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MSc Thesis

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Incorporating the effect of expiration date-based pricing on consumer decision making in an inventory model

Operations Research & Logistics and Marketing & Consumer Behaviour

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Abstract

Food waste is a significant problem. Knowing that 15 percent of perishable products go to waste in grocery retailing due to damage and spoilage, reducing food waste in this sector offers significant opportunities for improvement. The main objective of this research is to incorporate the effect of expiration date-based pricing on consumer decision making in an inventory model in order to reduce food waste. Based on a literature study, the actual product choice of consumers is determined by the equivalence of the price of the product, including discounts, and the willingness to pay of consumers for that product. An inventory model is developed in MatLab which covers the product-flow of a perishable product through the stock of a grocery retailer including this willingness to pay decisions structure. By experimentation through simulation, evaluation of the performance measures determines which inputs effectively and efficiently reduce food waste. Results show that the usage of discounts has a positive influence on a retailer's profit, mean weekly sales, and reduction of food waste and is therefore advised to apply in practice. Comparing models with and without a willingness to pay decisions structure, show results in favour for the model without the structure. Therefore, it can be stated that not including the willingness to pay of consumers is an optimistic way of modelling consumer selection behaviour.

Keywords: Pricing; Expiration date; Consumer decision making; Inventory model; Simulation

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PREFACE

This report is the result of my master thesis project, performed in partial fulfilment of the requirements for the degree of Master of Science in Operations Research and Logistics at the Wageningen University.

Finishing this report means finalizing my student life and start a new phase in my life; the working life. Although I have enjoyed the student life, I am looking forward to apply my developed skills and knowledge in practice and make the best of my career.

I would like to thank my supervisors; René Haijema and Andres Trujillo-Barrera for the support during the thesis process. I am grateful for the provided feedback and I liked the sparring sessions where I gained useful insights to integrate in my thesis.

Hopefully you enjoy reading it.

Bart Bijlsma

Wageningen, March 2016

EXECUTIVE SUMMARY

The main objective of this research is to incorporate the effect of expiration date-based pricing (EDBP) on consumer decision making in an inventory model in order to reduce food waste. To achieve the objective, this research is divided into three different phases; a literature study, the model development and the experimentation phase.

The literature study operationalized the relation between EDBP and consumer decision making. Relevant theoretical concepts are defined and turned into measurable variables for the purpose of modelling. Based on the literature study, the conjunctive decision rule is chosen to model consumer decisions. This means that the actual product choice consumers make is based on cut-off levels for product attribute values. In this study, the product attribute value is the objective price of the product including discounts, and the cut-off level the willingness to pay (WTP) by consumers for that product. Thus if the objective price, is lower than or equal to the WTP of consumers, this particular product is picked.

The developed inventory model covers the product-flow of a perishable product through the stock of a grocery retailer and includes the WTP decision structure. The article of Tsiros and Heilman (2005) provided the data for the WTP of consumers and how this WTP differs for an increasing age of the product. This research shows how consumer decision making can be modelled and how the integration of consumer behaviour in this model differs from current practices. An important modelling modification is the input for the average amount of consumers entering the model per weekday. To equate mean weekly sales between the model with WTP and without WTP, the average amount of consumers entering the model needed to be tripled. Using the WTP decision structure results in less consumers who actually pick a product, since also consumers with a low WTP are included in the model. Differences in mean weekly sales influences the total model and corrupts the outcomes. Consequently, different inputs for the average amount of consumers entering the model are used for experiments including WTP and experiments excluding WTP.

The design of experiments entails three factors; the shape of WTP curve, the fraction of consumer picking LIFO, and the application of different discounting levels. Through simulation with variable inputs for the three experimental factors, evaluation of the performance measures determines which inputs effectively and efficiently reduce food waste. Furthermore, a comparison of the performance measures is made between

implementing and not implementing a WTP decision structure. The effectiveness is measured in terms of the percentage food waste and the efficiency in terms of the loss of revenue. The percentage food waste is the fraction of products disposed from the total amount of products. The loss of revenue is calculated by multiplying the estimated lost sales with the retail price plus the loss of revenue due to discounting.

Results of the different experiments show that if no discounting is applied, about 14% of the products will go to waste. In contrast, using high discount levels (up to 60% on the last day of the remaining shelf life of a product) decreases this percentage to less than 1%. However, using these high discount levels increases the loss of revenue since more consumers pick discounted, and thus cheaper, products. Despite the loss of revenue, gross profit mainly increases when discounting is applied due to the increase in mean weekly sales. The lower prices attract more consumers who actually pick a product. However, the gross profit shows a tipping point when applying higher discount levels. The increase in mean weekly sales does not accommodate anymore for the loss of revenue when applying high discounts, which results in a lower gross profit. Therefore, it can be concluded that increasing the effectiveness of EDBP in order to reduce food waste is at the expense of the efficiency of EDBP by losing more revenue. Nevertheless, it is concluded that, up to a certain level, applying discounting has positive effects for retailers and is therefore advised to apply in practice. Compared to the base scenario, using 35% discount on the last two days of the remaining shelf life shows a decrease in the percentage food waste and the loss of revenue. This strategy is based on practice, but is now proven to be the best strategy regarding the effectiveness and efficiency of EDBP. Furthermore, results show that while increasing the fraction of LIFO consumers in the model, food waste increases and mean weekly sales and gross profit decreases. It is advised that retailers implement tactics in their daily operations to prevent consumers from picking LIFO. One tactic might be using deeper discounts earlier in a products shelf life. This appears to be necessary to influence LIFO consumer to pick older products. This research also compares two different models. Namely between a model where WTP is included and a model where WTP is not included. This comparison shows how consumer behaviour is differently integrated in this research compared to current operation research practices. Results show differences in favour of the model without WTP, since for this model the percentage food waste is lower, the loss of revenue is lower, and gross profit is higher compared to the model including WTP. Therefore, it can be stated that not including WTP is an optimistic way of modelling consumer selection behaviour.

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INTRODUCTION

Food waste is a significant problem. The United Nations Food and Agriculture Organization (FAO) estimates that one third of human food production (around 1.3 billion tonnes per year) is lost or wasted globally (FAO, 2011). When converted into calories, one out of every four food calories intended for people is not ultimately consumed by them (Lipinski et al., 2013). The waste of food has many negative economic and environmental impacts. Economically, food waste represents a wasted investment and increase expenses of consumers (FAO, 2014; Lipinski et al., 2013). Environmentally, food waste contributes heavily to global carbon emissions (FAO, 2015) and inefficient uses of water and land can lead to diminished natural ecosystems (Nellemann et al., 2009). Moreover, food waste is ethically unjustifiable in a world where almost 1 billion people remain undernourished.

Although consumers themselves are the biggest wasters, food waste occurs in all stages of the supply chain, from agricultural production to distribution to retailers (Wyman, 2014). The industry has already responded with associations such as the Food Waste Reduction Alliance in the US, the Waste and Resource Action Programme (WRAP) in the UK, and the Retailers' Environmental Action Programme (REAP) in Europe. These programmes are established with the reduction of food waste as their primary goal. This study will focus on the reduction of waste in the retail sector, the final stage in the food supply chain where products are sold to the consumers. Reducing food waste benefit the retailer primarily economically. WRAP (2015) estimate that the typical cost of food waste for retailers is between 4% and 5% of a company's turnover, but can be as high as 10% in some cases. Besides, food waste is a problem that attracts significant political and media attention, which could provide or cost the retailer its competitive advantage (Wyman, 2014). Moreover, due to stricter legislation from the European Union (Council of the European Union, 2014), retailers have a duty to operate according to this principle. Food waste in the retailing sector is mainly avoidable, thus at some point prior to disposal, edible (WRAP,

2009). Knowing that 15% of perishable products go to waste in grocery retailing due to damage and spoilage (Ferguson & Ketzenberg, 2005), reducing food waste in this sector offers significant opportunities for improvement.

Perishable products have to move fast from field to fork to maintain product quality, leaving the seller unable to store the product awaiting favourable market conditions (Hobbs, 1999). The FAO (2015) and the BIO Intelligence Service (2010) indicate that inventory management is a key issue affecting food waste within the retail industry, where overstocking is often the result of difficulties in anticipating demand. If supply is larger than demand, more products will pass their expiration date before being purchased. This results in the disposal of these products and thus large expenses for retailers (BIO Intelligence Service, 2010). The opposite of overstocking, out-of-stock situations, is also unwanted by retailers since this leads to consumers not purchasing products, substituting stores or brands, or delaying their purchase (Gruen et al., 2002). Without changing the product availability and service level of a retailer, this study seeks possibilities to reduce avoidable food waste and thus costs through the influence of pricing on consumer decisions. In retailing, it is common to offer a fixed percentage markdown on items that near their expiration date, to influence the consumer's buying behaviour and reduce waste (Bakker et al., 2012; Van Donselaar et al., 2006). In literature, this pricing tactic is referred to as expiration date-based pricing (EDBP) (Theotokis et al., 2012). According to the review of Bakker et al. (2012) about deteriorating inventory models, many papers address price-dependent demand by including a fixed percentage markdown on products that almost reach their expiration date. However, these studies (Abad, 2003; Anjos et al., 2005; Bitran et al., 2006; Chatwin, 2000; Chew et al., 2014; Chun, 2003; Maihami & Kamalabadi, 2012) make assumptions about consumer effects in their models, based on very little empirical evidence from real life scenarios. In contrast, this study builds on the empirical evidence of the effect of expiration dates on consumer purchasing behaviour by Tsiros and Heilman (2005). Their results and findings are used to develop an inventory model based on a real life case. The present study is also different from those mentioned previously, since the purpose of this study is to reduce food waste, using the effect of pricing on decision making, where other studies seek optimal parameter values for their models or aim to maximize the profitability of retailers. The paper of Theotokis et al. (2012) has a similar spirit, here the effects of EDBP on brand image perceptions are studied. They suggest additional research to focus on the effects of EDBP on purchasing intentions or decisions. The main contributions of this study are twofold:

1) Providing theoretical insights in the relation between EDBP and consumer decision making;
2) Propose how EDBP can contribute to the reduction of food waste by incorporate the effect in an inventory model.

1.1 Research objective & questions

The main objective of this study is to incorporate the effect of expiration date-based pricing on consumer decision making in an inventory model in order to reduce food waste.

To achieve the main objective, this study is divided into three different phases. The first phase entails a literature study where the relation between EDBP and consumer decision making is operationalized. Relevant theoretical concepts are defined and turned into measurable variables for the purpose of modelling.

1. *What is the relation between EDBP and consumer decision making?*

- How does EDBP differ from other pricing policies?
- How do consumers make decisions regarding perishable products?

The second phase of this study entails the development of an inventory model. This model covers the product-flow of a perishable product through the stock of a grocery retailer. The relation between EDBP and consumer decision making will be integrated within this model. The fixed and variable parameter values for the model will be collected via desk research and primarily via the article of Tsiros and Heilman (2005) on the influence of expiration dates on purchasing behaviour.

2. *How can the product-flow of a perishable product be modelled by incorporating the relation between EDBP and consumer decision making?*

- Which key performance indicators evaluate the effectiveness and efficiency of EDPB in order to reduce waste?
- Which parameters and variables are necessary to develop a perishable inventory model?
- How are the necessary parameters and variables connected including the relation between EDBP and consumer decision making?

The third phase is the experimentation phase. By experimenting through simulation with variable parameter inputs, evaluation of the outcomes determines which inputs have the greatest impact in order to reduce food waste. For retailers, also an evaluation of the loss of revenue is given. Besides, a comparison is made between implementing and not implementing EDBP. The effectiveness of EDBP is measured in terms of the reduction of food waste and the efficiency of EDBP approximates whether the effectiveness is profitable for retailers.

3. How effective and efficient is EDBP in order to reduce food waste?

- How do different parameter inputs perform compared to each other?
- How much food waste can be prevented?
- How much loss of revenue can be prevented?

1.2 Research framework

This study develops an inventory model, incorporating the flow of a perishable product through a stock within the environment of grocery retailers.

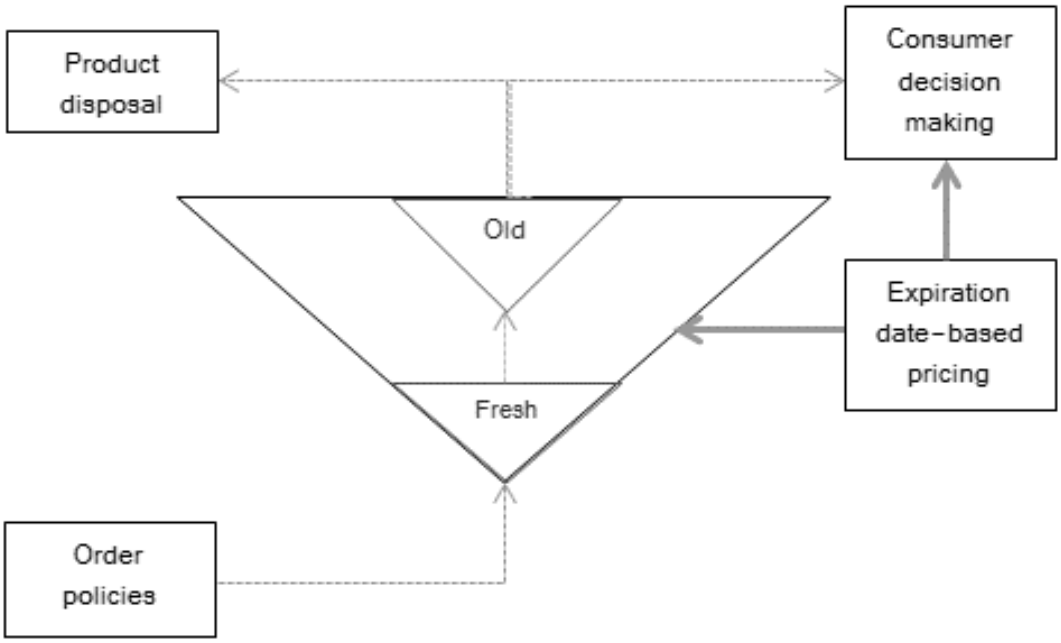

Figure 1: *Representation of proposed inventory model*

The representation in Figure 1 is the basis for this research and will be used to develop the inventory model and perform the experiments. The larger triangle represents the stock of perishable products, and within this stock there are multiple products of the same type ordered based upon their remaining shelf life. Products that are not sold before reaching their expiration date due to too little demand, will be disposed. From literature it appears that consumers prefer a last in first out (LIFO) withdrawal, since these are the products with the highest degree of freshness (Broekmeulen & van Donselaar, 2009). Whether consumers pick the freshest product (LIFO) or the oldest product (FIFO) extensively influences the dynamics of the inventory and is therefore within the scope of this research. The oldest products, thus the products that are closest to passing their expiration date, will be provided with a percentage markdown to influence consumer decision making. The dotted lines represent the product-flow of the inventory model and the bold lines indicate that EDBP is provided on the products in the stock and is related consumer decision making. The total

process of the product-flow including EDBP and consumer decision making will be modelled and simulated. Due to variable parameter inputs, this model gives insights in how efficient and effective EDBP is in order to reduce food waste and the loss of revenue. Paragraph 1.4 elaborates on the mentioned main concepts to better understand the relations between them.

1.3 Materials and methods

To answer the research questions and achieve the objective, this study entails two research strategies. An extensive literature study will be done, where books, articles, and journals will be reviewed to give insights in the relation between theoretical concepts. The study forms the foundation of the inventory model, since this study describes the relation between EDBP and consumer decision making. The second research strategy is experimentation through simulation. The process of Figure 1 will be modelled and simulated to gain insights in the performance of the variable parameter inputs.

1.3.1 Literature study

The main issue within the literature study is a description of the relation between EDBP and consumer decision making to answer the first research question. As mentioned previously, this study builds on the empirical evidence of Tsiros and Heilman (2005) who already investigated how consumer purchasing behaviour differs for different ages of perishable products. The results of the literature study will be integrated in the inventory model and therefore form the foundation of this research.

1.3.2 Modelling and simulation

The performance of variable parameter inputs will be evaluated through simulation to achieve the proposed objective. Simulation can be seen as the process of designing a model of a system, which in this case is the model of Figure 1, and conducting experiments with this model for the purpose either of understanding the behaviour of the system or of evaluating various strategies for the operation of the system (Shannon & Johannes, 1976). The inventory model in this study is described as an external and explicit representation of a stock where products are held available, in this case, for consumers (Claassen & Hendriks, 2007; Pidd, 1999). This model thus approximates a real stock in a grocery retail environment in order to understand, change, manage, and to control the product-flow within this stock. Models can be divided into physical and mathematical models (Kelton & Law, 2000). Where physical models refer to, for example, cockpit simulators, mathematical models represent a system in terms of logical and quantitative relationships. For this study, a mathematical simulation model will be developed where the relationships between the components of

the model explained. The experimental factors of the model are changed to see how the model reacts, and thus how the actual system would react, provided that the model is valid. The proposed inventory model of Figure 1 will be stochastic of nature, since demand uncertainty plays a large role in this study. In order to develop a well-structured inventory model and to be able to answer the second research question, a conceptual model will be proposed according to following pillars: objectives of the model, experimental factors, responses, and model content. Since variables vary at distinct, separate points in time, namely weekdays, discrete time simulation is used to mimic the process of a stock-flow over time and to answer the third research question. Simulation and experimentation will be done via a computer model implemented in MatLab, which is technical computing software enabling the design, simulation and experimentation of proposed models, developed by MathWorks. A design of experiments gives substance to the experimental phase where adjustable parameters are defined to gain insights in the effectiveness and efficiency of EDBP in order to reduce food waste.

1.4 Definitions and boundaries

In Figure 1 several theoretical concepts are used to explain the flow of a product through a stock of a grocery retailer. Several definitions and boundaries may be related to the product-flow in this research. To avoid misconceptions about the concepts and to be able to better understand the relations between the concepts, here the definitions and boundaries of the main concepts are given.

Retailing

The inventory model developed in this study is applicable for a grocery retailing environment, for example supermarkets. Grocery retailing is the final stage in the supply chain and is defined as the process of selling goods to consumers to make profit.

Perishability

A product is perishable if during the planning period its physical status noticeably worsens, and/or its value decreases in the perception of consumers, and/or if there is a danger of future reduced functionality in some authority's opinion (Amorim et al., 2013). Van Donselaar et al. (2006) distinguish between perishables with a maximum shelf life of 9 days, called Days Fresh and perishables with a shelf life between 10 and 30 days, called Weeks Fresh. The

focus in this study will be on Days Fresh perishables since the waste of this product category is the largest (FAO, 2015). In this study, the shelf life of Days Fresh perishables entails the period from arriving at the retailer till the expiration date of the product.

Product scoping

Beef is a typical Days Fresh product and this product will be used as example of how EDBP can be used to reduce food waste in a retailing environment. Main reasons for the choice of beef are: (1) the expiration date of beef is an important product characteristic for consumers regarding the purchase of beef (Erikson et al., 1998), (2) beef is a fairly expensive product compared to other Days Fresh products, (3) the department of meat loses more products due to waste, compared to overall waste (Tsiros & Heilman, 2005), (4) producing beef has a large environmental impact (Herrero et al., 2013), the more reason to reduce the waste of this product.

Expiration-date based pricing

EDBP is explicitly defined as a pricing tactic with which a retailer charges different prices for the same perishable products, according to their respective expiration dates (Theotokis et al., 2012). Different terms may be applicable for this definition (dynamic pricing, markdown pricing, discounting), which is valid as long as the price of the product is determined by the age of the product. More in-depth theory on this concept is given in paragraph 2.1.

Expiration dates

Food dating is typically provided in one of three forms: “Best before”, “Use by”, and “Sell by”. The definition most applicable for retailing is used in this study; the expiration date indicates the last day a product should be sold, thus “Sell by”. The expiration date thus indicates a products remaining

shelf life and is often in literature referred to as freshness date.

Consumer decision making Consumer decision making is defined as a process that can be summarized in four steps: (1) problem recognition, (2) information search, (3) evaluation of alternatives, and (4) the product choice (Solomon, 2013). More in-depth information on this concept is given in paragraph 2.2.

