed an optimization model where demand is not only price dependent but also dependent on remaining shelf life. Although the scope of each study is slightly different, the conclusions are closely related. The conclusions of the studies generally show that the costs of price changes, speed of deterioration and consumer behaviour influences the optimal price (policy) (Berk et al., 2009; Lin et al., 2016; Qin et al., 2014).

2.2. Dynamic shelf life

Only a few researchers implement a DSL, shelf life based on the quality status of the product. Tromp et al. (2012) and Wang and Li (2012) implemented DSL in combination with discounting. Both use a simulation model to determine the effect of a DSL compared to a FSL. Tromp et al. (2012) models a pork supply chain and incorporates food safety by modelling food quality with a microbiological growth model. In their research they include a stochastic consumer demand divided in FIFO and LIFO demand. Without discounting, this ratio is fixed, but when a discount is applied, it is assumed that more consumers will buy FIFO. They show that a DSL is a promising concept compared to a FSL when evaluating opportunity losses that occur due to stock-outs and waste. Wang and Li (2012) developed a similar model, but modelled food quality more generally and therefore did not include food safety. Furthermore, they work with deterministic settings. They show that setting prices according to a dynamically identified food quality can improve the retailers' benefits and reduces waste at retailers. Herbon et al. (2012) evaluate the effect of using a TTI on retailers' profit for a luxurious fish product. They

Table 1
Literature review.

Author	Dynamic pricing/ Discounting	Price based on quality	Shelf life	Demand (*)	Optimization focus	SC scope	SC simulation
Avinadav et al. (2013)	x	x	Fixed	D	Price, order quantity and replenishment period	Single echelon	no
Berk et al. (2009)	x		Fixed	St	Price	Single echelon	no
Chew et al. (2014)	x	x	Fixed	St	Price and order quantity	Single echelon	no
Farughi et al. (2014)	x		Fixed	D	Price, order quantity and replenishment time	Single echelon (retailer)	no
Herbon et al. (2012)	x	x	Dynamic	St	–	retailer	yes
Ketzenberg et al. (2015)			Dynamic	St	–	retailer	yes
Lin et al. (2016)	x	x	Fixed	D	Price and replenishment cycle	Supplier and retailer	no
Liu et al. (2008)	x	x	Fixed	D & St	Price and ordering decision	Single echelon (retailer)	no
Qin et al. (2014)	x	x	Fixed	D	Price and lot sizes	Single echelon	no
Rabbani et al. (2016)	x		Fixed	D	Price and replenishment quantity and time	Single echelon	no
Tromp et al. (2012)	x	x	Dynamic	St	–	Warehouse and retailer	yes
Wang and Li (2012)	x	x	Dynamic	D	–	Single echelon (retailer)	yes
Zhang et al. (2015)	x		Fixed	D	Price and replenishment cycle	Single echelon	no
This paper	**x**	**x**	**Dynamic**	**St**	**Discount and replenishment quantity**	**(Producer), Warehouse and retailer**	**yes**

* St = stochastic, D = deterministic.

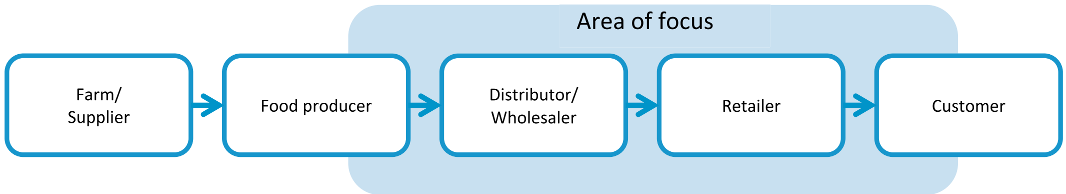

Fig. 1. Research scope of meat supply chain.

developed a non-linear stochastic model, which they solve by simulation. Demand is price dependent and stochastic. They evaluated four levels of discount (from 0 till 20%) and two types of TTI (simple and cheap or sophisticated and more expensive). They conclude that applying a simple TTI increases profit. A sophisticated TTI can decrease profit because the cost reduction is less than the price of the tag. Furthermore, they found that applying discounts is beneficial. Ketzenberg et al. (2015) focus on the value of using a TTI by formulating a Markov Decision Process, solved with a heuristic. They measure the value of information (VOI) of the TTI as the reduction in average costs when information is available. A simulation study is performed to evaluate the VOI. The results give a high VOI for the majority of the experiments. This implies a large uncertainty present in the model that will affect the retailers' performance.

2.3. *Research gap*

The literature review shows that for dynamic pricing the effect on replenishment is well described, although, not always under assumptions that hold for a retailer. Most of the studies deal with deterministic demand, which is preferable from a mathematical perspective. Deterministic demand might be applicable for situations where demand is high and variability low however when dealing with real life situations at a grocery store, stochastic demand is more realistic. The effect of a DSL on the replenishment (quantity) has not yet been incorporated as far as we know. Neither is the effect of a demand shift (from LEFO to FEFO) studied when applying a discount. Almost all the research mentioned above assumes an increase in demand when price decreases. There does not seem to be a paper that compares discounting and DSL, and their impact on food waste, shortages, profit and replenishment levels.

3. Methods

In order to analyse the effect of DSL and discounting on profit, waste, shortages and product quality, simulation-based optimization is applied. This allows the SC to be modelled at the right level of detail for monitoring quality decay at both the retailer and the distribution centre (DC). Factors, such as uncertain demand, temperature fluctuations and order lead time can be included as well.

3.1. *Simulation model*

The core of the simulation model is an inventory model, describing part of a meat supply chain (Fig. 1). The main focus of the model is a retailer which is supplied by a DC. The DC is supplied by a production company. The DC serves multiple retailers at the same time but the evaluation is focussed on one retailer. The consumer is within the scope of this research, but only at the moment of purchase. What happens after purchasing the product is out of the research scope. Transport by truck will take place between the processing company and the DC and between the DC and the retailer. Next to the inventory model, a microbiological growth model is included to track the quality of the products. The modelling of the product is done in batches based on their remaining shelf life at the DC and retailer however, consumers purchase a single product out of those batches.

