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Master Thesis

- Reducing food waste in the poultry industry by addressing the challenge of supply chain aging -

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Abstract

The consumer-packed good industry is facing significant challenges of reducing vast amounts of food waste along its entire supply chain. Throughout the last few years, the food industry, consumers, and politics have become increasingly aware of the general problem of food waste. In the literature and at all levels of government, the causes of food waste and how to reduce it is discussed.

The focus of this thesis is on waste associated with product expiration. Product expiration is one of the dominant drivers of food waste and involves many actors in the food supply chain. This study aims to determine how to reduce food waste along the food supply chain by addressing one of the major challenges connected with product expiration - supply chain aging. In this context, supply chain aging is defined as the reduction in shelf life of goods caused by time spent throughout the supply chain.

To develop an actionable optimisation approach, a case study with three companies operating in the poultry industry (chicken producer, wholesaler, order processing and retail replenishment company) was conducted. Following the collection of appropriate data, targeted data analyses were conducted on food waste generation and its causes along their food supply chain. Based on this a mixed-integer linear programming model was constructed. Different scenarios concerning chicken availability were included in the model, followed by a sensitivity analysis.

The results showed that currently most food waste is generated at the retailers. Optimising the supply chain reduced product aging throughout the supply chain, increased product lifespan at the retailers on average by 20% and reduced food waste towards zero at the retail level. However, food waste at the producer increased significantly. But since in real life, the producer's production processes leftover chickens in a more flexible manner, this shift in waste generation is justifiable.

The results suggest that shelf life integrated planning can reduce food waste due to product expiration drastically. Nevertheless, further research is recommended to evaluate the model results on a larger scale to identify other aspect of this manifestation and its behaviours.

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List of abbreviations

Central distribution centre	CDC
Consumer packed goods	CPG
Food loss and waste	FLW
Food supply chain	FSC
High Level Panel of Experts on Food Security and Nutrition	HLPE
Regional distribution centre	RDC
Sustainable Development Goals	SDG
Store-keeping-unit	SKU

1. Introduction

413 million tons at the agricultural production stage, 293 million tons in post-harvest handling and storage, 148 million tons in processing, 161 million tons in distribution, and 280 million tons in consumption – these are the vast, estimated amounts of food loss and waste that were wasted along the food supply chain worldwide in 2013 (Read et al., 2020, p. 2).

1.1. The food waste problem

Every year 1.3 billion tons of food are wasted globally which is approximately one-third of all food produced (Ghosh et al., 2016, p. 1) and equivalent in weight to about 8.7 million blue whales[1] (it is estimated that there are only 10,000 to 25,000 blue whales left in the world). Looking at this enormous pile of waste, it is apparent that food waste is a major global challenge today.

Food that is thrown away not only contradicts ethical principles, but also incites social responsibilities to alleviate food poverty because of a continually fast-growing population in recent years. A major concern from an environmental perspective is food waste's effect on sparse resources (e.g., land, water, and fossil energy) and its contribution to CO2 emission at a time when climate change is unavoidable. Finally, it also has economic implications since it affects the profitability of each supply chain member as well as the entire food supply chain (FSC). (Caldeira et al., 2019, p. 479; Ghosh et al., 2016, p. 1; Rodrigues et al., 2021, p. 548)

The global food system is a complex network between producers, processors, retailers, and consumers. The waste situation indicates that the existing production, distribution, and consumption practices of food are not sustainable given the problems of today (Read et al., 2020, p. 2). In addition, it represents an inefficient use of the scarce resources used to produce food (FAO, 2013). Considering the anticipated growth of the global population, natural resources will become even more critical for food production in the close future.

Consequently, reducing food loss and waste (FLW) along the FSC is an essential step towards improving the overall efficiency of the entire food system and decreasing the negative impacts of it on the environment (Foley et al., 2011; Willett

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[1] A blue whale weights up to 150 tons.

et al., 2019). Furthermore, the resilience of a food system with less built-in waste provides an added buffer against complex effects of global change (Schipanski et al., 2016).

Over the last few years, the problem of food waste has gained increasing attention from food producers, processors, retailers, and consumers alike. The issue is discussed at all levels of government, from the international level to the national level to the regional level.

Globally, all 193 member states of the UN have set the target “[to] halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses, [by 2030] (SDG 12.3)” (UN). This statement is part of goal 12 “Responsible consumption and production” of the United Nations Sustainable Development Goals (SDG) adopted in 2015. Additionally, they have agreed on a common “Food Loss and Waste Accounting and Reporting Standard” (FLW Standard) (UN, 2016).

In Europe, FLW is one of the priority areas in the Circular Economy Action Plan (CEAP) adopted by the European Union in 2020 and aligned with the SDGs. This plan is a key component of the European Green Deal, which is the new agenda for sustainable economic growth in Europe. Moreover, it is essential to achieve the EU's 2050 climate neutrality target and halt the loss of biodiversity (European Commission).

With these determined steps forward, the huge issue of food waste is widely acknowledged and must be addressed now. Because “reducing food loss and waste is a component of the transformations necessary to keep the food system’s impact within planetary boundaries” (Read et al., 2020, p. 9).

1.2. Food loss and waste along the food supply chain

Every food product has its own life cycle, which begins on the farm and continues through various supply chain steps to eventually end up on a plate. FLW occurs along the entire supply chain process (see Figure 1). So, reducing FLW in any part of the value chain can possibly improve its efficiency and resilience while reducing food production and thereby reducing environmental impacts.

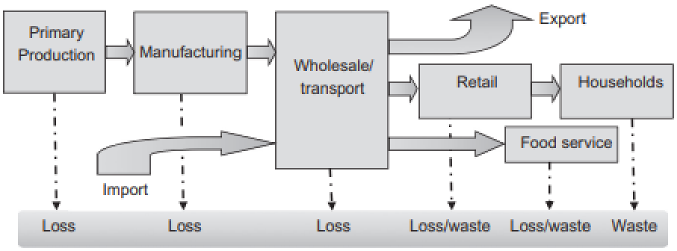

Figure 1: Food supply chain concept and its food loss and waste (Teuber & Jensen, 2020, p. 4).

FLW can be caused by a variety of factors for different food products at different stages of the FSC, resulting in varying waste quantities at these stages. For instance, at the primary production stage, farmers may leave part of their crop unharvested because the potential revenue from the sale of the crop may be less than the cost of harvesting (Johnson et al., 2018). At the intermediate stages, food is discarded in some cases, because it does not meet cosmetic or qualitative standards or because a logistical failure caused it to spoil (Jedermann et al., 2014). Consumers may throw out uneaten food because of poor meal planning, over purchasing, or confusing expiration dates. Table 1 provides a selected overview of such FLW causes at each FSC stage level.

Aside from these factors, food waste amounts at each step of the supply chain also vary depending on the food product itself. Due to a mass flow analysis by *Caldeira*[2] (see Figure 2), the largest share of food waste is generated during the consumption stage for most food groups.

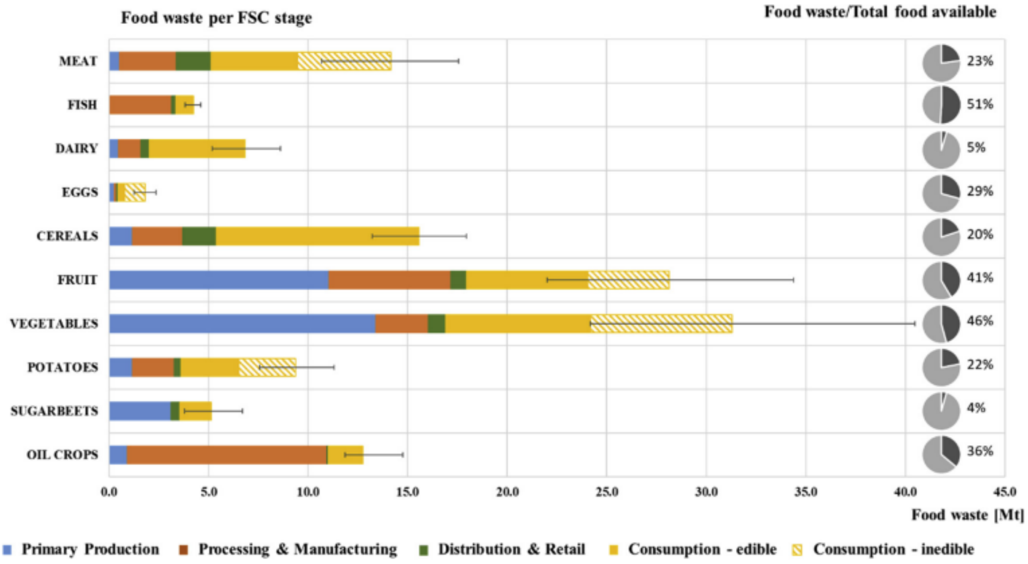

Figure 2: Quantification of food waste per product group along the food supply chain in the EU in 2019 (Caldeira et al., 2019, p. 485).

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[2] To quantify the food waste per product group along the food supply chain in the EU.

Table 1: Selection of causes of food loss and waste at different supply chain stages (Ghosh et al., 2016; NORSUS, 2020).

