

Inventory modeling of perishable goods

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Preface

This paper is part of the ‘Business Mathematics & Informatics’ (BMI) Master Programme at the VU University in Amsterdam. The purpose of the paper is to let the student apply the knowledge gained and techniques mastered over the past few years. The paper has to describe a business problem and should be handled using mathematics and/or computer science. The supervisor of this thesis was dr. René Bekker. I would like to thank him for his support and his significant contribution to this thesis.

Abstract

Outdating is a significant problem especially in the food industry. This thesis considers replenishment strategies for systems with perishable goods. After posing a model and reviewing literature, the paper tries to give insight on possibly beneficial parameters of order strategies. A special interest lies in finding a practical order strategy. Unfortunately analytical analysis is intractable due to a lack of scalability, therefore simulation is used to optimize various policy parameters. Finally, data obtained from a local supermarket was used to compare the best policy to a real-life situation. The best result was obtained with a strategy with time-dependent safety stock levels and further decreased orders if sales have been low for a specific period.

Keywords: periodic review model, order policies, perishable goods, simulation

Summary

Goal of this thesis

Inventory modeling is a very important subject in logistics. Reducing costs while maintaining a certain level of customer satisfaction is the core subject in every retail company. The goal of this thesis is to find a decent order strategy with practical value for a system containing perishable goods. Furthermore, this paper analyzes the parameters that might influence the order strategies of perishable products. The optimal strategy has as a result both little outdating and little lost sales.

Assumptions

Customer arrivals are supposed to be a stuttered Poisson process. The interpretation is that at Poisson moments, a customer buys n items ($n \geq 1$), where n is a geometric random variable with a given parameter q . Since many customers compare expiry dates before purchasing fresh food, we assume 40% of the customers to purchase FIFO, whereas the other 60% purchases the youngest items, which are usually at the back of the shelves. Furthermore, we assume a 24 hour lead time for delivery, and our shop is opened seven days a week.

Simulation results

Finding the right order policy has everything to do with managing the safety stock. Having too little safety stock might lead to lost sales, whereas having too much safety stock leads to outdating. All of the chosen policies are based on a linear safety stock model, meaning that the safety stock is a certain percentage of the expected sales. The optimal order quantity Q obviously depends on the current amount of stock S . D_L is the expected demand during the lead time. α accounts for the amount of safety-stock ordered. More safety-stock means less lost sales but increases the chance of outdating. This leads to policy (1). In policy (2) weights are added to the current stock build-up for every age groups. If products last m days, then there are m different age groups and each group gets its own weight w_i . In the optimal scenario, fresher items are valued more heavily than older items. In policy (3), a different α is used for every day of the week. Note that outdating and lost sales are considered to be equally “wrong” and therefore the “result” is the sum of the percentage of lost sales and the percentage of outdated items.

Policy number	Order policy formula	Optimal result:
(1)	$Q = \alpha * D_L - S$	5.35%
(2)	$Q = \alpha * D_L - \sum_{i=1}^m w_i S_i$	5.06%
(3)	$Q = \alpha_j * D_L - \sum_{i=1}^m w_i S_i$	4.89%

In policy (4), we stop using weights for the different stock groups since in many cases it is not realistic to assume the age build-up of the stock to be known. Instead, a new variable β is added, which is less than one in certain cases where the probability of outdated is imminent and is exactly one otherwise. The optimal parameters of β are determined by extensive simulation.

$$\beta = \begin{cases} < 1 & \text{if orders are low for three days in a row} \\ 1 & \text{else} \end{cases}$$

This policy is the most practically oriented one, since it only uses information which is usually known; expected sales, total amount of stock and the realized sales of the past couple of days. In the final policy (5), the weights for different age groups of stock is added back.

Policy number	Order policy formula	Optimal result:
(4)	$Q = \beta * \alpha_j * D_L - S$	4.83%
(5)	$Q = \beta * \alpha_j * D_L - \sum_{i=1}^m w_i S_i$	4.75%

Main findings:

- Systems with higher alphas have much more safety stock and a higher average stock age. Therefore a low alpha leads to less outdated and more lost sales, while a high alpha leads to more outdated and less lost sales.
- Higher expected sales (λ) need less safety stock percentage-wise.
- If sales are spread over more customers (q increases), sales fluctuate less and therefore the system performs better.
- Higher FIFO-probabilities (p) increases performance and have a higher optimal alpha.
- Longer lifetime (d) increases performance and has a higher optimal alpha.
- Systems with higher alphas have larger average orders placed on peak days, and smaller average orders placed after peak days.
- Most outdated happens on d days after peak days, which leads to higher lost sales on days $d+1$ after the peak days.
- Greatly minimizing lost sales leads to greatly more outdated, and vice-versa.

Comparison to a real life situation:

To compare the practical use of the strategies, information from a local supermarket was used to evaluate the order strategy. For a period of six weeks, stock levels, outdating, sales and deliveries for twelve different products were registered and afterwards inserted into the computer program to compute how the order strategy would have scored in practice. The data was obtained from June 4th until July 15th 2011.

1 Broccoli	7 Shii take mushrooms
2 Diner Caesar Salad	8 Mushrooms
3 Spinach Stew	9 Sliced Leek
4 Soup vegetables	10 Italian Salad
5 Raw beet salad	11 Wok vegetables with mushrooms
6 Parisian Carrots	12 Biological onion flakes

- 8 out of 12 products had less lost sales using our best practical strategy than the supermarket.
- 7 out of 12 products had less outdating using our best practical strategy than the supermarket.

Where our policy had better results they were significantly better. Where our policy performed worse it did so only slightly. But our assumption of only forty percent FIFO sales might not be accurate. Especially the broccoli performed particularly well in real life, which might be caused by the fact that there is a discount on products with only one day until expiry.

Finding the right order strategy can make a lot of difference but is more complicated than it seems. Generally speaking, the more information known about the system, the better the results can become. Unfortunately, some information is unavailable or might take a pricy investment to gather. Still, the simulation showed that the order strategy of the super market performed worse than our strategy in certain cases, while our best practical policy only used information which is easily obtainable for large corporations. Changing to our best practical order policy could not only increase revenues and customer satisfaction but might decrease outdating as well, which saves money and leads to a cleaner environment as well. Still, one should note that conclusions on comparisons of a real life situation with a simulation afterwards should be taken with a pinch of salt. More research should be done on order strategies for perishables since there is still room for improvement and lots of money can be saved.

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1. Introduction

Inventory modeling is one of the most important concepts in logistics. Having a solid inventory strategy could not only save a company lots of money, but might be the difference between not being able to compete against the competition and having a prominent position in the market segment.

One of the most important aspects of inventory modeling is the prediction of demand for a certain good. If it would be known beforehand at which moment a certain good will be sold, inventory management would be much simpler. However, planning becomes much more complicated when demand behaves stochastically. Stochasticity causes severe fluctuations in demand with which companies need to deal with. Firms tend to keep their stock high enough to minimize the amount of lost sales, but storage of redundant goods costs both time and money. Since having an adequate balance between these two aspects is essential, it is vital to find the optimal strategy of how much to replenish and at which moment. The optimal strategy depends on the interests of the management team; what level of lost sales is acceptable and how much money are the storage cost allowed to accumulate to?

Since supply chains are important for nearly every type of industry, the demand for this type of research has increased over the past decades. However, relatively little attention has been devoted to the inventory modeling of perishable goods. Dealing with perishable goods, especially in the food industry, appears to be a significant problem. Outdating in the food industry occurs on a very broad spectrum of products. On one hand there is canned food which is sometimes preservable for over two years, while on the other hand fish and vegetables perish in a few days. Obviously these two different types of products require different approaches and therefore different order strategies. For example, for products which expire rather quickly, the focus might be less on minimizing lost sales and more on preventing these products passing their expiration dates and minimizing the amount of thrown away goods.

The main purpose of this paper is to identify and quantify the factors influencing the optimal strategy to aid companies in their quest for the optimal replenishment strategy. The best order strategy uses all available information to calculate the optimal replenishment quantities. For instance, the theoretical optimal strategy will probably be influenced by the age distribution of the products, but it is impractical to count the number of items with a certain expiration date for every product on a daily basis. In practice, the optimal model is the one which satisfies best a certain set of constraints; demand should be met to a certain degree, the amount of perished goods should be small and stock levels should be manageable. Therefore, the goal of this thesis is to find an operable strategy for perishable goods.

2. The inventory model

2.1 The topic of this thesis

The goal of this thesis is to find a decent order strategy with practical value for a system containing perishable goods. Furthermore, this paper analyzes the parameters that might influence the order strategies of perishable products. But to find such a strategy a correct model has to be created first. Our model is based on replenishment in supermarkets. This means dealing with perishable goods in an environment with stochastic demand and periodic delivery. The chosen model is based on a few crucial assumptions, which are listed below.

2.2 Assumption 1: Replenishment

The first assumption regards the replenishment cycle. Deliveries are supposed to arrive at the start of every day, and orders for the next day need to be placed directly after the delivery. Furthermore, the product can only be ordered in batches of size B . For example, wine is usually shipped in boxes containing six bottles. Stock shelves are assumed to be abundant and backorders are not allowed.

2.3 Assumption 2: Product lifetime distribution

The second assumption has to do with the lifetime of these goods. In many cases lifetimes are deterministic. This implies that goods perish in exactly d days. This is the case with all kinds of prepacked foods and applies to the regulation regarding donations in blood banks as well; blood has to be used within a certain number of days by law. In completely different cases exponential lifetimes are assumed. Exponential lifetime means an item has a certain probability to perish in a certain amount of time (at a certain rate r), no matter how long the item has been in the system. This applies for instance to radioactive decay, and this assumption makes computations a lot simpler. A lifetime assumption combining both properties is chosen; the so-called shifted exponential distribution. This way products are assumed to last at least d days, and then perish at a certain exponential rate r . Note that assuming r to be infinite or d to be zero leads to respectively the deterministic or exponential distributions mentioned above.

2.4 Assumption 3: FIFO versus LIFO

Most models assume the oldest goods to be purchased first, which is called *First-In-First-Out* (FIFO). In the context of supermarkets FIFO models are usually preferred over other models since they have less outdating than, for example, *Last-In-First-Out* (LIFO) models. In certain scenarios, the freshness of the products influences customer satisfaction. In those cases hybrid models are used to combine the advantages of the two policies. FIFO purchases cannot be guaranteed since customers in supermarkets are usually free to pick a product to their liking, and tend to choose the freshest products available. A fraction p of the customers is assumed to purchase their groceries FIFO and a fraction $(1-p)$ to purchase LIFO. For quickly perishable goods such as meat and vegetables, up to sixty percent¹ of the Dutch consumers explicitly choose products with the longest shelf life.

¹ This percentage was taken from an online article from a research group from the University of Wageningen but is not available anymore.

2.5 Assumption 4: Demand

There is supposed to be weekly pattern in sales, meaning the expected demands on day i and $i+7$ are equal. The effects of this weekly pattern was studied by Kahn et al [9]. They found a clear dependency between customer visits on a specific day and visits exactly one week later, but this specific dependency is not included to reduce unnecessary complexity. The demand for the observed product is assumed to be a ‘stuttered’ Poisson process. Customer arrivals are alleged to be a time-dependent Poisson process with a known arrival rate (λ_i) which changes over time. The interpretation is that at Poisson moments, a customer buys n items ($n \geq 1$), where n is a geometric random variable with a given parameter q . The assumption of sales following a Poisson process could be sufficient. But for the Poisson distribution the variance is equal to its mean, whereas empirical data shows the variance of sales sometimes even doubles the mean. The geometric random variable is used to account for this additional variance, because we now deal with a random sum of random variables.

Let X_1, X_2, \dots be a sequence of independent random variables where each variable has a geometric distribution with parameter q . It is well known that $E[X_i] = \frac{1}{q}$ and $\text{Var}(X_i) = \frac{1-q}{q^2}$.

$$\text{Then } E[X_i^2] = \text{Var}(X_i) + E[X_i]^2 = \frac{1-q}{q^2} + \left(\frac{1}{q}\right)^2 = \frac{2-q}{q^2}$$

Let N be a Poisson variable with parameter λ , then $E[M] = \lambda$ and $\text{Var}(M) = \lambda$.

Now the expected demand is:

$$E\left[\sum_{i=1}^N X_i\right] = E[X_i] * E[M] = \frac{1}{q} * \lambda = \frac{\lambda}{q}$$

Now the variance of the demand is:

$$\begin{aligned} \text{Var}\left(\sum_{i=1}^N X_i\right) &= E[M]\text{Var}(X_i) + E[X_i^2] \text{Var}(M) \\ &= \lambda \frac{1-q}{q^2} + \frac{2-q}{q^2} \lambda \\ &= \frac{(3-2q)}{q^2} \lambda \end{aligned}$$

Apparently, the variance is linear in λ . The process simplifies to a regular Poisson arrival process when $q=1$. The variance increases exponentially with rate $\frac{1}{q}$ as q moves to zero. There is a combination of λ and q possible for every situation where variance \geq mean > 0 . Examples are given in table 1.

q	λ	mean	variance	Variance-to-Mean
1	25	25	25	1
0.9	22.5	25	33.33	1.33
0.8	20	25	43.75	1.75
0.75	18.75	25	50	2
0.5	12.5	25	100	4
0.25	6.25	25	250	10

Table 1: Different variances with the same expected sales

Figure 1 contains the Variance-to-Mean ratio for different values of q . This ratio reflects the effect of q on the variance. Note that when q decreases, λ has to decrease as well to keep the mean constant. Finally, we assume that Friday and Saturday have twice as customers as the other days of the week.