3.1.1. *In- and outputs*

The simulation model evaluates and compares different scenarios in terms of average profit per week, waste, shortages and microbiological counts of sold products. Waste is chosen because it is the main focus of this research. In 3.1.6 it is explained how waste occurs at the retailer for scenarios with fixed and DSL. Profit calculations are shown in 3.1.7. And shortages are counted as the percentage of demand that cannot be fulfilled. The microbiological count is explained in 3.1.2. Profit margin, selling price and consumer demand are used as inputs, to calculate waste and profit. We need the initial contamination of the product after packaging and the temperature in the supply chain, to obtain the average microbiological count of sold products.

3.1.2. *Microbiological model*

A microbiological growth model is used to determine the quality of the products. For fresh meat products shelf life is mainly determined by bacterial growth. The (modified) Gompertz curve is one of the most used model in modelling microbiological growth (Bruckner, 2010; Tromp et al., 2012). In this research an adapted version of the Gompertz curve is used, based on the research of Tromp et al. (2012). This adapted Gompertz curve can deal with temperature changes more easily than the original Gompertz curve. $N(\tau)$ is the microbiological count of a product that has been produced τ days ago and kept since then at temperature T (in °C).

$$N(\tau) = A + C^{*} e^{-e^{-B(T)(\tau - M(T))}} \qquad \left[\log_{10}\frac{\text{cfu}}{\text{g}}\right] \tag{1}$$

where *A, B, C* and *M* product specific parameters. Parameters *B* and *M* are temperature dependent according to:

$$B(T) = \alpha_B e^{\beta_B{}^{*} T} \tag{2}$$

$$M(T) = \alpha_M e^{\beta_M{}^{*} T} \tag{3}$$

The Gompertz model is a continuous time growth model, i.e. $N(\tau)$ is a continuous function of τ. However, in the simulation model the microbiological count of the products are updated at discrete points in time, e.g. at the start and end of a process like transhipment. During time intervals in between time points the temperature is assumed to be constant. Temperature changes are modelled at these time points. At the end of the day, microbiological growth for every batch in stock is calculated as follows.

At the end of the day t product batch r was exposed to a constant temperature T during τ_{step} units of time. At its last update, τ_{step}, time units ago, the cell count was N_{tr}. That value corresponds to the point $\tau = \varphi$ at the Gompertz curve. The value of φ follows from the inverse of (1).

$$\tau = \varphi = \frac{\log\left(-\log\left(\frac{N_{tr}-A}{C}\right)\right)}{-B(T)} + M(T) \tag{4}$$

At the start of the next day, $t+1$, batch r will be labelled batch r-1; the bacterial count on a product is:

$$N_{t+1,r-1} = A + C^{*} e^{-e^{-B(T)((\varphi+\tau_{step}-M(T))}} \qquad \left[\log_{10}\frac{\text{cfu}}{\text{g}}\right] \tag{5}$$

Besides an update on microbiological count every day, updates also take place when products are transshipped.

3.1.3. Producer and DC

The simulation model starts at Monday ($t = 0$), at the moment a producer packages the product (Fig. 1). We assume that the DC orders three times a week, on Monday, Wednesday and Friday at the end of the day. The producer delivers at the DC within 12 h, before the retail outlets open. Effective lead time is therefore zero and incoming products at the DC will have a shelf life of *m-1* days. Delivery of the producer to the DC is described with an order-up-to level:

$$Q_t^{DC} = \begin{cases} S^{DC} - \sum_{r=1}^{m-1} I_{tr}^{DC}, & if\ mod(t,7) = \{0,2,4\} \\ 0, & else \end{cases} \tag{6}$$

where Q_t^{DC} is the delivery quantity and I_{tr}^{DC} the number of products with remaining shelf life r still in stock at the DC upon ordering at the end of day t. The DC serves e retailers, each with a Poisson distributed daily demand with mean μ products. The DC places an order every R = 2 working days. The demand at the DC over the next R working days has a mean demand $e\mu R$ and a standard deviation of $\sqrt{e\mu R}$. The order-up-to level of the DC, S^{DC}, is set by:

$$S^{DC} = e\mu R + z^{DC} * \sqrt{e\mu R} \tag{7}$$

where z^{DC} is a safety factor, which will be large enough such that enough products are available at the DC. The order policy for the focal retailer is explained in section 3.1.4. The DC sells products to retailers with a FEFO policy and when products are delivered of different age categories, they are equally distributed among the retailers. For example, if the DC meets 60% of the total demand by products from the 'oldest' batch and 40% from the 'next-to-oldest' batch, then 60% of the focal retailer's demand is met by products from the oldest batch and 40% by products of the next-to-oldest batch. Similarly, shortages are equally spread over the retailers by the ratio of their demands.

Inventory of the DC is updated at the end of each period.

$$I_{t+1,r-1}^{DC} = \begin{cases} I_{tr}^{DC} - PS_{tr}^{DC} + Q_t^{DC}\delta(r = m-1) - W_{tr}^{DC}\delta(r=1) & for\ FSL \\ I_{tr}^{DC} - PS_{tr}^{DC} + Q_t^{DC}\delta(r = m-1) - W_{tr}^{DC}\delta(N_{tr} \geq \eta_{waste}) & for\ DSL \end{cases} \tag{8}$$

where:

- PS_{tr}^{DC} are the products sold by the DC at period t with remaining shelf life r
- δ is a Kronecker delta where $\delta(x) = 1$ if x is true, and 0 otherwise.
- W_{tr}^{DC} the products wasted in period t with a remaining shelf life r calculated in a similar way as for the retailer, explained in section 3.1.6

3.1.4. Ordering policy focal retailer

The retailer is open 6 days a week from Monday to Saturday. The number of days passed since the start of the simulation is indicated by index t. The related weekday is indexed $d = \text{mod}(t,7)$ {0 = Monday, 1,2, …, 6 = Sunday}. At the beginning of day t the retailer places an order (Q_t^{Ret}) at the DC excluding Sundays. Products are replenished with a weekday dependent order-up-to-level S_d^{Ret}. Products are ordered in multiples of a pack G. Furthermore the order size depends on the total number of products in stock $\sum_{r=1}^{m} I_{tr}^{Ret}$ at the moment of ordering (at the start of day t), and the estimated amount of products to be wasted at the end of a period (EW_t). EW_t is the amount of products with a remaining shelf life of one day subtracted by the expected FEFO sales during that day, which is a fraction of the mean demand μ_d on a weekday d. To keep the rule simple to use, we do not subtract the part of demand of LEFO consumers that is met from that category. Thus the order quantity set by the retailer at day t is:

$$Q_t^{Ret} = \begin{cases} \left[\dfrac{\left(S_d^{Ret} - \sum_{r=1}^{m} I_{tr}^{Ret} + EW_t \right)}{G} \right] * G, & if\ mod(t,7) \in \{0,1,2,3,4,5\} \\ 0, & otherwise \end{cases} \tag{9}$$

where:

- the squared brackets indicate Q_t^{Ret} is rounded to the nearest multiple of pack size G

$$EW_t = \begin{cases} max\left[0, I_{t1}^{Ret} - (1-a)^* \mu_d\right] & if\ FSL \\ max\left[0, \sum_{r=1}^{m} I_{tr}^{Ret} \delta(N_{tr} \geq \eta_{waste}) - (1-a)^* \mu_d\right] & if\ DSL \end{cases} \tag{10}$$

3.1.5. Consumer demand and withdrawal at retailer

Consumer demand (D_t) is assumed to be stochastic, and Poisson distributed with weekday dependent mean demand μ_d and standard deviation $\sigma_d = \sqrt{\mu_d}$. The meal weekly demand at a retailer is 6μ, and on average a fraction f_d of the week demand occurs on weekday d. Thus, we have:

$$\mu_d = f_d * 6\mu \tag{11}$$

where:

- f_d determines the demand per day dependent on total weekly demand.

Total consumer demand is separated in consumers who buy FEFO and LEFO. It is assumed that LEFO consumers will buy products before FEFO consumers arrive, as they are pickier about product quality and therefore might put more effort into getting products earlier. Division is done as follows:

$$DL_t = D_t * a \tag{12}$$

$$DF_t = D_t - DL_t \tag{13}$$

With DL_t is the LEFO demand and DF_t is FEFO demand and a the fraction of total demand which is LEFO. When a discount is applied it is assumed that the ratio between LEFO and FEFO consumers shift more towards FEFO consumers. Based on the discount percentages (x) a similar percentage of the LEFO consumers will pick the discounted product and therefore into FEFO consumers. The new LEFO demand DL_t^{Disc} is calculated by

$$DL_t^{Disc} = DL_t - \min\left\{ x^* DL_t, a^* IDisc_{tr}^{Ret} \right\} \tag{14}$$

where:

- $IDisc_{tr}^{Ret} = I_{t1}^{Ret}$ the products with a discount at time t when FSL applies.

- $IDisc_{tr}^{Ret} = I_{tr}^{Ret}\delta(N_{tr} \geq \eta_{discount})$ the products with a discount at time t when DSL applies.

In the case of LEFO withdrawal, products picked by the consumer (PL_{tr}^{Ret}) at period t with remaining shelf life r, is the minimum of the products available of a batch *(tr)* and the remaining demand which is unsatisfied from fresher batches. For $r = m, m$-1, …, 1,

$$PL_{tr}^{Ret} = \min\left\{I_{tr}^{Ret},\ DL_t - \sum_{i=r+1}^{m} PL_{ti}^{Ret}\right\} \tag{15}$$

In case of FEFO withdrawal products picked by a consumer at period t (PF_{tr}^{Ret}) are the minimum of the remaining products in the batch and the remaining demand which is unsatisfied from older batches on the shelf, for $r = 1, \ldots, m$,

$$PF_{tr}^{Ret} = \min\left\{I_{tr}^{Ret} - PL_{tr}^{Ret},\ DF_t - \sum_{i=1}^{r-1} PF_{ti}^{Ret}\right\} \tag{16}$$

3.1.6. Wasting policy for FSL and DSL at retailer

At the end of the shelf life products are wasted. For a FSL this will happen when products have a remaining shelf life of one day left after closing the shop. The wasted products are:

$$W_t^{Ret} = I_{t,1}^{Ret} - PF_{t,1}^{Ret} - PL_{t,1}^{Ret} \tag{17}$$

With a DSL, the moment of wasting the product is determined by the amount of bacteria present on the product. When products have a higher bacterial count than η_{waste} they will be wasted at the end of a day.

$$W_t^{Ret} = \sum_{r=1}^{m}\left(I_{tr}^{Ret} - PF_{tr}^{Ret} - PL_{tr}^{Ret}\right)*\delta(N_{tr} \geq \eta_{waste}) \tag{18}$$

In the final evaluation, waste is defined as the percentage of products bought by the retailer.

At the end of the day, the inventory at the retailer is updated for the remaining shelf life and time period.

$$I_{t+1,r-1}^{Ret} = \begin{cases} I_{tr}^{Ret} - PL_{tr}^{Ret} - PF_{tr}^{Ret} + QS_{tr}^{Ret} - W_{tr}^{Ret}\delta(r=1),\ for\ FSL \\ I_{tr}^{Ret} - PL_{tr}^{Ret} - PF_{tr}^{Ret} + QS_{tr}^{Ret} - W_{tr}^{Ret}\delta(N_{tr} \geq \eta_{waste}),\ for\ DSL \end{cases} \tag{19}$$

where:

- QS_{tr}^{Ret} are the incoming products at the retailer at time t of age class r. Depending on the demand of all other retailers, and the inventory levels of the DC.

3.1.7. Profit

In this research profit is defined as revenues minus purchasing and holding costs. Fixed ordering costs are neglected as perishables at supermarkets are usually replenished daily or transport costs are shared over many products (Haijema and Minner, 2016).

$$Profit_t = \sum_{r=1}^{m}\left(\left(PF_{tr}^{Ret} + PL_{tr}^{Ret}\right)*p_{tr} - I_{tr}^{Ret}*h - QS_{tr}^{Ret}*p*(1-\pi)\right) \tag{20}$$

$$p_{tr} = \begin{cases} p(1-x),\ if\ IDisc_{tr}^{Ret} > 0 \\ p,\ \quad if\ IDisc_{tr}^{Ret} = 0 \end{cases} \tag{21}$$

where:

- p the sales price at the retailer
- x the discount given
- π is the profit margin at the retailer, and
- h the holding costs per item, which is determined by p, π and γ (fraction) as follow:

$$h = \gamma*\frac{p}{(1-\pi)} \tag{22}$$

3.2. Optimization

Optimization is carried out for two values, the safety factor z and the discount level x. The optimization gives input values to the simulation model and can therefore be seen as a layer over the simulation model.