Food supply chain stage	**Cause of food loss and waste**		
Primary Production (Farm & harvest)	No demand right at that time of harvest		
	Wrong forecast/withdrawal of demand from retailers		
	Failure to meet quality standards		
	Lack of coordination within the supply chain		
Storage	Lack of storage facilities		
	Livestock death and unsuitability for slaughter		
	Lack of suitable refrigeration		
Producer (Manufacturing)	<u>Raw material stock</u>	<u>During processing</u>	<u>During packaging</u>
	Past storage date	Production errors	Faulty production
	Poor raw material quality	Production stops	Damaged packaging
	Breakage	New production operations	Accidents/items dropped on floor
	Discontinued product	Accidents/items dropped on floor	Labelling errors
Distribution & Transport (Wholesaler)	Past expiry date (products such as meat and milk before being shipped)		
	Damaged during storage		
	Excessive transportation		
	Defective/returned goods from customers		
Retail	Reduced quality		
	Past expiry date (products such as meat and milk before being purchased)		
	Packaging size not suitable for buyers		
	Product/packaging damage and being not attractive to consumers		
Consumer	Buying behaviour and purchasing pattern		
	Forgotten about the product in the fridge or elsewhere		
	Product expired and produce that is wilted/bruised/moulded and is thrown away		
	Misunderstanding/lack of knowledge about labelling		

1.3. Previous relevant studies

With the growing attention to FLW and questions about its prevention, an increasing number of scientific studies analysing different aspects of FLW along the FSC have been conducted (for a meta-analysis, see (Chen et al., 2017)). Many of these explore the extent of FLW for different countries (e.g. *Switzerland* (Beretta et al., 2013), *EU-27 member states* (Bräutigam et al., 2014)) and different stages of the FSC (e.g. *primary production*: (Hartikainen et al., 2018), *retail*: (Cicatiello et al., 2017), *food service*: (Eriksson et al., 2017), *consumer*: (Edjabou et al., 2016)). Additionally, several studies have addressed the underlying causes of FLW, particularly at private households (e.g. (Hebrok & Boks, 2017), (Romani et al., 2018)).

To resolve the food waste problem effectively, however, it is not enough to have a solid understanding of the reasons for and the scale of food waste generation along the FSC, but also practical and actionable solutions. These two sides together can provide tangible recommendations to policy makers and other stakeholders involved in the FSC.

Over the last years, studies of food waste have shifted from focusing on purely analysing food waste and its potential valorisation to addressing FLW and possible solutions to mitigate it (Teuber & Jensen, 2020, p. 4). Yet, most research still investigates this phenomenon in terms of its significance rather than the logistics associated with it. *Stenmarck et al.* (2011), for example, addressed the food waste problem in the Nordic wholesale and retail sector, but does not elaborate on the operational mechanics behind the waste issue.

Within the context of perishable inventory management and the problem of unsaleable goods at retail stores, *Akkas et al.* (2018) provided an in-depth understanding of various mechanisms, such as drivers of product expiration and shipment policy solutions. They described the role of manufacturers and retailers in the topic of perishable goods in a real-world setting and identified the cause and impact of supply chain execution variables such as rotation compliance, supply chain aging, case size, and sales incentives.

Since food waste can be approached through various operational strategies within the supply chain, the solutions range from demand forecasting to inventory management. *Goh et al.* (1993), for example, investigated two-stage inventory models for blood banks. *Lütke Entrup et al.* (2006) looked at the integrated planning of shelf life in the yoghurt production. Several of these studies have in common that they focus on a two-tier supply chain and use either simulation- or dynamic models.

1.4. Thesis scope and research questions

In this current context, the question arises how to contribute towards minimizing FLW. This thesis approaches this problem from a supply chain- and data analytics perspective. The underlying objective of all our research attempts is to develop a mathematical optimisation model that minimizes FLW along the FSC to contribute to the sustainability goals and to bring economical/business value to one or several organisations in the food industry by providing precise proposals for action.

Each of us as a private person and consumer has a responsibility to make a difference to reducing food waste. However, changing consumer consumption habits is particularly challenging and hard to control/optimise. In fact, there is little hope to suggest consumer waste of food is decreasing (NORSUS, 2020, p. 7). Thus, it is easier to change the way industries operate than the way consumers behave. Besides, “it is possible that waste reduction would be more politically and logistically tractable than other changes such as large-scale dietary shifts” (Read et al., 2020, p. 2; Smith, 2013). Therefore, this thesis will not focus on the consumer stage. Instead, it investigates the upper parts of the supply chain before it lands on the plate or even in the retail shelves.

Retail stores rely heavily on perishable goods as they are the backbone of their profitability (Duan & Liao, 2013, p. 658). The financial and environmental costs of throwing away these goods are significant. This thesis examines the unsaleable problem faced by retail stores and the associated food waste at the retailer and at the supply chain stages before it. Our focus is on product expiration (related to remaining shelf life) since it is more of a concern for the industry and more amenable to optimisation compared to the other two types of unsaleables (i.e., product damage and product discontinuation) (Akkas, 2015; Akkas & Honhon, 2018).

The FSC areas explored and analysed in this thesis are located in Norway. Norway itself throws away approximately 420,000 tons of food every year which corresponds to a value of almost NOK 21 billion and 1.3 million CO2 equivalents (Government, 2020; NORSUS, 2020). Figure 3 illustrates that households account for more than half of the waste in the Norwegian food system (55%), followed by producers (22%), retailers (15%), hotels, employee cafeterias, restaurants, the public sector, and convenience stores (estimated at 7%) and the wholesale sector (1%).

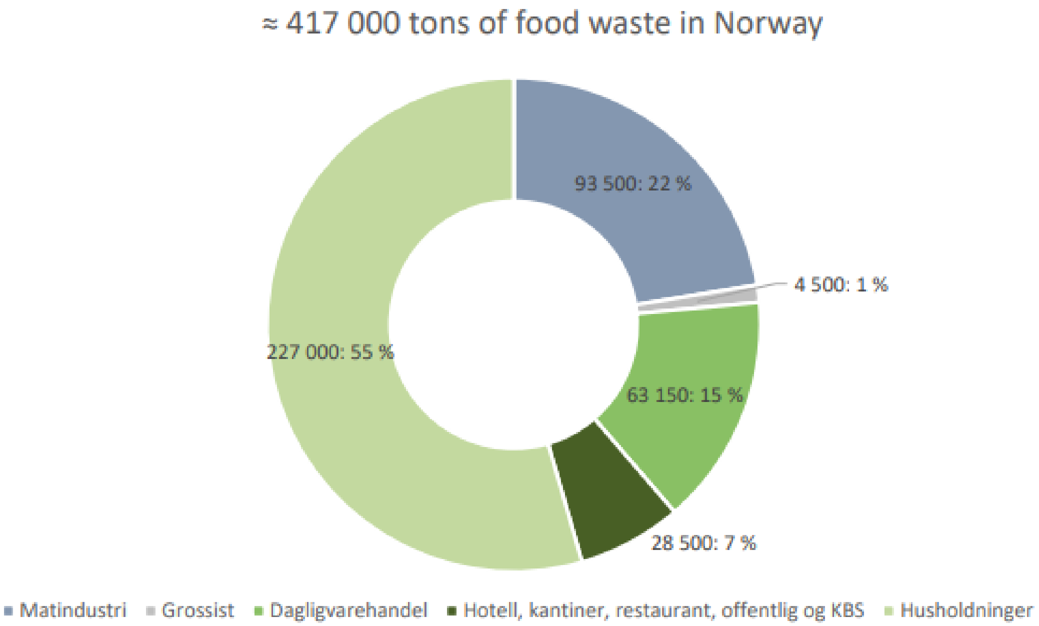


Figure 3: Estimated total amounts of food waste in Norway by supply chain actor in 2019 (excluding fish products) (NORSUS, 2020, p. 5).

We collaborate with two companies (food producer and wholesaler) of Norway's largest trading house. Their supply chain can be viewed holistically, along with their interactions and interdependencies (see Figure 4). The optimisation approach does not confine itself to just one supply chain stage, so it promises to be a great benefit in finding efficient ways to reduce FLW for a greater part of the FSC and to not shifting the problem simply to the next stage.

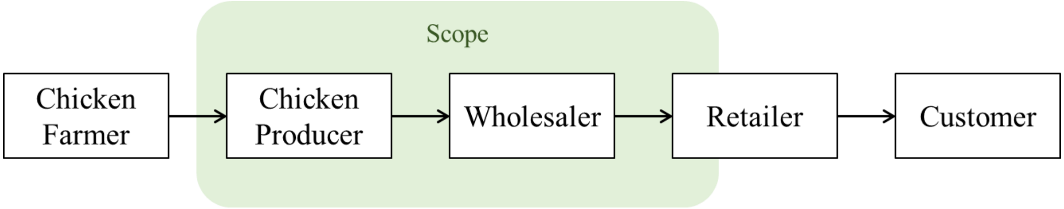


Figure 4: Scope of food supply chain (own figure).

As the FSC for every food product is slightly different and has its own special treats, this paper focuses on fresh poultry products. To be precise this includes whole chickens, chicken fillets, chicken thighs, chicken wings and chicken upper wings. By finding a way to minimize FLW in the poultry industry, this use case might be replicable for other food products or extendable to other FSC participants.

The premises of this thesis lies in reducing the total amount of FLW. One crucial component to consider is the expiry date and consequently the age of the products in every single step through the FSC. The paper does not assess the environmental impacts of reducing poultry waste at these companies for Norway or any other direct benefits resulting from it. It will give a detailed solution how to avoid throwing away chicken products along the FSC participants but will not go beyond that. Although we do not analyse in-depth the financial implications and outcomes for each supply chain actor, we strive to consider their general interests of selling as many chicken products as possible and not imposing additional costs on them.

We aim to provide suggestions for our industry collaborators to minimize FLW by reducing product expiration occurring in retail supply chains. Specifically, we address the following research questions:

(1) How much FLW does every actor in the poultry supply chain generate?
(2) How does product aging along the supply chain effect FLW?
(3) How can we set up production planning for the manufacturer (to control the remaining shelf life of products moving into the retailer's supply chain) in order to minimize FLW?

1.5. Structure of the thesis

The thesis consists of seven chapters. Chapter 2 provides a brief literature review of general research on the topic of food waste and its reduction. It elaborates on existing research in the area of perishable goods and product expiration and overviews existing modelling approaches for reducing food. In chapter 3, the case study companies and their supply chain operations are introduced. The research design and details of data collection and data preparation are presented in Chapter 4. In chapter 5, we define FLW and explore the problem of product expiration in retail stores. By connecting food waste to product expiration and analysing the causes, this study provides a thorough understanding of the issue. In chapter 6, we discuss our modelling approach to addressing the reduction of food waste along the FSC by optimising the supply of chicken products to increase the remaining shelf life. Chapter 7 presents the results of our analysis and discusses their implications. The current situation is compared to different scenario outcomes of our model and a sensitivity analysis is conducted. A final conclusion is provided in Chapter 8.