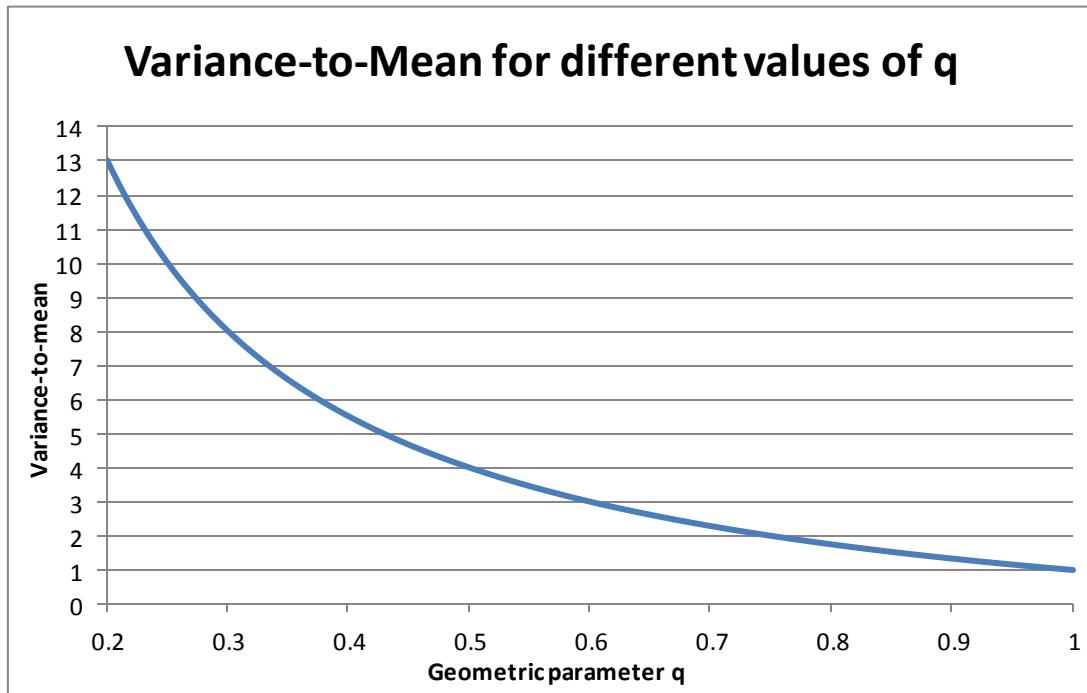


Figure 1: The curve of the variance-to-mean ratio depending on q

2.6 Assumption 5: External influences on demand

The product itself is homogenous and is assumed to have no complementary or substitute goods. The effect of substitution is studied by Smith and Agrawal [11]. They conclude that computation is rather complex and requires many substitution probabilities which might be difficult to obtain, but that substitution effects can have a significant effect on cost reduction and the optimal order policy. Chen and Plambeck [7] show that the usage of substitute goods could lower total stock levels by using hybrid safety stock. The effects of price changes on the optimal inventory policy for perishable goods are studied by Shah [18] and [19]. All of these effects are neglected here for computational reasons.

2.7 Assumption 6: Costs

Another important assumption deals with the costs involved. Most inventory models only include costs for holding inventory to minimize stock, and costs for lost sales to obtain a certain service level. Our model obviously includes costs for perished goods as well. Costs for delivery are neglected, since in nearly all cases a single product does not affect the decision of the store to receive a delivery. Also, the costs of placing the product on the shelves will never have a significant effect on the replenishment policy.

3. Literature review of order policies

3.1 The history of order policies

Inventory modeling is an important topic in Operations Research and has made great progress during the twentieth century. Basically, inventory theory deals with two questions:

- How many units should be ordered?
- At which time should the order be placed?

This is a brief overview of the development of inventory theory. Listing all models could be a thesis on its own, as shown in [6] and [8], therefore only the more important ones are noted. Inventory theory started being fully deterministic, and over the years expanded to dealing with stochastic demand and perishability.

3.2 The Economic Order Quantity

The EOQ-model was the first mathematical inventory model and was developed in 1913 [22]. The model calculates the optimal order quantity (Q^*) using the demand per time unit (D), order costs (S) and holding costs (H). The change in the amount of stock over time is shown in figure 2.

$$Q^* = \sqrt{2DS/H}$$

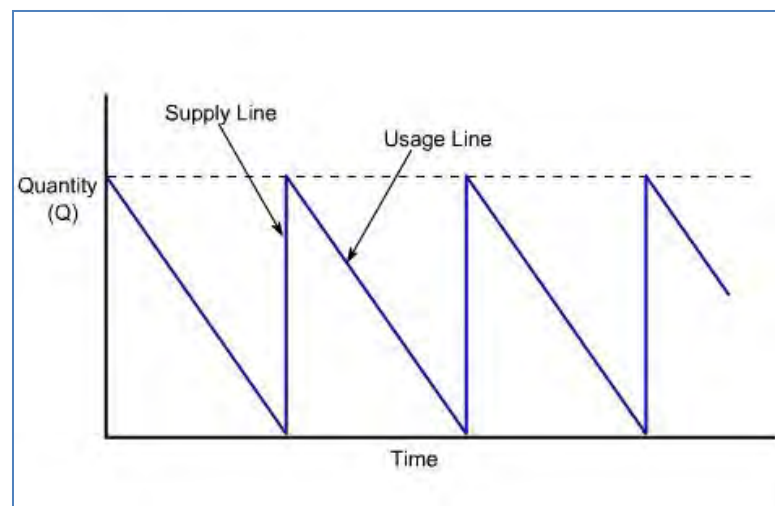


Figure 2: stock build-up in the EOQ-model

The lead time (L) needs to be fixed, and demand and costs have to be constant for this model to work properly. Q^* is the amount of stock ordered when the stock level equals the expected sales during the lead time. Over the years, the model has been expanded to deal with quantity discounts, backordering and multiple items. If items have a fixed lifetime of m , then the optimal order size is $\min(Q^*, Dm)$. It is easy to see that this way no units expire.

3.3 The (s,S)-type replenishment policy.

A new inventory policy dealing with stochastic demand over multiple periods was introduced by Arrow, Harris and Marschak in 1951 [21]. This (s,S) policy states that stock should be replenished to a certain level S at the moment it reaches level s, with $s < S$. The lead time is considered to be zero and the amount to be replenished is obviously S-s. This type of policies are called continuous review models. This policy was proven to be optimal for most models with non-perishables and a linear cost structure. Fries [4] proved that the (s,S) policy is not optimal for multi-period models with perishables.

3.4 The Newsvendor problem

The first model regarding perishable goods with stochastic demand was the classical single period problem [20]. This model is also known as the Newsvendor problem, Newsboy problem or Christmas tree problem. It models a newsvendor who has to decide how many copies of the papers to stock, knowing that leftover newspapers are worthless and that demand is uncertain. There are two possible types of costs in this situation: the costs of having leftovers (h) and the costs of having lost sales (k). If the demand distribution D is known, then the optimal order is

$$F_D^{-1} \left(\frac{k}{k+h} \right).$$

Here F_D^{-1} denotes the inverse distribution of the demand. For example, if $\frac{k}{k+h} = 0.75$, then the optimal order quantity states there should be shortages in 25 percent of the cases. This is an inventory policy which deals with single-period perishable goods and probabilistic demand. However, the scope of this thesis could be classified as a multi-period newsvendor problem which appears to be much more complicated. Fries [4] has extended the newsvendor problem to ≥ 2 days, and assumes zero lead time and a FIFO policy.

3.5 Stochastic multi-period models for perishables

Liu and Lian [17] extended the (s,S) replenishment policy to perishables. They assume immediate replenishment and choose $s \leq -1$. This means that a new order will not be made until at least one customer arrives as soon as the entire stock has been depleted. So they not only allow backorders, but actually encourage it. Schmidt and Nahmias [2] use a special case, fixing $s = S-1$. This $(S-1,S)$ model deals with items with fixed shelf life, disallows backordering and places an order as soon as an item has perished or is sold. They use it in context of functioning machines that either brake down or are removed for maintenance. Lian and Neuts [15] adapted the (s,S) model to a discrete time model by rewriting states to a Markov Chain. Nahmias and Wang [1] on the other hand model a (Q,r) system, which is basically an (s,S) policy with positive lead times. Ravichandran [3] shows how complex the (s,S) model is for more realistic assumptions, like non-instantaneous lead times, constant shelf life and stochastic demand. He concludes such models to be quite complex and intractable, and meaningful analysis can only be obtained by simulation. Tekin et al. [14] propose a (Q,r,T) model, in which Q units are ordered when stock levels drop below r or when T units of time have passed since the last order. This way, the order policy is not only based on the current stock levels but indirectly on the remaining shelf life of the items as well. This is a periodic review model, just like the newsvendor problem, where the other models assume continuous reviewing. This policy is observed to outperform the regular (Q,r) system.

3.6 The topic of this thesis

Apparently, a multi-period, perishable inventory model without backorders and non-stationary probabilistic demand seems to be intractable and too complex to solve analytically. Therefore resorting to simulation is required to find a suboptimal heuristic.

4. Order strategies

4.1 The complexity of perishables

The truly optimal inventory strategy takes every possible piece of information into account, including the weather forecast, upcoming social events, the age distribution of the customers and inflation. But due to computational limitations and a lack of data, a trade-off between completeness and simplicity has to be made. This trade-off is acceptable because the vast majority of the variation lies within the nature of the demand process itself. For example, an adequate strategy for non-perishable goods basically needs just three pieces of information; the current amount of stock, information about the lead time and the distribution of the demand for the following period. The ratio between lost sales and overstocking depends on their respective costs.

For perishables, the policy becomes more complex. Because costs for outdating are usually much higher than holding costs, limiting outdating becomes crucial, especially in a non-FIFO environment. Intuitively, products with longer expected shelf lives should be allowed to have more safety stock than their quickly deteriorating counterparts. In non-FIFO environments, when the current stock approaches its expiration date, less safety stock should be held to decrease outdating. So the perishable order strategy not only depends on the current stock and expected demand, but on the expected shelf life, the expected fraction of FIFO sales and the age distribution of the stock as well. In the following subsections different order strategies are discussed that try to deal with this complexity.

4.2 A non-perishable approach (up-to-S)

The first policy is a control group model. It does not take into account any of the perishable-specific information and only depends on current stock level and the expected sales during the lead time. If D is the expected demand per time unit and the single lead time is T , then D_L equals $2 * D * T$ in most cases. Note that with this lead time the time between the placement of this order and the arrival of the next order is meant. So it is not just the time until this order is delivered, but the time until the next order could arrive. The system is replenished with a certain order quantity Q given by:

$$Q = \alpha * D_L - S, \quad (1)$$

where D_L is the expected demand during lead time, S the current stock level and $\alpha \geq 0$.

If $\alpha = 1$, then no safety stock is held. To effectively deal with the stochasticity, α might range from 1.0 to 2.5 depending on the expected sales, and the cost of outdating and lost sales. Take $\alpha = 1.5$ for example. Note that if we are dealing with regular Poisson sales with $\lambda = 4$, $P(X \geq 6) \approx 0.21$, whereas if $\lambda = 40$, $P(X \geq 60) \approx 0.002$. This shows that for higher expected demands, a smaller fraction of safety stock is needed and a lower α can be taken. It is trivial that $\alpha < 1$ is not optimal in any practical scenario. Instead of using safety stock with a linear dependency on the expected demand, a safety stock function with a root or a logarithmic function could also be used, but that is beyond the scope of this thesis.

4.3 Age-dependent policies

The age-dependent policy also takes into account the information regarding possible outdating. There is very little literature regarding such policies in a practical setting, i.e. non-instantaneous lead times and not fully FIFO sales. When sales are assumed to be fully FIFO, the amount of safety stock is only a little less than its non-perishable equivalent. The difference in safety stock depends on the expected lifetime of the items. As the expected lifetime of goods increases, the stock level starts to behave more similar to non-perishables.

The policy for LIFO sales is more sensitive to outdating since the freshest products are sold first. Finding the right balance between minimizing lost sales and minimizing outdating is more difficult. Much less safety stock is held, since the risk of outdating is more imminent. Define S_i as the amount of stock with i remaining days of shelf life. This creates a total of m age categories.

Now remember the non-perishable order formula:

$$Q = \alpha * D_L - S \quad (1)$$

where D_L is the expected demand during lead time, $\alpha \geq 0$ and $S = \sum_{i=0}^m S_i$; the current stock level. We can make (1) age-dependent by changing S into a weighted function:

$$Q = \alpha * D_L - \sum_{i=1}^m w_i S_i \quad (2)$$

Adding more or less weight to certain classes of stock might cause the system to order more when the stock is relatively young, and order less when the stock is relatively old. Also, if the system expects a significant amount of items to be outdated at the end of the day, it might want to increase the order for the following morning. These weights can be more influential in LIFO situations than in FIFO situations. This is because having an old stock is much more troublesome in LIFO situations, since getting rid of the old stock before outdating gives a high exposure to lost sales. Note that in (1) all w_i are equal to 1.

If goods have a shelf life of five days, one could understand that orders which arrive on Thursday can safely be somewhat increased, since the Friday and Saturday are coming up and any leftovers from Thursday should be easily sold during the weekend. On the other hand, placing a massive order on Sunday might be risky. This is why we introduce α_j to the order formula, with j being the day of the week. The utility of this variable heavily depends on the expected lifetime of the goods. This variable is for example more useful in LIFO than in FIFO systems.

All of these additions lead to the following formula:

$$Q = \alpha_j * D_L - \sum_{i=1}^m w_i S_i \quad (3)$$

4.4 Policy using previous order information

Using weights for different ages of stock mentioned earlier is not very practical. It would require optical inspection of all inventory on a daily basis to know exactly how much of each type is in stock, which is not practical at all. This means we will need to find another way to add information about the age distribution of our stock.

As stated before, Tekin et al. [14] proposed a (Q,r,T) policy. This policy orders Q units when stock levels drop below r or when T units of time have passed since the last order. The last part makes sure the order policy is not only based on the current stock levels but on the remaining shelf life of the items as well. The model was proven to outperform models lacking that addition in the area of reaching a certain service level. So information is needed that could be an indicator for having rather young or old stock. We could add something similar here as well. We can use any information about daily sales and order quantities, since these are usually digitally available and often easy to obtain.

For example, it could be an indication of old stock, if order quantities have been rather low for a few days. Having placed a gigantic new order could indicate rather young stock. So the weighting of stock is removed and a new variable β is introduced, which value decreases an order if orders have been low enough for a certain amount of time. The optimal parameters of β can be determined by extensive simulation.

$$Q = \beta * \alpha_j * D_L - S \quad (4)$$

5. Simulation: settings and programming

The policies from chapter 5 were tested in the model specified in chapter 3 by means of simulation. A program was written in JAVA which simulated the stock levels for a series of n days, using the expected demand for each day. Most parameters were varied to give a sensitivity analysis of the order strategies.