3.2.1. Safety factor (z)

The optimal z^* value for the retailer is determined by maximizing profit. To determine the right safety factor a full enumerated search is done. Values tested for z range from 0 to 3 with intervals of 0.1. Optimization over z is chosen as demand varies among days and therefore the order-up-to level will be different each day. The order-up-to level is calculated with the z^* as follow:

$$S_d^{Ret} = \begin{cases} \mu_d + \mu_{d+1} + z^{*}*\sqrt{\sigma_d^2 + \sigma_{d+1}^2},\ if\ d\varepsilon\{0,1,2,3,4\} \\ \mu_5 + \mu_6 + \mu_0 + z^{*}*\sqrt{\sigma_5^2 + \sigma_6^2 + \sigma_0^2},\ if\ d = 5 \\ 0,\ otherwise \end{cases} \tag{23}$$

Note, in our case the retailer is not open on Sunday, hence $\mu_6 = \sigma_6 = 0$.

3.2.2. Discount level (x)

Discounting will occur on the last day products can be sold. For FSL this will be at $r = 1$, for DSL when microbiological count is $\geq \eta_{discount}$. When discount is applied, a range from 0% up to 100% is tested with intervals of 5%. Then the optimal z^* is determined for every discount level.

4. Numerical results

In this section, we investigate the effectiveness of DSL and discounting and evaluate performance at the retailer on profit, waste and shortage levels and microbiological count. Section 4.1 describes the design of experiments and the data used. From section 4.2 onwards results are listed and discussed.

4.1. DoE and data

Table 2 gives the parameters settings for 32 experiments. Scenarios differ according to profit margins, mean demand, shelf life (different product) and whether discounting applies or not. For all experiments the safety factor z is optimized. In experiment 19 to 32, the impact of optimal discounting is investigated, as well as the moment of discounting and the effect of the LEFO-FEFO ratio. The scenarios and results are discussed in detail in section 4.3, 4.4 and 4.5.

4.1.1. Shelf life setting

Shelf life setting for FSL is based on the predicted growth of bacteria during the life span of a product. As temperature is the main influencer, producers have to estimate the SC temperature to set a shelf life. Producers who define the use-by date of products want to ensure food safety and want to avoid selling products that are spoiled. Temperatures in the SC can vary considerably from the desired temperature, for instance while the products are unloaded from trucks. On average the SC temperature is around 4.5 °C (Tromp et al., 2012). To be safe and allow for some temperature variation we determine the use-by date for the meat product at a temperature of 5.5 °C. Meat products are considered to spoil at a microbiological count of $\eta_{unsafe} = 6$ log cfu/g. In order to avoid selling products to consumers too close to that spoilage point, we use a limit of $\eta_{waste} = 5.3$ log cfu/g at the retailer, in line with Tromp et al. (2012). At 5.5 °C η_{waste} is reached after 8.45 days, therefore we use a shelf life of 8 days in the basic scenario for FSL. Fig. 2 shows the development of bacterial count according to the modified Gompertz. The initial increase

Table 2
Design of experiments: (a) Scenario 1–5, (b) Scenario 6 and 7.

(a) Scenario 1 to 5: varying profit margin, mean demand, product type and ordering strategy of DC (with a = 0.4 (LEFO fraction) and no discounting)

Scenario	Experiment	Shelf life (m), (days)	Profit margin (π)	Weekly demand (6μ)	Order DC per week
1 (Basic)	1	Fixed (8)	33%	30	3
	2	Dynamic	33%	30	3
2 (Profit margin)	3	Fixed (8)	20%	30	3
	4	Dynamic	20%	30	3
	5	Fixed (8)	50%	30	3
	6	Dynamic	50%	30	3
3 (Demand)	7	Fixed (8)	33%	18	3
	8	Dynamic	33%	18	3
	9	Fixed (8)	33%	48	3
	10	Dynamic	33%	48	3
4 (Different product)	11	Fixed (5)[a]	33%	30	3
	12	Dynamic	33%	30	3
	13	Fixed (10)[a]	33%	30	3
	14	Dynamic	33%	30	3
5 (Different order moment DC)	15	Fixed (8)	33%	30	2
	16	Dynamic	33%	30	2
	17	Fixed (8)	33%	30	6
	18	Dynamic	33%	30	6

(b) Scenario 6 and 7 on optimal discounting, the effect of moment of discounting and the effect of selection behaviour of consumers (other parameters as in scenario 1)

Scenario	Experiment	Shelf life (m), (days)	LEFO fraction (a)	Discount moment
6 (Moment of discount and optimal discount)	19	Fixed (8)	0.4	$r = 1$
	20	Dynamic	0.4	$\eta_{discount} = 4.7$ log cfu/g
	21	Fixed (8)	0.4	$r = 2$
	22	Dynamic	0.4	$\eta_{discount} = 4.3$ log cfu/g
7 (Consumer picking and optimal discount)	23	Fixed (8)	1	$r = 1$
	24	Fixed (8)	0.75	$r = 1$
	25	Fixed (8)	0.5	$r = 1$
	26	Fixed (8)	0.25	$r = 1$
	27	Fixed (8)	0	$r = 1$
	28	Dynamic	1	$\eta_{discount} = 4.7$ log cfu/g
	29	Dynamic	0.75	$\eta_{discount} = 4.7$ log cfu/g
	30	Dynamic	0.5	$\eta_{discount} = 4.7$ log cfu/g
	31	Dynamic	0.25	$\eta_{discount} = 4.7$ log cfu/g
	32	Dynamic	0	$\eta_{discount} = 4.7$ log cfu/g

Using the fractions f_d the mean weekly demand 6μ is transformed to the mean demand μ_d confirm Equation (11).
[a] Different shelf life is based on equation (1) by using a conversion factor (ζ) to change the speed of quality decay accordingly, as explained in more detail in section 4.1.1.

is low (lag phase), followed by exponentially growth and slows down when it reaches the upper limit. The tree curves relate to 3 different products (scenario 4) that have different growth times. In the plotted example, η_{waste} is reached after a FSL of respectively 5, 8 and 10 days at 5.5 °C by multiplying τ in equation (1) by a factor (ζ). ζ is calculated by dividing the new shelf life (in days) by the old shelf life.

For DSL we use the same limit for η_{waste}. For practical reasons we mimic the DSL in the simulation model by calculating with a maximum shelf life (m) three times as high as used for FSL.

4.1.2. Data

In Table 3, the supply chain time and temperatures are given for the incorporated part of the SC, needed for the microbiological growth model.