1.6. Case companies

We collaborate with two companies of Norway's largest trading house, which we will refer to as AlphaCo in this thesis. AlphaCo is an integrated retail cooperation (see Figure 5) with around 1,200 business partners, a nationwide wholesaler and over 1,800 grocery stores. For several years, it has been working to reduce food waste in its value chain and operations to address economic, environmental, and social problems. Each supply chain member is hereby committed to doing their part. Since 2015, AlphaCo has cut 38% of their total food waste.

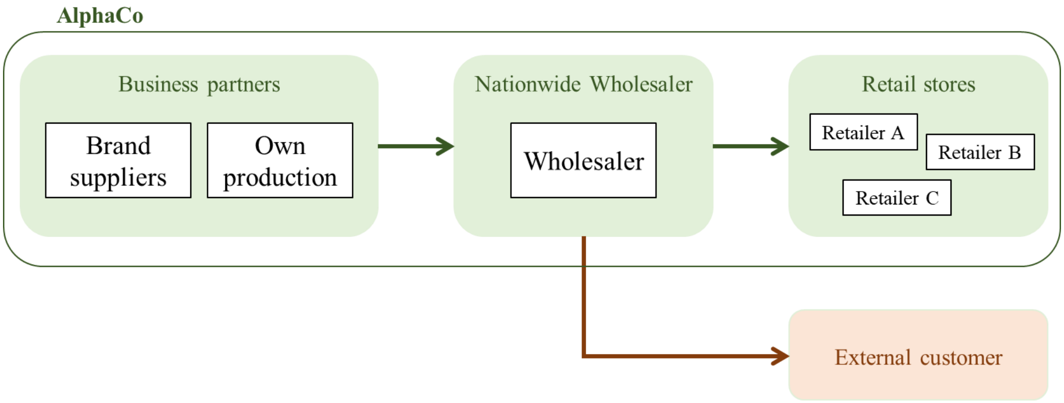


Figure 5: AlphaCo trading house (own figure).

As part of this study, we collaborate with the chicken producer, which we will refer to as ChickenCo, and the wholesale branch – or more specifically their central warehouse - , which we will refer to as WholesaleCo, with its own order processing and retail replenishment section, which we will refer to as OrderCo. Among ChickenCo's customers, WholesaleCo is the largest one. Each of these business areas is independent and decisions are decentralised. However, as they operate under the same roof, their supply chain can be viewed holistically, along with their interactions and interdependencies (see Figure 6). In this sense, optimisation is not limited to one stage of the supply chain and is thus capable of reducing FLW for a larger part of the FSC rather than simply passing on the problem to another stage.

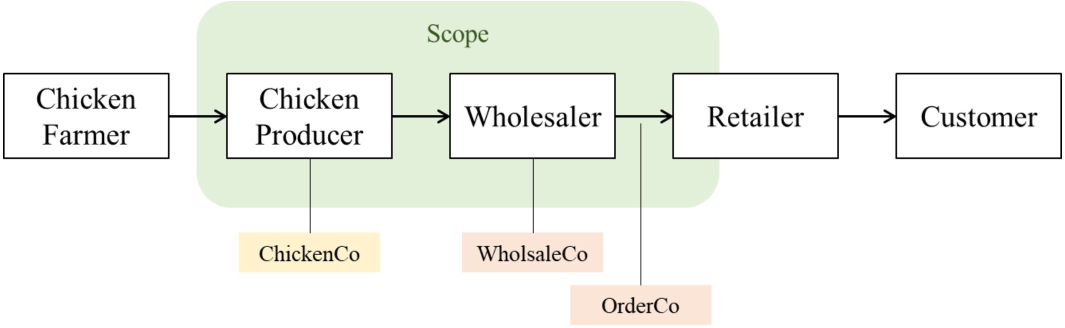


Figure 6: ChickenCo, WholesaleCo and OrderCo within the food supply chain (own figure).

2. Literature review

The following section provides a general overview of studies on the production and management of FLW. The literature was examined from several perspectives: the issue's importance and relevance, the degree to which the matter is addressed, and the method used to approach the food waste problem.

2.1. General research on the food waste problem

Until recently, few analytical and empirical studies have been conducted on sustainable food management. Most of the work prior to the 2000s focuses on age-differentiated inventory systems.

Since our research concentrates on reducing FLW in the food industry, we only reviewed the literature related to various players in the supply chain. While there is a lot of research on the retailer side of the issue, there is less research on the manufacturer and producer side. This is mainly due to the fact that most food waste occurs at the retail level, where it is easier to measure. With our study, we hope to contribute to this research gap because "when a food item is wasted, all of the upstream resources that went into its production, processing and distribution are wasted" (Birisci & McGarvey, 2018, p. 986).

Several studies looked at the food waste issue in a broader sense. *Ghosh et al.* (2016) looked at trends in waste for a variety of food sectors, including fruits and vegetables, fisheries, meat and poultry, grain, milk, and dairy. Factors contributing to food waste, effective cost/benefit food waste utilisation methods, sustainability and environment considerations, and public acceptance are identified as hurdles in preventing large-scale food waste processing. The research by *Garrone et al.* (2014) addressed the multifaceted concept of food supply chain sustainability by developing a conceptual model of surplus food and waste generation and management. They presented three confirmatory case studies, from different supply chain stages to demonstrate how the conceptual model can be used to identify food waste reduction strategies.

2.2. Perishable goods and product expiration

Many industries, such as food, blood banks and pharmaceuticals, face the challenge of managing perishable goods. The classic single-item, multiperiod inventory model is extended to a situation where a good in storage expires exactly n time periods after it is received.

In the 1970s, *Nahmias* (1975) and *Fries* (1975) initiated important research in this area. They examined the optimal inventory and order policy under a cost minimizing dynamic program, accounting for expiration and order/holding/shortage costs. According to their findings, the optimal policy is not stationary and is determined by the age distribution of the inventory. Later, *Nahmias* (1982) presented a comprehensive review of literature on decision models for issuing and replenishing perishable inventory for products with fixed lifespans and continuous exponential decay. Most of the literature discusses single-location models while ignoring supply chain aging.

Using a two-stage system (retailer with a single supplier) with supply chain aging and order batching, *Ketzenberg & Ferguson* (2006) evaluated how the sharing of product life information from the supplier can benefit retailers. Using a simulation study, the authors demonstrated that sharing product life information increases the retailer's profit by around 4%, increases the average remaining shelf life of retail inventory at the time of replenishment by 8%, and decreases the incidence of product expiration by 40%. They established that information sharing is a vital part of achieving substantial benefits, and they identified certain conditions under which this can be accomplished. It is , for example, most beneficial for retailers to share information when the demand for the items is uncertain, if the product lifetimes are short, and if the item is costly.

Akkas' et al. (2018) work follows on from this previous research by examining how it applies to a real-world, CPG industry situation. They described the role of manufacturers and retailers in the topic of perishable goods and identified the cause and impact of supply chain execution variables such as rotation compliance, supply chain aging, case size, and sales incentives. Further, they exploited the statistical characteristics of product expiration and discussed the implications of different aspects of supply chain operation on waste.

2.3. Modelling approaches to reduce food loss and waste

FLW can be addressed using a variety of approaches: demand forecasts, production planning, inventory management, shipment rules, or a combination of these.

The unpredictability of demand is one such position. At the 34th International Symposium on Forecasting, *Nari Sivanandam* presented a model which tries to account for all the effects due to the demand influencing factors, to forecast the daily sales of perishable foods in a discount retail store. As the author explained, "using an efficient sales forecasting system which accounts both accuracy and uncertainty is a basic and significant measure to reduce food waste" (Nari Sivanandam Arunraj et al., 2014, p. 1).

Gružauskas focused on "the ways a logistics cluster can provide the abilities to share information and thus improve the forecasting accuracy" (Gružauskas et al., 2019, p. 1). In this research, the findings showed that sharing information across the FSC's many participants improve forecasting accuracy under a variety of circumstances.

With regard to food waste, the uncertainty associated with the demand is a subproblem of inventory management. "Inventory management challenges are worsened by three factors: uncertain consumer demand, product lifetimes, and consumer substitution among the product range" (Duong et al., 2018, p. 1). *Duong's* aim was to understand the effect of each of the aforementioned factors on the inventory performance. A relevant finding of this study is that "when the substitution ratio is greater […] suppliers' performance is affected largely by the existence of the bullwhip effect in the model" (Duong et al., 2018, p. 1).

Goh et al. (1993) studied two-stage perishable inventory models for blood banks. There are two stages in the supply chain - fresh and older blood units - with separate sources of demand. Over time, units are transferred from the first stage to the second. The question is whether the first-stage inventory should satisfy the second-stage demand when the second stage does not have any inventory.

Somkun (2020) presented a mathematical model applied to an inventory replenishment problem for perishable products that have a shelf life of less than seven days. The study focused on the consumer- and the retailer level. However, they propose for future research to try and incorporate other parts of the FSC.

Another great research on the inventory replenishment problem of perishable goods was done by *Janssen et al.* (2018). It proposes a micro-periodic inventory replenishment policy for quickly perishable goods with fixed known lifetime.

Regarding shipment policies, industry experts advocate the Ship-Oldest-First policy to manage product shelf lives. This policy has been proven to be effective in a single location. However, *Akkas & Honhon* (2018) studied its optimality in a two-stage supply chain. They concluded that in most practical applications, it is sub-optimal.

Takey & Mesquita (2006) also focused on the manufacturer's side of the supply chain. They developed a linear optimisation model for a Brazilian food manufacturer that determines the monthly production rates and the inventory levels of finished products as well as work-force requirements to accomplish productions plans.

Regarding the FSC's production side, *Leung et al.* (2007) developed an optimisation model to solve the production planning problems for perishable products under uncertain environments. Despite the fact that the study was not conducted on food goods, it has considerable value for the food industry.

2.4. Contribution of this thesis

With our thesis, we aim to contribute to the growing literature on optimisation approaches to reduce food waste in multi-tier supply chains. By combining data from the producer, the wholesaler, and the retailer, we can gain a more holistic view – compared to a two-tier supply chain - of how food waste occurs, as well as the mechanisms and logistics involved. It also prevents shifting the problem of food waste to another actor in the supply chain.