5.1 Parameter settings

- $\lambda_i \geq 0$ The expected number of customer arrivals for day i .
Statistics from two local supermarkets showed that total sales on Monday, Tuesday, Wednesday, Thursday and Sunday are roughly the same (λ). Sales on Friday and Saturday are roughly twice as much as on the other days (2λ). Note that this weekly pattern was used for convenience only, but other values can be given as input as well.
- $q \in (0,1]$ The variance in total sales
In some cases the variance is nearly twice as much as the average sales. According to Figure 1, q has to be around 0.75 in these cases.
- $p \in [0,1]$ The fraction of customers buying FIFO
The (expected) fraction of FIFO sales has a major influence on the probability of outdating. Scenarios with FIFO ($p=1$), LIFO ($p=0$) and hybrid sales ($p=0.4$) were simulated.
- $d \geq 0$ The minimum (deterministic) lifetime of the goods
The standard minimum lifetime was chosen to be $d = 5$ days.
- $r \geq 0 \in [0,1]$ The exponential decay rate
For convenience, we choose r as the expected percentage of the population to perish after d days. We neglect this exponential decay in the standard situation, but this will be part of the sensitivity analysis.
- $B \geq 1$ The number of items per batch
Most simulations were run with $B=1$, since other values for this parameter did not seem to have a significant effect on the optimal settings, but only seemed to blur the results. For completeness, a sensitivity analysis was done with $B=4$.

Default settings:

During simulation we chose “default settings” to make comparing easier:

$\lambda = 5$, $q = 0.75$, $p = 0.4$, $d = 5$, $r = 100\%$, $B = 1$

Furthermore, we assumed the lead time to be exactly one day, which is quite realistic for supermarkets. It is convenient to assume delivery arrives “between days”; either after closing or just before opening. By organizing the replenishment and outdating outside of the sale window, there is no need to make a distinction between the daily sales before and after delivery. This assumption makes calculations simpler, and the application of the theory more practical. Moreover, it is not unusual for supermarkets to receive their deliveries either late in the evening or early in the morning. In many of these cases, the expected sales after or before delivery can be neglected and therefore fit our assumptions.

5.2 Batch-means and statistical significance

One long simulation run of n days is simulated to obtain the number of outdated items D_1, \dots, D_n for a large n . An obvious estimator for the expected percentage of thrown-away items would be the sum of these values divided by the total number of items held in stock.

$$\bar{P} = \frac{\sum_{k=1}^n D_k}{\text{total orders}}$$

Unfortunately the corresponding confidence interval is not as accurate as it should be, because these values are strongly correlated. The batch-means method is used to solve this problem. In the batch-means method, the simulation is divided into k smaller subruns. Each subrun covers a period of $b = \frac{n}{k}$ days. The averages of each subrun are nearly uncorrelated as long as b is large enough. These subrun averages are used to create reliable confidence intervals. Another advantage is that because the subruns are uncorrelated, only one period of warm-up data has to be thrown away. For this simulation, $b = 25000$ days and $k = 41$. b is chosen such that the confidence interval around the average is negligible. The warm-up period is arbitrarily chosen to be nearly a year; that is 52 weeks.

5.3 Pseudo code

Pseudo code of the three main methods is shown below; the full code is available in the appendix. Basically, each day consists of four functions: replenishing, ordering, outdating and selling. The order of the first three functions is interchangeable. This particular order is chosen because it is intuitive. Replenishing and ordering might as well be the final tasks of the day instead of the first.

program start():

```

do_warmup_period ();
for (1 to r subruns)
    for (1 to b days)
        simulateDay();
    }
}

```

end program

method simulateDay():

```

replenish_stock();
place_order();
double lambda = expectedArrivals(current_day);
int customers = simulatePoisson(lambda)
for (1 to customers){
    processCustomer();
}
age_stock_and_outdate();

```

end method

method processCustomer():

```

int sales = geometricDrawing(q);
lostsales = max (sales – stock, 0)
sales = min (sales, stock)
stock -= sales;
double random = new Random(0,1);
if (random < FIFO-fraction) -> takeOldest(sales);
else -> takeNewest(sales);

```

end method

5.4 Performance measures

The inventory strategy only has to deal with three measures; the amount of lost sales, the amount of outdating and holding costs. Holding costs seem less important in the context of supermarkets, since the risk of outdating usually has much more influence on the orders than holding costs. Outdating costs can be difficult to calculate. For example, what are the material values and what is the price of eliminating the items? The costs of lost sales are even more difficult to determine. In certain cases, customers tend to buy a similar good instead if the good is out of stock. So what is the cost of lost sale then? And what if the substitute good is more expensive? And what is the value of having a high customer satisfaction level? Anyway, finding the right balance between these two measures is a vital as it is arbitrary. Some managers focus on customer service; everything has to be perfect for the customer and not a single product should be out of stock. For these managers, outdating is just a necessary evil. Other managers prefer to minimize outdating, for both economical and ecological reasons. They accept lost sales more easily, since customers tend to buy substitution goods instead. So finding the right balance depends on how heavily each measure is supposed to be weighted.

In this thesis, both measures are weighted equally. After all, both lost sales and outdating can be seen as a wrong order in some sense. In the results section, percentages of outdating and lost sales are listed. Both of these values are compared to the total amount ordered instead of the total demand, since the emphasis in this thesis lies in finding the correct order amount and not on optimizing sales. This implies that if one hundred products are in stock, and there has been a total demand of 105 items, then the total lost sales are considered $\frac{105-100}{100} \approx 5\%$ (of the ordered amount) whereas usually this percentage would be $\frac{105-100}{105} \approx 4.8\%$. So in our cases, lost sales are not the percentage of demand which could not be fulfilled, but the percentage that the ordered amount should have been bigger. After all, we need to optimize our orders and not our sales. Note that for long-term simulation, this gives nearly the same result.

6. Simulation: results

6.1 Understanding stock behavior using the basic policy

The first inventory strategy simulated was the non-perishable approach explained in Section 5.2. The effect of this strategy depends on finding the optimal alpha, which is a measure for the safety stock:

$$Q = \alpha * D_L - S, \quad (1)$$

where D_L is the expected demand during lead time, S is the current stock level and $\alpha \geq 1$.

All the other policies are based on this type of policy strategy. Alpha is also the most influential variable in our policies. Before expanding the complexity of our order policies, we first need to understand which model parameters influence alpha the most and what the effects of alpha on the optimal results are.

The optimal value of alpha depends on the perishability (d and r), expected sales (λ and q) and the fraction of customers buying FIFO (p).

Main findings:

- A low alpha leads to less outdating and more lost sales, while a high alpha leads to more outdating and less lost sales.
- The optimal value of alpha depends on the balance between lost sales and outdating caused by the characteristics of the system.
- Systems with higher alphas have much more safety stock and a higher average stock age.
- Larger batch sizes (B) slightly decreases performance, but has no effect on the optimal alpha.
- Higher expected sales (λ) cause relatively less fluctuations in demand, which leads to less outdating. These systems perform better and can afford lower alphas.
- If sales are spread over more customers (q increases), sales fluctuate less and therefore the system performs better.
- Higher FIFO-probabilities (p) increases performance and have a higher optimal alpha.
- Longer lifetime (d) increases performance and has a higher optimal alpha.
- Exponential decay ($r < 100\%$) instead of deterministic decay with the same average shelf life ($r = 100\%$) performs worse and has a lower optimal alpha.
- Systems with higher alphas have larger average orders placed on peak days, and smaller average orders placed after peak days.
- Most outdating happens on d days after peak days, which leads to higher lost sales on days $d+1$ after the peak days.
- Severely minimizing lost sales leads to much more outdating, and vice-versa.

The higher the expected sales are, the larger the difference between the optimal LIFO strategy and the optimal FIFO order strategy. For example, the difference in average stock is over sixty percent for $\lambda=20$ but only twenty percent for $\lambda=2$. Every scenario has a specific optimal value for alpha. An example of parameters and their optimal alphas are shown in table 2. Some simulations were done for three different arrival intensities; 2, 5 and 20 customers per day. The first entry is always the standard situation. In the other five cases, parameters (printed in bold) are changed to show their effects on the results.

λ	q	p	d	r	Alpha that minimizes the unweighted costs	Lost sales	Outdating	Sum
2	0.75	0.4	5	100%	1.61	5.13%	8.50%	13.64%
2	0.75	0.4	9	100%	2.00	1.36%	2.70%	4.06%
2	0.75	0.4	5	50%	1.61	4.78%	6.18%	10.87%
2	0.75	0.4	2	25%	1.60	4.88%	15.21%	20.10%
2	0.75	0	5	100%	1.44	8.68%	10.55%	19.19%
2	0.75	1	5	100%	1.64	4.72%	3.50%	8.22%
*5	0.75	0.4	5	100%	1.40	2.95%	2.40%	5.35%
5	0.75	0.4	9	100%	1.78	0.32%	0.27%	0.59%
5	0.75	0.4	5	50%	1.47	1.83%	2.39%	4.23%
5	0.75	0.4	2	25%	1.32	4.49%	6.85%	11.34%
5	0.75	0	5	100%	1.32	4.96%	6.54%	11.50%
5	0.75	1	5	100%	1.63	0.83%	1.02%	1.84%
20	0.75	0.4	5	100%	1.31	0.38%	0.32%	0.70%
20	0.75	0.4	9	100%	1.71	0.000%	0.001%	0.001%
20	0.75	0.4	5	50%	1.33	0.23%	0.29%	0.51%
20	0.75	0.4	2	25%	1.21	1.30%	2.84%	4.13%
20	0.75	0	5	100%	1.14	2.85%	2.61%	5.46%
20	0.75	1	5	100%	1.55	0.01%	0.01%	0.02%

Table 2: optimal settings. all percentages have 95% confidence interval within less than $\pm 0.05\%$ accuracy

The line with the asterisk shows the standard setting, which has a result of 5.35%.

Take for example the scenarios with $\lambda=20$, $q=0.75$, $d=5$, $r=100\%$ and three values for p: 0, 40% and 100%. These scenarios have the following alphas: 1.14, 1.31 and 1.55 respectively. Remember that all of these scenarios are dealing with the same demand and that only 3% of the sales is lost in the worst case. This means that in all of these scenarios roughly the same amount is ordered. So if alpha is supposed to correlate with the amount of stock ordered, but the total order is roughly the same for every alpha. This raises questions about the ordering behavior.

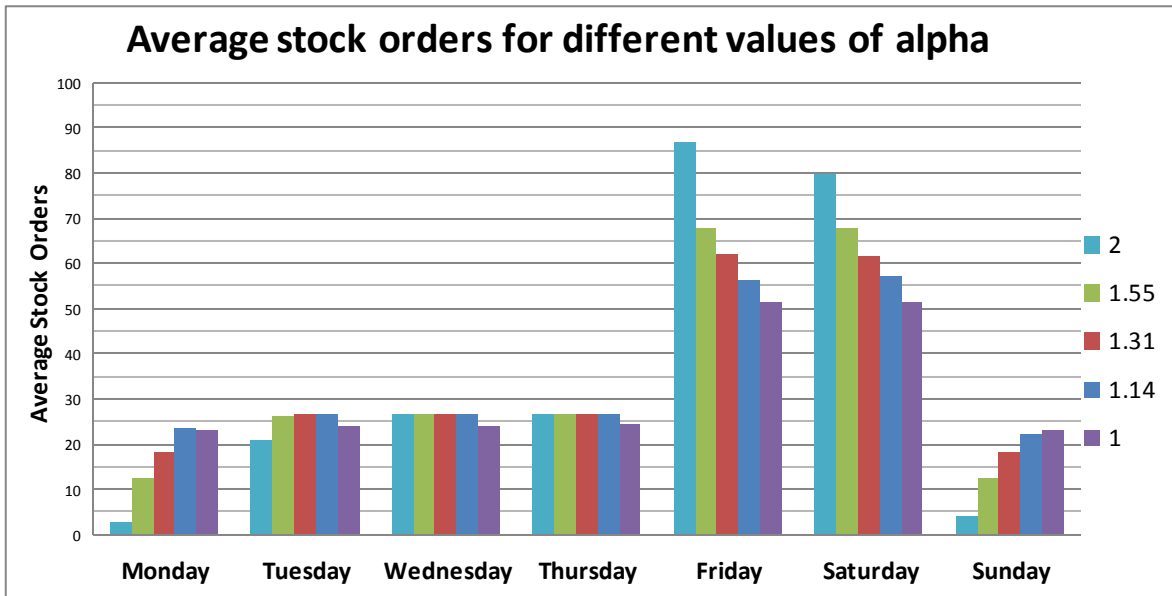


Figure 3: Average order levels for FIFO with 20 customers on weekdays and 40 on Friday and Saturday

Basically, the alpha correlates to the amount of movement around the expectations. For example, figure 3 shows that with higher alphas larger deliveries arrive at Friday and Saturday mornings (or the evening before), which often causes a surplus on Sunday and Monday. Situations with smaller alphas tend to have less difference between the orders on Friday and Monday. Notice that the higher alpha, the higher the impact of the weekend-bulk. This could be troublesome for systems that are LIFO or have low expected sales. As we have seen before, LIFO systems perform better with low alphas, since ordering less exuberantly leads to fewer old products.

The optimal value for alpha depends on the situation. Situations that allow more safety stock, like high demand and longer lifetimes, perform better with higher alphas. Situations which are more prone to outdated, like LIFO systems and situations with exponential decay perform better with lower alphas. Figures 4, 5 and 6 show the correlation between different parameters and the optimal alpha. These figures show, for example, that the FIFO percentage influences alpha much less than the expected shelf life of the product.