4.2. Food quality analysis

Food quality is important in dealing with perishable products. For meat products food quality is closely related to food safety, as micro-

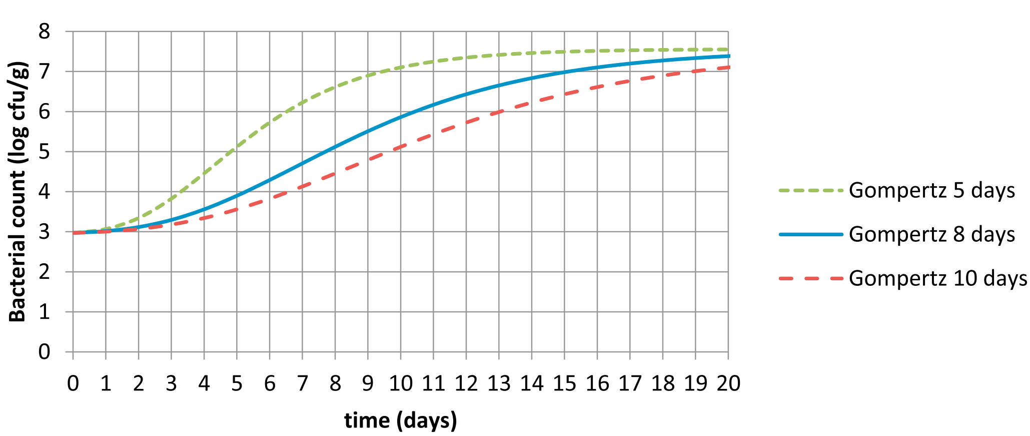

Fig. 2. Example of increase in bacterial count according to modified Gompertz curve at T = 5.5 °C.

Table 3
Time and temperature of supply chain based on Tromp et al. (2012).

Activity	Time (days)	Temperature distribution
Transport from processing company to DC	0.208	Normal (μ = 2 °C, σ = 0.5 °C)
Unloading at DC	0.031	Normal (μ = 2 °C, σ = 0.5 °C)
At DC	Depending on demand retailers	Normal (μ = 2 °C, σ = 0.5 °C)
Transport DC-retailer	0.125	Normal (μ = 2 °C, σ = 0.5 °C)
Unloading at retailer	0.031	Normal (μ = 15 °C, σ = 0.25 °C)
Retailer	Depending on demand customer	Normal (μ = 4 °C, σ = 0.5 °C)

Values of other parameters for simulation are given in Table 4; e.g. selling price but also values of parameters of the microbiological growth model.

Table 4
Value of parameters based on Tromp et al. (2012) and Broekmeulen and van Donselaar (2009) Van Donselaar et al. (2006).

Parameter	Value
Initial contamination	$\mu_N = 2.95$, $\sigma_N = 0.1{*}\mu_N$
A	2.95
C	7.56-A
α_B	0.104
β_B	0.1573
α_M	14.525
β_M	−0.1365
η_{waste}	5.3 log cfu/g
η_{unsafe}	6 log cfu/g
z^{DC}	1.96
e	101
G	4
f_d	[0.12 0.11 0.125 0.16 0.255 0.23 0]
a	0.4
p	€2.98
γ	0.0003

organisms will cause quality decay and safety hazards ($N_{tr} \geq \eta_{unsafe}$). In Table 5, the average microbiological count for products sold with FSL and DSL without discount is listed. We see that the difference in average microbiological count at the point of sales is small, and below η_{waste}. However, we see that for FSL a small amount of spoiled products ($N_{tr} \geq \eta_{unsafe}$) is sold, where products sold with DSL are always safe.

4.3. Effect of dynamic shelf life at retailer

For experiment 1–18 an optimal replenishment policy is determined by optimizing the safety factor z for 100 runs of 1846 days of which 21 are regarded as warming up period. For experiments 19–32 the optimal replenishment policy is determined by optimizing the safety factor for each discount percentage x for a two runs of 1846 days. The thus obtained optimal setting is evaluated at high accuracy of 100 runs. With this we obtain an accuracy that implies a standard deviation of about 3% of the mean profit for all optimal solutions.

In Table 6 results for the optimal z^*, S^*, profit per week for the retailer and waste and shortages are given for scenario 1 to 4.

4.3.1. Basic scenario

In the basic scenario with FSL the optimal safety factor z^* is 0.6, resulting in an average S^* level of 12. Profit obtained per week at the retailer is €26.94 and 1.87% of the products are wasted. Furthermore, shortage levels are 5.27%. In comparing those results with a DSL we see increased z^* and S^* values, a higher profit and a reduction in waste and shortages. The results are in line with what we expected as shelf life setting is often rather conservative (Soethoudt et al., 2012). Actual shelf life might be longer than the FSL indicates. A DSL can show the actual shelf life of a product, which seems to be longer and therefore results in more time to sell the product. More selling time results directly in less waste as demand uncertainty is becoming less important. Products that are not sold on one day can be sold the next day. Less waste also reduces the amount of shortages. Although the model corrects for expected waste shortages will always occur due to uncertain demand.

Table 6
Results scenario 1 to 4.

Scenario	Experiment	z^*	S^*	Profit Retailer	Waste	Shortages
1 (Basic)	1	0.6	12	€ 26.94	1.87%	5.27%
	2	1.3	14	€ 28.23	1.33%	1.87%
2 (Profit margin)	3	0.4	11	€ 15.67	1.49%	6.81%
	4	0.9	13	€ 16.72	0.75%	3.61%
	5	0.9	13	€ 42.02	2.96%	3.44%
	6	1.6	15	€ 43.50	1.84%	1.22%
3 (Demand)	7	0.4	7	€ 14.76	5.14%	7.58%
	8	1	8	€ 16.31	2.46%	4.18%
	9	1	20	€ 44.79	1.14%	2.57%
	10	1.6	22	€ 45.94	0.68%	0.98%
4 (Different product)	11	0.1	10	€ 13.01	20.61%	7.16%
	12	0.5	12	€ 24.95	4.05%	7.81%
	13	1.6	15	€ 28.88	0.64%	1.05%
	14	2	16	€ 29.01	0.65%	0.56%

4.3.2. Effect of profit margin

Products at a supermarket have different profit margins. Some products are used to attract consumers and therefore have a low profit margin where as other products are used to gain profit. Changing the profit margin influences profit and order-up-to levels and therefore the waste and shortage levels. Waste is increased compared to the basic scenario and shortages decreases with a higher profit margin. Out-of-stock (OOS) situations become more expensive and therefore safety factor is increased to prevent OOS. As a result of increasing S^*, more waste is obtained. The opposite results are obtained when profit margins are lower.