Furthermore, this research is relevant to the management of effective shelf lives which is often overlooked in related operation studies. It contributes to this line of research by examining how supply chain aging and remaining shelf life affect product expiration and including a penalty cost for older products reaching retailers in our model objective.

Additionally, we are focusing on how the supply of chicken products can be optimised to reduce food waste across the food supply chain. Research papers generally address food waste reduction at one stage of the supply chain (review (Nahmias, 1982)) and by optimising inventory management or shipment policies (e.g., (Goh et al., 1993) and (Akkas & Honhon, 2018)). Our linear model focuses on production planning. The model also differs from others in that it employs the formulation of facility location models to calculate the aging of the products throughout the supply chain and combines this with production lot-sizing. Based on our knowledge, this approach is unique.

3. Supply chain operations in the poultry industry

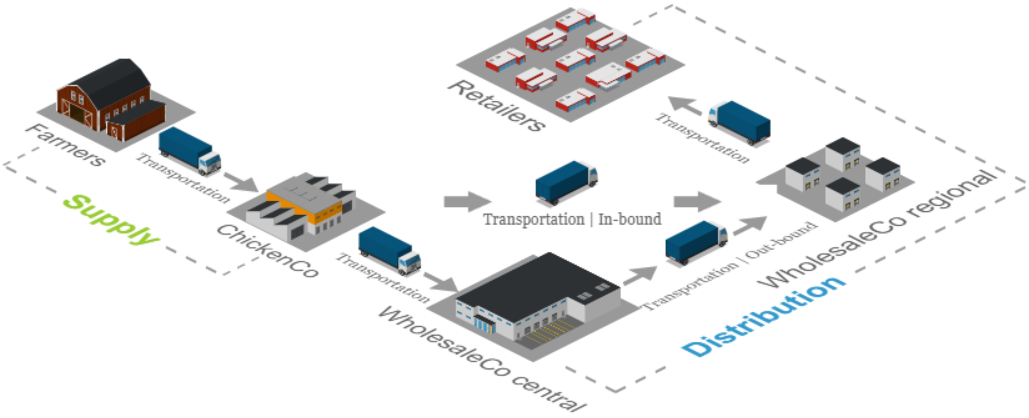
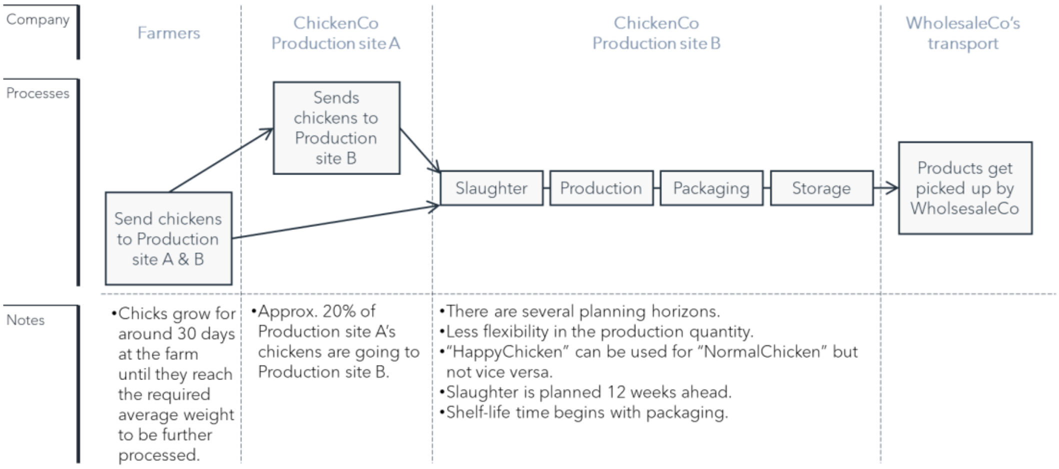


Figure 7: Overview of the poultry food supply chain at AlphaCo (own figure).

AlphaCo’s overall process chain from a living chicken to a consumer-packed good arriving in the retail stores is a multi-tier supply network (illustrated in Figure 7). Several chicken farmers deliver chickens ready for consumption to ChickenCo's production facilities. The produced and packed chicken products go then either to the single central distribution centre (CDC) or the 14 regional distribution centres (RDC) of WholesaleCo. Popular and high velocity items are typically transported to the regional warehouses directly, whereas exceptional and low velocity items are normally forwarded first to the central warehouse. The products arriving at the CDC are then distributed to the RDCs. The RDCs follow a direct-store-delivery (DSD) sales and distribution model in which products are delivered directly to retail stores without going through the retailer's distribution centre. Retailers, however, retain full responsibility for the inventory management of their stores.

3.1.1. ChickenCo chicken production



- Chicks grow for around 30 days at the farm until they reach the required average weight to be further processed.

- Approx. 20% of Production site A’s chickens are going to Production site B.

- There are several planning horizons.
- Less flexibility in the production quantity.
- “HappyChicken” can be used for “NormalChicken” but not vice versa.
- Slaughter is planned 12 weeks ahead.
- Shelf-life time begins with packaging.

Figure 8: ChickenCo process map (own figure).

In this thesis, ChickenCo is the starting point for any further optimisation process. Nonetheless, it is crucial to recognize that planning chicken production takes a long planning horizon that begins way before the animals arrive at the facility.

The chicken used to produce chicken products is a third-generation chicken. So, the whole planning process starts already with the so-called “grandparent” chickens and then goes down to their chicks (the “parent” chickens). A female chicken starts to lay eggs after it is around 6 months old. The eggs from the “parent” chickens are the ones going to the hatchery. After the chicks have hatched (which takes around 20 days), they come to the farms where they stay around 30 days until they are big enough for slaughter.

Due to this tight supply chain, several planning horizons of varying timeframes are required. First, AlphaCo and ChickenCo have a high-level discussion about chicken demand for the next 3 years. Based on the number of eggs/chickens needed for production, it indicates how many "grandparent" chickens might be needed. The final decision about the “grandparent” chickens is then made 18 months in advance.

In the so-called “Autumn hunt” AlphaCo and ChickenCo bargain with their retailers about product assortments, product prices and product demands for the next year. This also includes general campaign information. ChickenCo receives a first estimate 3 months before an actual campaign, which is further clarified by OrderCo's forecast numbers 5 weeks earlier and fixed 3 weeks before the campaign.

ChickenCo then decides on a product production plan formed on its own forecasts. These forecasts predict for the next 12 weeks what WholesaleCo might order for the retailers from them. However, the number of chickens that arrive each day limits the production plan. The farmers, on the other hand, know precisely how many chicks they will get from the hatchery over the next 3 months. Based on that again, ChickenCo plans how many chickens of what average weight it will receive each day for the next 8 weeks to arrange their slaughter. As the chickens are now aligned for production, not much can be changed. Once they arrive, they must be processed into something. Chickens, unlike pigs for example, cannot be stored for a day or two more before slaughter because they need to have a certain average weight. Even storing them for a short period of time will alter their weight before slaughter which is not acceptable.

ChickenCo has two production facilities – production site A and production site B (see Figure 8). While production site A does not cut any chickens and grills the whole chicken for retail stores, production site B cuts the chickens and process them into consumer packed goods (CPG) or raw material for further industry production (e.g., sausages). To produce CPG ChickenCo uses two types of chickens – “HappyChickens” and “NormalChickens”. HappyChickens are chickens that received extra treatment at the farm, for example they had special feed or more space. HappyChickens can be used to produce NormalChicken products, but not vice versa.

The production is split into online and offline production. Online production includes products that are produced every day (from Monday to Friday) which are cut chicken products. Offline production produces not every day which refers to e.g., marinated or grilled chicken products.

Once the chicken arrives at the facility, it is slaughtered and then spent three hours cooling in a tunnel. From there it is directly processed as a whole chicken or cut into pieces. Production facility B has four production lines and there is no machine changeover time between different products. After the chicken is packed, it is stored in the inventory and gets picked up by WholesaleCo.

3.1.2. WholesaleCo order process

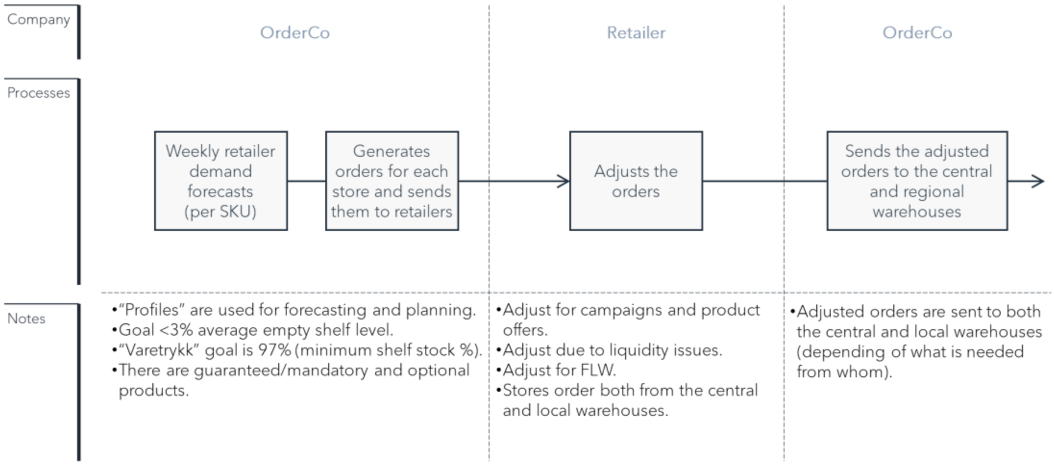


Figure 9: Order process at OrderCo (own figure).

The wholesale business of AlphaCo operates a value chain based on a nationwide distribution network, advanced logistics and warehouse solutions. OrderCo is their automated item ordering for over 1,000 grocery stores. It creates weekly demand forecasts on store-keeping unit level (SKU[3]-level). These forecasts are based, among other things, on so-called “profiles” which are historically seasonal or trend

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[3] For each product, for each store.

patterns in demand. Their goal is to ensure at least 97% shelf stock[4] and less than 3% empty shelf level[5]. Based on its weekly forecasts, OrderCo gives every store an order proposal every day (see Figure 9).