Picking order The picking order is a process in inventory management that determines, in this case, how consumers pick products from the stock, also referred to as consumer selection behaviour. Several policies may describe this picking process, but LIFO (Last in, First out) and FIFO (First in, First out) have the largest influence on this research. LIFO entails picking the freshest product and FIFO entails picking the oldest product.

1.5 Reading guide

The remaining of this report is organised as follows. Chapter 2 presents theory on the relationship between EDBP and consumer decision making. The last paragraph of that chapter is summarizing and answering the first research question. Chapter 3 explains how the model is developed and answers the second research question. The first part of this chapter is a description of the conceptual model including the model objective, experimental factors, responses, and content. The second part explains the parameterized model which is the mathematical elaboration of the model. Here decisions for the model are justified and explained together with the identification of used indices, parameters, variables, and performance measures. Chapter 4 justifies the input values for the model parameters. A design of experiments is developed to give an overview of the input values of the experimental factors which evaluate the effectiveness and efficiency of EDBP in order to reduce waste. Chapter 5 discusses the results of the experiments. Finally, chapter 6 gives the conclusions and explains how the main objective is achieved.

2

THEORY ON EDBP AND CONSUMER DECISION MAKING

By reducing the food waste due to spoilage, a retailer may be able to increase its profits by as much as 15% (Hennessy, 1998). Using discounts on older perishables may be an effective way, since the effectiveness of price promotions is greater for perishable products than for other categories (Nijs et al., 2001). Therefore, this literature study investigates how EDBP and consumer decision making are related to be able to use pricing as a tool to influence consumer decisions in order to reduce food waste. The outcomes of this study indicate how the relation is operationalized and positioned within the proposed framework of Figure 1.

The first paragraph elaborates the concept of EDBP and how it differs from other pricing policies. The second paragraph explains theory on consumer decision making. Within each subparagraph is indicated how consumer decision making is related to EDBP. The third paragraph gives a final summary to answer the first research question.

2.1 Expiration date-based pricing

Price is an intensively researched strategic marketing variable, which has a significant influence on consumer purchasing behaviour and consequently on firm sales and profits (Han et al., 2001; Konuk, 2015). Jacoby and Olson (1977) distinguish between the objective price (the actual price of a product) and the perceived price (the price as encoded by the consumer). In traditional economic sense, the objective price is thus the amount of money that consumers must pay to acquire a particular product or services (Kukar-Kinney et al., 2012). From a consumer's point of view, price is defined as what is given up or sacrificed

to obtain a product (Zeithaml, 1988). This definition is related to the concept of perceived price, specifically what constitutes as value for consumers. Researchers differently define the construct of perceived value, although most of them meant the same concept with all a 'give' and a 'get' component (Woodruff, 1997). For this research, the definition of Zeithaml (1988) is adapted where perceived value is defined as a consumer's overall assessment that examines the utility of an object, based on perceptions of what is received and what is given. How this assessment is related to EDBP is discussed in paragraph 2.2.3 and 2.2.4. In order to reduce the 'give' component, companies often use sales promotions to stimulate consumer buying behaviour for a particular product or service (Kukar-Kinney et al., 2012). Markdowns, coupons, two-for-one deals, gifts, etc., are examples of a wide variety of short-term tactical promotion tools, with all the similar aim to stimulate purchasing decisions (Grewal et al., 2011). In the context of perishability, marketing researchers emphasise the importance of expiration dates. Research shows that consumers take this product characteristic into account when making decisions about perishables (Sen & Block, 2009; Tsiros & Heilman, 2005). For beef in particular, Erikson et al. (1998) investigate which characteristics affect consumer purchasing decisions in the United States, Japan, and Australia. Their study shows that the expiration date is the most important characteristic (out of eleven items) in the United States and Australia influencing the purchase decisions towards beef, and the second most important characteristic in Japan. Tsiros and Heilman (2005) state that 84% of the consumes researched, believed that the quality of beef deteriorated as the product approaches its expiration date. To accommodate for this believe and stimulate purchasing decisions, retailers reduce the price of this perishable product according to its remaining shelf life (Theotokis et al., 2012). This tactic is already applied in practice and referred to as EDBP, but is a relatively new and unknown phenomenon in research (Grewal et al., 2012).

Theotokis et al. (2012) define EDBP explicitly as a pricing tactic in which a retailer charges different prices for the same perishable products, according to their respective expiration dates. EDBP is a form of second-degree price discrimination where the expiration date represents the physical rate fence that discriminates prices (Theotokis et al., 2012). This is justifiable from a consumer's perspective, if the price differences can be attributed to quality differences (L. E. Bolton et al., 2003). EDBP has some particular characteristics that distinguish it from other pricing practices. Firstly, EDBP provides consumers with options, since consumers can choose whether they will buy a discounted, older product or a regularly priced, fresher version of the product (Theotokis et al., 2012). If discounting was not applied, consumers typically prefer products with the highest degree of freshness (Broekmeulen & van Donselaar, 2009). This primarily holds in an environment where consumers are able to see the expiration date on the package and where they are allowed to select the item, which is the case in retailing. Providing consumers with the option to select the older and

discounted product instead of the fresher and regular priced alternative, could change the picking order of consumers and thus the flow of the stock. Secondly, EDBP can solely be applied to perishable product categories, which are of increasing importance for grocery retailers. Around 50% of the total turnover of grocery retailers can be accounted to the sale of perishable products (Thron et al., 2007). Besides perishables are largely accountable for a retailers image (Tsiros & Heilman, 2005). Thirdly, in contrast with in-store promotions, the discounted product in EDBP is presented right next to the fresher, regular price alternative. The expiration date functions as a signal of product quality or as an attribute that defines the value of the product (Grunert, 1997; Sen & Block, 2009; Tsiros & Heilman, 2005). Therefore, the price-quality trade-off is immediately presented to consumers.

2.2 Consumer decision making

As indicated, EDBP offers consumers with options, namely a regular priced, fresh product or a discounted, less fresh version of the product. This study assumes consumers cannot have both options, and therefore they need to make a decision. There is a vast amount of literature regarding consumer decision making, since the decisions consumers make are not only of great importance to themselves, but also to marketers and policymakers (Bettman et al., 1991). The disciplines of marketing and psychology have developed decision-making theories for over 60 years which resulted in different perspectives concerning to approach to consumer decision making. Traditionally, consumer researchers approached decision-making from a rational perspective, where it is assumed consumers form expectations of the value of additional information and continue to search to the extent that the rewards of doing so exceed the costs (Solomon, 2013). However, this perspective assumes that decisions are based on unlimited information that can easily be utilized with full knowledge about options (Plous, 1993), which forms a major issue due to bounded rationality of consumers (Simon, 1955). Researchers are now realizing that consumers seek satisfaction, not maximization (Shams, 2013). A consumer evaluates the effort required to make a particular choice, and then choose a strategy best suited to this level of effort (Solomon, 2013). This study considers the problem solving decision process from a satisficing perspective. The process of decision making can be summarized in four steps: (1) problem recognition, (2) information search, (3) evaluation of alternatives, and (4) the product choice (Solomon, 2013).

In order to characterize the decision-making process in this study, the extent to which a decision solves a particular problem is taken into account. Deshpande and Hoyer (1983) show in their study that consumers put significantly less effort in choosing peanut butter than in choosing an automobile. Decisions regarding grocery shopping are often found to

be limited problem-solving, where choices are made with little cognitive effort based on little information (Hoyer, 1984).

2.2.1 Problem recognition

The first step is problem recognition, where consumers should recognise that there is a gap between their ideal state and actual state (Gordon & Richard, 1988), which can occur in two ways. On one hand, a consumer's actual state can move downwards or decrease, which leads to need recognition. On the other hand, a consumer's ideal state can move upwards, which leads to opportunity recognition. In the case of grocery shopping, consumers recognise a need if run short of a particular product, since their actual state is decreasing (Solomon, 2013). This study focuses primarily on the actual decisions made between the options EDBP provides. Therefore, it is assumed that consumers have already an inherent motivation to fulfil their consumption goals, which entails the purchase of beef.

2.2.2 Information search

Consumers need adequate information to make the decision between purchasing a regularly priced, fresh product or a discounted, older version of the product. Information search is the process where consumers acquire appropriate data to make a reasonable decision (Solomon, 2013). Within this process the distinction between different perspectives towards consumer decision making becomes clearest. From the rational perspective it is said that consumers seek the best possible result by acquiring as much external and internal information as possible. Although, nowadays researchers realize that consumers simply try to yield an adequate satisficing solution. With common repeat purchases, as with grocery shopping, consumers may apply very simple choice rules or tactics (Hoyer, 1984) and thus not acquire as much information as possible. Examples of these tactics could be related to price (buy the cheapest product) or affection (buy the most pleasing product). Research on common behaviour shows that consumers base their decision on limited information search (Moorthy et al., 1997) rather than a detailed evaluation off all possible alternatives (Chernev, 2003).

Relation to EDBP

A relevant piece of information for a perishable product is its expiration date (Tsiros & Heilman, 2005). The expiration date of a perishable product is often used to indicate the freshness of the product (Erikson et al., 1998; Harcar & Karakaya, 2005; Sen & Block, 2009; Tsiros & Heilman, 2005). Cardello and Schutz (2003) state that the importance of food freshness in terms of the expiration date, is ranked just below taste and nutrition and on par with price regarding the purchase of a perishable product. It is found that the expiration date as a product attribute is one of the most important product attribute (together with

cleanliness of display case) influencing decisions for consumers when purchasing beef (Erikson et al., 1998). Besides the indication of a product's freshness, expiration dates influence all consumers regarding consumer protection and safety (Harcar & Karakaya, 2005).

As stated in the research of Harcar and Karakaya (2005), a consumer review report from A.C. Nielson Company indicated that 91% of the consumers surveyed, claimed that they were aware of product expiration dates. The same study showed that 88% of the respondents always or frequently look for this type of information. However, Harcar and Karakaya (2005) found that 62% of the respondents of the United States checked the expiration date before purchasing the product. In the case of beef, it is found that 78% of the people surveyed are aware of the expiration date and 58% always or usually check this type of information, although 84% of the respondents believe that the quality deteriorates as the product approaches its expiration date (Tsiros & Heilman, 2005).

Price is, besides the expiration date, also an attribute that differentiates the two provided options of EDBP from each other. As indicated in paragraph 2.1, Jacoby and Olson (1977) distinguished between the objective price and the perceived price. The objective price is often associated to quality, value and purchase intentions and when making purchasing decisions, consumers often compare the objective price with their internal reservation price (Chang & Wildt, 1994). The reservation price hypothesizes that each consumer has a maximum price he or she is willing to pay for a particular product (Kalish & Nelson, 1991). If a consumer believes that the quality deteriorates as a product perishes, it becomes more likely that this consumer will pick the fresher version of the product for the same price, since the reservation price and objective price of the older version of the product do not match. The decision consumers eventually make, therefore depends on the equivalence of the objective price and the reference price. This idea is based on the satisficing heuristic from (Simon, 1955), where values of attributes of alternatives are compared to a predefined cut-off level. Although Jacoby and Olson (1977) conclude that marketers and consumer behaviourists do not know which consumers will seek price information for which products under which circumstances, price is included as a relevant piece of information consumers for due to its relation with purchasing decisions (Chang & Wildt, 1994).

Several studies show that the majority of the consumers, at least 58% (Tsiros & Heilman, 2005), check the expiration date before purchasing a product. Moreover, the importance of expiration dates regarding the purchase of perishable products is indicated. For these reasons it is assumed that during the information search, consumers evaluate the different options EDBP provides, based upon the expiration date. Whether the actual purchase is

done, depends on if the consumers are willing to pay the objective price asked for the product. Therefore, price is also assumed to be an attribute consumers search for.

In practice, many other information cues may influence a decision of consumers. For example, it is showed that brand names and store names often influences purchase intentions (Grewal et al., 1998; Rao & Monroe, 1989). Also more product attributes may be of importance to consumers, for example colour of the beef or knowing where the meat was produced (Erikson et al., 1998). These attributes do not contribute to the main objective of this research and are outside the scope of focus although they might be of importance regarding decision making. As mentioned, the decision making process is characterized as limited problem-solving. Solomon (2013) stated that for limited problem-solving decisions, consumers use little search and the decisions are likely to be made in-store. Therefore, this study solely focuses on price and the expiration date as information cues and assumes the purchase decision is made in-store, since EDBP is an in-store promotional strategy (Theotokis et al., 2012).

2.2.3 Evaluation of alternatives

Much effort is done by researchers to understand why a particular choice is made consumers. For consumers making a purchasing decisions has also become increasingly difficult in modern consumer society with a wide variety of choices. For example with deodorant, where there are dozens of brands to choose from, with each brand having multiple variations of the product. During the evaluation phase, consumers compare the different alternatives presented by EDBP, thus regular priced, fresh products and discounted, less fresh versions of the product. All alternatives in this research are assumed to be in a consumers consideration set, which is the set of product that consumers actually consider buying (Solomon, 2013), since the amount of alternatives is limited and all alternatives are relevant for the consumers. As typical for limited problem-solving decisions, only key criteria are used to evaluate the alternatives (Solomon, 2013). According to means-end model of Zeithaml (1988), the actual purchase depends on consumer's perceived value of the product. Perceived value is expected to significantly influence purchase intentions (Broekhuizen, 2006) and by measuring its predictors, it provides insights in how consumers evaluate the different alternatives of EDBP. This study focuses on the meaning of value identified by Woo (1992), which refers to the amount of utility that consumers see as inseparable from a particular product they aim to maximize out of purchasing or consuming. This definition entails the value that is derived from the purchase, consumption and disposition of a product. Although literature confirmed that value has a multi-dimensional nature (Broekhuizen, 2006), the focus in this research is specifically on the functional value of the product. Sheth et al. (1991) indicate that the functional value is concerned with the utility derived from the product attributes determining product quality and product

performance, which in this case is related to a product's expiration date (Grunert, 1997; Sen & Block, 2009; Tsiros & Heilman, 2005). Previous research shows that perceived value has a context-dependent nature (R. N. Bolton & Drew, 1991; Parasuraman, 1997; Zeithaml, 1988), which means that the perceived value differs between product types, individuals, and circumstances (time, location, and environment). EDBP is only applicable for the same type of product (Theotokis et al., 2012) and the circumstances in which consumers purchase their products are outside the scope of this research, therefore the focus here is on the perceived value of individuals. The WTP is used in this study to measure the perceived value of consumers for the different alternatives of EDBP and how this WTP differs with an increasing age of the product. Using other tools to evaluate the alternatives, like perceptual mapping or importance scoping, will be difficult to implement, since the products in the consideration set are almost identical. They do not differ by brand and it is assumed that all product attributes are the same, except for the expiration date and the price. How the WTP differs for the products will actually distinguish the preferences for the alternatives. This process is elaborated in paragraph 2.2.4.

Relation to EDBP

The results and findings about the WTP of consumers for beef of Tsiros and Heilman (2005) are used as input for this study and the statistics are presented in Table 1. Tsiros and Heilman (2005) estimate the WTP across the shelf life of perishables to be able to sell the products before they expire. The expiration date measures the likelihood of spoilage, since this date determines the remaining shelf life of the product. From a consumer's point of view, Tsiros and Heilman (2005) reason that as the product approaches its expiration date, the perceived value of the product, and thus a consumer's WTP for it, should decrease. In Table 1, it is shown that the WTP drastically decreases when the remaining shelf life decreases respectively.

Table 1: *Summary statistics for beef of Tsiros and Heilman (2005)*

	Shelf Life (Days)	Retail Price	WTP (7 days)	WTP (4 days)	WTP (1 day)
Average	7	$2.68	$2.33	$1.54	$1.20
St. dev.	-	-	0.83	0.82	0.90

The WTP for a beef is not equal for all consumers. Several properties influence the WTP of consumers like the age, sex, income, or household size (Tsiros & Heilman, 2005). Therefore, this research uses fractions of the standard deviation of the WTP as input statistic in the calculation of the WTP of a consumer.

Tsiros and Heilman (2005) reason that perishable food have caused health concerns among consumers and have brought significant changes in their purchasing habits. Erikson et al. (1998) indicate that concerns of consumers towards product freshness and health issues are related to the expiration date of a perishable. Tsiros and Heilman (2005) relate these concerns with the perceived risk regarding purchasing and consumer unhealthy perishable products. Perceived risk can be defined as a belief that the product has a potentially negative consequence from using it (Dunn et al., 1986; Solomon, 2013). Tsiros and Heilman (2005) operationalize this belief into two factors. The first factor, Product Quality Risk, entailed functional, performance, and physical risk about the product itself and captured the perceived risk associated with product quality. Product Quality Risk is related to EDBP, since retailers discount perishable products to accommodate for this type of risk (Theotokis et al., 2012). The second factor, Personal Risk, entailed psychological, social, and financial risk and measured the risks associated with the negative emotions a consumer experiences when a product fails. The latter one showed to be of little importance to their research.

The decrease in WTP in Table 1 follows an exponential negative function, which was typical for products with a high product quality risk, such as beef and chicken. Tsiros and Heilman (2005) find that for products with a low product quality risk, such as lettuce, carrots, milk, and yoghurt, the WTP decreased according to a linear function.

2.2.4 Product choice

Once the alternatives of the consideration set are evaluated through the WTP of consumers, the actual product choice has to be made. These choices will be simulated in this research and therefore an approximation approach is used where choices are based upon decision rules. Solomon (2013) mentions five rules that determine the dynamics of the consideration set. These rules are divided into two categories: compensatory and non-compensatory. The compensatory rules entail the simple additive and the weighted additive rule, where a product can make up for its shortcomings. By implementing this rule, it is assumed that consumers are willing to compensate bad product attributes for good ones. In this research, the two main attributes of interest: the expiration date and the objective price. These attributes are related to each and can thus not compensate for one another. Therefore, consumers are assumed to choose based on the simpler non-compensatory rule, which entails the conjunctive, the elimination-by-aspects, and the lexicographic rule. The conjunctive rule, like the satisficing heurist of Simon (1955), involves making a particular decision if a product attribute meets the cut-off levels, while failure to meet the cut-offs means rejection of the product (Parkinson & Reilly, 1979). The conjunctive rule thus describes consumer evaluations as a binary choice: acceptance or rejection (Park, 1976), which makes the conjunctive rule well applicable for modelling and simulation purposes with clear demarcations. When using the lexicographic rule, the product that is the best on

the most important attribute is selected. If the alternatives are equally good, the second most important attribute is evaluated. Using the elimination-by-aspects rule, the alternatives are also evaluated by the most important attribute, but with predefined cut-off levels. The difference between the conjunctive and elimination-by-aspects rule is that by using the latter one, alternatives are chosen based on the most important attribute, where the conjunctive rule requires all attributes to meet the cut-off levels. In cases with more complex products (e.g. products with more attributes), the decision making process could become more extensive problem-solving, where alternatives are carefully weighted by the consumers (Solomon, 2013). From the non-compensatory rules, the conjunctive rule is most applicable for this research. Whereas the lexicographic and the elimination-by-aspects rule involve processing by attribute, the conjunctive rule entails processing per product (Parkinson & Reilly, 1979; Solomon, 2013). In this research the relation between EDBP and consumer decision making is operationalized. Due to the incorporation of EDBP, the objective price and the expiration date are related. Consequently, a most important attribute does not exist. Therefore, consumers are assumed to use the conjunctive rule to make a particular product choice. This rule is incorporated in the model and determines the selection behaviour of consumers.

Relation to EDBP

As can be seen in Figure 1, the selection of a products expresses the outflow in terms of sales. Following the conjunctive rule, whether a consumer picks a product depends on how the cut-off level for the attribute meets the actual product attribute value. The actual product attribute value in this research is the objective price, including a possible discount percentage depending on the expiration date of the product. Whether a consumer selects a product depends on the cut-off level for the objective price of this product. The cut-off level in this research is the WTP of consumers for the product, since this equals how consumers value the product. How much a consumer is willing to pay for a particular product also depends on the expiration date of the product. The WTP thus functions as a consumers reservation price, which hypothesizes that each consumer has a maximum price they are willing to pay for a particular product (Kalish & Nelson, 1991). There will be some variation per consumer regarding the maximum price due to the standard deviation of the WTP presented in Table 1. If the WTP of a consumer for product is equal to or higher than the objective price of the same product, determines whether a product is accepted or rejected.