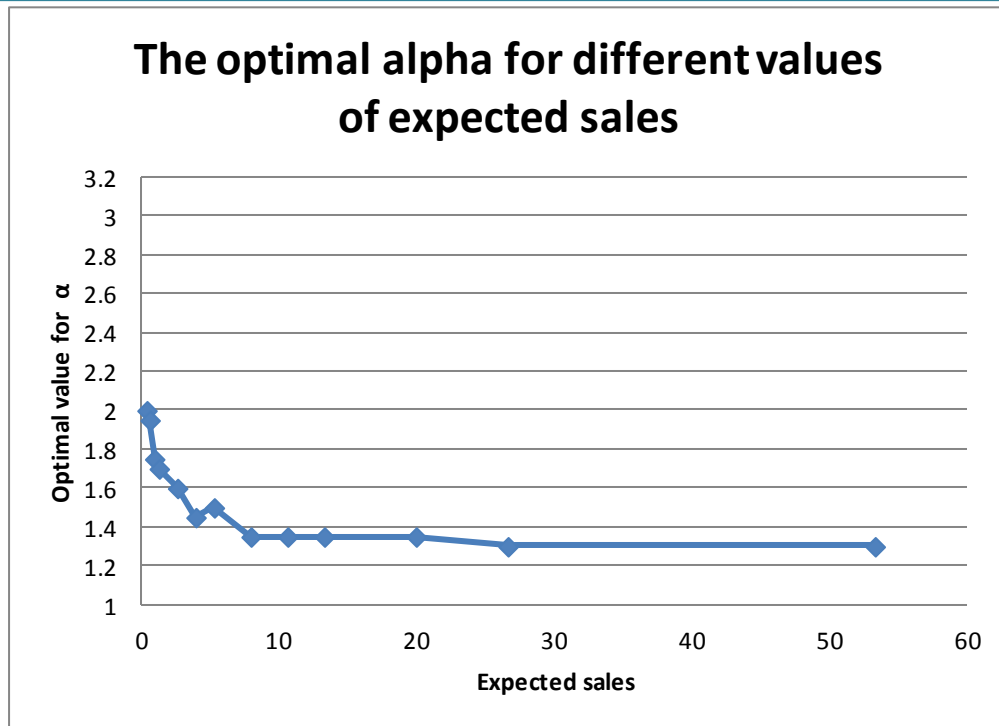


Figure 4: Impact of expected sales on the optimal alpha

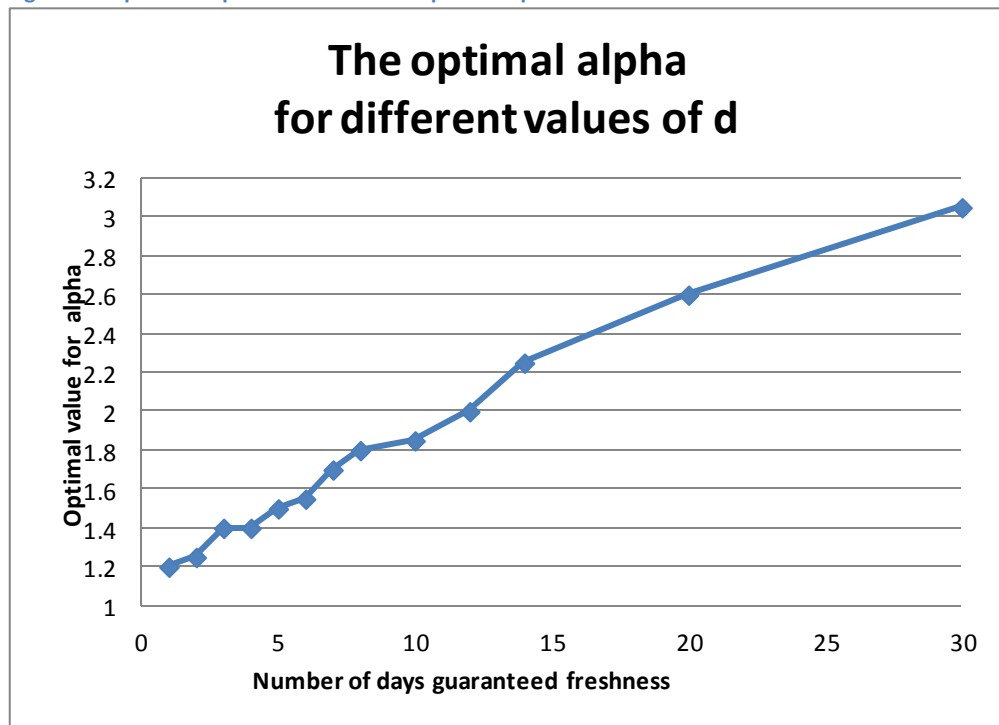


Figure 5: Expected lifetime affects the optimal alpha

Figure 5 shows a nearly linear correlation between optimal alpha and the shelf life of a product. Note that since our policy does not contain any holding costs, the tangent in real life might not be so steep after all. Still, the length of the shelf life obviously has a great impact on the risk of outdated and therefore on the optimal value of alpha.

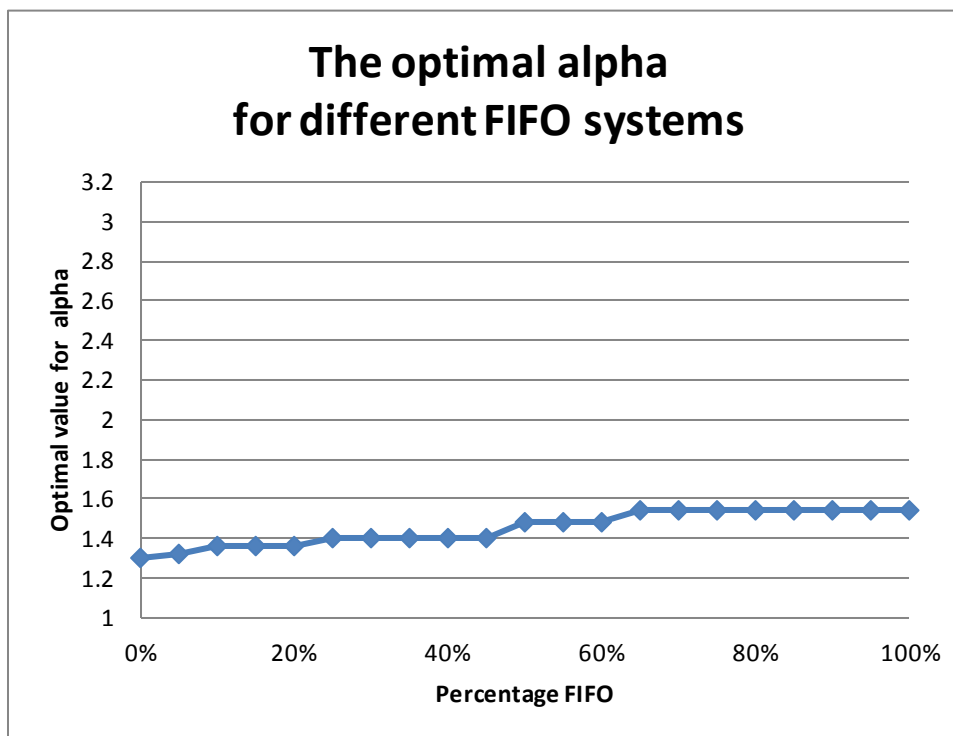


Figure 6: FIFO percentages affect the optimal alpha

Figure 7 shows the trade-off between lost sales and outdating. In our case, outdating and lost sales are treated equally. Finding the optimal alpha can be done by moving the red tangent line until it touches the blue curve, which is here between $\alpha = 1.4$ and 1.5 . The angle of the tangent line depends on the manager's interest. For instance, a manager finding lost sales twice as important as outdating should move the green tangent line to find the optimal value, which is around $\alpha = 1.35$. This particular graph also shows that tight constraints on the maximum amount of lost sales (or outdating) lead to significant outdating (or lost sales). For example, to guarantee 99% availability (and therefore less than 1% lost sales) an alpha around 1.25 has to be chosen and one would need to accept nearly 6% outdating. Guaranteeing that less than 1% of the ordered goods is outdated requires an alpha around 1.65 and leads to over 7% lost sales. Appendix B contains two tables similar to table 2 with constraints on outdating or lost sales and gives interesting examples of the trade-off between outdating and lost sales for various model parameters.

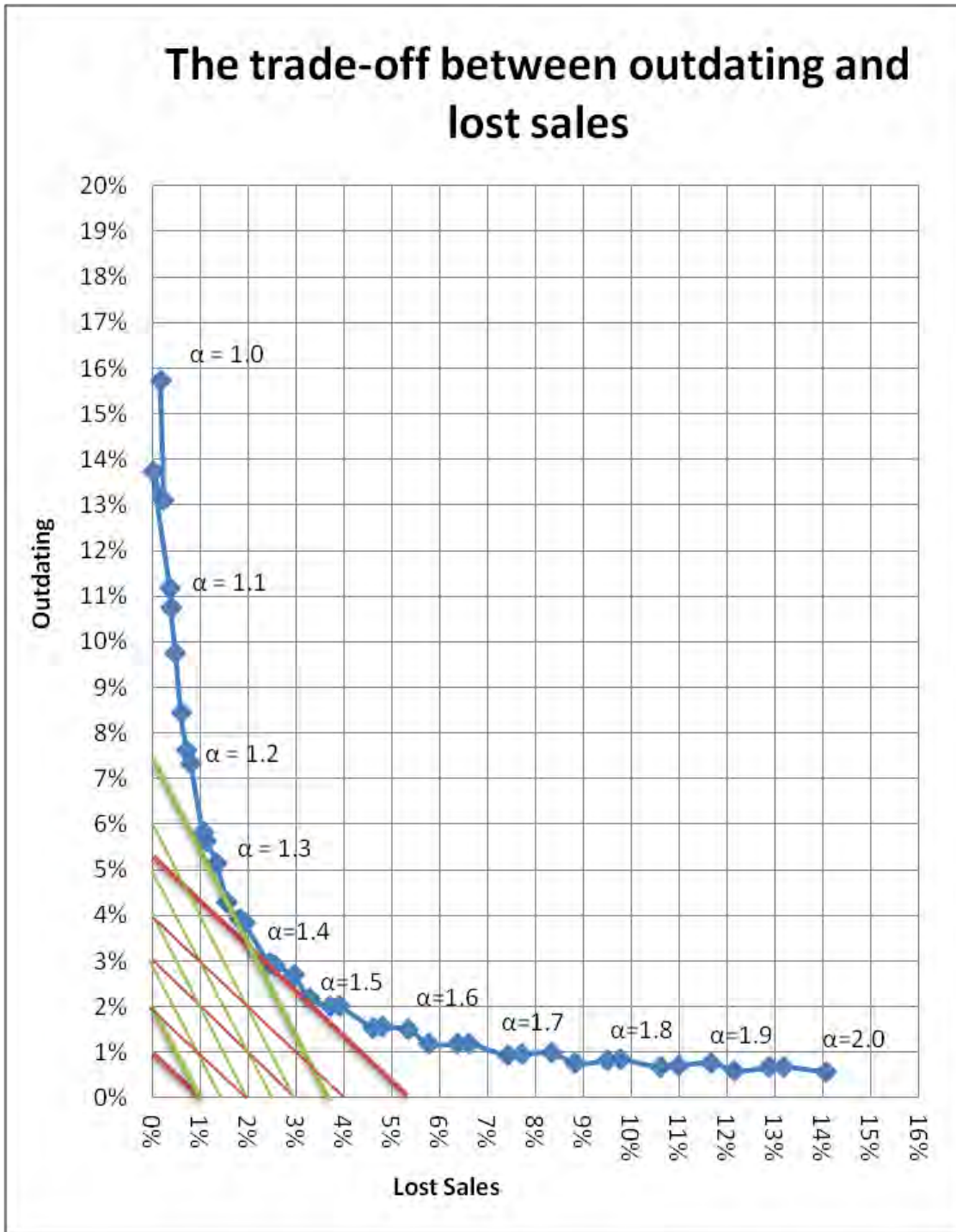


Figure 7: The trade-off between outdating and lost sales under standard settings

Figure 8 shows the performance for different values of alpha under the standard settings. The curve seems to resemble a parabola with minimum around $\alpha=1.4$, which corresponds to the optimal value found before.

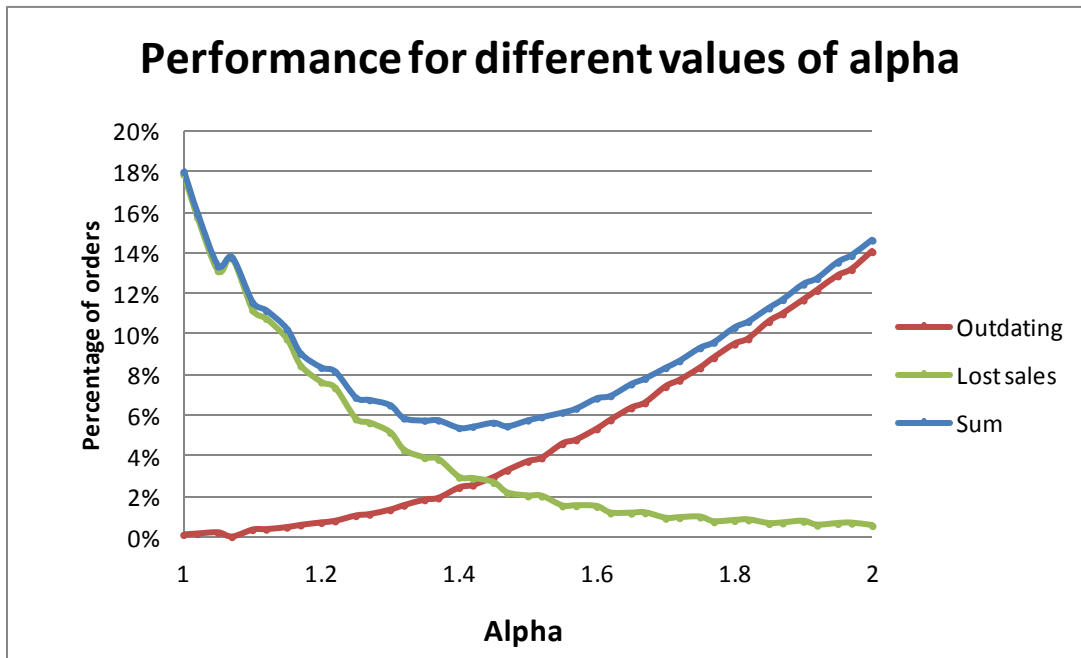


Figure 8: Performances of different values of alpha under standard settings

The simulation shows a clear weekly pattern in outdating as can be seen in figure 9. The outdating on Tuesday correlates to orders arriving on Friday morning, and the Wednesday outdating is caused by the goods that arrived on Saturday morning. So most outdating is caused by leftovers from the weekend. As figure 3 showed, the orders on Friday and Saturday are much higher than on the other days, which appears to cause high outdating in certain cases.