The store has then the opportunity, within a certain time frame, to adjust this proposal. Reasons for this can be campaigns, special product offers, liquidity issues or food waste goals. These adjusted orders are forwarded to the central and regional warehouses affected by it.

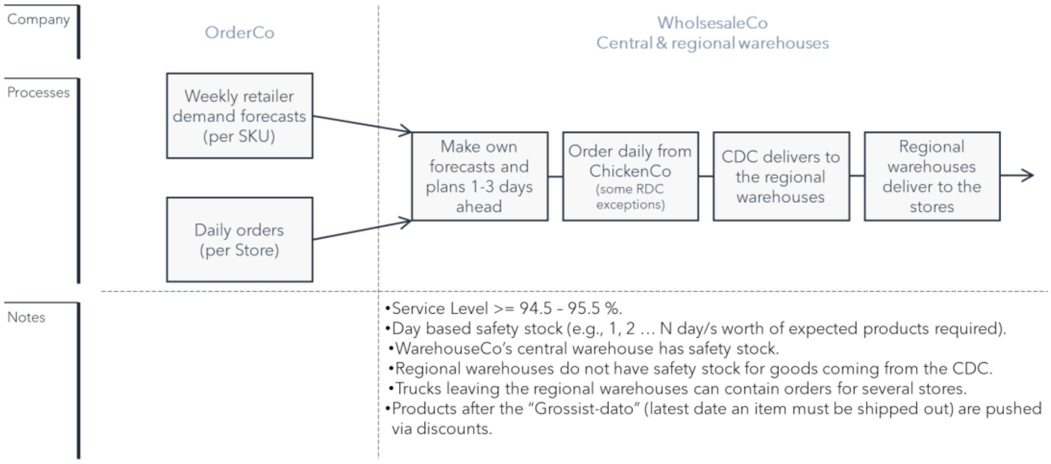

Figure 10: Order process at WholesaleCo's warehouses (own figure).

Warehouses receive OrderCo's weekly forecasts per SKU and daily orders and use them to make their own weekly forecasts and plan a few days in advance (see Figure 10). Each warehouse creates its own weekly forecast and orders individually from ChickenCo daily (day-to-day order). To keep their goal of a minimum service level to the retailers of 94.5%, they set their safety stock accordingly inflicting a daily order point and order quantity. Products arriving from ChickenCo directly to the regional warehouses go into their inbound area which has a safety stock. On the other hand, products from the CDC only stay at the RDC for a few hours, which is why they are instantly forwarded to the outbound area (cross-docking) and do not require a safety stock. One day before delivery, ChickenCo receives the order from each WholesaleCo's warehouse.

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[4] Every shelf of each product in all stores is filled at least 97% all the time.

[5] Almost no stockouts occur.

4. Research methodology

In the following chapter the general research framework and the methods used in data collection and preparation are shown.

4.1. Research design

This thesis will use an empirical approach to develop a practical solution to reduce food waste in the poultry industry. Especially, because our model is based on real-world data.

Every empirical research method collects and analyses empirical data in different ways. The choice of the right method depends on the composition of three important conditions: (1) the form of the research question, (2) the control of the researcher over what is happening, and (3) the actuality of the event (Yin, 2018, p. 9).

In this thesis, the research questions are exploratory in nature. The aim is thus to provide an in-depth exploration of the topic, which is characteristic of a "how"-question. It should be noted at this point that although different methods have different advantages for different purposes, in principle all methods can be used for explorative, descriptive as well as explanatory purposes.

Table 2: Different empirical research methods (based on (Yin, 2018, p. 9)).

Method	**(1) Form of research question**	**(2) Requires control over behavioural event?**	**(3) Focus on contemporary events**
Experiment	How, why?	Yes	Yes
Survey	Who, what, where, how many, how much?	No	Yes
Archival Analysis	Who, what, where, how many, how much?	No	Yes/no
History	How, why?	No	No
Case Study	How, why?	No	Yes

The topic to be researched is a current event, in which any influence by the researcher is undesirable. On the basis of these three criteria the case study emerges as the most advantageous empirical research method (see Table 2).

A case study is an "empirical method that investigates a contemporary phenomenon (the "case") in depth and within its real-world context, especially when the boundaries between phenomenon and context may not be clearly evident" (Yin, 2018, p. 15). A case study is thus conducted when one wants to understand a reality-based case in depth and assumes that the insights gained from it regarding the contextual conditions are highly relevant to the case. In addition, the case study is an extremely useful method when the field of research is relatively unknown. This all applies to the present thesis.

After defining the research question, the case study proceeds to a detailed definition and limitation of the case. The case definition should be consistent with the theoretical framework of the Master thesis and the research questions. This case relates to food waste reduction in the poultry industry covering whole Norway. This branch is chosen because it has fresh products with extremely limited and short shelf life. In addition, the entire process is more complicated since this industry works with livestock. The focus was narrowed even further to not include the entire poultry supply chain, but just the producer, wholesaler, and partly retailers. The purpose of this step is (1) to keep the optimisation model computationally and time-wise practical while incorporating as many supply chain actors as possible and (2) because the shelf life of a chicken product begins to expire only after the slaughtered and processed chicken is packaged.

The research design of the case study (see Figure 11) is an "embedded single-case". This means that different companies are considered within the same case and within the same context. As all three companies represent a different part of the same supply chain and operate under the same trading house, they together contribute to a single-case. This allows to see the different results in relation and within the big picture of general food waste in the poultry industry.

Another advantage of the case study compared to other research methods is that a case study can make use of the complete arsenal of instruments for data collection. These include, among others, documents, archival material, interviews, direct and indirect observation, and physical artefacts (Yin, 2018, p. 114).

Case studies can be both quantitative and qualitative. The present work will deal with a quantitative case study analysing the current status of topics of interest at ChickenCo, WholesaleCo and the retailers as well applying mathematical programming and deterministic modelling approaches. The present research logic is subject to the inductive approach. Therefore, the purpose of this work is not to test theories, but rather to attempt to form a theory related to the subject matter.

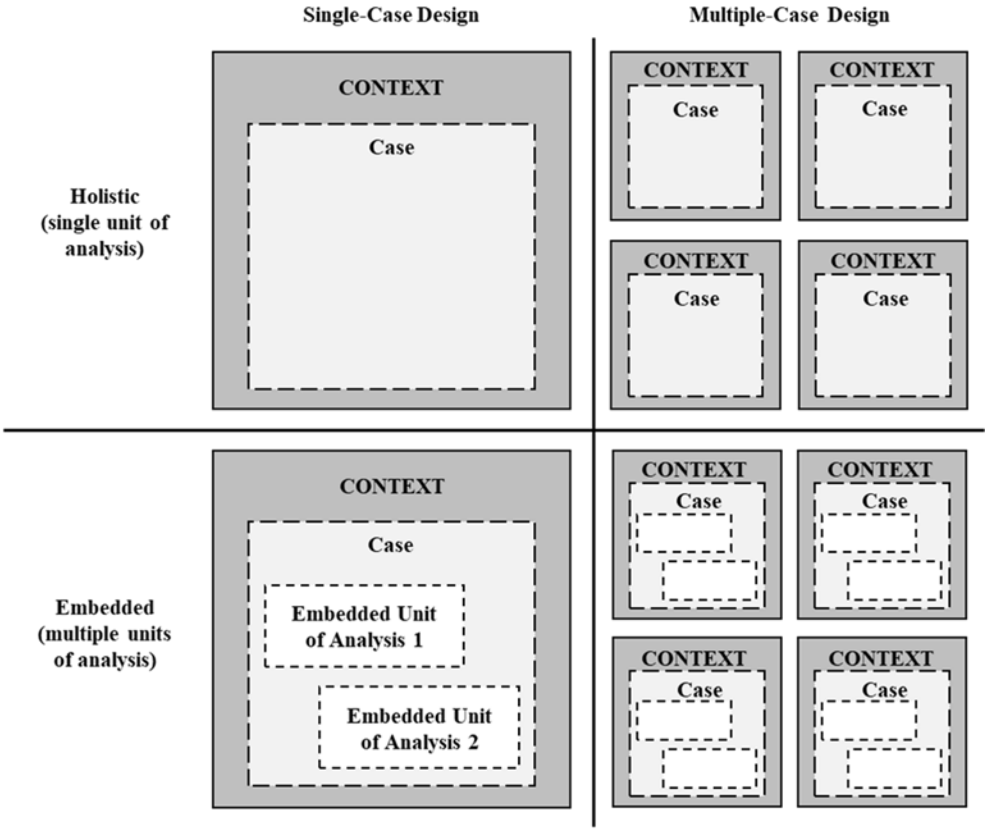

Figure 11: Case study design (based on (Yin, 2018, p. 48)).

Case studies do not claim to be able to generalise the research results to the entirety, nor do they represent samples. They should rather be seen as an opportunity to shed empirical light on theoretical concepts and principles. Case studies thus do not aim at a statistical generalisation, but certainly at an analytical generalisation related to theories. They represent both the learning process of a case as well as the product of this learning process. We hope that the findings and analyses of our case study might be used to infer and estimate a more general point about how to contribute towards solving the food waste problem.

4.2. Data collection

Our data are obtained in a structured way from three sources: (1) face-to-face interviews, (2) site visits and (3) files with historical company data.

The face-to-face interview protocol varied by organisation, as it is focused on their role and responsibilities within the supply chain. From this, an overall picture and holistic understanding is formed (see chapter 3). Table 3 lists the specific interview topics for each company.

Table 3: Face-to-face interview topics per company (own table).

ChickenCo	**WholesaleCo**	**OrderCo**
FLW and waste management	FLW and waste management	FLW and waste management
Product information	Order processing and fulfilment	Ordering processes
Production capacity	Inventory management and replenishment (including safety stock)	Retailers' replenishment schedule
Production planning	Planning horizon and forecasts	Forecasts horizon and dimensions
Order fulfilment	Transportation and logistics	

Visiting each of the firm's main locations was a vital part of the data collection process in an indirect fashion. It provides a better understanding of the supply chain's scope, size, and nuances, as well as its operations. Chapter 3 of this thesis has presented a fraction of the information obtained during the aforementioned data gathering procedure.