***Table 2**: Example product choice for beef according to the conjunctive rule*

	Product 1	Product 2
Remaining shelf life	7	1
Objective price	2.68	1.07
WTP	2.33	1.20

To put this in perspective, a simplistic example will be given. Suppose the products presented in Table 2 are considered by a consumer. The first product has a remaining shelf life of 7 days. Therefore, the full objective price is asked by the retailer, which for this product is $2.68. The WTP of the consumer is $2.33 for this product. According to the conjunctive rule, this product is rejected since the product attribute value, the objective price, is higher than the cut-off level, the WTP of the consumer. The second product has a remaining shelf life of 1 day. According to the expiration date of the product, the retailer applies a discount percentage of 60% on the product which means that the objective price becomes $1.07. The WTP of the consumer is $1.20 for this product. The WTP is higher than the objective price and according to conjunctive rule the product is therefore accepted by the consumer.

2.3 Relation EDBP and consumer decision making

In paragraph 2.1 & 2.2 is explained how stages of the decision making process of consumers relate to EDBP. This paragraph gives a final summary to clarify what the relation between EDBP and consumer decision making is and how it actually will be modelled and simulated.

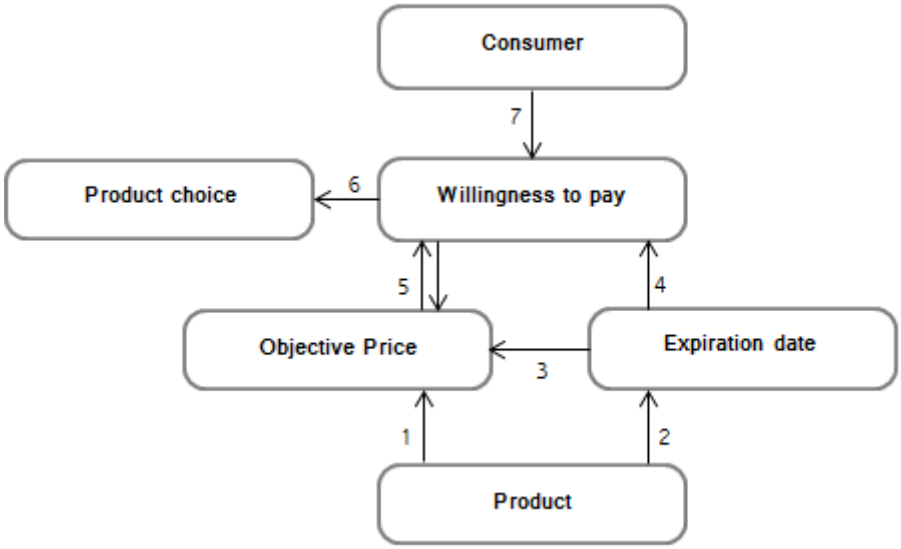

***Figure 2:** Overview relation EDBP and consumer decision making*

In paragraph 2.1 it became clear that applying EDBP on a particular product group provides consumers with options. The overview presented in Figure 2 is applicable for all alternatives presented by EDBP. The box 'product' could thus be a fresh, regular priced product as well as a discounted, less fresh version of the product. In order for a consumer to fulfil their need for a product, he or she has to make a decision about the alternatives. In paragraph 2.2.2 it was concluded, that consumers adapt two information cues from the product, presented in Figure 2 by the boxes objective price (1) and expiration date (2). It was discussed that the objective price is depending on the expiration date (3), therefore these two attributes are related in Figure 2. In paragraph 2.2.3, results from Tsiros and Heilman (2005) are presented in Table 1. They studied how to WTP of consumers decreased for an increasing age of the product. In Figure 2, the expiration date as an product attribute is therefore related to the WTP of consumers (4). The actual product choice is based on cut-off levels for product attribute values according to the conjunctive rule discussed in paragraph 2.2.4. In this study, the product attribute value is the objective price and the cut-off level the WTP of consumers (5), where WTP is used as a measure to predict the perceived value of a product. If the objective price is lower than the WTP of consumers, they will accept the product and if not, they will reject the product (6). The WTP is not equal for all consumers. Several properties influence the WTP of consumers like the age, sex, income, or household size (Tsiros & Heilman, 2005). Therefore, this research also uses the standard deviation of the WTP, shown in Table 1, as input statistic for this study (7).

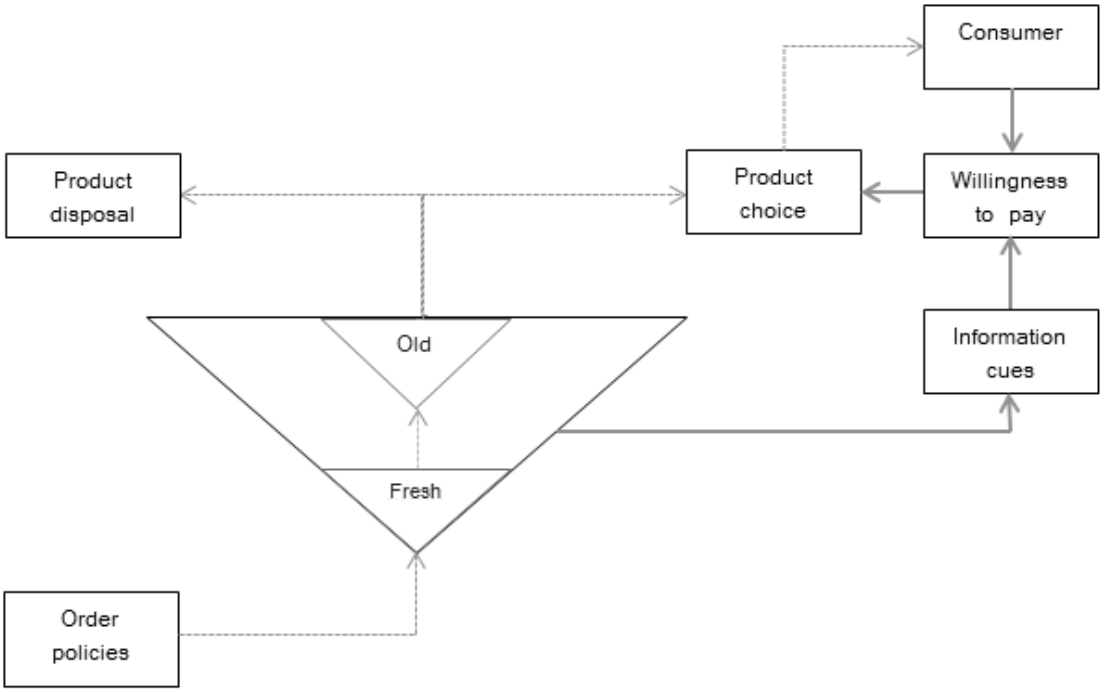

Figure 3: *Representation of incorporating the relation between EDBP and consumer decision making in the proposed inventory model*

As mentioned in the introduction, the framework of Figure 1 is the basis of this research. Incorporating the relation between EDBP and consumer decision making within this framework results in the representation of Figure 3. In this figure, the bold lines represent the relation between EDBP and consumer decision making and the dotted lines represent the product flow of the perishable product. The expiration date and objective price as information cues are assumed to be observed by the consumers from the products in the stock. Hereafter, the consumer determines his or her willingness to pay for that product and eventually, based on the conjunctive decision rule, he or she chooses a product. The accepted product therefore flows to this consumer.

3

THE MODEL

This chapter explains in-depth how the product-flow of a perishable product is modelled by incorporating the relation between EDBP and consumer decision making. To understand how this research differs from current practices and how the relation between EDBP and consumer decision making is modelled and measured, this chapter explains how the model is developed.

The first paragraph is a description of the conceptual model including the modelling objectives, experimental factors, model content, and assumption. The second paragraph explains the parametrized model which is the mathematical elaboration of the model including an identification of the Key Performance Indicators (KPI's). The actual programmed and simulated model in MatLab can be found in the Appendix: MatLab code.

3.1 Conceptual model

Conceptual modelling is the process of abstracting a model from a real system (Robinson, 2008), which is said to be the most important aspect of a simulation study. According to Robinson (2008), the conceptual model itself consists of four main components: objectives, experimental factors , responses, and the model content.

3.1.1 Modelling objective

The main objective of this research is to incorporate the effect of expiration date-based pricing on consumer decision making in an inventory model in order to reduce food waste. The relation between EDBP and consumer decision making is operationalized in the previous chapter, so this chapter focusses in the inclusion of the last part of the objective, the reduction of food waste.

The modelling objective is:

- Measuring the performance of EDBP on the reduction of food waste and the loss of revenue by including consumer decision making in the model

3.1.2 Experimental factors

The experimental factors are those elements of the model that can be altered, to evaluate the effectiveness and efficiency of EDBP in order to reduce waste and answer the third research question. The model is simulated using three experimental factors:

1 Shape of the WTP curve
2 Fraction of consumers picking LIFO
3 Discount levels

The first experimental factor is the shape of the WTP curve of consumers according to the remaining shelf life of the products. As discussed in paragraph 2.2.3, the WTP follows an negative exponential shape with an increasing age of the product. However, to gain more knowledge about the influence of pricing on consumer decisions for perishable products other shapes are estimated as well.

The second experimental factor is the fraction of consumer picking according to LIFO principle. The remaining consumers pick according to the FIFO principle. The picking order of consumers have an influence on the inventory dynamics and therefore also on the responses of the model and is therefore an experimental factor.

The third experimental factor is the discount level which is different for various ages of the product. Naturally, this factor is included to evaluate the effectiveness and efficiency of EDBP on consumer purchasing decisions in order to reduce food waste.

3.1.3 Responses

The responses report the average results or outputs from multiple runs of the simulation model. These responses are included to determine whether the modelling objectives have been achieved and to point to reasons why objectives are not being achieved. Therefore, the responses are referred to as performance measures of the model. Flowing from the research question 3, there are four KPI's in this research. The first KPI is the percentage of products disposed from the total amount of products ordered to measure the effectivity of the experimental factors in order to reduce waste.

The second KPI is the loss of revenue for the retailer to measure the efficiency of the experimental factors in order to reduce waste. The loss of revenue is calculated by multiplying the estimated lost sales with the retail price plus a particular loss due to discounting.

The third KPI is the gross profit for the retailer to measure the profitability of the experimental factors in order to reduce waste. The gross profit is calculated by subtracting the total ordering costs and costs due to product waste from the total revenue. The total revenue is calculated by the total sales times the objective price.

The fourth KPI is mean sales per week corrected for lost sales. This KPI measures the influences of pricing on demand and determines whether different experiments are comparable. As mentioned in the introduction, many articles make assumptions about the effect of pricing on consumer behaviour. To indicate the difference between this research and other studies, there are two experiments where WTP is not included in the model and consumers simply pick products based on availability and not based on the conjunctive rule. To be able to compare the performance measures of experiments where the WTP is included with experiments where the WTP is excluded, the mean sales volume per week should be equal. Excluding the WTP of consumers implies that there are, besides availability, no conditions for consumers to select a certain product, which leads to all the consumers picking a product. To be able to compare the performance measures of different experiments, the mean weekly sales volume should be equal. Therefore, the amount of consumers entering the model is different for the experiments where the WTP is excluded. More in-depth explanation on the difference between the amount of consumers as input and the mean weekly sales volume including a correction for lost sales as a performance measure can be found in paragraph 3.2.3 & 4.1.6.

3.1.4 Model content

The representation of the inventory model in Figure 1 is modelled and simulated. This proposed model is applicable for a grocery retailer environment. The model is stochastic of nature, since most inventory management situations deal with uncertain demand. Modelling decisions including the relation between EDBP and consumer decision making of Figure 2 are described in detail in paragraph 3.2. Used inventory model parameters are summarized in Table 4 and the inventory variables are summarized in Table 5.

3.1.5 Assumptions & simplifications

- The model involves a single supplier, single retailer, and a single deteriorating item.
- Consumers visiting the supermarket have an inherent motivation to fulfil their consumption goals, which in this study entails the purchase of beef.
- Consumers pick available products based on the conjunctive rule.
- Each consumer arrives one by one and they do not pick more than one product.
- The products in the inventory are assumed to be always sorted based on their remaining shelf life, where the oldest products are presented in the front, and the freshest products are presented in the back of the shelf.
- Ordering takes place at the end of a simulation day and the order arrives at the beginning of the next simulation day, therefore the lead time is one day.
- The supermarket is closed on Sunday.
- Mean weekly sales is assumed to be 20 products.
- More consumers enter the model than there are products picked
- A product perishes after passing the expiration date without any salvage value.
- The ordering costs are assumed to be only variable, since fixed costs for one product category for supermarkets are almost negligible.
- Holding costs are not included, since it is assumed that the inventory space in supermarkets is already allocated to particular products which results in zero carrying costs.
- Backlogging is not allowed and is outside the scope of this research.

Ramanathan and Muyldermans (2010) indicate that, apart from promotional elements, there are other factors that influence demand, such as weather, temperature and holiday periods. These factors are external to the supply chain and hence difficult or impossible to control and are therefore not taken into account in this model. Besides, internal factors as product substitution, shelf placement, and other promotional activities besides EDBP will not be implemented in this model.

3.2 Parameterized model

This paragraph explains the parameterized model which is the mathematical elaboration of the model. Here, decisions for model are justified and explained together with the identification of used indices, parameters, variables, and performance measures including the KPI's. The actual programmed and simulated model in MatLab can be found in the Appendix: MatLab code.

Table 3: *Inventory model indices*

Symbol	Value	Short explanation	Unit
r	$\in$ 1,...,M	Remaining shelf life (RSL)	Day
t	$\in$ 1,...,T	Number of days	Day
w	$\in$ 1,...,7	The day of the week (Mon = 1, ..., Sun = 7)	Day
j	$\in$ 1,...,C_t	Consumers per day t	Consumer
i	$\in$ 1,...,$\frac{T}{7}$	Week number	Week
y	$\in$ 1, 2	Model with WTP = 1, model without WTP = 2	

Indices used for the parameters and variables are shown in Table 3. Here r is the remaining shelf life which can take values between 1 and a maximum shelf life of M. Day t takes value between 1 and T. There are seven days in a week, therefore w can take values between 1 and 7. Index j indicates the consumer on a day which can take values between 1 to C_t. Index i is the week number. Index y represents whether the model with WTP or the model without WTP is used.

Table 4: *Inventory model parameters*

Symbol	Short explanation	Unit
N	Number of runs	
T	Number of days	Days
M	Maximum remaining shelf life	Days
RP	Retail price per product	Dollar
OC	Ordering costs per product	Dollar
SF	Safety factor	
Λ_{wy}	Average amount of consumers per weekday w (w =Mon,...,Sun) for model y	#Consumers
ε	Shape of the WTP curve	
Δ_r	Discount level for products with RSL r	Percentage
P	Fraction of consumers picking LIFO	Percentage

The parameters in Table 4 are used as inputs for the model. Their input values are justified in paragraph 4.1. Table 5 displays the important inventory variables used for the model.

Table 5: *Inventory model variables*

Symbol	Short explanation	Unit
S_{tw}	Order-up-to level on day *t,* for weekday *w*	#Products
$DLIFO_{tr}$	Sales by LIFO consumers on day *t,* for products with RSL *r*	#Products
$DFIFO_{tr}$	Sales by FIFO consumers on day *t,* for products with RSL *r*	#Products
D_{tr}	Total sales on day *t*, for products with RSL *r*	#Products
μ_w	Mean sales per weekday *w*	#products
I_{tr}	Starting inventory on day *t*, for products with RSL *r*	#Products
$Iend_{tr}$	End inventory on day *t*, for products with RSL *r*	#Products
Q_t	Order quantity on day *t*	#Products
$CLIFO_t$	Amount of LIFO consumers on day *t*	#Consumers
$CFIFO_t$	Amount of FIFO consumers on day *t*	#Consumers
C_t	Total amount of consumers on day *t*	#Consumers
OP_r	Objective price for inventory *r*	Dollar
Z_j	Random number from ~N(0,1) distribution for variation of WTP per consumer *j*	
WTP_{jr}	WTP of consumer *j,* for products with RSL *r*	Dollar
$stockout_t$	Amount of consumers facing an empty inventory per day *t*	#Consumers
$waste_t$	Amount of products disposed on day *t*	#Products
exp_t	Amount of consumers rejecting the products since all the products evaluated were too expensive per day *t*	#Consumers
discloss	Loss of revenue due to discounting	Dollar
$pick_j$	Amount of products picked by consumer *j*	#Products

3.2.1 Ordering policy

The inflow of products is modelled via a periodic review system, which is the most common system used in the grocery industry (Ferguson & Ketzenberg, 2005). A periodic review system indicates that the inventory is checked at regular intervals (R) and an order is placed to raise the inventory to a specified threshold, the order-up-to level (S). In this model, the (R, S) policy will be used, where the reorder cycle and the lead time is one day. The order-up-to level S_{tw} is updated each simulation day *t* in terms of a rolling horizon. This indicates that the order-up-to level S_{tw} is not fixed, but updated each day based on mean sales per weekday.

The weekday is determined by a modulus after division where Mondays are $w = 1$ and Sundays are $w = 7$, equation *(1)*.

$$w = 1 + \text{Mod}\,[t - 1\,, 7] \tag{1}$$

The order-up-to level of the model is based on equation *(2).* The order-up-to level for a particular day of the week is based on mean sales on the review day plus the mean sales during the lead time, in this research the mean sales of the next day since the lead time is one simulation day. The order-up-to level includes a particular safety stock which is based on a safety factor times the standard deviation of the mean sales of the review period plus the lead time. Note that $S_{t7} = 0$, since on Sunday the supermarket is closed, therefore the order-up-to level for Saturday (S_{t6}) includes the mean sales for Monday, equation *(3).*

(2) $$S_{tw} = \text{round}(\mu_w + \mu_{w+1} + SF * \sqrt{\mu_w + \mu_{w+1}})$$ w = 1,...,5

(3) $$S_{t6} = \text{round}(\mu_6 + \mu_7 + \mu_1 + SF * \sqrt{\mu_6 + \mu_7 + \mu_1})$$

(4) $$S_{t7} = 0$$

Each simulation day μ_w is updated using equation *(5)*, where μ_w is the sum of the total sales on weekday w divided by the week number. The expression between the Iverson brackets is 1 if day t is weekday w.

(5) $$\mu_w = \frac{\sum_{t=1}^{T}\sum_{r=1}^{M} d_t * [1 + \text{mod}(t-1, 7) = w]}{i}$$ w = 1,...,7

The order quantity becomes the difference between the order-up-to level S_{tw} and the current stock level of day t, equation *(6).* If the stock level is higher than the order-up-to level S_{tw} nothing should be ordered.

(6) $$Q_t = \max(S_{tw} - \sum_{r=1}^{M} I_{tr}, 0)$$ t = 1,...,T

3.2.2 Pricing policy

The objective price of products in inventory r is calculated by subtracting a particular percentage discount from the average retail price, equation *(7).*

(7) $$OP_r = RP * (1 - \Delta_r)$$

The amount a consumers is willing to pay for different product ages is based on the values from Tsiros and Heilman (2005), shown in Table 1. An exponential, quadratic, and linear line are fitted through these values, which gave the results shown in Figure 4.