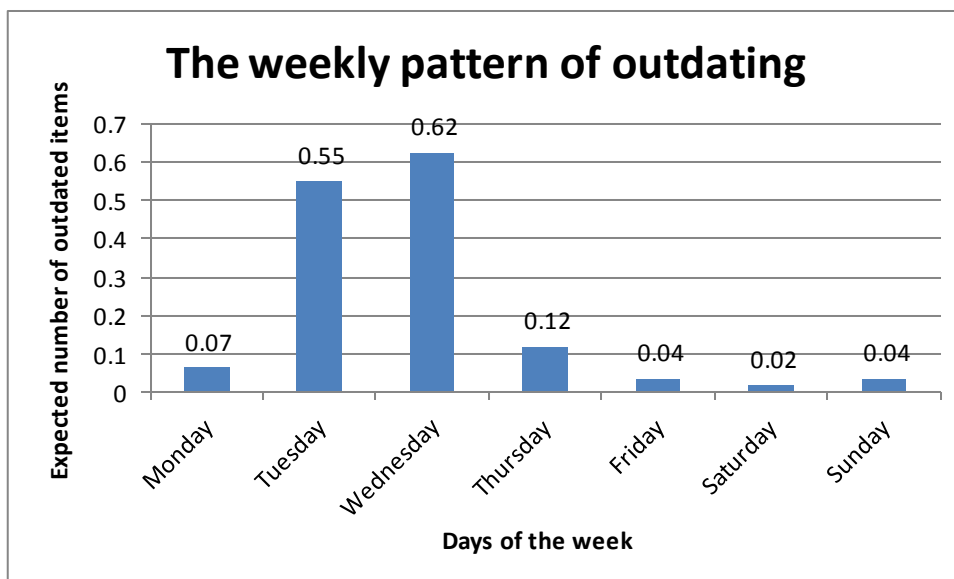


Figure 9: The weekly pattern of outdating under standard settings

Lost sales do not have such a significant pattern as outdating does, which is shown in figure 10. The somewhat higher Wednesday and Thursday lost sales could be caused by the high amount of outdating the days before. Saturday outperforms the other days because the order quantities of Friday and Saturday are quite large. For example, according to figure 3, having $\alpha=1.31$ and an expected sales of 50 on those two days, causes the average order to be around 60 on both days.

Let N and M be Poisson variables with parameters λ_1 and λ_2 . Then $N + M$ is also a Poisson variable, but with parameter $\lambda = \lambda_1 + \lambda_2$. So the combined sales of Friday and Saturday is a Poisson variable with expectation $50+50=100$. The probability that over 120 items (twice the average order) are sold is approximately 2.8%. Now suppose there still were 10 old items on Friday morning. The chance of selling over 130 items is less than 0.3%. That explains why Saturday performs so well.

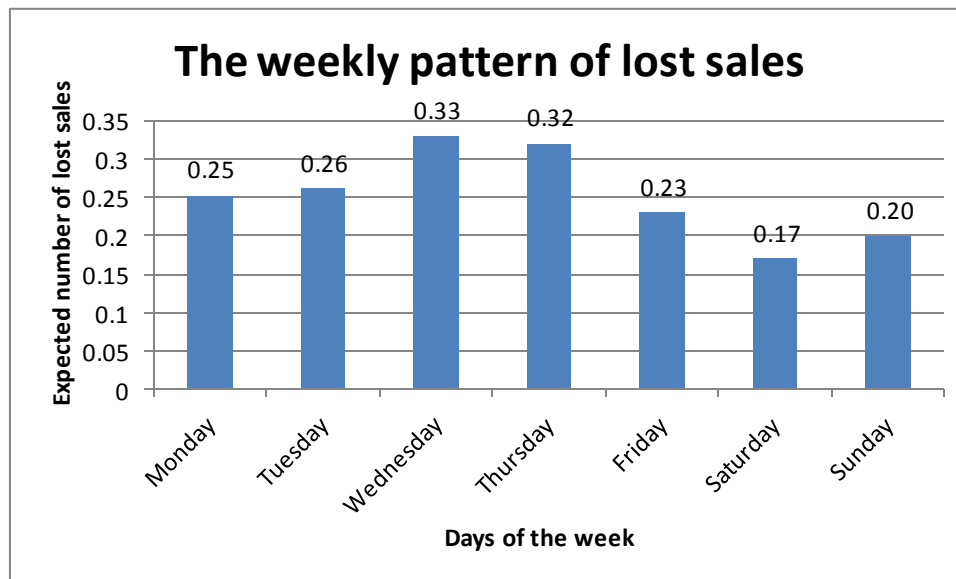


Figure 10: The weekly pattern of lost sales under standard settings

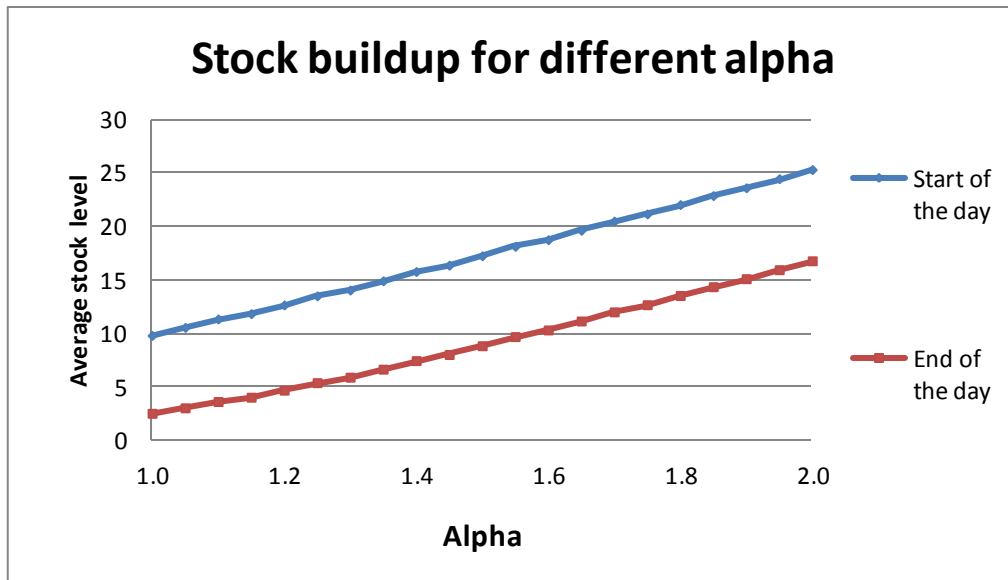


Figure 11: Average number of items in stock for different values of α under standard settings

Figure 11 shows the average stock buildup for different values of alpha under standard settings. The difference between start and end of the day increases slightly as alpha rises because a higher alpha correlates with less lost sales.

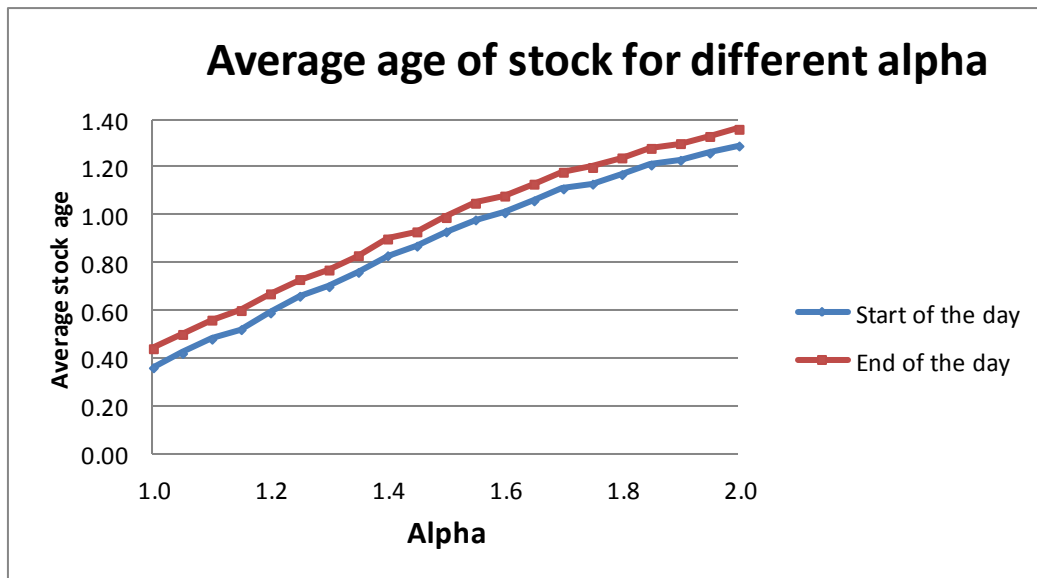


Figure 12: Average age of stock for different values of α under standard settings

Figure 12 shows the average stock age. Items are tagged as being 0, 1, 2, 3 or 4 days in stock and the average of these value is measured. The values are measured in the morning right after delivery and before opening. The end-day values are measured right before the products age and expire. The average age at the end of the day is slightly older than the one at the beginning because only 40% is FIFO, so most sales are LIFO.

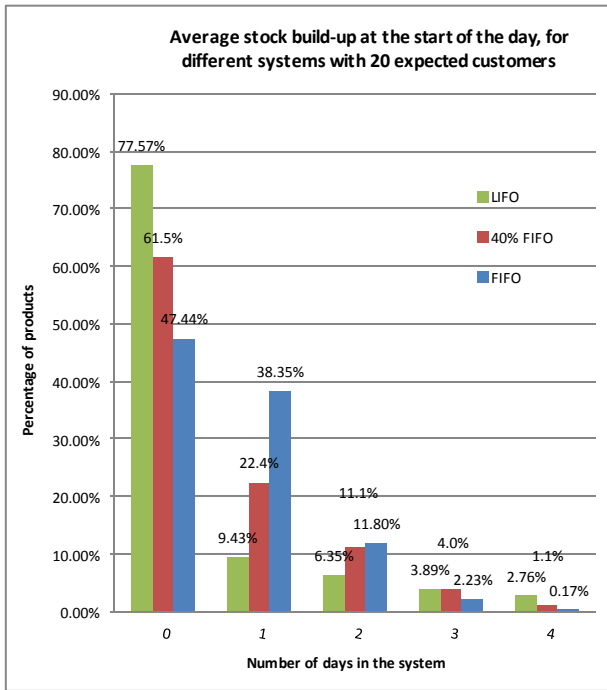


Figure 13: Stock build-up at the start of the day

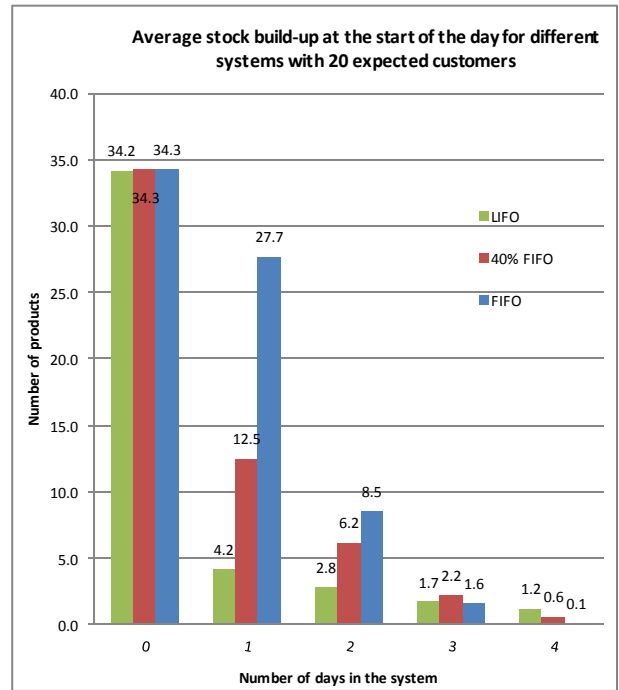


Figure 14: Stock build-up at the start of the day

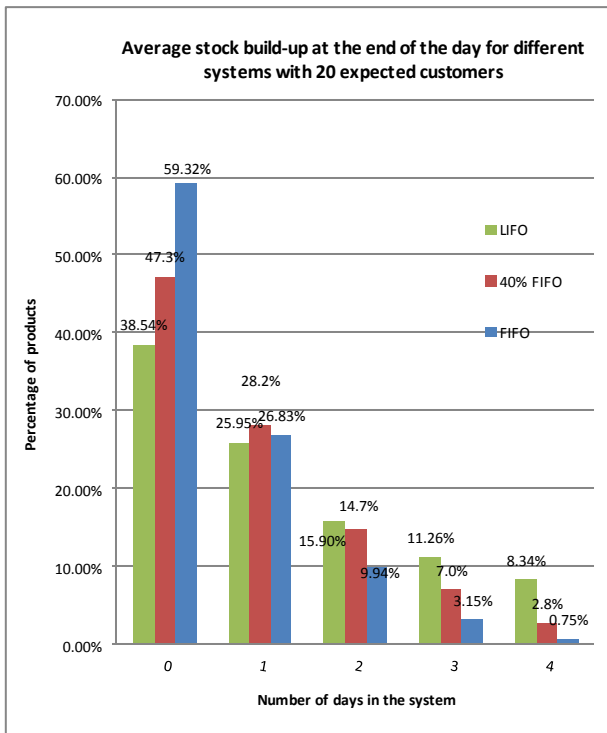


Figure 15: Stock build-up at the end of the day

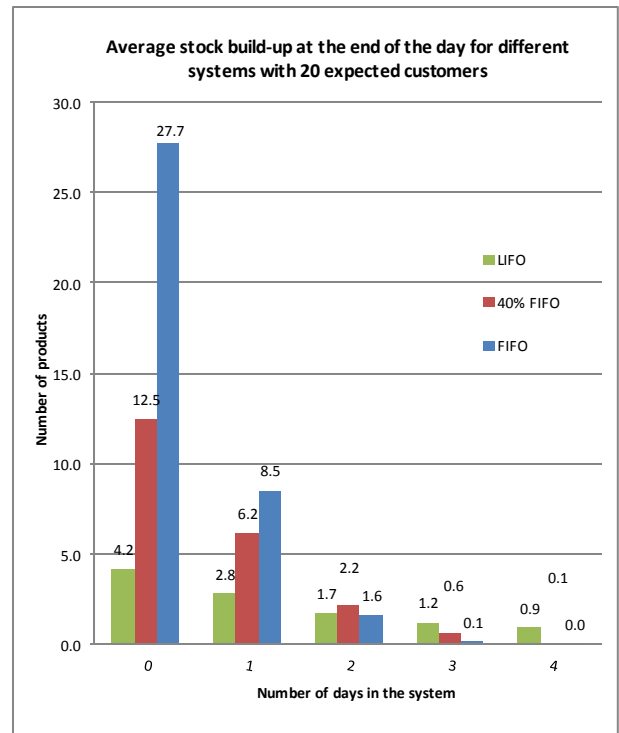


Figure 16: Stock build-up at the end of the day

Figures 13 to 16 show the stock build-up of three systems with standard settings at the start (upper) and end of the day (lower), but with different FIFO percentages. The values are shown as a percentage of the total stock (left) and as average number of items (right).