4.3.3. Effect of demand

The results of scenario 3, show that a decrease in demand reduces profit, not only because less products are sold but also because waste and shortages increase. With a lower demand, the safety factor decreases and vice versa for higher demand. This occurs for both FSL and DSL, although z^* for DSL is always higher. When demand decreases, relative variance increases for Poisson demand, which causes the increase in waste and shortages. As waste reduces profit more than OOS situations it is optimal to reduce the safety factor.

4.3.4. Effect of shelf life (different product)

Scenario 4 tests the effect of shelf life. Scenario 1 included a shelf life of 8 days. In scenario 4, shelf life was reduced to 5 days for experiment 11

Table 5
Microbiological count and percentage of spoiled products sold of experiment 1-10.

Experiment	Fixed shelf life		Dynamic Shelf Life	
	Microbiological count (log cfu/g)	% spoiled products	Microbiological count (log cfu/g)	% spoiled products
1 + 2	3.33	0.004%	3.37	0.000%
3 + 4	3.32	0.004%	3.33	0.000%
5 + 6	3.35	0.006%	3.40	0.000%
7 + 8	3.37	0.004%	3.38	0.000%
9 + 10	3.33	0.003%	3.35	0.000%

and 12 and increased to 10 days for experiment 13 and 14. A decreased shelf life decreases z^*, S^* and profit while waste and shortages increases. Results show that a decreased shelf life makes it complicated to have the right amount of products in stock and sell them before they spoil compared to a longer shelf life. With a short shelf life products are moving too slowly in the chain resulting in high waste figures. After production products arrive 1 day later at the DC and it will take at least 1 day as well before the retailer receives the product. The DC is only delivered 3 times a week therefore products delivered at the retailer can be stocked at the DC for more than 1 day. When the shelf life is 5 days, the delay in moving products through the SC can result in the delivery of products with a low remaining shelf life at the retailer. This increases the amount of products wasted at the retailer as there is a limited time to sell them. For a longer shelf life it is easier to anticipate on the uncertainty in demand and the retailers' performance is improved. This implies that investing in shelf life extension might be worth to investigate for products with a short shelf life to improve SC performance. Furthermore benefits of DSL increase when shelf life decrease.

4.4. Evaluation of DC ordering policy

The DC is evaluated on shortages and waste. In Table 7 results of scenario 1 and 5 are given. In scenario 0, the DC orders three times a week on Monday, Wednesday and Friday. Shortages obtained are low for both FSL and DSL. Waste is not present in both experiments (1 and 2). When changing the number of ordering days for the DC to only twice a week (experiment 15 and 16) or to 6 days a week (experiment 17 and 18) we see that there are no significant changes in results. Waste levels at DC are obviously still zero, and shortages at the DC are hardly affected.

The order strategy of the DC does influence the performance of the retailer. When a DC orders every working day ($R = 1$), products arriving at the retailer will have a longer remaining shelf life. This reduces waste levels and therefore shortage levels. On the other hand, shortage and waste levels increase when the DC orders less frequently.

4.5. Effect of discount

When incorporating discounting, two different factors are tested, first the moment of discounting, either at the last day of shelf life or one day earlier. Secondly, the influence of the picking order (initial LEFO-FEFO ratio) is evaluated. When a discount is applied we assumed that the percentage of consumers shifting from LEFO to FEFO purchase is equal to the discount given.

4.5.1. Timing

To test the effect of the moment of applying the discount, we compared applying a discount on the last day of shelf life with applying a discount one day earlier. The results shown in Fig. 3 show that profit and shortage levels are affected by changing the moment of discounting. When discounts are applied two days instead of only on the last day, profits decrease and shortages are increased. Optimal order-up-to levels are slightly decreased when discounts are applied earlier. Waste levels are mainly affected by the discount percentage rather than the moment of discount.

Table 7
Shortages and waste obtained at DC and retailer.

Scenario	Experiment	Shortage DC	Waste DC	Shortage Retailer	Waste Retailer
1	1	0.03%	0.00%	5.30%	1.87%
	2	0.03%	0.00%	1.87%	1.33%
5	15	0.02%	0.00%	10.65%	2.10%
	16	0.03%	0.01%	2.74%	1.95%
	17	0.04%	0.00%	3.48%	1.36%
	18	0.05%	0.00%	1.80%	0.93%

4.5.2. Picking order

It is assumed that benefits of discounting products are influenced by the LEFO-FEFO ratio. Discounting attracts consumers to cheaper but less fresh products and discounting will have more of an effect when more consumers initially buy fresher products. Therefore, the effect of discounting is tested with different LEFO-FEFO ratios. As the previous results indicate that applying a discount only on the last day of shelf life is more attractive from a retailers perspective, this setting is used. Fig. 4 shows the average optimal order-up-to level for a FSL and DSL of different LEFO ratios with the optimal z^*. For FSL the S^* decreases or remains the same when more discount is given For DSL we see that S^* changes with different discount rates and becomes almost similar for all LEFO percentages. Furthermore we see that S^* levels for FSL are lower than for DSL as we already concluded with previous results.

Fig. 5 shows the profit, waste and shortages for FSL and DSL. Comparing profit levels (A and B) a clear distinction can be made between FSL and DSL. For FSL, profit is always decreasing for every LEFO-FEFO ratio where for DSL profit increases as long as there are initially more LEFO than FEFO consumers. When products of lower quality are sold as well, the retailer waste less products and S^* can be increased. When there are more FEFO consumers than LEFO consumers, discounting decreases profit but it still reduces waste.

In graph C and D the waste reduction for FSL and DSL at different discount percentages is shown. Both graphs show a similar decrease although initial waste levels are lower for DSL, which indicates that discounting is an effective strategy to reduce waste. Results show a somewhat irregular pattern. This is caused by the discretization of the order-up-to level, based on profit maximization, although the profit difference might be small. S^* is rounded towards the nearest integer number, which can result in a change in S^* where the initial difference in z^* is small between two discount levels.