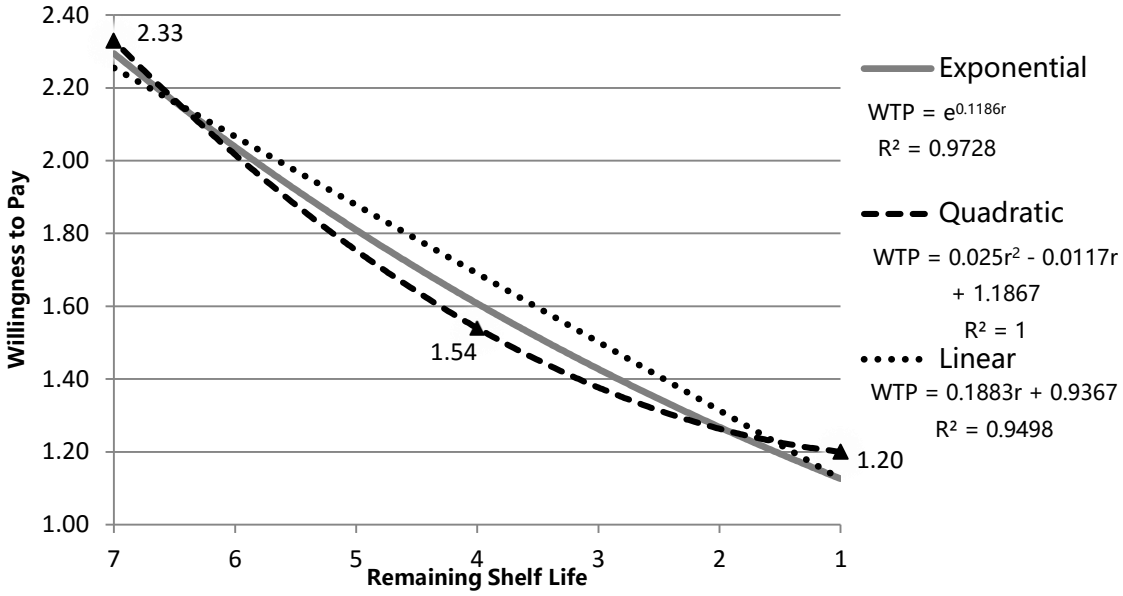

Figure 4: *Shapes of the WTP curve*

The WTP of consumer *j* for inventory *r* is calculated by taken the maximum of either zero or the shape of the WTP curve plus random number *Z* multiplied by the mean standard deviation for the WTP, which is 0.85 according to the findings of Tsiros and Heilman (2005). Due to this standard deviation is can be stated that the WTP is not homogeneous for all consumers and therefore *Z* is added to vary the WTP per consumer, equation *(8)*.

$$\text{(8)} \qquad \mathrm{WTP_{jr}} = \max(\varepsilon + \mathrm{Z_j} * 0.85, 0) \qquad \begin{array}{l} j = 1,\ldots,C_t \\ r = 1,\ldots,M \end{array}$$

3.2.3 Consumer demand and selection behaviour

In this research the number of consumers visiting the store to buy the product does not equal the amount of sales since consumer demand and selection behaviour is modelled differently from current developed inventory models. Demand is often modelled as an univariate variable (Anjos et al., 2005; Chew et al., 2014; Jia & Hu, 2011; Li et al., 2012) or assumptions are made about consumer demand or selection behaviour (Amorim et al., 2014; Bitran et al., 2006; Chun, 2003). In this research, whether a consumer picks a particular product depends on the availability of the product and on the conjunctive rule. This rule, as discussed in paragraph 2.2.4, determines the actual product choice of consumer, where the objective price functions as the product attribute and the WTP of consumers as the cut-off level. If the objective price is lower than or equal to the WTP of consumers, they will accept the product and if the objective price is higher, they will reject the product. Therefore the amount of sales depends on the objective price of the product, including a particular discount percentage, equation *(7)*, and on an partly random function for each individual

consumer, equation *(8)*. Thus in contrast to the precious mentioned other articles, in this study the amount of consumers entering the model determines how large the total sales will be, where the amount of consumers is the potential amount of sales and not the actual amount sales.

The amount of consumers entering the model on day *t* is determined by a generated random number from the Poisson distribution with parameter *Λ* for the weekday corresponding to day *t,* equation *(9)*. A Poisson distribution is chosen since the weekly pattern for sales in Dutch supermarkets also follows a Poisson distribution according to the article of Van Donselaar et al. (2006). A Poisson distribution is commonly used when describing a number of independent events, in this case consumer purchasing decisions, within a time frame, in this case on day (Rijgersberg et al., 2010).

(9) $$C_t = \text{Poisson}(\Lambda_{wy}) \qquad t = 1,\ldots,T$$

Whether consumers pick the freshest product (LIFO) or the oldest product (FIFO) extensively influences the dynamics of the inventory and is therefore within the scope of this research. As mentioned in the assumptions, the products in the inventory are assumed to be always sorted based on their remaining shelf life, where the oldest products are presented in the front, and the freshest products are presented in the back of the shelf. Some consumers will simply pick the product in the front whereas others will select products at the back of the shelf, hoping to pick the freshest product. This so-called picking order of consumers consequently influences to a large extend the dynamics of the inventory model and the outcomes of the simulation. The consumers hoping to pick the freshest product evaluate the inventory according to the LIFO principle. The amount of consumers doing this depends on a random number generated from a binomial distribution where parameter *C* is the number of trials and parameter *P* the success rate, equation *(10)*.

(10) $$\text{CLIFO}_t = \text{Bin}(C_t, P) \qquad t = 1,\ldots,T$$

The remaining consumers evaluate the inventory according to the FIFO (First in, First out) principle, equation *(11)*.

(11) $$\text{CFIFO}_t = C_t - \text{CLIFO}_t \qquad t = 1,\ldots,T$$

To avoid any misconception and clearly display whether consumers pick a product and how they evaluate the inventory, the selection behaviour of LIFO and FIFO consumers is written in pseudo code on the next page in Figure 5.

```
Input:      I_tr          = Products available on day t for inventory r
            OP_r          = Objective price for inventory r
            WTP_jr        = WTP of consumer j for products in inventory r
            CLIFO_t       = Amount of LIFO consumers on day t
            CFIFO_t       = Amount of FIFO consumers on day t

Output:     DLIFO_tr      = Sales by LIFO consumers on day t, for inventory r
            DFIFO_tr      = Sales by FIFO consumers on day t, for inventory r
            exp_t         = Number of times a consumer is not willing to buy a
                            product since all the products evaluated were too
                            expensive per day t
            stockout_t    = Number of times a consumer faces an empty inventory
                            per day t
begin
   1. DFIFO_tr = 0 DLIFO_tr = 0 exp_t = 0 stockout_t = 0
   2. Meet LIFO demand:
      for consumer j = 1 to CLIFO_t do
            pick_j = 0
            if sum(I_tr) = 0
                  inc(stockout_t)
            else
                  r = 7
                  repeat
                        if OP_r ≤ WTP_jr & pick_j < 1 & I_tr > 0 then
                              inc(DLIFO_tr)
                              dec(I_tr)
                              pick_j = 1
                              r = 0
                        else
                              r-1
                  until r = 0
                  if pick_j = 0
                        inc(exp_t)

   3. Meet FIFO demand:
      for consumer j = 1 to CFIFO_t do
            pick_j = 0
            if sum(I_tr) = 0
                  inc(stockout_t)
            else
                  r = 1
                  repeat
                        if OP_r ≤ WTP_jr & pick_j < 1 & I_tr > 0 & then
                              inc(DFIFO_tr)
                              dec(I_tr)
                              pick_j = 1
                              r = 8
                        else
                              r+1
                  until r = 8
                  if pick_j = 0
                        inc(exp_t)
stop
```

Figure 5: *Pseudo code to determine consumer selection behaviour on day t*

In this research LIFO consumer evaluate the inventory before the FIFO consumers, but whether a consumer actually decides to pick a particular product depends on three conditions. Firstly, the conjunctive rule where the objective price of a product should be lower than or equal to the WTP of a consumer for that product, which is determined by the

equivalence between equations *(7)* & *(8)*. Secondly, there should be products in the stock, otherwise the consumer faces a stock out, which is counted by $stockout_t$. And thirdly, cannot have more than one product, therefore $pick_j$ should be equal to or lower than 1. If these conditions hold, sales for the corresponding picking order of the consumer increases, thus $DLIFO_t$ *or* $DFIFO_t$. Besides, consumers who evaluated all available products without picking one, were not willing to buy a product since the products were too expensive for him or her, which is counted by exp_t.

The total sales on day *t* for inventory *r* is calculated by the sales by LIFO consumers plus the sales by the FIFO consumers, equation *(12)*.

$$D_{tr} = DLIFO_{tr} + DFIFO_{tr} \qquad t = 1,\ldots,T \quad r = 1,\ldots,M \tag{12}$$

As mentioned before, this study makes a comparison between experiments where the WTP of consumers is included with experiments where the WTP is excluded. The consequences of excluding a WTP is that more consumers pick a product, since consumers simply pick products based on availability and not based on the conjunctive rule. Moreover, including WTP means that more consumers reject the products, since also consumers with a low WTP are included in this research. To be able to compare the performance measures of experiments where WTP is included with experiments where WTP is excluded, the mean sales volume per week should be equal. To get comparable sales volumes, the amount of consumers entering the model is different for the experiments where WTP is excluded. In the calculation for the mean weekly sales, this research includes a correction for lost sales. The lost sales are not estimated equally for the model including the WTP compared to the model without the WTP. Including WTP means that the estimated percentage lost sales is determined by the fraction consumers who picked a product times the fraction consumers who faced a stock out, equation *(13)*. These consumers were actually willing to buy a product, but could not since the product was not available and are therefore lost sales.

$$PLOSTSALE_1 = \left(\frac{\sum_{t=547}^{T} \sum_{r=1}^{M} D_{tr}}{\sum_{t=547}^{T} C_t}\right) * \left(\frac{\sum_{t=547}^{T} stockout_t}{\sum_{t=547}^{T} C_t}\right) \tag{13}$$

For the case where WTP is not included, all the consumer can be converted into actual sales if the products are available. Consequently, all the stock outs are lost sales. Hence, the estimated percentage loss sales is determined by dividing the number of times consumers faced stock outs by the total amount of consumers entering the model, equation *(14)*.

$$PLOSTSALE_2 = \left(\frac{\sum_{t=547}^{T} stockout_t}{\sum_{t=547}^{T} C_t}\right) \tag{14}$$

3.2.4 Inventory dynamics

The freshest inventory (r = M) on an new day, is the amount of products ordered the previous day, equation *(15)*.

$$I_{t+1,M} = Q_t \qquad t = 1,\ldots,T \quad r = 1,\ldots,M \tag{15}$$

The end inventory of day *t* is the remaining of the starting inventory minus the sales during the day *t*, equation *(16)*

$$Iend_{tr} = I_{tr} - D_{tr} \qquad t = 1,\ldots,T \quad r = 1,\ldots,M \tag{16}$$

The starting inventories, besides for r = M, for a new day are determined by the remainders of the previous day, equation *(17)*.

$$I_{t+1,r} = Iend_{t,r+1} \qquad t = 1,\ldots,T \quad r = 1,\ldots,M-1 \tag{17}$$

All products of inventory *r* = 1, the oldest inventory, remaining on the end of day t are disposed, equation *(18)*.

$$waste_t = Iend_{t,1} \qquad t = 1,\ldots,T \tag{18}$$

3.2.5 Performance measures

This research entails four KPI's, which flow from the main modelling objective and the responses described in paragraph 3.1. Besides the KPI's, there are several other performance measures used for the comparison of different experiments shown in Table 6.

Table 6: *Performance measures after simulation*

Symbol	Short explanation	Unit	Equation
PWASTE	KPI 1: percentage products disposed	%	*(19)*
$LOSSREVENUE_y$	KPI 2: loss of revenue for model *y*	$	*(21)*
PROFIT	KPI 3: Gross Profit	*$*	(22)
$MWSALES_y$	KPI 4: mean weekly sales corrected for lost sales for model *y*	%	*(23)*
TREVENUE	Total revenue	$	*(24)*
COSTWASTE	Costs of product disposal	$	*(25)*
TCOSTORDER	Total ordering costs	$	*(26)*
TCOST	Total costs	$	*(27)*

Symbol	Short explanation	Unit	Equation
PSTOCKOUT	Percentage consumers facing stock out	%	*(28)*
PEXPENSIVE	Percentage consumers facing too expensive products	%	*(29)*
PPICK	Percentage consumers who picked a product	%	*(30)*
$PLOSTSALE_1$	Estimated percentage lost sales for model *1*	%	*(13)*
$PLOSTSALE_2$	Estimated percentage lost sales for model *2*	%	*(14)*
AGEPRODUCT	Average age of the picked products	days	*(31)*
$FIFORSL_r$	Distribution of sales percentages of FIFO consumers over the remaining shelf life *r* of the products	%	*(32)*
$LIFORSL_r$	Distribution of sales percentages of LIFO consumers over the remaining shelf life *r* of the products	%	*(33)*

KPI 1: The percentage of waste is used to measure the effectivity of EDBP on the reduction of food waste, equation *(19)*.

(19) $$\mathrm{PWASTE} = \frac{\sum_{t=547}^{T} \mathrm{waste}_t}{\sum_{t=547}^{T} Q_t}$$

KPI 2: The loss of revenue measure the efficiency of EDBP to reduce food waste for model *y,* equation *(21)*.

(20) $$\mathrm{discloss} = \left(\sum_{t=547}^{T}\sum_{r=1}^{M} D_{tr} * \mathrm{RP}\right) - \left(\sum_{t=547}^{T}\sum_{r=1}^{M} D_{tr} * \mathrm{OP}_r\right)$$

(21) $$\mathrm{LOSSREVENUE}_y = \mathrm{PLOSTSALE}_y * \sum_{t=547}^{T} C_t * \mathrm{RP} + \mathrm{discloss}$$ y = 1, 2

KPI 3: Gross profit is the remainder of the total revenue minus the total costs, equation *(22)*.

(22) $$\mathrm{PROFIT} = \mathrm{TREVENUE} - \mathrm{TCOST}$$

KPI 4: Mean weekly sales corrected for lost sales for model *y,* equation *(23)*.

(23) $$\mathrm{MSALES}_y = \frac{\mathrm{PLOSTSALE}_y * \sum_{t=547}^{T}\sum_{r=1}^{M} d_{tr} + \sum_{t=547}^{T}\sum_{r=1}^{M} d_{tr}}{(T-547)/7}$$ y = 1, 2

Total revenue is the total sales times the price presented by the retailer, including discount levels *(24)*.

(24) $$\mathrm{TREVENUE} = \sum_{t=547}^{T} \sum_{r=1}^{M} D_{tr} * OP_r$$

The costs of product disposal are calculated by multiplying the total number of disposed products with the ordering costs, equation *(25)*.

(25) $$\mathrm{COSTWASTE} = \sum_{t=547}^{T} \mathrm{waste}_t * \mathrm{OC}$$

The total ordering costs are calculated by multiplying the total amount ordered times the ordering costs, equation *(26)*.

(26) $$\mathrm{TCOSTORDER} = \sum_{t=547}^{T} Q_t * \mathrm{OC}$$

The total costs are the sum of the costs of product disposal and the ordering costs, equation *(27)*.

(27) $$\mathrm{TCOST} = \mathrm{COSTWASTE} + \mathrm{TCOSTORDER}$$

The percentage consumers facing a stock out is calculated by dividing the number of times a consumer faces stock out by the total number of consumers entering the model, equation *(28)*.

(28) $$\mathrm{PSTOCKOUT} = \left(\frac{\sum_{t=547}^{T} \mathrm{stockout}_t}{\sum_{t=547}^{T} C_t} \right)$$

The percentage consumers facing too expensive products is calculated by dividing the number of times a consumer faces too expensive products by the total number of consumers entering the model, equation *(29)*.

(29) $$\mathrm{PEXPENSIVE} = \left(\frac{\sum_{t=547}^{T} \mathrm{exp}_t}{\sum_{t=547}^{T} C_t} \right)$$

The percentage consumers who picked a product is calculated by dividing the total sales by the total number of consumers entering the model, equation *(30)*.

(30) $$\mathrm{PPICK} = \left(\frac{\sum_{t=547}^{T} \sum_{r=1}^{M} D_{tr}}{\sum_{t=547}^{T} C_t} \right)$$

The calculations for the estimated percentage lost sales are already displayed in equations *(13)* & *(14)*.

The average age of the product is the sum of the sales per inventory *r* times their age divided by the total amount of sales, equation *(31)*.

(31) $$\mathrm{AGEPRODUCT} = \left(\frac{\sum_{t=547}^{T}\sum_{r=1}^{M} D_{tr} * (M + 1 - r)}{\sum_{t=547}^{T}\sum_{r=1}^{M} D_{tr}}\right)$$

The distribution of sales percentages of FIFO consumers over the remaining shelf life of the products is calculated by dividing the sales of the FIFO consumers by the total amount of sales, equation *(32)*. The same holds for LIFO consumers, equation *(33)*.

(32) $$\mathrm{FIFORSL}_r = \left(\frac{\sum_{t=547}^{T} \mathrm{DFIFO}_{tr}}{\sum_{t=547}^{T}\sum_{r=1}^{M} \mathrm{DFIFO}_{tr}}\right) \qquad r = 1,\ldots,M$$

(33) $$\mathrm{LIFORSL}_r = \left(\frac{\sum_{t=547}^{T} \mathrm{DLIFO}_{tr}}{\sum_{t=547}^{T}\sum_{r=1}^{M} \mathrm{DLIFO}_{tr}}\right) \qquad r = 1,\ldots,M$$

4

DATA & EXPERIMENTS

Data is needed to measure the effectivity and efficiency of EDBP in order to reduce waste. This chapter justifies the input values for the model parameters. The fixed values are used for each experiment and the variable values depend on the experiment number. A design of experiments is developed to give an overview of the input values of the experimental factors which evaluate the effectiveness and efficiency of EDBP in order to reduce waste.

4.1 Fixed input data

Fixed input data is data that is kept the same in all experiments. An overview of the fixed input data is shown in Table 7. In subsections below the parameters and their values are explained.

Table 7: *Fixed input parameters*

Symbol	Name	Value
N	Number of runs	200
T	Number of days	1456
M	Maximum remaining shelf life	7
RP	Retail price per product	$2.58
OC	Ordering costs per product	$1.29
SF	Safety factor	2.326
Λ_w	Average number of consumers per weekday w (w = Mon,....,Sun)	Excluding WTP: [2.4 2.2 2.6 3.2 5.0 4.6 0] Including WTP: [7.056 6.468 7.644 9.408 14.7 13.524 0]

4.1.1 Number of runs

The value input for the number of runs is based on equation *(34)*. During the calculation for the number of runs, a t-value of 1.96 is used.

$$\bar{X}_N \pm t \cdot \frac{S_N}{\sqrt{N}} \quad (34)$$

This formula determines the accuracy of the average of the results after N runs. In order to gather accurate results through the simulation, with 95% confidence, results should not have a relative inaccuracy of 2% from the mean. Based on the results of the formula on the four KPIs shown in Table 8, Table 9, Table 10, and Table 11, the number of runs is set to 200.

Table 8: *Deviations from average for percentage waste*

N	Average Waste		Half width of 95% CI of mean	Relative inaccuracy
10	6.69%	±	0.267	4.0%
20	6.77%	±	0.309	4.7%
50	6.55%	±	0.214	3.3%
100	6.50%	±	0.146	2.2%
200	6.61%	±	0.108	1.6%

Table 9: *Deviations from average for loss of revenue*

N	Average loss of revenue		Half width of 95% CI of mean	Relative inaccuracy
10	$570	±	16.544	2.9%
20	$569	±	7.663	1.4%
50	$567	±	5.175	0.9%
100	$570	±	3.615	0.6%
200	$569	±	2.757	0.5%

Table 10: *Deviations from average for gross profit*

N	Average gross profit		Half width of 95% CI of mean	Relative inaccuracy
10	$2297	±	78.596	3.4%
20	$2374	±	31.284	1.3%
50	$2348	±	27.418	1.2%
100	$2338	±	20.897	0.9%
200	$2331	±	14.248	0.6%

Table 11: *Deviations from mean for average weekly sales*

N	Average weekly sales		Half width of 95% CI of mean	Relative inaccuracy
10	20.19	±	0.376	1.9%
20	19.83	±	0.175	0.9%
50	19.99	±	0.117	0.6%
100	20.10	±	0.081	0.4%
200	20.01	±	0.057	0.3%

4.1.2 Number of days

The order policy of the model includes an order-up-to level S_{tw} that is updated each simulation day t in terms of a rolling horizon. The order-up-to level S_{tw} is primarily based on average sales per weekday. However, the averages have a large fluctuation at the beginning of the simulation and are therefore not accurate. In order to gather accurate results, a warming-up period for the order-up-to level is included. The warming-up period is set to 546 days since based on experiments with 200 runs the changes in the mean S_{tw} are minimal, shown Table 12.