The final step of the data collection procedure was the gathering of historical data files from each collaborator. The main objective is to quantify all relevant aspects of the study subject to conduct empirical analyses and present reliable findings. Approximately 6 GB of data were collected from all related companies for every topic we discussed in the interviews.

In this study, we gathered data from companies on the following dimensions:

- Time period - whole 2021 and the beginning of 2020 (on a daily and/or weekly basis)
- Products - 63 chicken products
- Retailers - around 1,600 stores
- Warehouses - 15 distribution warehouses

Data files may differ from one another in terms of the above figures. The actual dimensions used, the pre-processing steps, and the data engineering methods used to prepare the datasets for analysis and modelling are covered in the appropriate sections. Detailed information about all datasets is included in Attachment 1 – Dataset overview.

4.3. Data preparation

Between the datasets received by the companies and the data provided as input to the model, some data preparation has taken place. The following modifications have been made to the data:

- *Processing the weekly forecasted demand dataset*

The received dataset is on a weekly basis, whereas our model is built on a daily one. According to the model's needs, the weekly forecasted demand is divided by 6 (number of working days in a week) and for each of the working days we used the decimal part of the result as the probability of it being rounded up. Considering the probability of a given product selling on any given working day would have been a better approach. This, however, is beyond the scope of this thesis.

- *Classifying chicken part (sub-)groups*

Each of the products discussed in this thesis was classified into a chicken part group and a chicken part subgroup. Table 4 shows these groups and subgroups and the connections between them.

Table 4: Chicken part groups (own table).

Group	Subgroup
Fillet	Fillet
	Grilled Fillet
Thigh	Upper thigh
	Thigh club
	Thigh fillet
	Grilled thigh
	Salad meat
	Thigh
Upper wings	Grilled upper wings
	Upper wings
Whole	Whole
	Grilled whole
Wings	Wings
	Grilled wings

- *Number of chickens necessary to meet the product's requirements*

We calculated the number of chickens necessary to produce each item (see “Attachment 2 – Calculation of required number of chickens” for more insight). Given the grams of chicken part subgroups in each product and the respective grams in an average chicken, you are able to divide the first by the second to estimate how many chickens are necessary to manufacture the product. To find the total number of chickens required for x amount of products, the number of chickens required within the same chicken part group must be added together. Next, we add together the number of chickens required for the whole group and the maximum number required for the rest of the groups.

- *Waste loss*

Another important metric to include in the model is the loss value per gram of wasted chicken part group. Based on discussions with our industry partners, the waste loss for each of the chicken part group, it is computed as follows:

$$\frac{1}{n}\sum_{i=n}^{n}\frac{\frac{value\ of\ product\ i}{chickens\ required\ for\ i}}{grams\ of\ chicken\ part\ in\ 1\ chicken},$$

where 1 to n are all the products made of the given chicken part group.

- *Time horizon*

As a base planning period, we have chosen the first three weeks of 2022 for our model to run - it is the period for which the most data are available. As a result, we have adjusted the data inputs so there are 11 extra empty periods before the planning period. The reason for this is that the model needs some time to produce and deliver the goods before the demand period.

- *Production capacity*

ChickenCo's data on its production capacity captures all its customers (also aside from AlphaCo) and all AlphaCo's retail stores. Given that we are focusing only on AlphaCo, and even then just on a subset of stores and products, we have adjusted it to a reasonable amount. It is based on the ratio between the forecasted demand the model will satisfy and the total production during that period.

- *Sample dataset*

For computational efficiency, we do not estimate our model on the entire data set. Instead, we draw a random sample of 100 stores and 25 products. Thus, our model considers 2,500 store-SKU level observations across a 3 week planning period and 100 stores.

- *Scenario analysis input data*

We have estimated three different capacity datasets with regard to the number of chickens available for slaughter each day for the scenario analysis:

Scenario 1:	*The exact capacity required.* Given the constraints, we run the model with a huge amount of chicken capacity to determine how much capacity is necessary to reach the best condition. We then adjusted the dataset to the exact number of chickens required.
Scenario 2:	*Additional capacity.* For each planning period and each chicken type (HappyChicken, NormalChicken), we increased capacity by 10% using the dataset from scenario 1.
Scenario 3:	*Insufficient capacity.* For each planning period and each chicken type (HappyChicken, NormalChicken), we decreased capacity by 10% using the dataset from scenario 1

5. Product expiration in retail

The retail industry is a highly competitive market with extremely narrow profit margins. As the driving force of their profitability, perishable products play a crucial role for supermarkets (Duan & Liao, 2013, p. 658). Therefore, the waste that occurs from expiring products is a significant issue for the retail industry - both environmentally and financially.

5.1. Food loss and waste definition

The way terms such as "food loss and waste", "food waste", or "food loss" are used and defined is disputed among researchers and politicians alike. In this sense, the understanding of these terms determines how policies are formulated and how food waste is quantified across the different stages of the FSC.

According to FUSIONS[6], “food waste is any food, and inedible parts of food, removed from the food supply chain to be recovered or disposed (including composted, crops ploughed in/not harvested, anaerobic digestion, bio-energy production, co-generation, incineration, disposal to sewer, landfill or discarded to sea)” (EU, 2014, p. 6). Food removed from the FSC to be valorised, for example, as animal feed is not considered food waste under this framework and not under the Waste Framework Directive (WFD). The scope of this definition is wider than many other existing ones.

The High Level Panel of Experts on Food Security and Nutrition (HLPE) states meanwhile that “food loss and waste refers to a decrease, at all stages of the food chain from harvest to consumption in mass, of food that was originally intended for human consumption, regardless of the cause” (HLPE, 2014, p. 22). Skin, bones, shells, and other inedible fragments of food are not considered as FLW in this definition. Moreover, food that was intended for human consumption and was removed from the FSC is still considered FLW even if it is valorised for a non-food use like animal feed or bioenergy – unlike in FUSIONS. Using this approach, "planned" non-food uses are distinguished from "unplanned" non-food uses (FAO, 2011, p. 2). This aligns also with the Norwegian Sector Agreement.

In addition, some papers distinguish between the terms "food loss" and "food waste", in that food losses occur before the consumer level whereas food

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[6] An EU-funded project to support member states in measuring food waste.

waste occurs at the consumer level (Teuber & Jensen, 2020, p. 5). Others consider the retail sector to be part of "food waste" (FAO, 2011, p. 2), and yet others, in turn, do not make any distinction between these terms at all.

This study will follow the definitional framework of HLPE and the Norwegian Sector Agreement stating that "food waste is defined as all useful parts of food produced for humans which are either discarded or removed from the food chain for other purposes than human food, from the time of slaughter or harvesting" (NORSUS, 2020, p. 14). Furthermore, there will be no differentiation between the wordings "food loss and waste", "food waste" or "food loss" – if not stated otherwise.

5.2. Perishable goods

The food supply chain describes the process steps involved in bringing food from the farm to the consumer's table. The food industry has distinctive characteristics that differentiates it immensely from other industrial sectors and adds to its complexity. The most succinct differentiator lies in the perishable nature of its products. The holding times of inventory and requirements for handling and storage environments differ depending on the product (Bresler et al., p. 2). Furthermore, food product demand can be affected by seasonality, holidays, and promotions. The challenge for a retailer is to sell a perishable product before it is considered unsaleable.

The issue of unsaleables is a serious concern in the industry because of its significant financial and environmental implications. Unsaleables are classically defined as "products that are removed from the primary channel of distribution for any reason, e.g., damaged, discontinued, or expired items. (This definition excludes product recalls and returns as those items are managed outside of unsaleables policy.)" (Grocery Manufacturers Association, Food Marketing Institute, Deloitte, 2008, p. 3).

Figure 12 shows that financial losses and CO2 emissions associated with food waste in Norway's retail sector have decreased over the last few years. Nevertheless, they still incur a financial loss of NOK 2.46 billion and a carbon footprint of 155,000 tons in 2019.

Figure 12: Financial loss (in billion NOK) (left) and tons of CO2 eq.(right) linked to food waste in Norway by stage of the value chain from 2015 to 2019 (NORSUS, 2020, pp. 23–24).

In the US, the total cost of unsaleables is estimated to be 1 to 2% of retail gross sales. Considering the narrow profit margins in the highly competitive retail environment worldwide (Chang et al., 2019), these numbers are striking. According to an American case study, this implies at their collaborator for example cost of unsaleables equivalent to 50% of their annual income[7]. This represents approximately 3% of their sales, even though unsaleables make up only 0.87% of total sales at their collaborator. (Akkas et al., 2018)

As mentioned, perishable products are generally removed from retailers for three reasons: damage, expiration, or product discontinuation. There are different reasons behind each type of removal. Damages typically occur because of inadequate packaging or poor handling techniques. Expiration can be caused by poor inventory management or forecasting, aging of products at the warehouses, or lack of shelf rotation. The decision to discontinue a product is usually made by the manufacturer or the retailer to allow for new products to be introduced, during a planogram reset, or as part of the SKU rationalisation process. (Akkas, 2015, p. 19)

The analysis of AlphaCo's total food waste along their poultry supply chain (see Figure 13) reveals that 97% of all wasted chicken products are wasted at the retail level. Retailers threw away more than 650 tons of chicken products in 2021, which is equivalent to over 500,000 chickens[8]. As a comparison to that, WholesaleCo's warehouses discarded around 25 tons of poultry products. ChickenCo reports that they do not have any logistical poultry waste. On average, retailers discard over 8% of the chicken products they receive. In light of the narrow profit margins, this represents a substantial amount of financial loss. WholesaleCo,

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[7] Assuming a profit margin of nearly 2%.

[8] Based on an average chicken weight of 1.3 kg.

on the other hand, discards only 0.3% of the poultry products it receives from ChickenCo.