The last two graphs (E and F) in Fig. 5 show the shortages. The results show that discounting increases shortage in some cases (DSL and LEFO% <75%) and that more LEFO consumers give higher shortage percentages. The increase in shortage over discount is caused by a lower S*, which is beneficial for waste levels, but increases shortage levels. The decrease over decreased LEFO% is in line with the higher waste percentages obtained at higher LEFO% as waste and shortages are directly linked to each other. Ordering new products is based on current inventory levels. When a lot of products are wasted during period, the replenishment quantity might be too low and shortages occur in the next period. Expected waste is incorporated in the replenishment order however it is based on the average FEFO sales during a period. As demand is stochastic, there can be a variation between actual and expected sales which causes the shortages. Moreover, shortages obtained for FSL are higher than for DSL, which can also be explained by the higher waste levels for FSL. Concluding that DSL results on average in more time to sell products, variation in demand will have less influence for DSL and shortages are less likely to occur.

5. Conclusion and discussion

In this research we studied the effect of discounting and DSL on the replenishment of a retailer and on its performance in terms of waste, profit, shortages and product quality. Discount levels and replenishment quantities are optimized integrally. We studied the effect of discounting and DSL separately and when combined. Both actions proved to be effective in reducing food waste, however applying DSL is more beneficial than applying a discount. The combination of both DSL and discounting proves to be the most effective strategy. Results show that, compared to a FSL, stock levels can be increased when a DSL applies. Furthermore, DSL results in less waste, more profit and less shortage compared to FSL. We also showed that DSL ensures food safety. When applying DSL the shelf life is based on the actual product quality and a retailer can be sure that he is selling safe products. Under DSL, products are wasted only if they are of (too) low quality; under FSL, also products

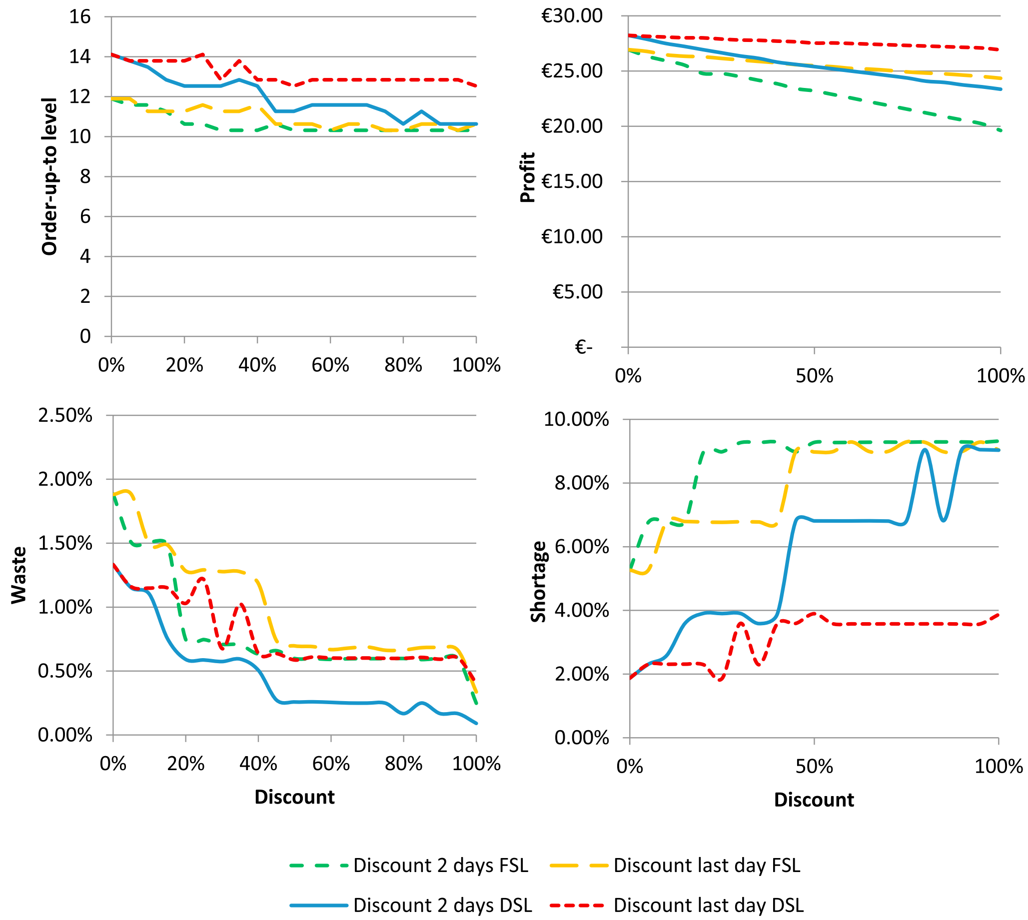

Fig. 3. Optimal ordering levels (S*), profit, waste and shortages for different moments of discount for FSL and DSL (Last day of shelf life or day before).

of good quality might be wasted. Discounting reduced food waste with FSL and DSL however a profit increase is only obtained when discounting is combined with DSL.

For shelf life setting we used a limit of $\eta_{waste} = 5.3$ log cfu/g is used a temperature of 5.5 °C. This is safe on two sides, first the actual spoilage point will be at $\eta_{unsafe} = 6$ log cfu/g (Tromp et al., 2012) and secondly the average temperature of the simulated SC is lower than 5.5 °C so shelf life might be longer than the 8 days used for FSL. However, Table 5 shows that spoiled products are sold, even with those boundaries. When we relax those boundaries, e.g. by extending FSL from 8 to 9 days, even more products will be sold spoiled.

Our research show that applying DSL increases profit, however this is

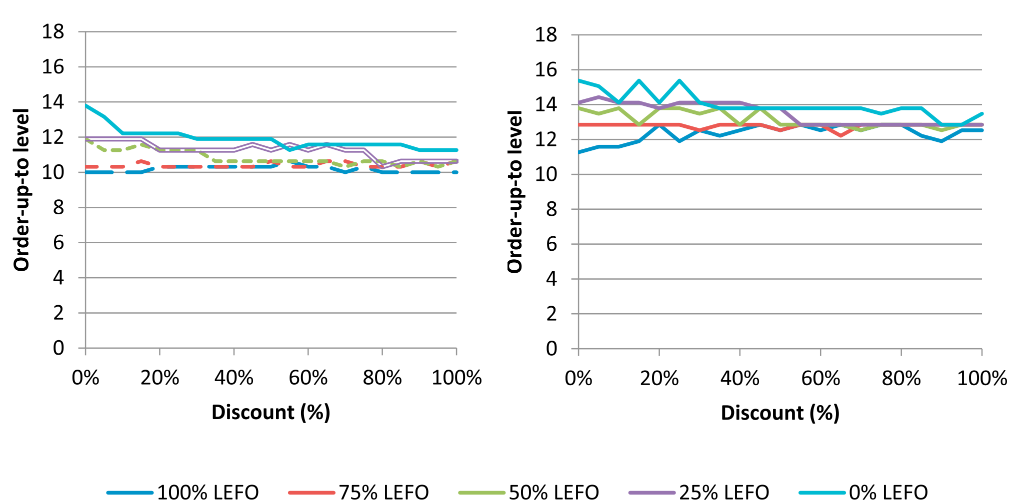

Fig. 4. Optimal S* values for Fixed shelf life (left) and Dynamic shelf life (right).