As you can see in figure 16, LIFO systems have way less safety stock. Since all three systems have nearly the same amount of sales (they only differ a few percent due to lost sales and outdating), they have different optimal alphas but nearly the same average order, and therefore nearly the same average new stock at the start of the day as can be seen in figure 14. It is remarkable to see how LIFO systems behave differently than their FIFO counterparts. LIFO systems seem to keep less older stock. Comparing figures 14 and 16 shows that LIFO systems indeed sell much less older products than FIFO systems, as one would expect. For example, the LIFO system starts the day with on average 1.2 final-day products and only sells around 0.3 of them. The remaining 0.9 items are outdated and thrown away. This means LIFO systems are discouraged to order a lot of safety stock and therefore tend to have much more lost sales than their FIFO counterparts.

6.2 Policies dealing with perishability

The second policy implemented was a policy with different weights for different stock ages. The formula from section 4.3 was used, that is

$$Q = \alpha * D_L - \sum_{i=1}^m w_i S_i . \quad (2)$$

Prolonged simulation of this policy resulted in the optimal combination of w_i and α . The non-weighted solution of the system with standard settings had an optimal result of 5.35%, as shown in table 2. Remember that the result is the sum of the lost sales and the amount of outdating. By adding weights to the current stock, a result of 5.06% was obtained, which is significantly better. The optimal alpha stayed the same. The difference in result was mostly found in a decrease in lost sales; the decrease in outdating was less than 0.03%. Table 3 shows the optimal weight values.

Remaining lifetime	Optimal weight
4 days	1.08
3 days	1.04
2 days	1.00
1 day	1.00
0 day	0.42

Table 3: Optimal weights for different stock age categories

Products with only one day remaining are weighted a lot less than the others, since these products might be outdated at the end of the day and therefore cannot be sold tomorrow. As figure 5 showed, outdating is high on Tuesday and Wednesday, which leads to increased lost sales on Wednesday and Thursday, as can be seen in figure 6. By giving older products less weight (only 0.42 instead of 1.00), we reduce the amount of lost sales tomorrow due to excessive outdating today. The optimal weights heavily depend on factors that increase the risk of outdating. For example, in LIFO systems the risk of outdating is higher, and the weights of the oldest products will be even less, whereas FIFO-systems will have a much smaller difference between the different product age groups.

The next policy uses the weights from the previous paragraph but adds the concept of having a different alpha for each day of the week.

$$Q = \alpha_j * D_L - \sum_{i=1}^m w_i S_i . \quad (3)$$

Orders arriving at	Adjusted Weight	Optimal weight (α_j)
Monday	+0%	1.40
Tuesday	+10%	1.54
Wednesday	+10%	1.54
Thursday	+10%	1.54
Friday	+5%	1.47
Saturday	+0%	1.40
Sunday	-5%	1.33

Table 4: Optimal weights for different days

Mainly, the alpha before the weekend is increased and the alpha in the weekend is decreased in the optimal situation. This is because the absolute amount of safety stock is smaller on weekdays than on the busy days. Furthermore, the chance of selling old leftovers is higher when the weekend is only a few days away. This leads to an optimal result of 4.89% in lost sales and outdateding.

6.3 A policy using previous order information

The next policy is a more practical one. It does not require information about the age distribution of the stock, which is traditionally hard to obtain in non-FIFO environments. Instead it uses a variable β which decreases stock orders by a certain fraction if orders have been low for a specific amount of time. The ordering amount is given by:

$$Q = \beta * \alpha_j * D_L - S \quad (4)$$

$$\text{where } \beta = \begin{cases} 0.55 & \text{if order} < 6 \text{ for third time in a row} \\ 1 & \text{else} \end{cases}$$

The parameters 0.55, 3 and 6 were found after exhaustive optimization.

Low orders for three days in a row might indicate aging stock. To decrease outdateding an even lower order is placed to get rid of more old stock. Note that this is only favorable in not fully-FIFO systems, since ordering smaller amounts of new stock does not increase the chance old stock is sold for FIFO systems. The optimal value was 4.83% which is the best result so far. Using β as an additive parameter instead of a multiplicative effect was tried as well but gave worse results.

Finally, when re-adding the weights for stock age groups from table 3 the optimal result further decreased even further to 4.75%.

$$Q = \beta * \alpha_j * D_L - \sum_{i=1}^m w_i S_i \quad (5)$$

An overview of all policies, their formulas and best results for the standard settings is shown below in table 5.

Policy number	Order policy formula	Optimal result:
(1)	$Q = \alpha * D_L - S$	5.35%
(2)	$Q = \alpha * D_L - \sum_{i=1}^m w_i S_i$	5.06%
(3)	$Q = \alpha_j * D_L - \sum_{i=1}^m w_i S_i$	4.89%
(4)	$Q = \beta * \alpha_j * D_L - S$	4.83%
(5)	$Q = \beta * \alpha_j * D_L - \sum_{i=1}^m w_i S_i$	4.75%

Table 5: Summary of the policies and their optimal results

7. Comparison to a real life situation

To compare the practical use of the model, information from a local supermarket was used to evaluate the order strategy. For a period of six weeks, stock levels, outdating, sales and deliveries for twelve different products were registered and afterwards inserted into the computer program to compute how the order strategy would have scored in practice. The data was obtained from June 4th until July 15th 2011.

7.1 Supermarket information

The chosen supermarket is located in a Dutch village with approximately 15,000 inhabitants and has a weekly turnover of over €200,000. It is part of a multinational supermarket chain with a prominent position in the Dutch supermarket sector.

7.2 Product selection

A wide range of products was chosen, each with different average weekly sales and minimum lifetime (d). In consultation with the local supermarket only products from the ready-to-cook vegetable department were chosen. The products in this department range from prepacked vegetables, like spinach and broccoli, to stir-fry vegetable mixes, mushrooms and prepacked lettuce and salads. This department is of interest because it is traditionally dealing with lots of outdating due to a rather short shelf life and has a somewhat larger profit margin than other products. A total of eighteen products were tracked, but not all could be used for the experiment, because during the interval, five products were on sale. This dramatically boosted sales that week, which is not incorporated in the model and makes forecasting and parameter estimation even more delicate. Furthermore, one product became unavailable due to shortages at the distribution centre. In the end, twelve products which are shown in table 6, were left for the real life analysis.

It should be noted that the precision of the stated “minimum lifetime in days” is not accurate. This value was obtained from the computer system but it is not very accurate. For instance, the Parisian Carrots are supposed to last a minimum of 3 days, but as the data set shows, carrots arriving Friday evening are not thrown away until Thursday, which is five and a half to six days after arrival. Therefore, a sample was taken from the supermarket to obtain the correct life times. In nearly all cases, the expected life time after delivery was five days instead of three, except for the Spinach Stew which did last ten days. In the simulation, the “sampled” life times were used instead of the “official” life times.

Product description	Weight or volume	Order quantity	“Official” minimum lifetime in days	Average daily sales	Total products outdated	outdating percentage of sales	Variance of sales	Variance-to-mean	number of days with low stock (<average/2)
1 Broccoli	300 grams	4	3	1.23	1	1.9%	1.5	1.18	7
2 Diner Caesar Salad	450 grams	4	3	2.88	0	0%	4.15	1.41	3
3 Spinach Stew	500 grams	4	10	1.64	3	4.3%	1.97	1.17	1
4 Soup vegetables	250 grams	6	3	4.39	8	4.3%	17.90	3.98	6
5 Raw beet salad	250 grams	1	3	0.64	3	11.1%	0.53	0.81	2
6 Parisian Carrots	300 grams	8	3	2.26	29	30.5%	4.77	2.06	2
7 Shii take mushrooms	100 grams	2	3	0.93	6	15.4%	1.05	1.10	7
8 Mushrooms	250 grams	12	3	42.98	0	0%	383	8.70	1
9 Sliced Leek	200 grams	4	3	3.21	4	3.0%	5.16	1.57	2
10 Italian Salad	250 grams	6	3	12.26	53	10.2%	28.33	2.24	4
11 Wok vegetables with mushrooms	400 grams	1	3	1.19	3	6.0%	1.13	0.92	0
12 Biological onion flakes	175 grams	4	3	2.71	3	2.6%	3.18	1.14	5

Table 6: Products selected from the supermarket with some of their statistics

7.3 Data analysis

A few points have to be noted before discussing the results of table 6. First of all, the column “outdating” might also include some items thrown away for being accidentally opened or damaged. Furthermore, all of these items do have substitute goods and sudden increases in sales might be caused by unavailability of those goods or by their price changes. Furthermore, the number of lost sales is unknown and is not easily deducted from the data. Knowing exactly how long the shelves have been empty would be a decent indicator for lost sales, but unfortunately that information is not available. Still, the data shows whether there are days starting with an amount of stock lower than half the average sales or no stock at all. Table 7 shows the lost sales and Friday seems to perform quite well, as predicted before. On the other hand, Mondays and Tuesdays perform much worse.

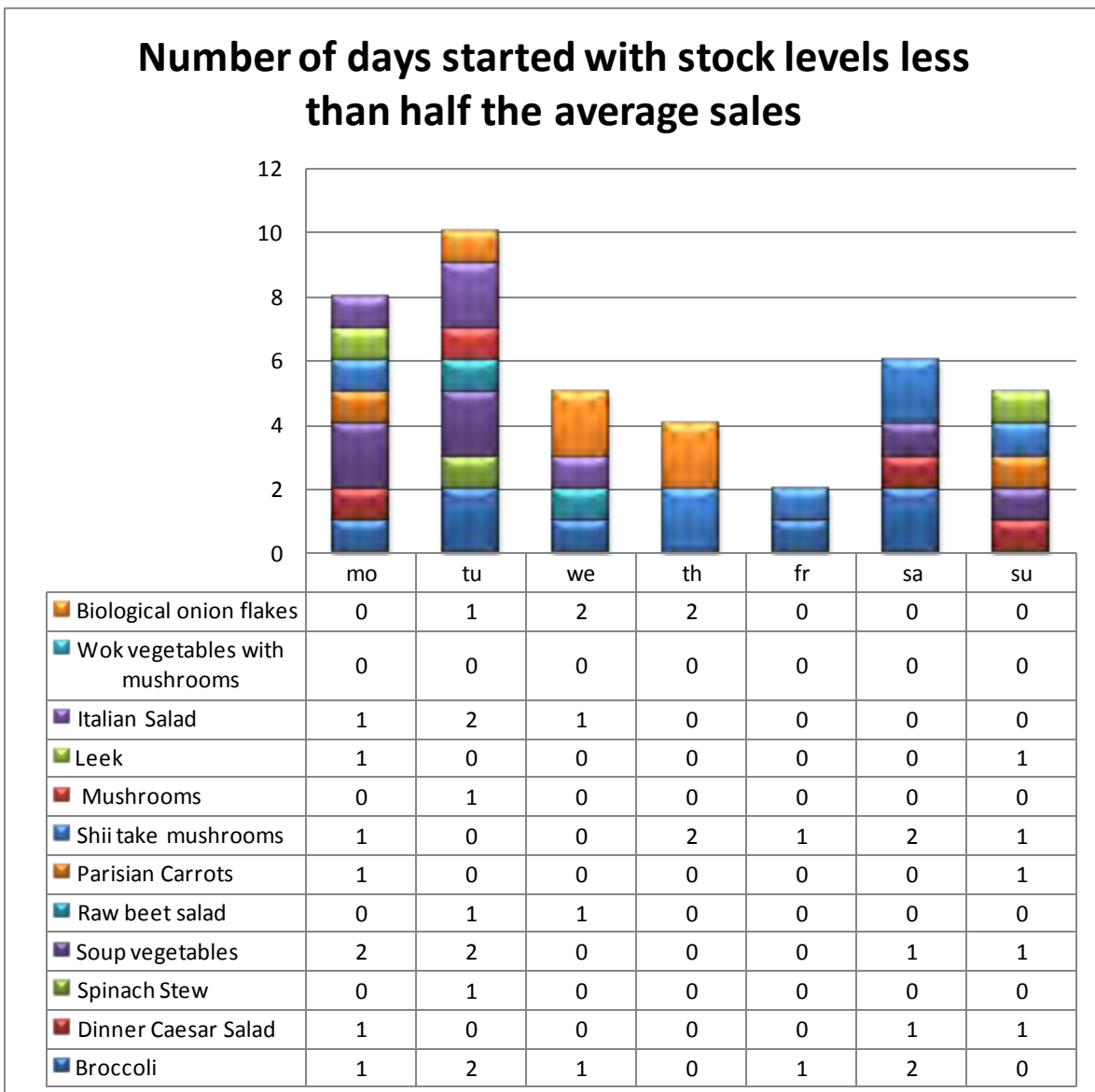


Table 7: Days with possible lost sales during the observation period

One of the first things to notice in table 8 is the significant amount of outdating. Even though six weeks is a rather short period of time, four out of twelve products had outdating percentages of over ten percent. The data showed that the Parisian carrots appeared to have a weekly pattern with major outdating on Thursday followed by a somewhat larger order on Friday. The Italian salad had peaks in outdating on Mondays and Thursdays, which were probably caused by large orders on Wednesdays and Saturdays, respectively. One thing to note is the large fluctuation in weekend sales for this product. Some Fridays and Saturday had over 25 sales but were followed by weekends with only half as much sales, apparently leading to piles of leftovers from the weekends resulting in outdating bulks.