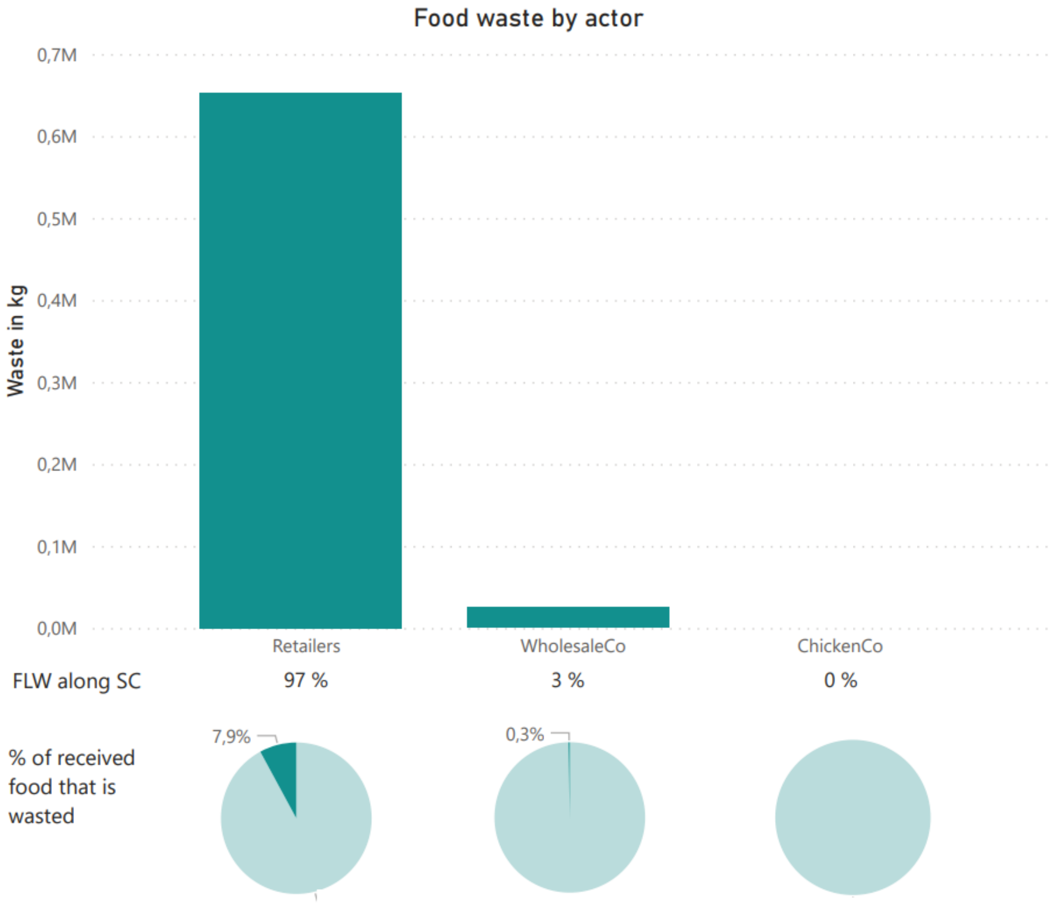

Figure 13: Food loss and waste along the food supply chain of AlphaCo (own figure).

Figure 14 illustrates why chicken products are wasted in AlphaCo's supply chain. It shows that product expiration accounts for over 70% of the food waste at the retailers, followed by damage (17%), and other reasons (10%). In WholesaleCo's warehouses, 25% of ChickenCo's products are thrown away due to direct expiration which corresponds to a value of NOK 630,000. However, WholesaleCo also considers that financial losses incurred as a result of discounts constitute "food waste", even though they are no actual (kilogram) food waste. Discounts are given when the retailer receives a product that is older than agreed upon (more to contractual agreements in chapter 6.1) or when WholesaleCo delivers more products than ordered because of excess inventory. These discounts – to some extent - are indirectly tied to the expiration of products and equivalent to almost NOK 1.7 million. Hence, they are included in the food waste argument for emphasis.

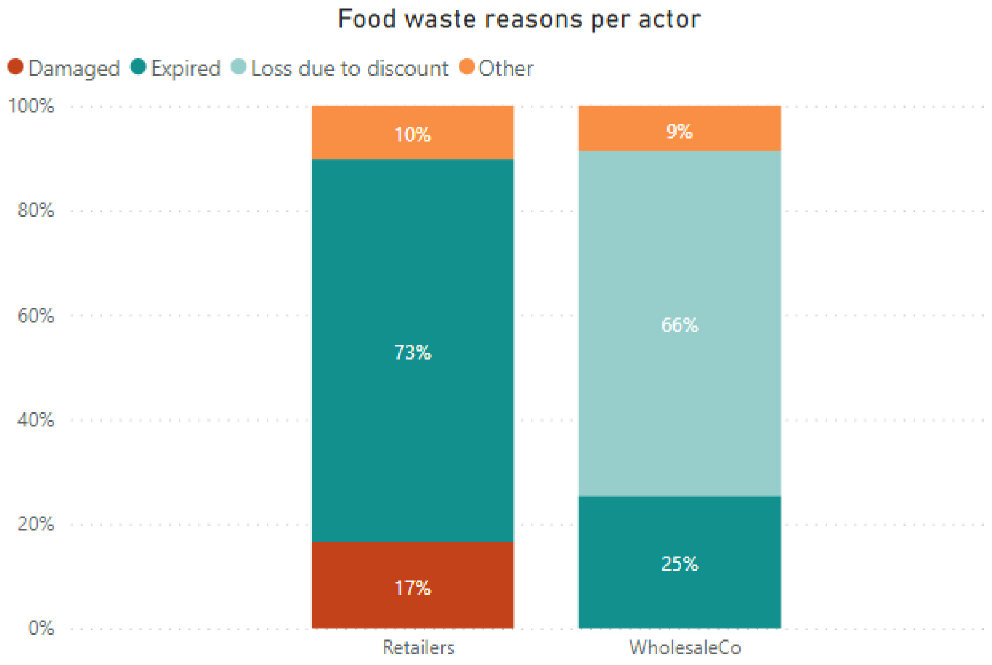

Figure 14: Different types of food waste at AlphaCo in 2021 (own figure).

It highlights the fact that the expiration of products does not only affect the retail stores, but also the wholesaler. Expiration of products is the largest driver of food waste in AlphaCo’s poultry supply chain, as it accounts directly or indirectly for over 70% FLW at its retail- and wholesale stage. With regard to perishable goods and the issue of unsaleables, this thesis will focus on the topic of product expiration since it is a more pressing issue than the other two types of unsaleables.

5.3. Drivers of product expiration

In this study, we explore food waste caused by product expiration. The topic of expiration and its drivers must be thoroughly explored to grasp the full implications of our optimisation approach.

Companies in the CPG industry commonly use audits and surveys to understand food waste and to document the root cause of unsaleable products. The auditing process involves visually inspecting unsaleables at sampled stores and recording each case of an unsaleable with a reason code. Visual inspection usually reveals the cause of the damage, like packing failure. However, it is not informative for expired products as the product on the retailer’s shelf can have expired due to any cause during its journey from the factory to the shelf. The causes of product expiration are numerous, from batching during production or transportation to inefficient inventory management in the warehouse to the placement of products on the shelf at the retail store. It is not possible to identify these causes by examining a product after it has expired. In other words, audits are useful in pinpointing the causes of damage and even product discontinuation, but not for determining why a product has expired. (Akkas et al., 2018, p. 2)

By contrast, surveys seek to find out what participants believe is the cause of unsaleables. But there are divergent views between manufacturers and retailers concerning the main causes of unsaleable goods (Grocery Manufacturers Association, Food Marketing Institute, Deloitte, 2008). Because of the lack of transparency in the supply chain and the numerous events that are dependent on expiration, it is an ongoing concern for manufacturers and retailers (Akkas et al., 2018, p. 3).

Therefore, it is important to study how store operations, supply chain performance, and product characteristics contribute to the occurrence of expiration. It also raises the question of whether product expiration in a CPG company is a natural outcome of random demand, or whether there might be a way to reduce the probability of it occurring. According to the results of an American study by *Akkas*, expiration is caused by reasons other than the randomness of demand, so it could be reduced by improving manufacturing and retail operations (Akkas et al., 2018).

In his study, *Akkas* identified five statistically significant drivers of product expiration: case size[9], minimum order rules, manufacturer's sales incentives, forecasting complexity and supply chain aging[10] (Akkas et al., 2018). These variables reflect different aspects of a food supply chain, such as store execution, back-end supply chain operations, and product characteristics. It shows that manufacturers and retailers are both responsible for product expiration happening on retail shelves.

Different perspectives can be taken into account when analysing the above drivers of product expiration. Sources of expiration can be classified, for example, as (i) drivers that reduce shelf life, and (ii) drivers that increase shipment quantity (Akkas, 2015, p. 48). Case size, minimum order rule, sales incentives, and forecasting complexity are among the root causes that can raise shipment quantities

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[9] Case is the unit by which products are shipped within the supply chain. Case size refers to the number of packs and eaches (consumer units of measurement; e.g., a 6-pack beer contains 6 eaches of bottles) included in one case.

[10] Supply chain aging can be defined as "the elapsing of a product's life in the supply chain before the product reaches the retail shelf" Akkas (2015, p. 37)

beyond the needed amount to match uncertain demand, hence contributing to increasing shipment quantities. In contrast, supply chain aging reduces effective shelf life directly.

In the following study, we are focusing on the effects of supply chain aging on product expiration and remaining shelf life at the retail stores.

5.4. Relationship between supply chain aging and expiration

A major factor contributing to the expiration of products at the retail stores (i.e., generating food waste) is the aging inventory throughout the FSC. Upon production/packaging, every product has a fixed shelf life. Supply chain aging refers to the reduction in this shelf life of goods caused by time spent throughout the supply chain.

Thus, by diminishing effective shelf life, supply chain aging increases the probability of product expiration at the retailers stage. Furthermore, the effect of supply chain aging on expiration is likely to vary depending on the demand rate, store inventory, and shelf rotation (Akkas et al., 2018, p. 12).

The reason for supply chain aging can be many factors, including poor forecasts, ordering policies, batching of production and transportation, high safety stocks, and unsynchronized product launches (Akkas et al., 2018, p. 12; Akkas & Honhon, 2018). These variables may be used to potentially reduce the aging of supply chains.