Table 12: *Changes in order-up-to level S_{tw}*

Number of day simulating	Rounded mean S_{tw} values						
	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.
10	7	3	0	0	0	5	0
50	9	8	8	8	7	7	0
100	9	9	10	11	11	9	0
200	9	9	10	13	14	11	0
300	9	10	11	14	15	11	0
400	9	10	11	14	16	12	0
500	9	10	11	15	16	12	0
546	9	10	11	15	16	12	0

The warming-up period is fixed at 78 weeks. The actual results are gathered over a simulation period of 130 weeks, 910 days. Therefore, the total number of days the simulation runs is 1456.

4.1.3 Remaining shelf life

This research focusses on beef, which is a Days Fresh product with a short shelf life. In the article of Tsiros and Heilman (2005) beef is used as a product with a maximum remaining shelf life of 7 days, which is also used as value input for this research. A product in the inventory could thus have a remaining shelf life of 7 to 1 day(s).

4.1.4 Retail price & ordering costs

This is the average retail price for beef is 2.58$ according to Tsiros and Heilman (2005). The unit ordering costs are assumed to be, like the study of Amorim et al. (2014), half the average retail price of Tsiros and Heilman (2005), thus 1.29$.

4.1.5 Safety factor

Since stock outs are unwanted by retailers, the aim is to serve 99% of the consumers. A service level of 99% leads to a safety factor of 2.326 based on a standard normal distribution N(0,1) according to Figure 6. This factor is used in the calculations of the order-up-to level S_{tw}. More specific, for the calculations of the safety stock, which is based on the safety factor times the standard deviation of the average sales during the review period plus the lead time.

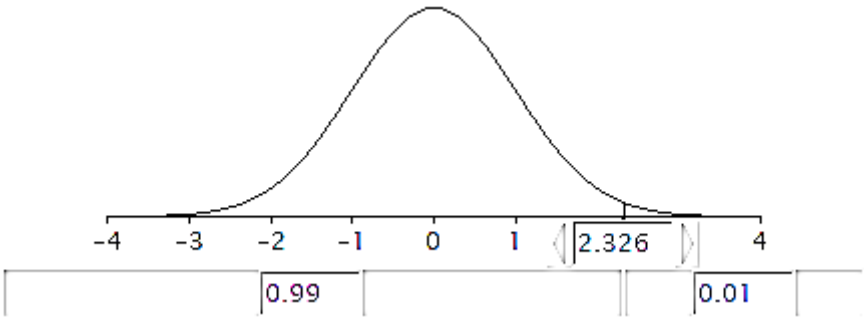

Figure 6: *Safety factor*

4.1.6 Average amount of consumers per weekday

Values for the average amount of consumers per weekday (Λ_{wy}) are based on mean weekly sales for beef, which is 20 units. Typical for an average Dutch supermarket, based on provided POS data. This value is fitted on the distribution of the weekly pattern for sales in Dutch supermarkets of Van Donselaar et al. (2006). Estimated sales are as follows:

- 12% on Monday
- 11% on Tuesday
- 13% on Wednesday
- 16% on Thursday
- 25% on Friday
- 23% on Saturday

Based on mean weekly sales of 20 products yielded the average amount of consumers visiting the supermarket per weekday shown in Figure 7.

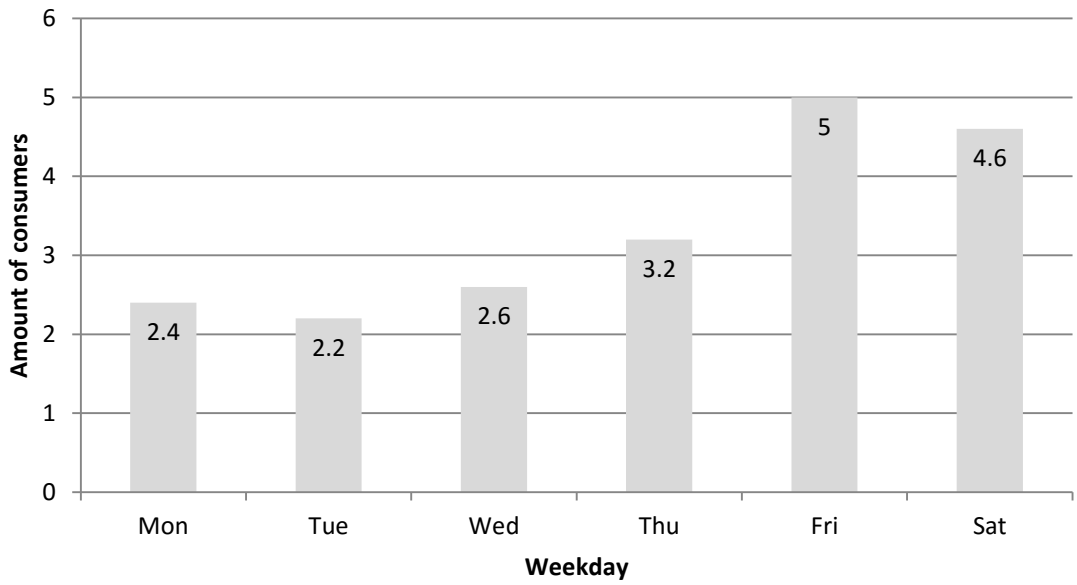

Figure 7: *Average amount of consumers per weekday excluding WTP*

Comparing results between experiments where the WTP of consumers is included with experiments where this factor is excluded is impossible without correcting for the average amount of consumers per weekday, thus $\Lambda_{wy.}$ Including the WTP of consumers implies more conditions for consumers before selecting a product, thus less consumers actually selecting a product. This leads to differences in mean weekly sales, which influences the total model and corrupts the outcomes. Therefore, the average amount of consumers per weekday entering the model should be different for the case where WTP is included to be able to compare results with cases where the WTP is excluded from the model. As explained in paragraph 3.2.3 & 3.2.5, the difference in sales volume should be corrected for lost sales, since a stock out for the model without WTP means that all stock outs are lost sales. For the model where WTP is included, this is not certain since this research also includes consumers with a low WTP. Those consumers are often not willing to pay the objective price. Therefore, Λ_{w1} has to be set higher to get comparable sales volumes compared to the model where the WTP is not included. Using the values of Figure 7 as input values for Λ_{w2} gave a mean weekly sales corrected for lost sales according to Table 13.

Table 13: *Results for mean weekly sales corrected for lost sales with and without WTP*

Λ_{wy}	**MWSALES$_2$ (no WTP)**	**MWSALES$_1$ (WTP)**
[2.4 2.2 2.6 3.2 5 4.6 0]	19.99	6.36
[7.056 6.468 7.644 9.408 14.7 13.524 0]	58.74	19.98

Using the same amount of consumes entering the model gives a mean weekly sales of 6.36 for the case where WTP is included, which makes the results incomparable since the amount of sales influences the total model and consequently bias the performance measures. For

the case where the WTP is included, more condition need to be met before an available product is selected. Therefore, more consumers should visit the store to gain the same mean weekly sales of 20 products. For the case where WTP is included, the average amount of consumers is tripled, since a mean weekly sales of 6.36 is almost one third of 20. Based on 1000 runs, including the WTP and a tripled average amount of consumer entering the model, 34% of the total consumers picked a product. If 34% of the consumers pick a product, then on average 58.8 consumers should visit the store per week to get a mean weekly sales of 20 products. Following the sales pattern of Van Donselaar et al. (2006) yielded the average amount of consumers shown in Figure 8.

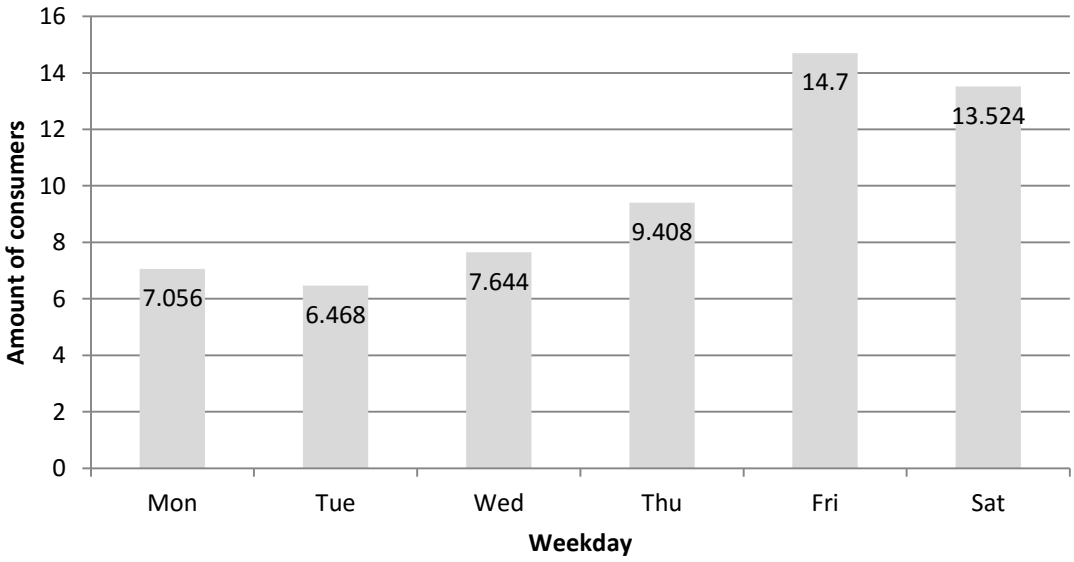

Figure 8: *Average amount of consumers per weekday including EDBP*

Using the above number as input values for Λ_{w1} gave a mean weekly sales according to Table 13. The first row, $\Lambda_{w2,}$ will be used as input values for experiments excluding a WTP and the second row, $\Lambda_{w1,}$ will be used as input values for experiments including a WTP. For both cases mean weekly sales is almost 20, which makes the results for the different experiments comparable.

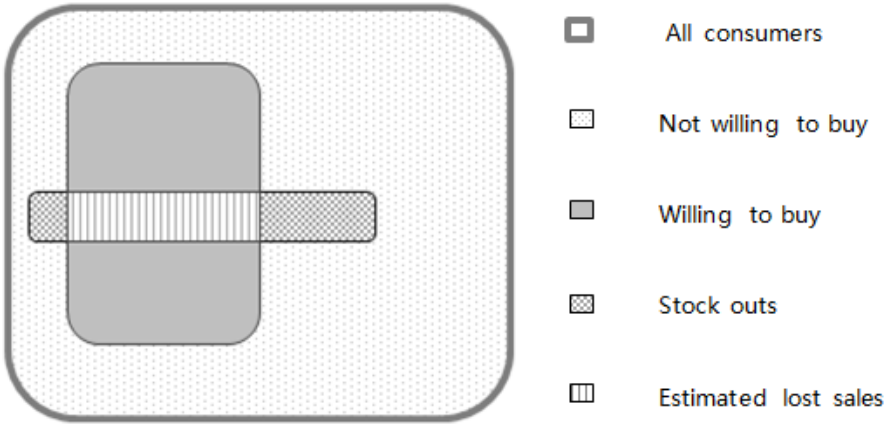

Figure 9: *Representation states of consumers including WTP*

Within the model including WTP, a consumer can have several 'states of being'. These are represented in Figure 9. A consumer can be willing to buy a product if their WTP is higher than or equal to the objective price of the product. If their WTP is lower than the objective price, the consumer is not willing to buy the product. If a consumer faces an empty stock, he or she is not able to determine their WTP. Thus regardless of whether a consumer is willing to buy or not, if a consumer faces an empty stock, this is counted as a stock out. However, from these stock outs, a small fraction of consumer was actually willing to buy a product if it was available. This fraction is the estimated lost sales, which is thus a multiplication of the fraction consumers who are willing to buy and the fraction consumers who faced a stock out. This representation of different consumer states holds for the model where WTP is included. For the model where WTP is not included, all consumers are assumed to be willing to buy a product. Consequently, all the stock outs are calculated as estimated lost sales.

4.2 Variable input data

The input for the three experimental factors will be variable, depending on the experiment number. The experimental factors with each their separate set of levels and values are shown in Table 14.

Table 14: *Variable input experimental factors*

Experimental factor	Description	Levels
ε	Shape of WTP curve	Exp = e0.1186r (R^2 = 0.9728) Quad = 0.025r2 + 0.0117r + 1.186 (R^2 = 1) Linear = 0.1883r + 0.9367 (R^2 = 0.9498)
P	Fraction of consumers picking LIFO	0% LIFO 40% LIFO 50% LIFO 60% LIFO 100% LIFO
Δ_r	Discount level for products in inventory *r = 1, … , M*	[0.60 0.50 0.40 0.30 0.20 0.10 0] [0.30 0.25 0.20 0.15 0.10 0.05 0] [0.35 0.35 0.35 0.35 0 0 0] [0.35 0.35 0 0 0 0 0] [0 0 0 0 0 0 0]

4.2.1 Shape of WTP curve

The shapes of the WTP curve are based on the outcomes of the fitted lines for an exponential form, equation *(35)*, quadratic form, equation *(36)*, and linear form, equation *(37)*, displayed in Figure 4. These equations are based on the remaining shelf life *r* of the product.

(35) $\mathrm{Exp} = \mathrm{e}^{0.1186\mathrm{r}}$

(36) $\mathrm{Quad} = 0.025^{\mathrm{r}} + 0.0117\mathrm{r} + 1.186$

(37) $\mathrm{Linear} = 0.1883\mathrm{r} + 0.9367$

4.2.2 Fraction of consumers picking LIFO

Which product is picked by the consumer depends to large extend on how the consumers evaluate the inventory in terms of the picking order. Tromp et al. (2012) estimated consumer selection behaviour by measuring product losses and out of stock situations in practice. This resulted into a percentage of 55% of the consumers LIFO and 45% selecting FIFO. In the model of Rijgersberg et al. (2010), a division of 40% of the consumers picking LIFO and 60% picking FIFO is used. The value for *P* determines the success ratio of the number of trials of equation *(10)* for which values between 40% and 60% for LIFO and FIFO are used.

Two extreme levels are added to investigate the sensitivity of the picking order on the performance measures.

4.2.3 Discount levels

To evaluate the effectiveness and efficiency of EDBP, different discount percentages will be used. Van Heerde et al. (2001) argue in their article for the existence of a threshold, and saturation point. A threshold point is the minimal percentage price discount required to change consumer's purchasing decisions, where the saturation point is the point above which the influence of price discounts on consumer purchase intentions is minimal (Gupta & Cooper, 1992). Based on the findings by Van Heerde et al. (2001), price discounts between 10-40% should be applied to change consumer decision making. Tsiros and Heilman (2005) show how the willingness to pay (WTP) is non-linear decreasing during the remaining shelf life of beef. Therefore, it might benefit to use price discounts earlier in during the remaining shelf life. To evaluate the effect of EDBP on consumer decision making, different discount percentages will be used on a different number of days before the product reaches its expirations date. The values for the discount level are chosen since these discounts are increasing as the remaining shelf life of the product is decreasing similarly. Tsiros and Heilman (2005) mention that deeper discounts may be necessary earlier in a products life cycle and based on the practice of Dutch supermarket chain Albert Heijn, the use of 35% discount levels is added. Two extreme levels are added to investigate the sensitivity of the picking order on the inventory model.

4.3 Design of experiments

Results are gathered using the linear design of experiments presented in Table 15. Each experiment varies with only 1 factor at a time, starting with base scenario 0. This results in a total of 13 scenarios. The 4th set of experiments do not include WTP and therefore model $y = 2$ is used during this simulation. This means that the lost sales, loss of revenue and mean weekly sales including the correction for lost sales are calculated somewhat different, as was explained in paragraph 3.2.

Table 15: *Linear design of experiments*

	Shape WTP (*S*)	Fraction consumers picking LIFO (*P*)	Discount level for RSL (Δ_r) 1	2	3	4	5	6	7
0 (base)	**Exp**	**60% FIFO / 40% LIFO**	**[0.30**	**0.25**	**0.20**	**0.15**	**0.10**	**0.05**	**0]**
1 a (quad)	Quad								
b (lin)	Linear								
2 c (FIFO)		100% FIFO / 0% LIFO							
b (50:50)		50% FIFO / 50% LIFO							
c (40:60)		40% FIFO / 60% LIFO							
d (LIFO)		0% FIFO / 100% LIFO							
3 a (high)			[0.60	0.50	0.40	0.30	0.20	0.10	0]
b (last-4)			[0.35	0.35	0.35	0.35	0	0	0]
c (last-2)			[0.35	0.35	0	0	0	0	0]
d (none)			[0	0	0	0	0	0	0]
4 a (noWTPF)	-	60% FIFO / 40% LIFO				-			
b (noWTPL)	-	40% FIFO / 60% LIFO				-			

5

RESULTS

This chapter starts describing the results for the KPI's of all the experiments. Hereafter, results are divided according to the different experimental factors, starting with the results for the different shapes of the WTP curve. This paragraph also focusses on the results for the base scenario. Then the results for the different fractions of LIFO and FIFO consumers are described. The fourth paragraph discusses the results for the different discount levels. In order to gain more insights in the selection behaviour of consumers, results of the distribution of percentages sales over the remaining shelf life are shown for all experiments. Results for the experiments excluding WTP finalize this chapter.

5.1 KPI's

Results for the KPI's are displayed in Table 16.

Table 16: *Results KPI's*

	Waste	Loss of Revenue	Gross Profit	Mean Weekly Sales
0 (base)	**6.57%**	**$571**	**$2356**	**20.02**
Shape WTP				
1a (quad)	6.51%	$568	$2420	20.43
1b (lin)	5.82%	$593	$2344	19.69
FIFO/LIFO ratio				
2a (FIFO)	2.39%	$704	$2599	20.45
2b (50:50)	8.05%	$523	$2275	19.90
2c (40:60)	9.60%	$473	$2186	19.78
2d (LIFO)	15.87%	$288	$1840	19.61

	Waste	Loss of Revenue	Gross Profit	Mean Weekly Sales
Discount level				
3a (high)	0.46%	$1512	$2523	24.01
3b (last-4)	2.19%	$1061	$2671	23.06
3c (last-2)	5.97%	$509	$2327	19.13
3d (none)	13.85%	$71	$2033	17.93
Excluding WTP				
4a (noWTPF)	2.78%	$52	$3145	20.05
4b (noWTPL)	6.04%	$54	$2892	19.96

Table 16 shows that exp. 1b (lin) yield the lowest percentage of products disposed of the first set of experiments, although this is at the expense of more loss of revenue and less mean weekly sales. Apparently more consumers select the products due to the quadratic trend type of the WTP, since mean weekly sales is the highest for exp. 1a (quad) compared to the base case (exp) and exp. 1b (lin). This result might be the consequence of the R^2 of the WTP curve displayed in Figure 4, which is the highest for the quadratic function. Besides, the WTP estimated by the quadratic function is the highest for the first and last day of a products shelf life, which also may have an influence on the differences in mean weekly sales. Exp. 1a (quad) yields a lower percentage product disposed as well as a lower loss of revenue compared to base case 0. This difference might be the result of a higher mean weekly sales for the exp. 1a (quad).

The usage of different fractions of LIFO consumers shows clear trends in the results of this experimental factor. If 0% of the consumers pick LIFO, waste is the lowest. Increasing the fraction of LIFO consumers, also increases the percentage products going to waste. This is expected, since LIFO consumer always evaluate the youngest products of the inventory first. Consequently, LIFO consumers pick younger products more often than older products. However, increasing the fraction of LIFO consumers, decreases the loss of revenue. This is due to less consumers picking products with higher discounts. When 100% of the consumers pick FIFO, more discounted products are selected, which results in a high loss of revenue. The gross profit is higher for larger fractions of the consumers picking LIFO, which could be correlated with the mean weekly sales, since both simultaneously increase. All these results are also visible for altering the picking order ratios less extreme, like in experiments 2b (50:50) and 2c (40:60).