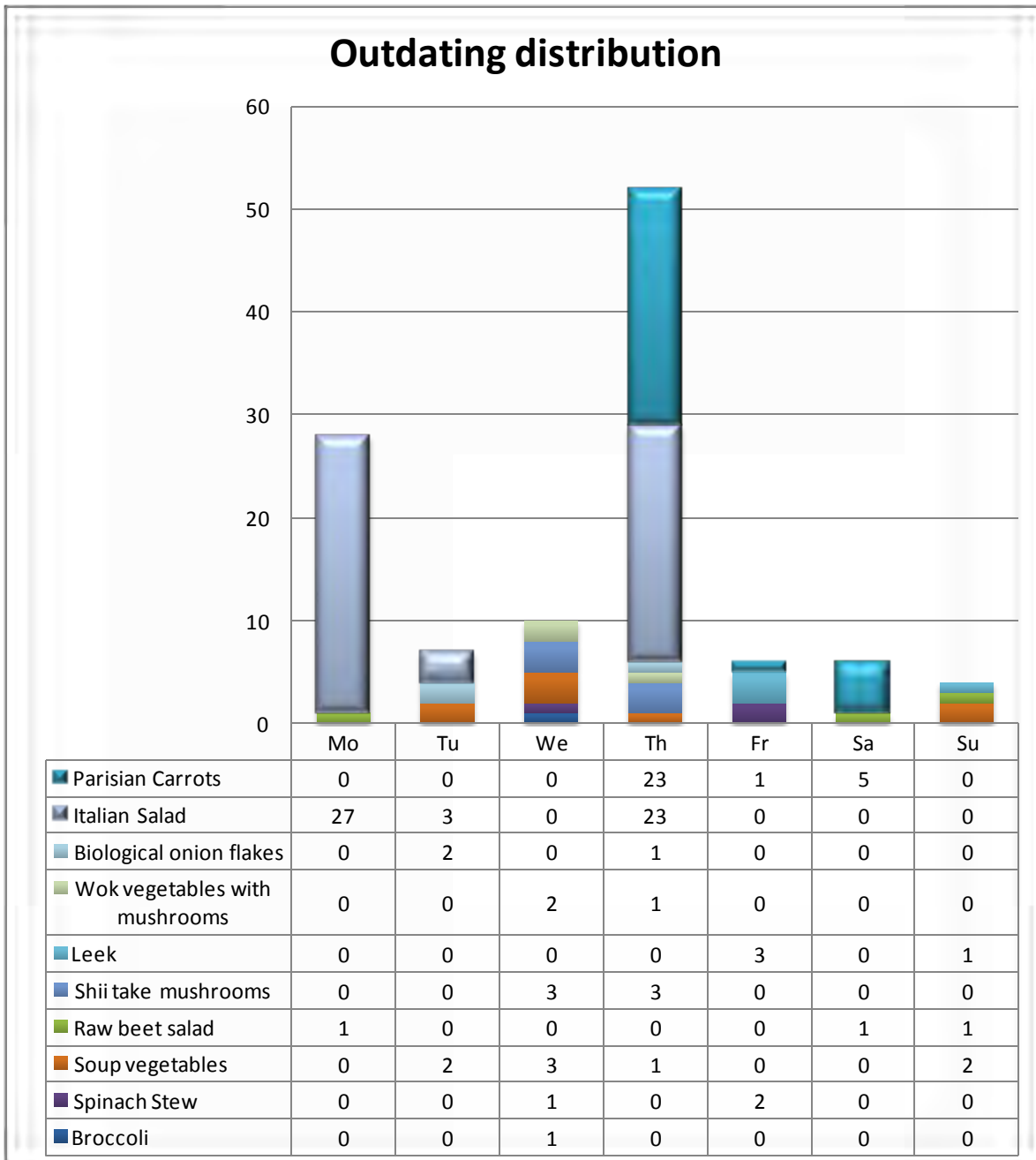


Table 8: Outdating during the observation period

Also, the supposed week pattern in sales seems to exist, but not as distinct as previously assumed. The distribution is shown in figure 17. Sales on Mondays to Thursdays seem to be nearly equal, sales on Sundays seem to be a little less and sales on Fridays and Saturdays seem to be about 1.4 times as large as Monday to Thursdays, instead of double the other days. The data was gathered in June and July, and this gradual spreading could be caused by the summer vacation period. People tend to have more time during these weeks to do their groceries on days, which normally would have been working days. It is also possible that it might depend on the product selection. For example, luxurious products like sushi are typically sold during the weekend and opposite could apply for some of our products.

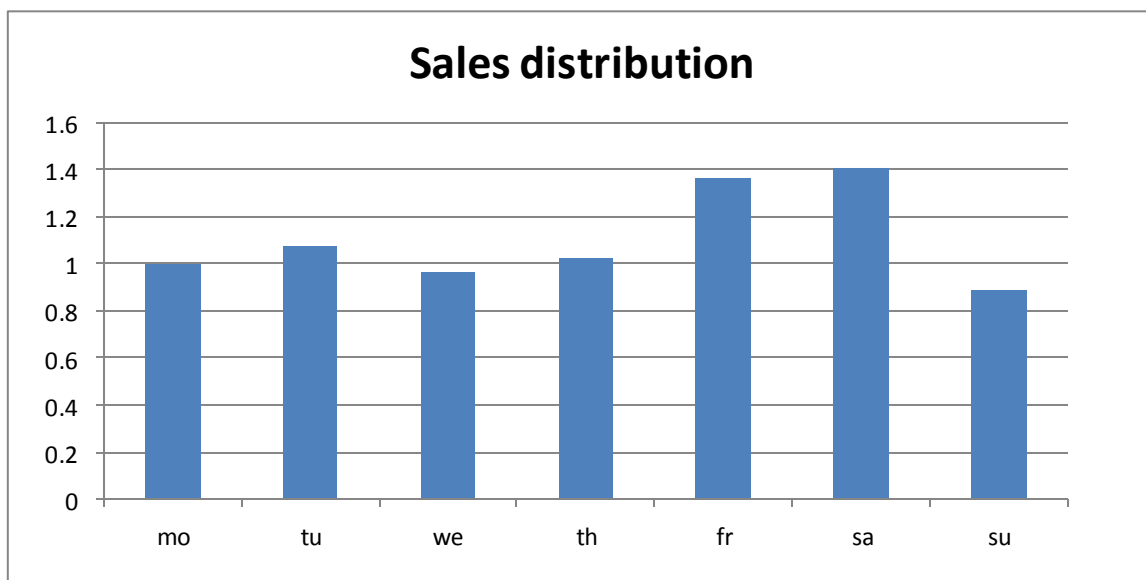


Figure 17: Distribution of the realized sales compared to Monday

8. Simulation results compared to the real life situation

8.1 Settings and assumptions

Simulations were run using the store's data to see if the strategies mentioned in chapter 4 perform properly. The data comprises a total of six weeks. We simulated cycles of 42 days, and did this for each product 100,000 times to obtain accurate results. One should note that we have a significant advantage since the realization of the demand is already known, whereas the store had to estimate it using historic data of hundreds of stores throughout the Netherlands.

Figure 17 showed a rather different week pattern, with Friday and Saturday only 40% above most of the other weekdays. To simplify the comparison between our policy and the real-life situation, we adjusted the weekend factor to 1.4 instead of using the 2.0 used before. Let us take the broccoli for example. The weighted average daily sales of broccoli was 1.03. This means that the average sale was 1.03 on weekdays, and $1.4 \cdot 1.03 = 1.442$ on Fridays and Saturdays. The average daily sales and weighted average daily sales of each product is shown below in table 9.

product	total sales	average daily sales	Weighted average daily sales
1 Broccoli	52	1.23	1.03
2 Diner Caesar Salad	121	2.88	2.40
3 Spinach Stew	69	1.64	1.37
4 Soup vegetables	184	4.39	3.65
5 Raw beet salad	27	0.64	0.54
6 Parisian Carrots	95	2.26	1.88
7 Shii take mushrooms	39	0.93	0.77
8 Mushrooms	1805	42.98	35.81
9 Sliced Leek	135	3.21	2.68
10 Italian Salad	515	12.26	10.22
11 Wok vegetables with mushrooms	50	1.19	0.99
12 Biological onion flakes	114	2.71	2.26

Table 9: Products and their (weighted) average daily sales

Using the results from table 8 as input variables, simulations were carried out for each of the specified products. The supermarket had a certain stock build-up at the begin of the measurements. The age distribution of the stock was unknown, but has a significant effect on simulation results. Starting with a clean sheet, i.e. entirely young stock, makes it easier for the system to keep outdating to a minimum than if the stock was randomly divided over all stock ages. Each simulation cycle starts with the same pre-specified amount of initial stock. The age distribution of the stock at the start of a new cycle is made to resemble the age distribution at the end of the previous cycle. Otherwise, the system would always start out with only fully fresh items, which would not be realistic. For the comparison, the forth policy was used, since this thesis is mainly interested in a practical policy and this policy does not use ‘uncommon’ information like the age distribution of the actual stock. The policy is given by:

$$Q = \beta * \alpha_j * D_L - S, \quad (4)$$

where α_j and β were optimized by simulation.

8.2 Comparison on lost sales

Since no information is known about lost sales in the supermarket, we use ‘the number of days with rather low stock’ as a performance measure. The number of days were counted on which the stock at the start of the day was less than half the expected sales of that day. Although it does not give an indication of the total number of lost sales, it does give some insight in how frequent orders are insufficient. We cannot compare our policy with the supermarket using the sum of the percentage of outdating and of lost sales, since we have no information on the amount of outdating. What we can do is fixing one of the two values and determine if our policy performs better. So the simulated policy tries to accomplish approximately the same number of days with low stock, but with less outdating.

Table 10 shows the comparison between de supermarket and our simulations. Especially the Parisian Carrots (6) and the Shii take Mushrooms (7) did far better than in practice. The four products listed in red in table 10 are the ones in which our policy performs worse. Note that the required alpha to match the supermarket is less than one for the Soup vegetables (4), Mushrooms (8) and Italian Salad (10). This means they actually deliberately have lost sales to match the low stock levels, which obviously decreases the outdating percentages. In real life, this is obviously never an optimal solution. One of the reasons why the mushrooms achieved such low outdating rates is that they are placed on the bottom shelf in a corner, which makes it very hard for customers not to buy FIFO, achieving no outdating at all. The Italian salad had rather full shelves but had terrible outdating as can be seen in table 10. This might be caused by an incorrect administrative stock level, i.e. the system contained more products than it knew about, which rarely happens.

Product description	Realized low stock in days	Simulated low stock in days	Realized outdating	Simulated Outdating	Simulated Lost sales	Optimal alpha
1 Broccoli	7	6.97	1.9%	4.18%	25.15%	1.28
2 Diner Caesar Salad	3	3.31	0%	1.22%	13.81%	1.2
3 Spinach Stew	1	1.2	4.3%	0.62%	8.94%	1.66
4 Soup vegetables	6	6.19	4.3%	0.46%	26.79%	0.98
5 Raw beet salad	2	2.31	11.1%	16.07%	10.76%	2.04
6 Parisian Carrots	2	2.47	30.5%	7.02%	12.80%	1.7
7 Shii take mushrooms	7	6	15.4%	4.94%	25.82%	1.19
8 Mushrooms	1	0.54	0%	0%	51.52%	0.47
9 Sliced Leek	2	2.16	3.0%	1.09%	12.67%	1.19
10 Italian Salad	4	3.68	10.2%	0%	49.46%	0.45
11 Wok vegetables with mushrooms	0	0.44	6.0%	9.45%	6.72%	1.75
12 Biological onion flakes	5	5.36	2.6%	0.77%	21.63%	1.17

Table 10: Comparison between the supermarket and simulation for a fixed amount of low stock

8.3 Comparison on outdating

The same comparison was done with outdating. Similar to the previous section, we fixed the amount of outdating and compared the difference in days with low stock. The five products colored red are the ones in which our policy performs worse.

Table 11 shows that seven out of twelve items would have performed better using our policy. Note that the alpha of the first two products are below one. Especially the broccoli results were difficult to obtain, since it has a rather low average daily sales and it is very hard to keep outdating to a minimum under our assumptions of not-fully FIFO. That is why the simulated lost sales are so high for that product. One of the reasons why the other 'red' products performed so well is that the supermarket had an active policy giving a significant discount to all items with one day until expiry, actively increasing the chance customers will take an old item over a younger one.

Product description	Realized outdating	Simulated Outdating	Realized low stock in days	Simulated average low stock in days	Simulated Lost sales	Optimal alpha
1 Broccoli	1.9%	3.31%	7	20.98	51.14%	0.83
2 Diner Caesar Salad	0%	0.1%	3	12.31	37.11%	0.77
3 Spinach Stew	4.3%	4.06%	1	2.51	14.52%	1.46
4 Soup vegetables	4.3%	4.18%	6	0.09	1.18%	2.41
5 Raw beet salad	11.1%	9.93%	2	3.34	18.65%	1.57
6 Parisian Carrots	30.5%	30.21%	2	0.17	0.88%	3.29
7 Shii take mushrooms	15.4%	15.17%	7	1.2	6.50%	2.07
8 Mushrooms	0%	0.04%	1	0.02	8.05%	1.1
9 Sliced Leek	3.0%	3.07%	2	0.78	5.78%	1.5
10 Italian Salad	10.2%	10.22%	4	0	0.00%	2.1
11 Wok vegetables with mushrooms	6.0%	5.84%	0	1.12	12.23%	1.59
12 Biological onion flakes	2.6%	2.52%	5	1.43	7.27%	1.41

Table 11: Comparison between the supermarket and simulation for a fixed amount of outdating

8.4 Analysis on the constraint that outdating < 2%

Of all the products sold over those six weeks, more than 3.5% was outdated. Table 12 shows the effects if the amount of outdating should be strictly below 2%. Observe that the higher the daily demand, the lower the amount of lost sales.