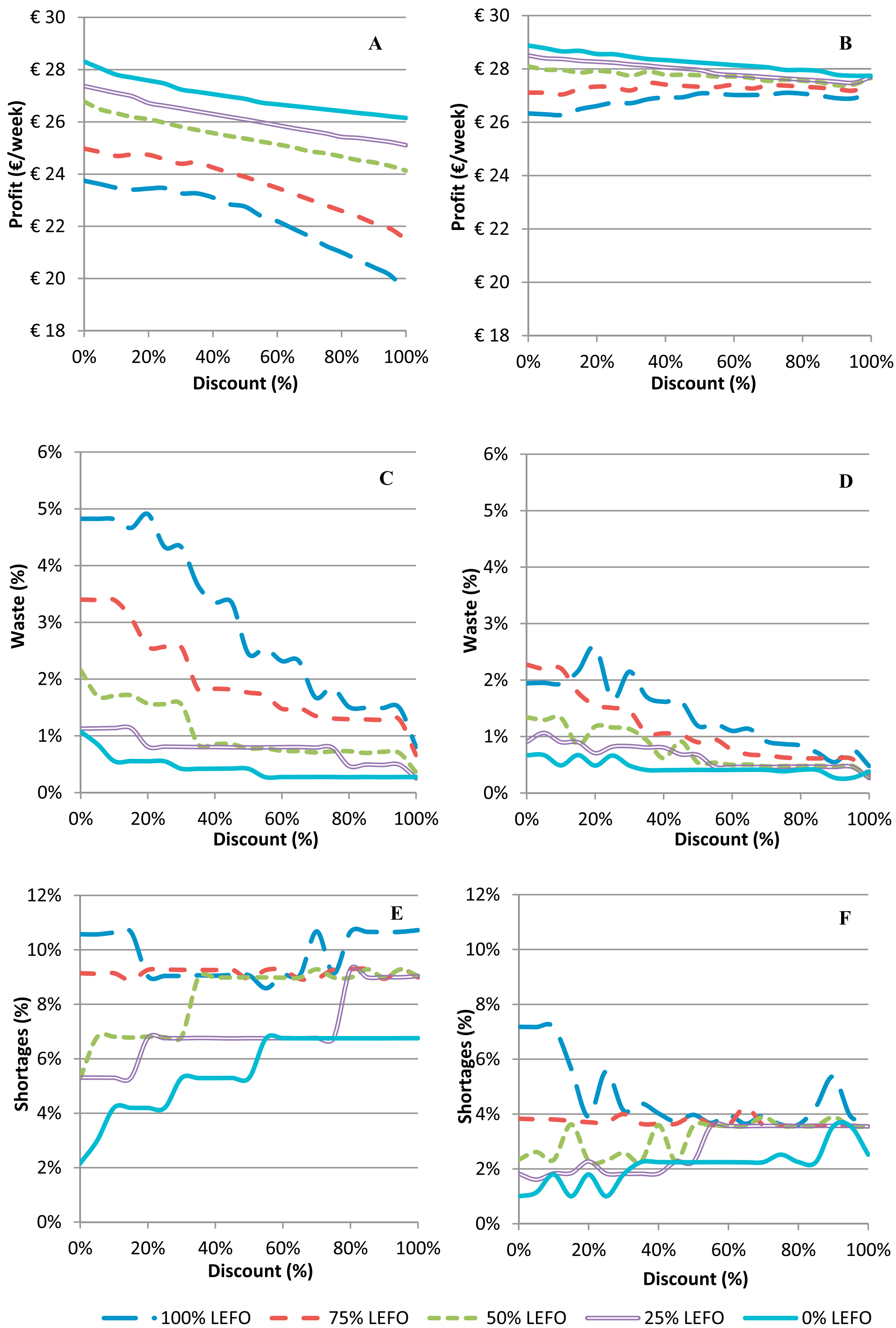

Fig. 5. A) Profit FSL, B) Profit DSL, C) Waste levels FSL, D) Waste levels DSL, E) Shortages FSL, F) Shortages DSL.

without accounting for the costs of DSL implementation. Costs for DSL can be related to the TTI to show the quality of the product. Instead of including those costs, this study helps in assessing how much it may cost by comparing the difference in profits between DSL and FSL. For example in the base case the profit difference is €1.29, which relates to €0.04 per product. Another assumption we made related to DSL, is a perfect TTI. In real life indicators might have an error, which can affect food safety. This can be included in the model but is omitted as no data is available on the accuracy of a TTI.

Unlike many studies (e.g. (Farughi et al., 2014; Liu et al., 2008; Qin et al., 2014)) we did include a shift in the LEFO-FEFO ratio instead of a demand increase when applying discount. We assumed the fraction of

LEFO consumers that switch to FEFO corresponds to the discount level. When a larger percentage of consumers will shift, waste can be further reduced with higher profit levels and/or lower discount levels. An increased demand will most likely decrease waste levels and increase profit levels, for both FSL and DSL. In practice it can happen that that consumers substitute their initial purchases by the discounted meat, increasing the demand of that product, but decreasing the demand of the other product. With this, the overall meat demand will then remain equal. We see that consumer behaviour impacts the retailer performance. Therefore, it is recommended for further research to focus more on the in-store consumer behaviour and investigate topics such as the LEFO-FEFO ratio and substitution.

The model we used here is specified to meat products, however by adjusting the quality model it can be applied for other fresh products. Our results show that discounting and a DSL are both effective strategies for reducing food waste by the retailer. Furthermore, this research highlights the importance of using DSL to both the retailer and the food producer. Another recommendation for producers would be for them to investigate shelf life extension as it would improve their performance as well.

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