The usage of different discount levels also shows clear trends in the result. If high discount levels are applied, less products are going to waste. Consequently, the loss of revenue is higher compared to experiments where the discount levels are lower. The gross profit shows a tipping point if high discount levels are applied due to the increasing loss of revenue. The

increase in mean weekly sales does not accommodate anymore for the loss of revenue when applying high discounts, which results in a lower gross profit. Exp. 3d (none) yields the lowest loss of revenue, but here the percentage waste is the highest. Practical scenarios 3b (last-4) and 3c (last-2) only apply 35% discounts on the last few days of the remaining shelf life. Both experiments show lower percentage waste compared to the base scenario. Moreover, exp. 3c (last-2) also shows a lower loss of revenue. Apparently using higher discount levels attracts more consumers who pick a product, which can be seen in the trend for mean weekly sales. More consumers are willing to pay the objective price, since the latter one is obviously lower due to higher discounts. As can be seen in the first and second set of experiments, a higher mean weekly sales, leads to a lower percentage waste.

Experiments 4a (noWTPF) and 4b (noWTPL) do not include WTP. These experiments show a slight decrease in mean weekly sales if the percentage LIFO consumer increases, which was also a trend for the second set of experiments, the fraction of LIFO consumers. Compared to the base case, both experiments 4a and 4b yield a lower percentage of product disposed. The lower percentage of waste is the result of all FIFO consumers picking the oldest product for this model even if no discounting is applied. In the model with WTP, not all FIFO consumers pick the oldest product. Loss of revenue for both experiments 4a (noWTPF) and 4b (noWTPL) is also lower, since the loss of revenue only includes the loss due to lost sales. The gross profit is much higher for these experiments compared to the other sets of experiments. This can be explained by the difference in loss of revenue. The loss of revenue due to discounting in the 4th set of experiments is $0, since no discounting is applied. Thus all product using the model without WTP are sold for the normal retail price, which results in a higher gross profit.

5.2 Experiment 1: shapes WTP curve

Table 17 shows the results for the experiments with the different shapes of the WTP curve.

Table 17: *Results experiments WTP parameter*

	0 (base)	**1a (quad)**	**1b (lin)**
PWASTE	6.57%	6.51%	5.82%
LOSSREVENUE	$571	$568	$593
PROFIT	$2356	$2420	$2344
MWSALES	20.02	20.43	19.69
PSTOCKOUT	0.73%	0.68%	0.77%
PEXPENSIVE	65.29%	64.67%	65.81%
PPICK	33.97%	34.64%	33.42%
PLOSTSALE	0.25%	0.24%	0.26%

	0 (base)	1a (quad)	1b (lin)
TREVENUE	$6177	$6314	$6046
COSTWASTE	$235	$238	$203
TCOSTORDER	$3585	$3656	$3498
TCOST	$3821	$3894	$3701
AGEPRODUCT	2.56	2.53	2.65

Exp. 1b (lin) leads to the lowest percentage of consumers who picked a product (PPICK) and the highest percentage of stock outs (PSTOCKOUT). As can be seen, the percentages of consumers who pick a product is related to mean weekly sales. Using the quadratic WTP curve yields the highest total revenue (TREVENUE), due to the higher mean weekly sales. However, exp. 1a (quad) also yields the highest total costs (TCOST), due to the higher ordering costs (TCOSTORDER). The linear WTP curve yields the mean weekly sales and therefore also the lowest total revenue, but also the lowest total costs. The product age is the highest for exp. 1b (lin), which means that the consumers in this experiment pick older products compared to the other experiments. Generally, the results of the base scenario 0 are in between the results of exp. 1a and 1b and do not differ very much from the base scenario.

This subsection will explain the results of scenario 0 with support of the results from exp. 1a and 1b to verify the validity of the model. From Table 17 it can be seen that mean weekly sales (MWSALES) are higher for exp. 1a (quad) compared to scenario 0. Consequently, the total ordering costs (TCOSTORDER) are higher. Simultaneously, higher percentages waste for scenario 0, lead to higher costs of the product waste (COSTWASTE). Besides, it can be seen that an increase in mean weekly sales lead to higher percentage of consumers who have picked a product (PPICK) and a lower percentage of consumers who rejected the products (PEXPENSIVE).

Figure 10 and Figure 11 show the distributions of sales percentages of FIFO and LIFO consumers over the remaining shelf life of the picked products for scenario 0 and exp. 1a and 1b.

Scenario 0 shows higher sales percentages for younger products. This also holds for exp. 1a (quad). Only exp. 1b (lin) shows a drop in sales for products with a remaining shelf life of 7 days. The distribution for FIFO consumers shows the highest peak for products with a remaining shelf life of 7 days for exp. 1a. This exp. also has the highest sales for products with a remaining shelf life of 1 day. This exp. shows a higher sales for products with a remaining shelf life of 2, 3, 4, 5, and 6 days, which corresponds with the higher WTP of the consumers for these ages of the product shown Figure 4.

The distribution of sales over the remaining shelf life for LIFO consumers is quite different compared to the distribution of sales of FIFO consumers. Almost all LIFO consumers of all experiments picked products with a remaining shelf life of 7 days and no LIFO consumers picked products with a remaining shelf life of 1 or 2 days.

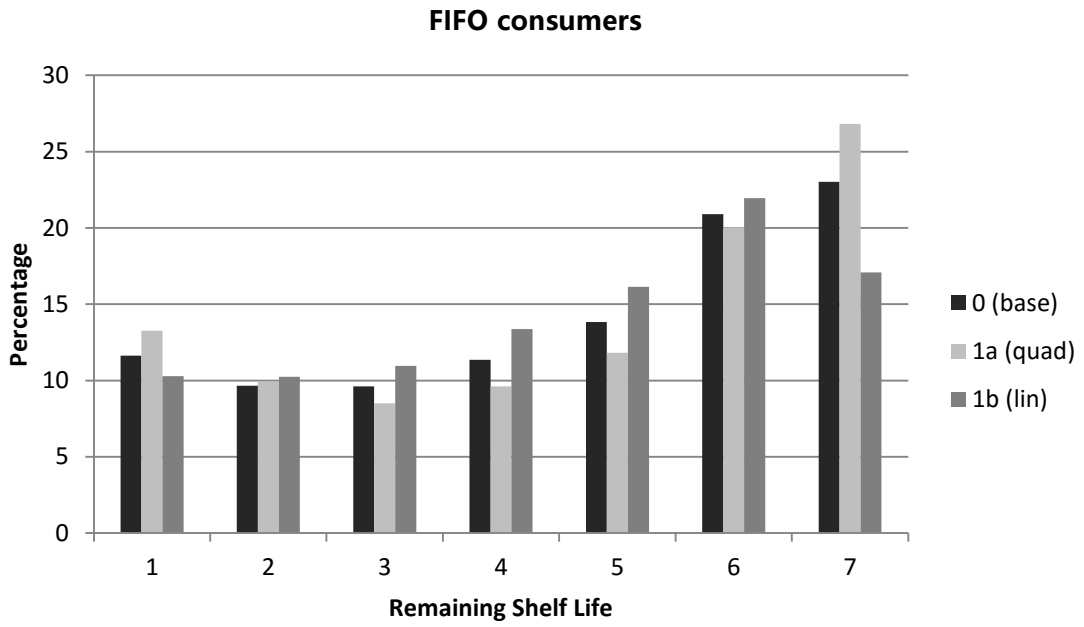

Figure 10: *Distribution of sales percentages of FIFO consumers over remaining shelf life for the different shapes of the WTP*

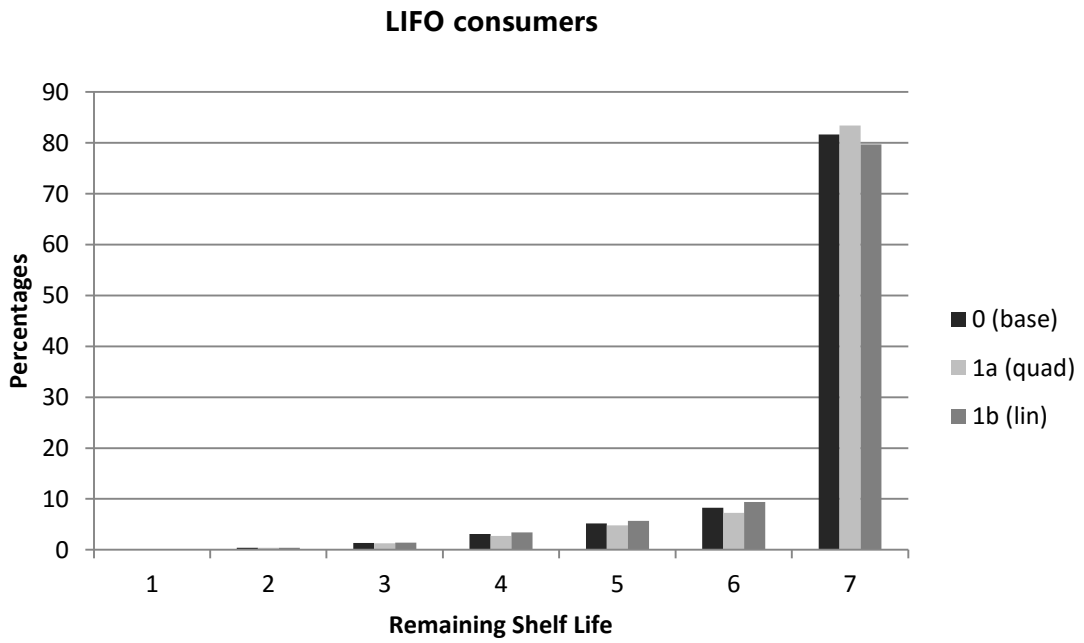

Figure 11: *Distribution of sales percentages of LIFO consumers over remaining shelf life for the different shapes of the WTP*

5.3 Experiment 2: Picking order

The second experiment entails different fractions of consumers picking LIFO. Table 18 shows the results for these experiments.

Table 18: *Results picking order ratios*

	0 (base)	2a (FIFO)	2b (50:50)	2c (40:60)	2d (LIFO)
PWASTE	6.57%	2.39%	8.05%	9.60%	15.87%
LOSSREVENUE	$571	$704	$523	$473	$288
PROFIT	$2356	$2599	$2275	$2186	$1840
MWSALES	20.02	20.45	19.90	19.78	19.61
PSTOCKOUT	0.73%	0.73%	0.79%	0.82%	1.39%
PEXPENSIVE	65.29%	64.53%	65.44%	65.63%	65.48%
PPICK	33.97%	34.74%	33.77%	33.55%	33.13%
PLOSTSALE	0.25%	0.25%	0.27%	0.27%	0.46%
TREVENUE	$6177	$6189	$6188	$6198	$6349
COSTWASTE	$235	$84	$291	$351	$618
TCOSTORDER	$3585	$3506	$3621	$3660	$3891
TCOST	$3821	$3590	$3912	$4011	$4509
AGEPRODUCT	2.56	2.91	2.41	2.27	1.60

Using a higher fraction of LIFO consumers in the experiments, resulted in higher percentages of stock out (PSTOCKOUT) and estimated lost sale (PLOSTSALE), but lower percentages of the lowest percentage of sales (PPICK). In verification of the model, the higher the percentage is of consumers who picked a product (PPICK), the higher mean weekly sales are (MWSALES).

The highest total revenue is yielded by exp. 2d (LIFO). Although, due to the high costs of product disposal (COSTWASTE), the lowest gross profit (PROFIT). Apparently more sales do not always lead to higher ordering cost, since exp. 2a (FIFO) have the highest MWSALES, but exp. 2d (LIFO) have the highest ordering costs (TCOSTORDER). In fact, increasing the fraction of LIFO consumers corresponds to an increasing in the total ordering costs (TCOSTORDER). LIFO consumers pick younger products than FIFO due to their picking order. Therefore, the age of the picked products (AGEPRODUCT) is the lowest in exp. 2d (LIFO) and the highest in exp. 2a (FIFO), which can also be seen in Figure 12 and Figure 13.

Figure 12 and Figure 13 show the distributions of sales percentages of FIFO and LIFO consumers over the remaining shelf life of the picked products for the picking order rations.

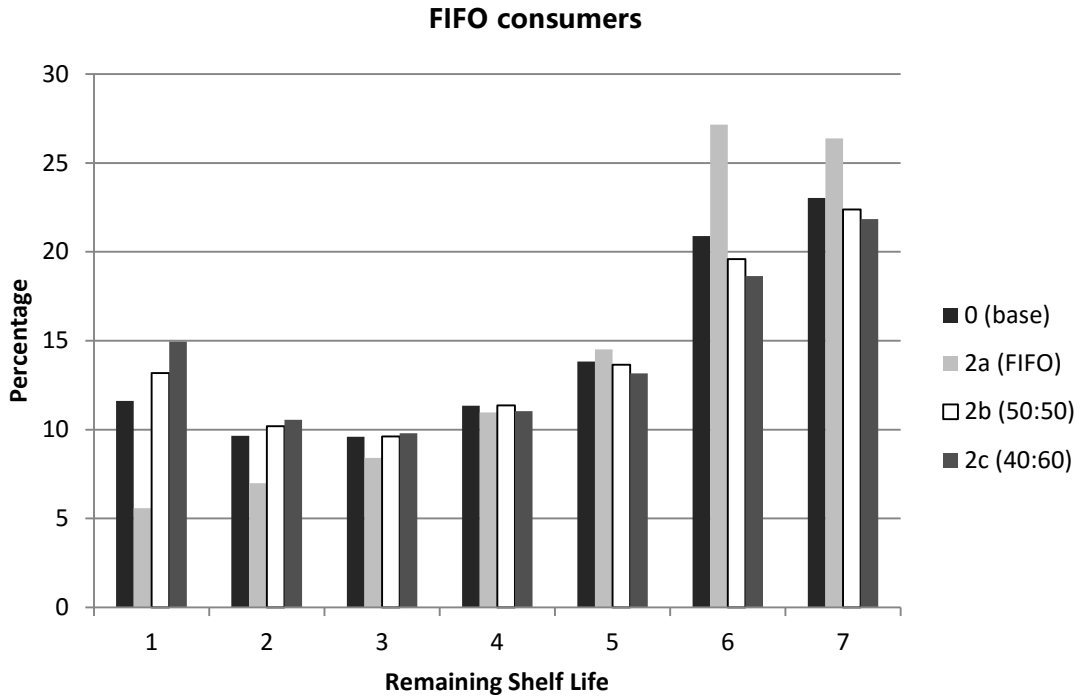

Figure 12: *Distribution of sales percentages of FIFO consumers over remaining shelf life for the picking order ratios*

The sales percentages of the FIFO consumers of the different experiments in Figure 12, are not evenly distributed over the remaining shelf life of the products. This was not expected since nothing changed between these experiments besides the fraction of LIFO consumer, which should not matter for the distribution of sales percentages of FIFO consumers. The percentages sales by FIFO consumers of exp. 2c (40:60) is the highest for products with 1 remaining shelf life day and the lowest sales for products with 7 remaining shelf life days. FIFO consumers of exp. 2a (FIFO) have the lowest percentage sales for products with 1 remaining shelf life day and the highest percentage sales for products with 5, 6 and 7 remaining shelf life days. These difference might be the consequence of modelling limitations where in this research, the LIFO consumers enter the model first on a simulation day, and therefore leave different inventories for the FIFO consumers.

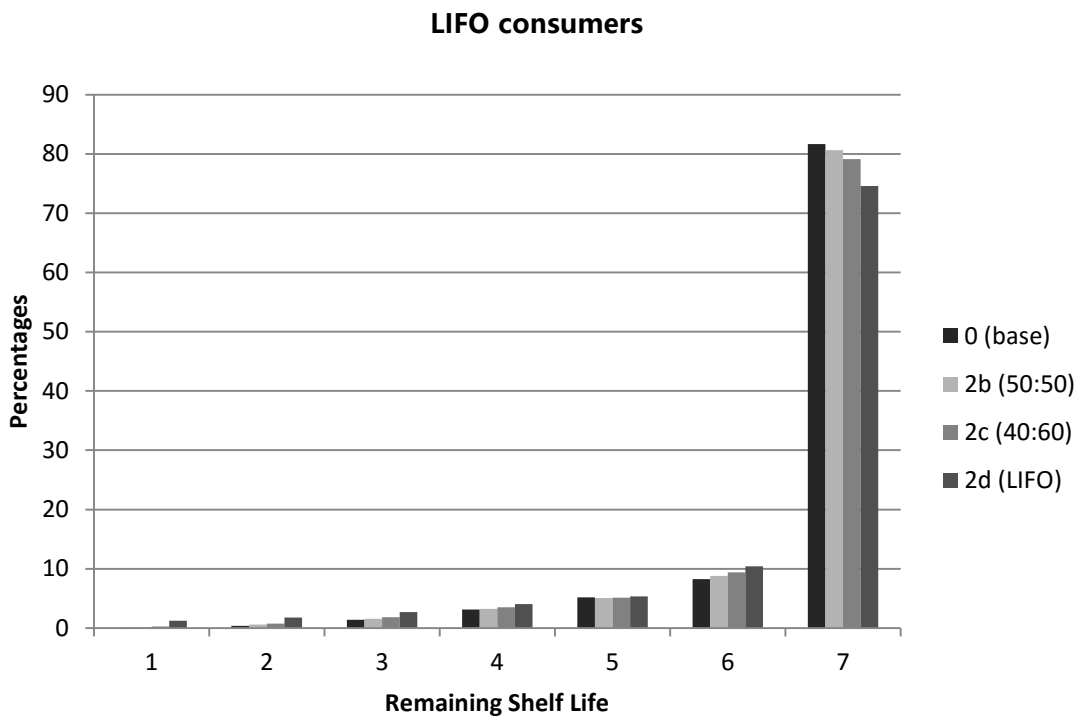

Figure 13: *Distribution of sales percentages of LIFO consumers over remaining shelf life for the picking order ratios*

The distributions of sales percentages of LIFO consumers in Figure 13 are more alike than the distributions of FIFO consumers in Figure 12. As with experiment 1, all experiments 2 show a high percentage of sales for products with 7 days of remaining shelf life. The consumers of exp. 2d (LIFO) show the widest spread over the remaining shelf life where base case 0 shows a narrow spread.

Comparing Figure 12 and Figure 13, it can be seen that LIFO consumers are far more committed to their principle of picking the youngest product than FIFO consumers are committed to their principle of picking the oldest products. This difference may explain the trends occurring while increasing the fraction of LIFO consumers. LIFO consumers primarily pick products without a discount, which explains the decrease in loss of revenue while increasing the fraction of LIFO consumers. Besides, it shows that LIFO consumers primarily pick the youngest product, thus more products while go to waste while increasing the fraction of LIFO consumers.

5.4 Experiment 3: Discount levels

The third experiment entails different discount levels. Table 19 shows the results for the remaining outcomes of these experiments.

Table 19: *Results discount levels*

	0 (base)	3a (high)	3b (last-4)	3c (last-2)	3d (none)
PWASTE	6.57%	0.46%	2.19%	5.97%	13.85%
LOSSREVENUE	$571	$1512	$1061	$509	$71
PROFIT	$2356	$2523	$2671	$2327	$2033
MWSALES	20.02	24.01	23.06	19.13	17.93
PSTOCKOUT	0.73%	0.73%	0.63%	0.65%	1.18%
PEXPENSIVE	65.29%	58.56%	60.26%	66.92%	68.43%
PPICK	33.97%	40.71%	39.11%	32.44%	30.39%
PLOSTSALE	0.25%	0.30%	0.24%	0.21%	0.36%
TREVENUE	$6177	$6576	$6704	$5936	$5994
COSTWASTE	$235	$18	$86	$203	$481
TCOSTORDER	$3585	$4034	$3946	$3406	$3480
TCOST	$3821	$4053	$4033	$3609	$3961
AGEPRODUCT	2.56	2.81	2.70	2.67	1.84

The results for the discount levels are as expected. A clear trend is that higher discount percentages lead to a higher percentages of consumers who pick a products (PPICK). Simultaneously, the percentages of consumers who face too expensive products decreases (PEXPENSIVE). However, as stated earlier, this also holds for the loss of revenue, the mean weekly sales and the percentage waste. The results of exp. 3c (last-2) tend more towards the results of no discounting in exp. 3d (none), although the percentage of products disposed is much lower. The results of exp. 3b (last-4) tend more towards the results of high discount levels in exp. 3a (high), although the loss of revenue is much lower. Exp. 3b (last-4) yields the highest total revue and the highest gross profit. The percentage lost sales are the highest for exp. 3a (high) and exp. 3d (none). Exp. 3d (none) yields the lowest total revenue and the lowest gross profit. However, the loss of revenue is much higher for exp. 3a (high), compared to ex. 3d none), due to discounting. Interestingly, results show that if the price does not accommodate for the ageing of the product, consumers prefer fresher products. Higher discounts at the end of a products shelf life, increases the age of the picked products. The picked products in exp. 3d (none) are namely the youngest. The picking products are the oldest in exp. 3a (high).