Product description	Simulated Outdating	Simulated average low stock in days	Simulated Lost sales	Optimal alpha
2 Diner Caesar Salad	1.96%	1.69	9.31%	1.33
3 Spinach Stew	1.84%	0.34	3.35%	2.08
4 Soup vegetables	1.95%	1.8	12.25%	1.32
8 Mushrooms	1.99%	0	0.49%	1.59
9 Sliced Leek	1.76%	1.47	9.18%	1.35
10 Italian Salad	2%	0	0.13%	1.64
11 Wok vegetables with mushrooms	1.76%	4.53	29.02%	1.09
12 Biological onion flakes	1.8%	2.06	9.52%	1.4

Table 12: Amount of lost sales for items that can achieve outdating < 2%

But not all of these products can achieve 2% outdating, since they arrive in batches. For example, broccoli cannot achieve less than 3.68% outdating even if it is only ordered as soon as the stock is depleted. This is because the average sales are only 1.03 per day and the probability that less than 4 items are sold in 6 days is either 8% or 11%, depending on the day of the week, i.e. $P[6X \leq 4] \approx 0.08$. So bigger batch sizes increase the chance on outdating. There are four missing products which could not achieve the two percent outdating target. The effect of batch sizes was examined for these products. For example, by reducing the batch size of Broccoli from 4 to 3, we could obtain outdating below 2%. Only the Raw beet salad could not achieve that limit. Even if the product can be ordered one at a time, the average daily sales (0.54 on a regular day) is too low to keep outdating to a minimum. Even if we only order as soon as the entire stock is depleted, having to wait a whole day before it arrives again, we get near the 2% but still not below it.

Product description	Simulated Outdating	Simulated average low stock in days	Simulated Lost sales	Optimal Alpha	Old Batch Size	New Batch Size
1 Broccoli	1.86%	9.46	34.58%	0.96	4	3
5 Raw beet salad	2.66%	13.28	48.53%	0**	1	1
6 Parisian Carrots	1.84%	6.02	27.86%	1.13	8	6
7 Shii take mushrooms	1.73%	11.7	45.73%	0.86	2	1

** Policy: Never have more than one item in stock. Order a new one as soon as the old one is sold.

Table 13: Amount of lost sales for outdating < 2% for products unable to have such low outdating with their regular batch sizes

8.5 Further discussion

Where our policy had better results they were significantly better. Where our policy performed worse it did so only slightly. But our assumption of only forty percent FIFO sales might not be accurate. Especially the broccoli performed particularly well in real life, which might be caused by the fact that there is a discount on products with only one day until expiry.

Finding the right order strategy can make a lot of difference but is more complicated than it seems. Generally speaking, the more information known about the system, the better the results can become. Unfortunately, some information is unavailable or can be pricy to gather. Still, the simulation showed that the order strategy of the super market performed worse than our strategy in certain cases, while our best practical policy only used information which is easily obtainable for large corporations. Changing to our best practical order policy could not only increase revenues and customer satisfaction but might decrease outdating as well, which saves money and leads to a cleaner environment as well. Still, one should note that conclusions on comparisons of a real life situation with a simulation afterwards should be taken with a pinch of salt. More research should be done on order strategies for perishables since there is still room for improvement.

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Appendix A: Basic Java code

```

import java.io.PrintStream;

class Simulation {

    static final int NUMBER_OF_SUBRUNS = 41;
    static final int SUBRUN_LENGTH = 25000;
    static final int WARMUP_LENGTH = 364;           // make sure it is a multiple of 7.
    static final double T_DISTR = 2.021;           // t-distribution for r=41 -> df = 40

    PrintStream out;
    double[] demand;           // average customer arrival rate
    int[] stock;               // stock levels for every value of m
    double[] ageweights;
    double[] dayweights;
    int lifetime;              // days till the product outdates
    int batch_size;           // 4 items in a single package.
    double decayRate;         // parameter for exponential decay
    double FIFO;              // percentage of customers that shops FIFO
    double geometric;         // parameter of people taking multiple items.
    double alpha;

    int order;                 // number of products to arrive the next day
    int totalStock;           // current number of products in stock
    int day;
    int lowordercounter;

                                // variables for analysis:
    double totalOutdated,totalLostSales,totalOrder,
           orderinfoLimit, orderinfoFactor,
           subrunorders,subrunoutdate,subrunlostsales,outdatesq,lostsalessq,
           result;

    Simulation(){
        init();
    }

    final void init(){
        out = new PrintStream(System.out);
        demand = new double[7];
        set_demand(5,2);
        batch_size = 1;        // 4 items in one package
        decayRate = 1000;     // see below
        FIFO = 0.4;           // 40% of customers buys FIFO
        geometric = .75;
        set_alpha(1.4);
    }

```

```

    setOrderInfo(6,0.55);
    set_lifetime(4);           //guaranteed freshness for m+1 days
    set_ageweights(new double[] {1,1,1,1});
    resetData();
    order = (int) demand[0];    //INITIAL_ORDER;
    this.set_dayweights(new double[] {1.1,1.1,1.1,1.05,1,0.95,1});
}

void set_ageweights(double input){
    ageweights = new double[lifetime+1];
    for (int i=0; i<=lifetime;i++){
        ageweights[i] = input;
    }
}

void set_ageweights(double[] input){
    ageweights = new double[input.length];
    System.arraycopy(input, 0, ageweights, 0, input.length);
}

void setOrderInfo(double limit, double factor){
    orderinfoLimit = limit;
    orderinfoFactor = factor;
}

void set_dayweights(double[] input){
    dayweights = new double[7];
    System.arraycopy(input, 0, dayweights, 0, input.length);
}

double get_result(){
    return result*100;
}

void set_lifetime(int input){
    lifetime = input;
}

void set_alpha(double input){
    alpha = input;
}

void set_demand(double input, double factor){
    demand[0] = demand[1]= demand[2] = demand[3] = demand[6] = input;
    demand[4] = demand[5] = factor*input;
}

void set_fifo(double input){
    FIFO = input;
}

int poissonDrawing(double mu){
    int x = -1;           // draws from a Poisson distribution with parameter mu.
    double a = Math.exp(mu);
    while (!(a<1)){
        x+=1;
    }
}

```

```

        a *= Math.random();
    }
    return x;
}

int geometricDrawing(){ // draws from a geometric-distribution
    double random = Math.random();
    return (int) Math.ceil(Math.log(random)/Math.log(1-geometric));
}
boolean exponentialDecay(){
    double test = -Math.log(Math.random())/decayRate; // exponential drawing
    return (test < 1);
    /* generates the remaining life length. if length < 1 then the item perishes.

* decay = 0.28 -> fail = 25%
* decay = 0.41 -> fail = 33%
* decay = 0.70 -> fail = 50%
* decay = 1.10 -> fail = 67%
*/

}

void processDayEnd(){
    performOutdating();
    stock[lifetime] += stock[lifetime-1];
    for (int i = lifetime-1; i>0;i--){ // all stock levels shift one day further
        stock[i] = stock[i-1];
    }
    stock[0] = 0;
    day++;
}

void performOutdating(){
    int numberOfOldProducts = stock[lifetime];
    for (int i = 0; i<numberOfOldProducts;i++) {
        if (exponentialDecay()) {
            subrunoutdate++;
            stock[lifetime]--;
            totalStock--;
        }
    }
}

void processCustomer(){
    int sales = geometricDrawing(); // geometric number of products
    if (sales > totalStock) {

```

```

        subrunlostsales += (sales - totalStock);
        sales = totalStock; // you cannot sell what you do not have
    }
    totalStock -= sales;
    double r = Math.random();
    if (r < FIFO) {
        takeFIFO(sales);
    }
    else takeLIFO(sales);
}

void takeFIFO(int sales) {
    int i = 0;
    while (sales > 0) {
        if (sales > stock[lifetime-i]) {
            sales -= stock[lifetime-i];
            stock[lifetime-i] = 0;
        }
        else {
            stock[lifetime-i] -= sales;
            sales = 0;
        }
        i++;
    }
}

void takeLIFO(int sales) {
    int i = lifetime;
    while (sales > 0) {
        if (sales > stock[lifetime-i]) {
            sales -= stock[lifetime-i];
            stock[lifetime-i] = 0;
        }
        else {
            stock[lifetime-i] -= sales;
            sales = 0;
        }
        i--;
    }
}

void replenish(){
    subrunorders += order;
    stock[0] += order;
    totalStock += order;
}

```

```

void orderStock(){
    double d;
    d = Math.max ( dayweights[day%7] * alpha*( demand[day%7] + demand[(day+1)%7] )
/geometric - currentStock(),0);
    order = (int) Math.round(d/batch_size)*batch_size; // can only order multiple packages.
    if (order < orderinfoLimit ) {
        lowordercounter++;
    }
    else lowordercounter=0;
    if (lowordercounter >= 3){
        d = Math.max ( orderinfoFactor*dayweights[day%7] * alpha*( demand[day%7] +
demand[(day+1)%7] ) /geometric - currentStock(),0);
        order = (int) Math.round(d/batch_size)*batch_size;
    }
}

double currentStock(){
    int som = 0;
    for (int i=0; i<=lifetime;i++){
        som+= ageweights[i]*stock[i];
    }
    return som;
}

void resetData(){
    totalOutdated = totalLostSales = totalOrder = day = totalStock = 0;
    outdatesq = lostsalesq = subrunorders = subrunoutdate = subrunlostsales= 0;
    lowordercounter =0;
    stock = new int[lifetime+1];
    for (int i = 0; i<=lifetime; i++) {
        stock[i] = 0;
    }
    lowordercounter = 0;
}

void simulateDay(){
    replenish(); // process order of yesterday
    orderStock(); // place order for tomorrow
    double expectedArrivals = demand[day%7];
    int realisedArrivals= poissonDrawing(expectedArrivals);
    for (int i =0;i<realisedArrivals;i++){
        processCustomer();
    }
    processDayEnd();
}

```

```

void start() {
    for (int k = 0; k<WARMUP_LENGTH; k++) {
        simulateDay();
    }
    resetData();
    for (int j = 0; j<NUMBER_OF_SUBRUNS;j++) {
        for (int i = 0; i<SUBRUN_LENGTH; i++) {
            simulateDay();
        }
        subrunEnd();
    }
    printAnalysis();
}

void subrunEnd(){
    totalOrder += subrunorders;
    totalOutdated += subrunoutdate;
    totalLostSales += subrunlostsales;
    outdatesq += subrunoutdate*subrunoutdate/subrunorders/subrunorders;
    lostsalessq +=subrunlostsales*subrunlostsales/subrunorders/subrunorders;
    subrunorders = subrunoutdate = subrunlostsales= 0;
}

void printAnalysis(){
    out.printf("Total days simulated: %d.\n", day);
    double mean = totalOutdated/totalOrder;
    out.printf("%.2f%% of the ordered amount gets outdated.\n", 100*mean);
    double stderror = Math.sqrt( (outdatesq - NUMBER_OF_SUBRUNS*mean*mean) /
((NUMBER_OF_SUBRUNS-1)*NUMBER_OF_SUBRUNS) );
    out.printf("95%% confidence interval: %.2f%% , %.2f%% .\n", (mean-
T_DISTR*stderror)*100 , (mean+T_DISTR*stderror)*100);
    double mean2 = totalLostSales/totalOrder;
    out.printf("%.2f%% of the ordered amount is a lost sale.\n", 100*mean2);
    double stderror2 = Math.sqrt( (lostsalessq - NUMBER_OF_SUBRUNS*mean2*mean2) /
((NUMBER_OF_SUBRUNS-1)*NUMBER_OF_SUBRUNS) );
    out.printf("95%% confidence interval: %.2f%% , %.2f%% .\n", (mean2-
T_DISTR*stderror2)*100 , (mean2+T_DISTR*stderror2)*100);
    out.printf("SOM = %.2f \n", (mean+mean2)*100);
    result = mean+mean2;
}

public static void main(String[] args) {
    new Simulation().start();
}

```

Appendix B: Additional graphs and tables

λ	q	p	d	r	Maximal α	Lost sales
2	0.75	0.4	5	100%	0.92	32,72%
2	0.75	0.4	9	100%	1.68	3.83%
2	0.75	0.4	5	50%	1.06	25.00%
2	0.75	0.4	2	25%	0.46	70.92%
2	0.75	0	5	100%	0.80	53.84%
2	0.75	1	5	100%	1.26	13.04%
5	0.75	0.4	5	100%	1.22	5.87%
5	0.75	0.4	9	100%	2.00	0.07%
5	0.75	0.4	5	50%	1.32	3.78%
5	0.75	0.4	2	25%	0.70	53.39%
5	0.75	0	5	100%	0.94	19.85%
5	0.75	1	5	100%	1.62	0.90%
20	0.75	0.4	5	100%	1.40	0.14%
20	0.75	0.4	9	100%	2.24	0.000%
20	0.75	0.4	5	50%	1.46	0.05%
20	0.75	0.4	2	25%	1.00	7.26%
20	0.75	0	5	100%	1.04	6.38%
20	0.75	1	5	100%	1.86	0.001%

Table B1: Table of variables keeping outdating below 1%

In real life situations, optimization is usually more constraint-based than classic optimization. Therefore, tables B1 and B2 were added to give insight in the trade-off between lost sales and outdating. Table B1 shows the optimal values with a constraint on less than one percent outdating, and table B2 shows the optimal values with a constraint on lost sales being less than one percent.

λ	q	p	d	r	Minimal α	Outdating
2	0.75	0.4	5	100%	2.92	33.45%
2	0.75	0.4	9	100%	2.16	4.09%
2	0.75	0.4	5	50%	2.18	14.90%
2	0.75	0.4	2	25%	2.18	25.00%
2	0.75	0	5	100%	2.94	37.15%
2	0.75	1	5	100%	2.54	21.36%
5	0.75	0.4	5	100%	1.70	7.42%
5	0.75	0.4	9	100%	1.62	0.07%
5	0.75	0.4	5	50%	1.62	3.52%
5	0.75	0.4	2	25%	1.68	13.83%
5	0.75	0	5	100%	2.00	21.11%
5	0.75	1	5	100%	1.62	0.98%
20	0.75	0.4	5	100%	1.24	0.10%
20	0.75	0.4	9	100%	1.24	0.000%
20	0.75	0.4	5	50%	1.24	0.05%
20	0.75	0.4	2	25%	1.26	2.96%
20	0.75	0	5	100%	1.32	6.90%
20	0.75	1	5	100%	1.24	0.000%

Table B2: Table of variables keeping lost sales below 1%