Figure 14 shows the distributions of sales percentages of FIFO consumers over the remaining shelf life of the picked products for the discount levels. Exp. 3b (last-4) uses discounting on the last four days of the remaining shelf life of a product. Exp. 3c (last-2) only uses discounting on the last two days of the remaining shelf life of a product. The effects of discounting in exp. 3b (last-4) and 3c (last-2) on sales percentages of FIFO consumers are clearly visible in Figure 14, as sales increases for the discounted products. Exp. 3a (high) uses discount levels twice as high as the base scenario. However, the sales percentages are dissimilarly distributed over the remaining shelf life. In Figure 14 it can be seen that the lower waste percentages are related to the lower sales percentages of products with 1 day remaining shelf life in exp. 3a (high) and exp. 3b (last-4). In these experiments, most products are probably already sold in the earlier stages of the products shelf life. The preference of consumers for fresher products is also clearly visible if no discounting is used like in exp. 3d (none), since the sales percentages are higher for products with 6 or 7 days remaining shelf life compared to the sales percentages of older products.

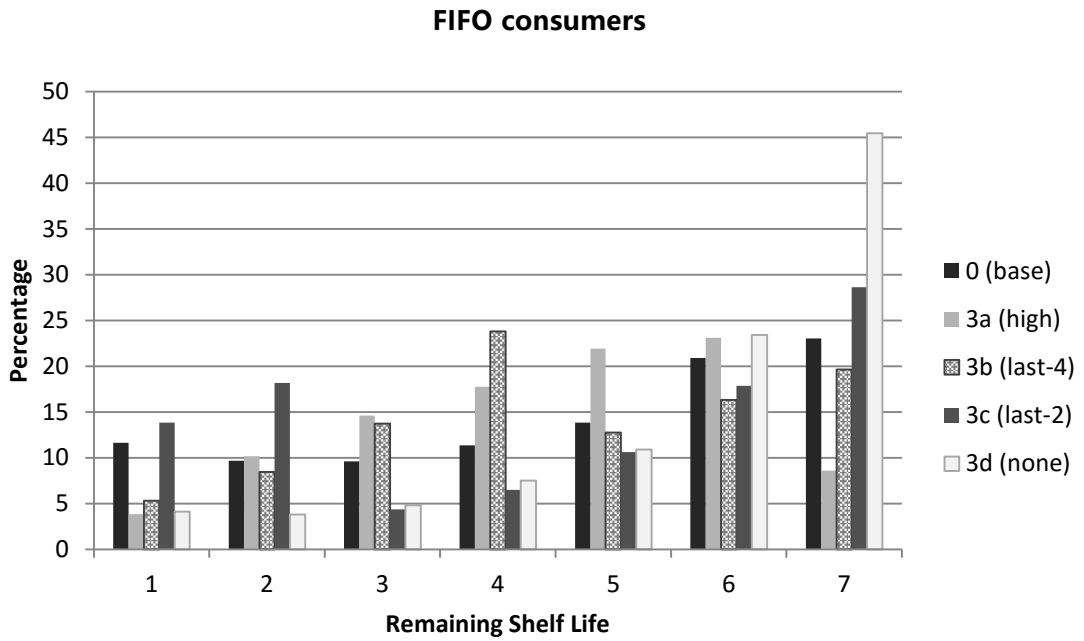

Figure 14: *Distribution of sales percentages of FIFO consumers over remaining shelf life for discount levels*

Figure 15 shows the distributions of sales percentages of LIFO consumers over the remaining shelf life. As in Figure 14, the effects of discounting in exp. 3b (last-4) and 3c (last-2) are visible. Sales show a peak for products with a remaining shelf life of 2 days for exp. 3c (last-2) and a peak for product with a remaining shelf life of 4 days for exp. 3b (last-4). The sales percentages of LIFO consumers of exp. 3a have a wider over the remaining shelf life than the other experiments.

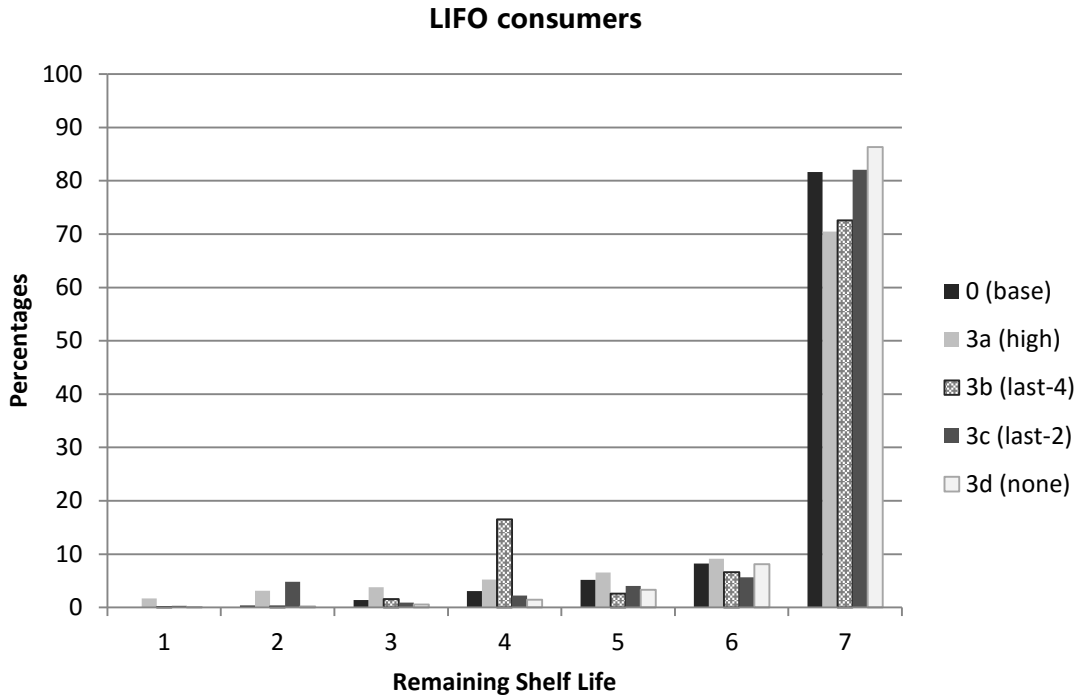

Figure 15: *Distribution of sales percentages of LIFO consumers over remaining shelf life for discount levels*

5.5 Experiment 4: Excluding a WTP

The fourth experiment excluded WTP, thus consumer selected products based on the availability. Table 20 shows the outcomes for these experiments.

Table 20: *Results excluding a WTP*

	0 (base)	**4a (noWTPF)**	**4b (noWTPL)**
PWASTE	6.57%	2.78%	6.04%
LOSSREVENUE	$571	$52	$54
PROFIT	$2356	$3145	$2892
MWSALES	20.02	20.05	19.96
PSTOCKOUT	0.73%	0.77%	0.85%
PEXPENSIVE	65.29%	0.00%	0.00%
PPICK	33.97%	99.23%	99.15%
PLOSTSALE	0.25%	0.77%	0.85%
TREVENUE	$6177	$6673	$6639
COSTWASTE	$235	$95	$213
TCOSTORDER	$3585	$3433	$3533
TCOST	$3821	$3528	$3747
AGEPRODUCT	2.56	2.89	2.63

As explained in paragraph 4.1.6, the average amount of consumers entering the model is different for experiments with WTP compared to experiments without WTP. Selection based on availability leads to higher sales percentages for exp. 4a (noWTPF) and 4b (noWTPL), compared to the base scenario. For this difference in percentage of consumer who picked a product is corrected in the average amount of consumers entering the model. The mean weekly sales are therefore more or less the same. The difference in the mean weekly sales between exp. 4a (noWTPF) and exp. 4b (noWTPL) might be due to the difference of fraction of consumers picking FIFO. The estimated lost sales are higher for the experiments without WTP compared to the base case, since every stock out equals a lost sale if consumers select based on availability. The loss of revenue of exp. 4a (noWTPF) and 4b (noWTPL) are the lowest of all experiments, since there is no loss due to discounting. Consequently, total revenue of these experiments is the highest. The picked products are the oldest in exp. 4a (noWTPF).

Figure 16 and Figure 17 show the distributions of sales percentages of FIFO and LIFO consumers over the remaining shelf life for the experiments excluding WTP 4a (noWTPF) and 4b (noWTPL). Exp. 4a (noWTPF) shows an increase in sales of FIFO consumers for younger products where exp. 4b (noWTPF) shows an increase in sales of FIFO consumers for older products. This difference might be due to modeled sequence of the picking order where LIFO consumer enter the model before FIFO consumers. Percentages sales of experiments without WTP are lower than the base scenario for products with a remaining shelf life of 7 days.

In exp. 4a (noWTPF) and 4b (noWTPL) there is less sales of LIFO consumers for products with a remaining shelf life of 7 days, but slightly more sales for older products. Apparently if consumers select product only based on availability, thus for the experiments without WTP, the preference of LIFO consumers for younger products is still clearly visible.

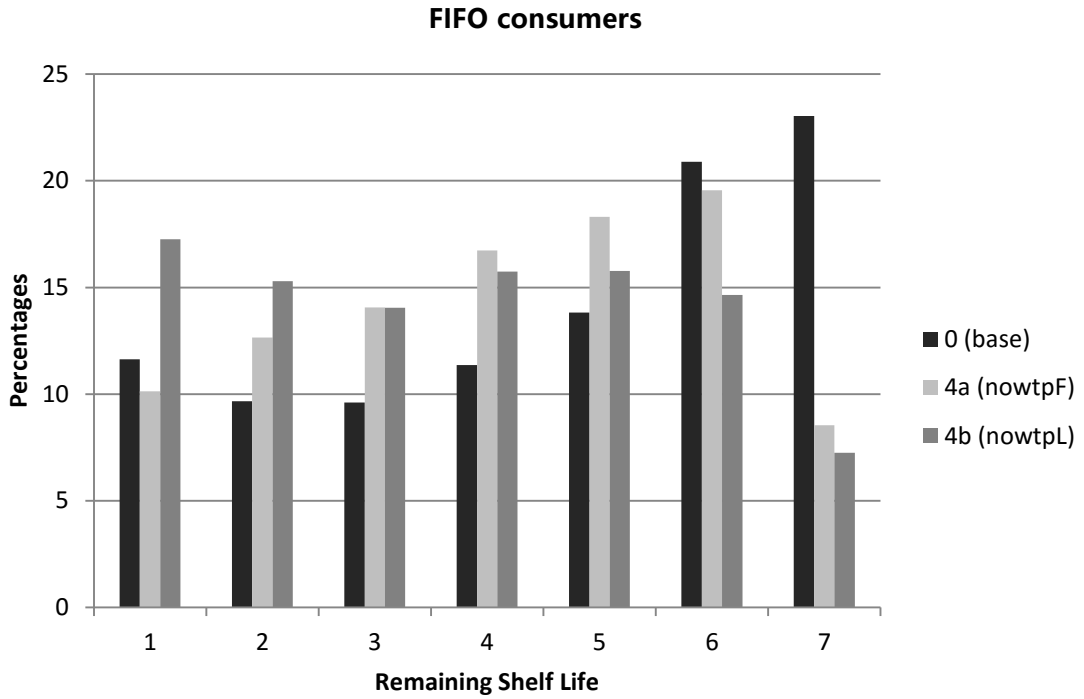

Figure 16: *Distribution of sales percentages of FIFO consumers over remaining shelf life excluding WTP*

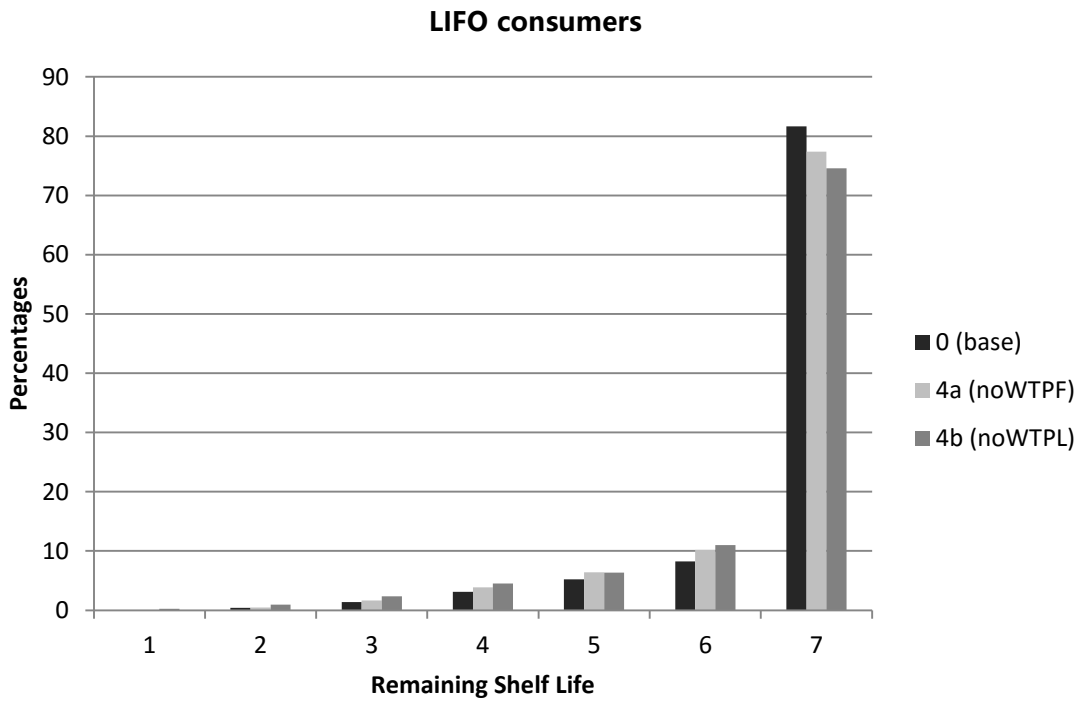

Figure 17: *Distribution of sales percentages of LIFO consumers over remaining shelf life excluding WTP*

In Table 21 the differences between models with WTP and without WTP are shown. The fraction of LIFO consumers is the same for both experiments. A correction is made in the average amount of consumers entering the model for the large difference the percentage of consumers who pick a product (PPICK) in order to equate mean weekly sales.

Table 21: *Results difference model with WTP and without WTP*

	0 (base)	**4a (noWTPF)**
PWASTE	6.57%	2.78%
LOSSREVENUE	$571	$52
PROFIT	$2356	$3145
MWSALES	20.02	20.05
PSTOCKOUT	0.73%	0.77%
PEXPENSIVE	65.29%	0.00%
PPICK	33.97%	99.23%
PLOSTSALE	0.25%	0.77%
TREVENUE	$6177	$6673
COSTWASTE	$235	$95
TCOSTORDER	$3585	$3433
TCOST	$3821	$3528
AGEPRODUCT	2.56	2.89

Obvious, the loss of revenue is higher for the model where discounting is included, but this does not explain why the percentage of waste is much lower for the model where WTP is not included. Besides, the difference in gross profit between the model is higher than the difference in loss of revenue. Moreover, the model without WTP assumes that consumers do not prefer fresher products if the price does not accommodate for the age of the product since the age of the picked products is higher for the model without WTP. For these unexplainable reasons, it can be stated that not including WTP is an optimistic way of modelling consumer behaviour.

6

CONCLUSIONS

This concluding chapter answers the three research questions, starting by recalling the relation between EDBP and consumer decisions making. Hereafter, it is explained how the product-flow of a perishable product is modelled by incorporating the relation between EDBP and consumer decision making. Finally, an indication is given about the effectiveness and efficiency of EDBP in order to reduce food waste based on the results of chapter 5 including conclusions regarding the selection behaviour of consumers are given in this chapter.

The main objective of this study is to incorporate the effect of expiration date-based pricing on consumer decision making in an inventory model in order to reduce food waste. How this objective is achieved will be explained by answering the three research questions in the following three paragraphs.

1. *What is the relation between EDBP and consumer decision making?*
2. *How can the product-flow of a perishable product be modelled by incorporating the relation between EDBP and consumer decision making?*
3. *How effective and efficient is EDBP in order to reduce food waste?*

6.1 The relation between EDBP and consumer decision making

The literature study operationalized the relation between EDBP and consumer decision making. Based on this study, two information cues flow from the products in stock: the expiration date and the objective price. Both are assumed to be observed by the consumers. Hereafter, the consumer determines his or her willingness to pay for that product. The actual product choice is based on the non-compensatory conjunctive decision rule. This means that the product choice of consumers is based on cut-off levels for product attribute values. In this study, the product attribute value is the objective price of the product including discounts, and the cut-off level the WTP by consumers for that product. Thus if the objective

price, including discounts, is lower than or equal to the WTP of consumers, this particular product is picked.

6.2 Modelling the product-flow

The developed model covers the product-flow of a perishable product through the stock of a grocery retailer and includes the relation between EDBP and consumer decision making. The article of Tsiros and Heilman (2005) provided the data for the WTP of consumers and how this WTP differs for an increasing age of the product. By incorporation the relation between EDBP and consumer decision making, this research differs from current practices in terms of modelling consumer behaviour. An important modelling modification is the value input for the average amount of consumers entering the model per weekday. To equate mean weekly sales between the model with WTP and without WTP, the average amount of consumers entering the model needed to be tripled. Using the WTP decision structure results in less consumers who actually pick a product. Differences in mean weekly sales influences the total model and corrupts the outcomes. Consequently, different inputs for the average amount of consumers entering the model are used for experiments including WTP and experiments excluding WTP.

There are four KPI's used to determine whether the modelling objectives have been achieved in this research. The first KPI is the percentage of products disposed from the total amount of products ordered to measure the effectivity of the experimental factors in order to reduce waste. The second KPI is the loss of revenue for the retailer to measure the efficiency of the experimental factors in order to reduce waste. The third KPI is the gross profit for the retailer to measure the profitability of the experimental factors in order to reduce waste. The fourth KPI is mean sales per week corrected for lost sales.

This research used a linear design of experiments. Each experiment varies with only 1 factor at a time, starting with base scenario 0. The design of experiments entails three factors; the shape of WTP curve, the fraction of consumer picking LIFO, and the application of different discounting levels. This results in a total of 13 scenarios. Through discrete time simulation with variable inputs for the three experimental factors, evaluation of the performance measures determines which inputs effectively and efficiently reduce food waste. Furthermore, a comparison of the performance measures is made between implementing and not implementing WTP in the model.

6.3 Effectiveness and efficiency of EDBP

The effectiveness of EDBP is measured in terms of percentage waste. The efficiency is measured in terms of loss of revenue. First, it is important to concluded that, according to the results in chapter 5, discounting decreases food waste. Results show that if no discounting is applied, about 14% of the products will go to waste. In contrast, using high discount levels (up to 60% on the last day of the remaining shelf life of a product) decreases the percentage waste to less than 1%. However, when applying discounts, the total loss of revenue increases with almost $600 per year since more consumers pick cheaper products. Despite the loss of revenue, gross profit mainly increases when discounting is applied. Profit increase due to the increase in mean weekly sales, since the lower prices attract more consumers who actually pick a product. However, the gross profit shows a tipping point when applying higher discount levels. The increase in mean weekly sales does not accommodate anymore for the loss of revenue when applying high discounts, which results in a lower gross profit. Therefore, it can be concluded that increasing the effectivity of EDBP in order to reduce food waste is at the expense of the efficiency of EDBP. Nevertheless, it is concluded that, up to a certain level, applying discounting has positive effects for retailers. Applying discounts up to a certain level increases a retailer's profit, mean weekly sales, and reduces food waste and is therefore advised to apply in practice. Retailers should weigh the outcomes and choose the discounting strategy closest to its corporative strategy. A retailer with a high corporate social responsibility might prefer the usage of higher discount level to reduce more food waste where other retailers are more sensitive to the loss of revenue and might prefer lower discount levels. Besides, consumer might expect a lower price for older products since they pick primarily younger products if discounting is not applied, which influence the percentage food waste drastically. Compared to the base scenario, using 35% discount on the last two days of the remaining shelf life shows a decrease in the percentage food waste and the loss of revenue. This strategy is based on practice, but is now proven to be the best strategy regarding the effectiveness and efficiency of EDBP.

Besides EDBP, this research also explored and integrated consumer selection behaviour and its influence on food waste. It can be concluded that by using a higher fraction of LIFO consumers in the model, food waste increases, mean weekly sales decreases, the loss of revenue decreases, but the gross profit also decreases. Therefore, it is concluded that LIFO consumers increase costs and increase food waste. Moreover, it is shown that FIFO consumers have a much wider spread of sales percentages over the remaining shelf life of products compared to LIFO consumers, who primarily pick the youngest products. Concluding, it is advised that retailers implement tactics in their daily operations to prevent consumers picking from picking LIFO. One tactic might be the use of deeper discounting levels earlier in a products shelf life. This appears to be necessary to influence LIFO

consumer to pick older products. However, more research is needed to investigate the differences between LIFO and FIFO consumers and how a LIFO consumer might be persuaded to pick FIFO. An odd finding is that increasing the fraction of LIFO consumers, resulted in an increase in the total order costs, which means that more products need to be ordered when the fraction of LIFO consumers increases. Interesting insights might be found if the relation between the ordering policy and selection behaviour is more intensively explored than in this research.

7

DISCUSSION

This research incorporated consumer decision making in the developed inventory model. This behaviour is approximated by including a WTP of consumers in the model. Whether a consumer picks a particular product depends on the conjunctive rule, where the objective price of the product should be lower than or equal to the WTP of consumers. This research included consumers with a low WTP, which resulted in not every consumer picking a product. Therefore, a correction in the average amount of consumers entering the model was made to equate the mean weekly sales of the models. Interestingly, including a WTP in the model increased the percentage food waste despite the usage of discount and the similar sales volume. Comparing the two models, results show differences in favour of the model without WTP. The percentage food waste is lower, the loss of revenue is lower, and gross profit is higher. Therefore, it can be stated that not including WTP is an optimistic way of modelling consumer selection behaviour. However, since consumer behaviour is complex to model, many assumptions are made to approximate consumer decision making. The conjunctive rule described consumer evaluations as a binary choice: acceptance or rejection, which made this well applicable for modelling and simulation purposes with clear demarcations. However, in practice consumers might not apply such hard boundaries for their product choice, especially not for low-involvement products like beef. More factors influencing decision making should therefore be taken into account, like the timeframe in which the decision has to be made, the mood of the consumer, the extent to which the decision solves a particular problem and the environment in which the consumer is situated. To include these variables within the research framework, a different research strategy should be chosen, since modelling and simulation will not fit the purpose of including these variables in the research.

This research did not account for the consequences of discounting perishables besides its effect on the performance measures of the model. Generally, pricing and promotion literature suggest that discounting may lead to negative consumer evaluations (Grewal et al., 1998) and future purchase intentions (DelVecchio et al., 2006). Tsiros and Heilman (2005)

concluded their study by noting that retailers should weigh the trade-offs between the potential benefits of discounting perishables to increase sales and its potential negative effects on store image. Discounting is advised to reduce food waste, but this advice is regardless of other potential consequences of discounting perishable products. Besides, product branding and product substitution where outside the scope if this research. Retailers should be especially careful when applying discounts on branded products, since this may lead to negative consumer evaluations about this brand. In the model with WTP, around two-thirds of the consumers rejected the products and did not close the gap between their actual and ideal state. How these consumers eventually pick a product or a similar product might by interesting further research where the effect of discounting on product substitution can be investigated and incorporated in the model.

A technical drawback is that this research did not test for the sequence in which the consumers enter the model. In the model developed in this research, LIFO consumer enter the model first, leaving different inventories for FIFO consumers than if they would have entered the model first. This sequence might have influenced the results of the different fractions of the LIFO consumers.

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APPENDIX: MATLAB CODE

```
option      = input('Enter: 1 (WTP - Fixed division), or 2 (Normal - Fixed division): ');

N           = 200;                              %number of runs
T           = 1456;                             %number of days
M           = 7;                                %maximum remaining shelf life
r           = 1:M;                              %remaining shelf life
RP          = 2.58;                             %average retail price per product
OC          = 0.5*RP;                           %ordering costs per product
Exp         = exp(0.1186*r);                    %WTP based on exponentional trend type
Quad        = 0.025*r.^2 - 0.0117*r + 1.1867;   %WTP based on quadratic trend type
Linear      = 0.1883*r + 0.9367;                %WTP based on linear trend type

%experimental factors
E           = Exp;                              %shape of the WTP curve
P           = 0.4;                              %percentage picking LIFO
discL(r)    = [0.3 0.25 0.2 0.15 0.1 0.05 0];   %discount levels

%parameter for rolling horizon
sf          = 2.326;                            %safety factor

switch(option) %switch between different demand for the models

    case 1
        lambda      = [7.056 6.468 7.644 9.408 14.7 13.524 0]; %potential demand for WTP
model
    case 2
        lambda      = [2.4 2.2 2.6 3.2 5 4.6 0]; %actual demand for LIFO/FIFO model
end

for run = 1:N %modelling N runs
    I = zeros(T,7);       %each new run starts with zero inventory
    D = zeros(T,7);       %each new run starts with zero demand
    DLIFO = zeros(T,7);
    DFIFO = zeros(T,7);
    Iend = zeros(T,7);

    %variables used for the calculations of S
    udemand = zeros(1,7);
    u = zeros(1,7);

    %variables used for output
    Nstockout=0;
    Nexp = 0;
    Nproductdisp = 0;
    Nconsumers = 0;

    %weekcount
    i = 0;

    fprintf('This will be run %d\n', run);
    for t=1:T % simulating T days

        %starting inventory for different days
        I(1,7) = 2;
        I(8,7) = 2;
        I(15,7) = 2;
        I(22,7) = 2;
```

```
%simulation starts on a monday (w = 1)
w = 1 + mod(t-1,7); % weekday of day t, 1 = monday to 6 = saterday and 7 = sunday
if w == 1
    i = i + 1;
end

%inflow with rolling horizon
S(1) = round(u(1) + u(2) + sf * sqrt(u(1)+u(2))); %monday inflow
S(2) = round(u(2) + u(3) + sf * sqrt(u(2)+u(3)));
S(3) = round(u(3) + u(4) + sf * sqrt(u(3)+u(4)));
S(4) = round(u(4) + u(5) + sf * sqrt(u(4)+u(5)));
S(5) = round(u(5) + u(6) + sf * sqrt(u(5)+u(6)));
S(6) = round(u(6) + u(7) + u(1) + sf * sqrt(u(6)+ u(7) + u(1))); %saturday inflow
S(7) = 0; %sunday inflow

%Q depends on total I for day t and the order-up-to level for weekday w+1
Q(t) = max(S(w) - sum(I(t,:)),0);

%pricing & demand
OP(r)= RP *(1-discL(r)); %objective price depending on the discountlevel

C = poissrnd(lambda(w)); %number of consumers per day
if t > 546
    Nconsumers = Nconsumers + C; %total consumers per run
end

switch(option) %switch between different cases

    case 1 %WTP model (Fixed division)

        for j = 1:C %each day t has C consumers

            CLIFO = binornd(C,P);
            CFIFO = C-CLIFO;
            for cl = 1:CLIFO % 40 percent of C per day, pick LIFO
                WTP = zeros(CLIFO,7);
                consPick = zeros(CLIFO); %the consumers starts with no product
                Numberoftry = 0;
                z = randn; %pick randomnumber from N(0,1) for the WTP of consumer j
                if sum(I(t,:)) - sum(D(t,:)) == 0
                    if t > 546
                        Nstockout = Nstockout + 1; % no stock for consumer j
                    end
                else
                    for r = 7:-1:1 %LIFO
                        if  I(t,r) - D(t,r) > 0 %inventory should be > 0
                            if consPick(cl) < 1 %consumer may pick 1 product
                                Numberoftry = Numberoftry + 1;
                                WTP(cl,r) = max(E(r)+z*0.85,0); %WTP for consumers j
                                if OP(r) <= WTP(cl,r); %conjunctive rule
                                    D(t,r) = D(t,r)+1;
                                    DLIFO(t,r) = DLIFO(t,r) + 1;
                                    consPick(cl) = 1;
                                    if t > 546
                                        if consPick(cl) == 1
                                            k = Numberoftry;
                                        end
                                    end
                                end
                            end
                        end
                    end
                    Revenue = sum(D(547:T,:))*OP(:);
                    DiscountLoss = (sum(sum(D(547:T,:))*RP)-sum(D(547:T,:)*OP(:)));
                    if consPick(cl) == 0
                        if t > 546
                            Nexp = Nexp+1; % too expensive
                        end
```

```
                end
            end
        end

        for cf = 1:CFIFO % the rest of C per day pick FIFO
            WTP = zeros(CFIFO,7);
            consPick = zeros(CFIFO); %the consumers starts with no product
            Numberoftry = 0;
            z = randn; %pick randomnumber from N(0,1) for the WTP of consumer j
            if sum(I(t,:)) - sum(D(t,:)) == 0
                if t > 546
                    Nstockout = Nstockout + 1; %no stock for consumer j
                end
            else
                for r = 1:7 %consumers start evaluating from first inventory
                    if  I(t,r) - D(t,r) > 0 %inventory should be > 0
                        if consPick(cf) < 1 %consumer may pick 1 product
                            Numberoftry = Numberoftry + 1;
                            WTP(cf,r) = max(E(r)+z*0.85,0); %WTP for consumer j
                            if OP(r) <= WTP(cf,r);%conjunctive rule
                                D(t,r) = D(t,r)+1;%if true demand increases
                                DFIFO(t,r) = DFIFO(t,r)+1;
                                consPick(cf) = 1;
                            end
                        end
                    end
                end
                Revenue = sum(D(547:T,:))*OP(:);
                DiscountLoss = (sum(sum(D(547:T,:))*RP)-sum(D(547:T,:)*OP(:)));
                if consPick(cf) == 0
                    if t > 546
                        Nexp = Nexp+1; %too expensive
                    end
                end
            end
        end
        break %this case has its own loop for C, therefore break
    end

case 2 %LIFO/FIFO (fixed division)

    for j = 1:C %each day t has C consumers
        CLIFO = binornd(C,P);
        CFIFO = C-CLIFO;
        for cl = 1:CLIFO % 40 percent of C per day, pick LIFO
            consPick = zeros(CLIFO);
            Numberoftry = 0;
            if sum(I(t,:)) - sum(D(t,:)) == 0
                if t > 546
                    Nstockout = Nstockout + 1; %no stock for consumer c
                end
            else
                for r = 7:-1:1
                    if  I(t,r) - D(t,r) > 0 %inventory should be > 0
                        if consPick(cl) < 1 %consumer may pick 1 product
                            Numberoftry = Numberoftry + 1;
                            D(t,r)  = D(t,r)+1; % if true demand increases
                            DLIFO(t,r) = DLIFO(t,r)+1;
                            consPick(cl) = 1;
                        end
                    end
                end
            end
        end

        for cf = 1:CFIFO % the rest of C per day pick FIFO
            consPick = zeros(CFIFO);
            Numberoftry = 0;
```

```
                    if sum(I(t,:)) - sum(D(t,:)) == 0
                        if t > 546
                            Nstockout = Nstockout + 1; %no stock for consumer c
                        end
                    else
                        for r = 1:7 %consumers start evaluating from first inventory
                            if  I(t,r) - D(t,r) > 0 %Inventory should be > 0
                                if consPick(cf) < 1 %consumer may pick 1 product
                                    Numberoftry = Numberoftry + 1;
                                    D(t,r)  = D(t,r)+1; % if true, demand increases
                                    DFIFO(t,r) = DFIFO(t,r)+1;
                                    consPick(cf) = 1;
                                end
                            end
                        end
                    end
                end
                Revenue = sum(sum(D(547:T,:))*RP);
                DiscountLoss = 0;
                break %this case has its own loop, therefore break.
            end
    end %end switch

    %mean demand values per weekday for roling horizon S
    dl = [6 5 4 3 2 1 0]; %days left in week (used for calculating u(w))
    if T - (i*7-dl(w)) >= 0
        udemand(w) = udemand(w) + sum(D(i*7-dl(w),:));
        u(w) = udemand(w) / i;
    end

    %end inventory
    for r = 1:7
        Iend(t,r) = I(t,r) - D(t,r); %end inventory is begin inventory - demand
    end

    %perishability
    for r = 1:6
        I(t+1,r) = Iend(t,r+1); %inventory perishes
    end
    for r = 7
        I(t+1,r) = Q(t); %inflow
    end

    if t > 546
        Productdisp = Iend(t,1); %these products are expired and disposed
        Nproductdisp = Nproductdisp + Productdisp;
    end
end
fprintf('This was run %d\n\n', run);

ML(run,:) = (L(:)/sum(sum(DLIFO(547:T,:))))*100;
MF(run,:) = (F(:)/sum(sum(DFIFO(547:T,:))))*100;
DistDemandFifo(run,:) = (sum(DFIFO(547:T,:))/sum(sum(D(547:T,:))))*100;
DistDemandLifo(run,:) = (sum(DLIFO(547:T,:))/sum(sum(D(547:T,:))))*100;

Stockout(Grunert) = Nstockout;
Disposed(Grunert) = Nproductdisp;
Expensive(Grunert)= Nexp;
orders(run,:) = S(:);

PercDisposed(Grunert) = (Disposed(run)/(sum(Q(547:T))))*100; %percentage waste
PercExpensive(Grunert)= (Expensive(run)/(Nconsumers))*100;   %percentage too expensive
PercStockout(Grunert) = (Stockout(run)/(Nconsumers))*100;    %percentage stockout
PercDemand(Grunert) = (sum(sum(D(547:T,:)))/Nconsumers)*100; %percentage demand

switch(option)

case 1
```

```
            EstLostSales(Grunert) =((PercDemand(run)/100).*(PercStockout(run)/100))*100;

        case 2
            EstLostSales(Grunert) = PercStockout(Grunert);
    end
    ProductAge(Grunert)= sum(sum(D(547:T,:)).*[7 6 5 4 3 2 1])/(sum(sum(D(547:T,:))));

    TotalRevenue(Grunert) = Revenue;
    LossRevenue(Grunert) = (EstLostSales(run)/100)*Nconsumers * RP + DiscountLoss;
    CostDisposal(Grunert) = Nproductdisp * (Sen & Block); %costs of product disposal
    OrderCosts(Grunert) = sum(Q(547:T)) * (Sen & Block); %odering costs
    demand(Grunert) = sum(sum(D(547:T,:)))/((T-546)/7);
    Profit(Grunert) = Revenue - (sum(Q(547:T)) * (Sen & Block)) - (Nproductdisp * (OC));

    switch(option)

        case 1
            demandcorrected(Grunert) =
((EstLostSales(run)/100)*sum(sum(D(547:T,:)))+sum(sum(D(547:T,:))))/((T-546)/7);

        case 2
            demandcorrected(Grunert) = (Stockout(run)+sum(sum(D(547:T,:))))/((T-546)/7);
    end
    if sum(sum(D(547:T,:))) == 0
    break
    end
end
disp('Key Performance Indicators:')
PWASTE = mean(PercDisposed); %mean percentage products disposed
fprintf('Percentage products disposed                                    = %.3f \n',
PWASTE)
LOSSREVENUE = mean(LossRevenue); %mean loss of revenue
fprintf('Loss of Revenue                                                 = %.2f \n',
LOSSREVENUE)
MD = mean(demand);       %mean demand per week
fprintf('Mean demand per week                                            = %.2f \n', MD)
MDEMAND = mean(demandcorrected); %mean demand corrected for shortages
fprintf('Mean demand per week corrected for shortages                    = %.2f \n\n',
MDEMAND)

disp('Other outputs:')
TREVENUE = mean(TotalRevenue); %mean revenue
fprintf('Total Revenue                                                   = %.2f \n',
TREVENUE)
TWASTEC = mean(CostDisposal); %mean costs of product disposal
fprintf('Costs of products disposal                                      = %.2f \n',
TWASTEC)
TORDERC = mean(OrderCosts);   %mean ordering costs
fprintf('Ordering costs                                                  = %.2f \n',
TORDERC)
TCOSTS = TWASTEC + TORDERC;            %mean total costs
fprintf('Total costs                                                     = %.2f \n',
TCOSTS)
PROFIT = TREVENUE - TCOSTS;            %mean total costs
fprintf('Gross profit                                                    = %.2f \n',
PROFIT)
PSTOCKOUT = mean(PercStockout); %mean percentage consumers who faced stockout
fprintf('Percentage consumers who faced stockout                         = %.2f \n',
PSTOCKOUT)
PEXPENSIVE = mean(PercExpensive);%mean perceantage consumers who thought the price was to
high
fprintf('Percentage consumers who faced too expensive products           = %.2f \n',
PEXPENSIVE)
PSALES = mean(PercDemand);%mean perceantage consumers who bought a product
fprintf('Percentage consumers who bought a product                       = %.2f \n',
PSALES)
AGEPRODUCT = mean(ProductAge);         %mean age of the products picked
fprintf('Average age of picked products                                  = %.2f \n',
```

```
AGEPRODUCT)
PSHORT = mean(EstLostSales);%mean estimated perceantage shortage
fprintf('Estimated percentage shortage                                    = %.2f \n\n',
PSHORT)

times = 1:7;
FIFORSL = mean(DistDemandFifo);         %distribution of demand over age of product
if sum(FIFORSL(:)) > 0
    disp('FIFO model');
    fprintf('Percentages of FIFO consumers who picked the product with 1 day remaining shelf
life    = %.2f\n',FIFORSL(1))
    fprintf('Percentages of FIFO consumers who picked the product with 2 days remaining
shelf life   = %.2f\n',FIFORSL(2))
    fprintf('Percentages of FIFO consumers who picked the product with 3 days remaining
shelf life   = %.2f\n',FIFORSL(3))
    fprintf('Percentages of FIFO consumers who picked the product with 4 days remaining
shelf life   = %.2f\n',FIFORSL(4))
    fprintf('Percentages of FIFO consumers who picked the product with 5 days remaining
shelf life   = %.2f\n',FIFORSL(5))
    fprintf('Percentages of FIFO consumers who picked the product with 6 days remaining
shelf life   = %.2f\n',FIFORSL(6))
    fprintf('Percentages of FIFO consumers who picked the product with 7 days remaining
shelf life   = %.2f\n\n',FIFORSL(7))
end
LIFORSL = mean(DistDemandLifo); %distribution of demand over age of product
if sum(LIFORSL(:)) > 0
    disp('LIFO model');
    fprintf('Percentages of LIFO consumers who picked the product with 1 day remaining shelf
life    = %.2f\n',LIFORSL(1))
    fprintf('Percentages of LIFO consumers who picked the product with 2 days remaining
shelf life   = %.2f\n',LIFORSL(2))
    fprintf('Percentages of LIFO consumers who picked the product with 3 days remaining
shelf life   = %.2f\n',LIFORSL(3))
    fprintf('Percentages of LIFO consumers who picked the product with 4 days remaining
shelf life   = %.2f\n',LIFORSL(4))
    fprintf('Percentages of LIFO consumers who picked the product with 5 days remaining
shelf life   = %.2f\n',LIFORSL(5))
    fprintf('Percentages of LIFO consumers who picked the product with 6 days remaining
shelf life   = %.2f\n',LIFORSL(6))
    fprintf('Percentages of LIFO consumers who picked the product with 7 days remaining
shelf life   = %.2f\n\n',LIFORSL(7))
end
```