Errors in forecasting can lead to excess warehouse inventory as safety stocks increase. Accordingly, goods tend to remain in the warehouse for longer periods of time. Order policies affect the supply chain inventory directly by determining the level of inventory received from upstream. Producing large batches lowers unit production costs but increases inventories which again would stay longer at the warehouse. Low velocity items are expected to show an even stronger correlation to that. Same applies to full pallet shipments. It reduces handling costs, but the distribution centres may end up holding excess inventory. (Akkas, 2015, p. 62)

We measure supply chain aging for all products as the cumulative average days at each supply chain stage. AlphaCo has a multi-tier supply network (see chapter 3). We map the multi-tier food supply chain for all products and compute the distribution of total shipped product age across the stages of ChickenCo and WholesaleCo’s warehouse as well as the average inventory age at ChickenCo over time.

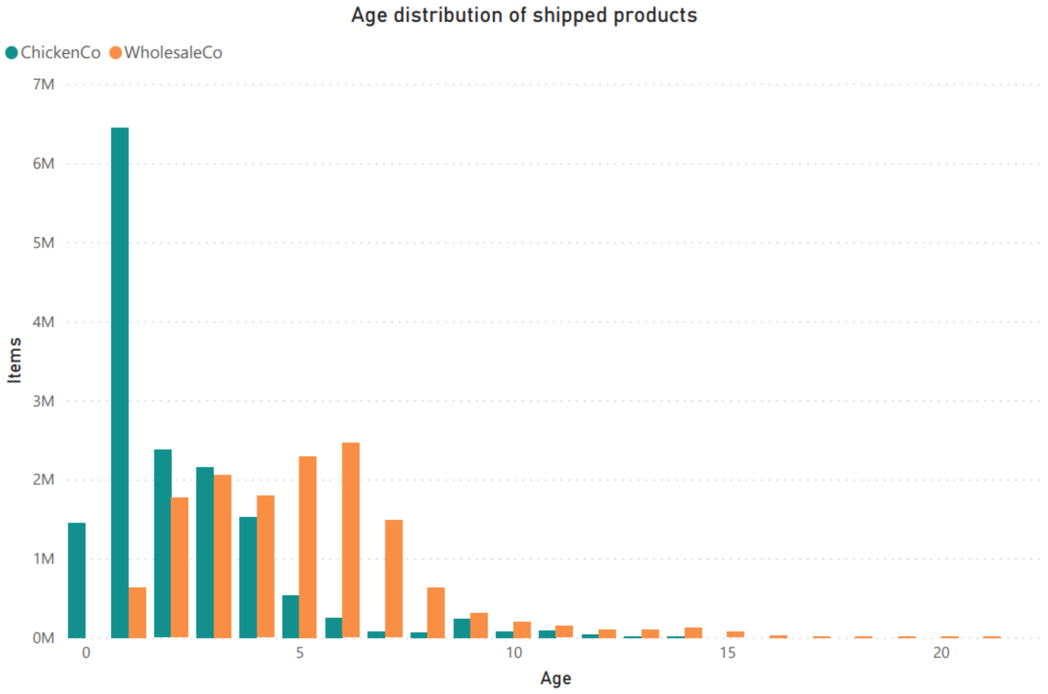

Figure 15: Product age when shipped from ChickenCo and WholesaleCo in 2021 (own figure).

The analysis of the ages of the shipments (see Figure 15) reveals that ChickenCo delivers products averaging 2.2 days in age to WholesaleCo and WholesaleCo ships items averaging 5.0 days in age to the retailers. Moreover, half of the products shipped by ChickenCo are 1 day old or younger[11], whereas half of the products shipped by WholesaleCo are 5 days old or younger.

The majority of ChickenCo's products are shipped a day after they have been produced, which by itself sounds positive. It is important to note, however, that the producer constantly had too few chickens in 2021 for a variety of reasons[12]. If this caused their shipped products to age in a more favourable manner, it can be inferred that there is still an opportunity for optimisation under normal circumstances. Also in the current context, there remain a backlog of older products that can be improved, such as almost 240,000 shipped chicken products that are 9 days old.

ChickenCo's overall inventory aging analysis (see Figure 16) indicates further that the company experienced an upward aging trend in inventory over the period of 2021 that was accompanied by a sudden jump in average inventory age in April. The average age of ChickenCo's inventory for every day of 2021 is calculated using a moving average of seven days. The method was used because the company does

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[11] Shipped products with an age of 0 have been produced and shipped on the same day.

[12] The closure of the border with Sweden during Covid-19 resulted in a large increase in the demand for chickens within Norway, while an illness led to the death of many chickens at the same time.

not produce over the weekend, but products are still picked up by WholesaleCo, causing outliers on the weekends. The overall trend of aging over the past year is another indicator of potential for optimisation approaches.

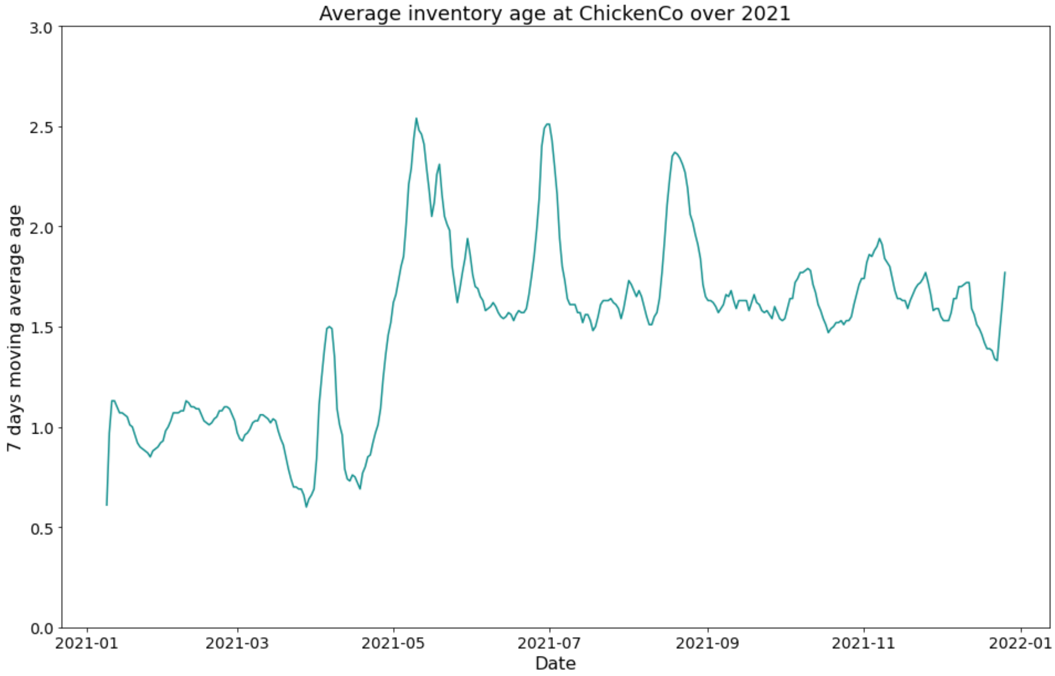


Figure 16: Inventory age distribution at ChickenCo over 2021 (own figure).

Due to its inflexible material inputs (fixed number of available chickens scheduled for slaughter), ChickenCo tends to be the bottleneck of operations and modelling constraints that can create a bullwhip effect of supply chain aging, affecting the entire supply chain. Therefore, our modelling approach will focus primarily on improving ChickenCo's production planning in order to ensure that fresh products are shipped out continuously in order to address supply chain aging and reduce product expiration at retail stores.

6. Production planning for a Three-tier supply chain for perishable poultry products

Optimising the supply of young chicken products can prolong the shelf life and reduce the amount of expired items (reduce FLW) in the FSC. This thesis aims to alleviate the inventory aging issue by establishing production planning policies for the producer.

The remaining shelf life of consumer packaged goods is currently a subject of contention in the industry. Many retailers complain that they receive products with little remaining shelf life (Akkas, 2015, p. 82). Because of this, manufacturers are becoming increasingly concerned with shelf-life management. To control the age of shipped products between supply chain participants, existing rules usually prescribe a minimum shelf life expressed as a percentage of the manufactured shelf life or a certain number of days for a product or product category.

To address this issue, we developed an optimisation model which focuses on waste and freshness of chicken products, while considering the business goals and constraints of all supply chain participants. It maximizes the “estimated value” built on three components: (1) revenue from selling products at the retailers, (2) penalty cost for older products at the retailer, and (3) costs for generated food waste at the producer. We solve this problem using our collaborator AlphaCo’s historical demand forecast, production, and product data.

6.1. The remaining shelf-life problem

Shelf life is an important aspect of fresh food production planning, but often it is overlooked (Lütke Entrup et al., 2006). Using food waste as a measure to evaluate the effectiveness of a strategy to reduce it can be difficult, so additional indicators should be incorporated such as the remaining shelf life (Bresler et al., p. 6).

A consumer is more likely to favour a product with a long shelf life over its price, as they will be able to store the product for longer (Hendalianpour, 2020). As a result, they tend to purchase the product with the longest shelf life (Hendalianpour, 2020; Lütke Entrup et al., 2006). Fresh meat products like chicken are even more influenced by their freshness due to their short shelf lives. This is why the demand for perishable products is partly determined by freshness associated with their expiration dates and should be thus accounted for as a new dimension apart from e.g. the selling price in the demand function (Chen et al., 2016; Hendalianpour, 2020, p. 1).

Fresh food producers and retailers gain a competitive advantage from being able to offer a longer shelf life than their competitors (Lütke Entrup et al., 2006, p. 1). It is therefore crucial to plan production systems in poultry or other fresh food industries according to shelf life.

In a Norwegian survey on the factors affecting food waste habits at households, consumer stated that “the measures that had reduced waste in their household were extra information on date labels, increased shelf life, good opening and closing mechanisms on packaging and information about a product’s shelf life and storage after it has been opened” (NORSUS, 2020, p. 6). In other words, extending remaining shelf life at the retailer contributes to not just reducing food waste at the retailer but also reducing food waste at consumers' homes.

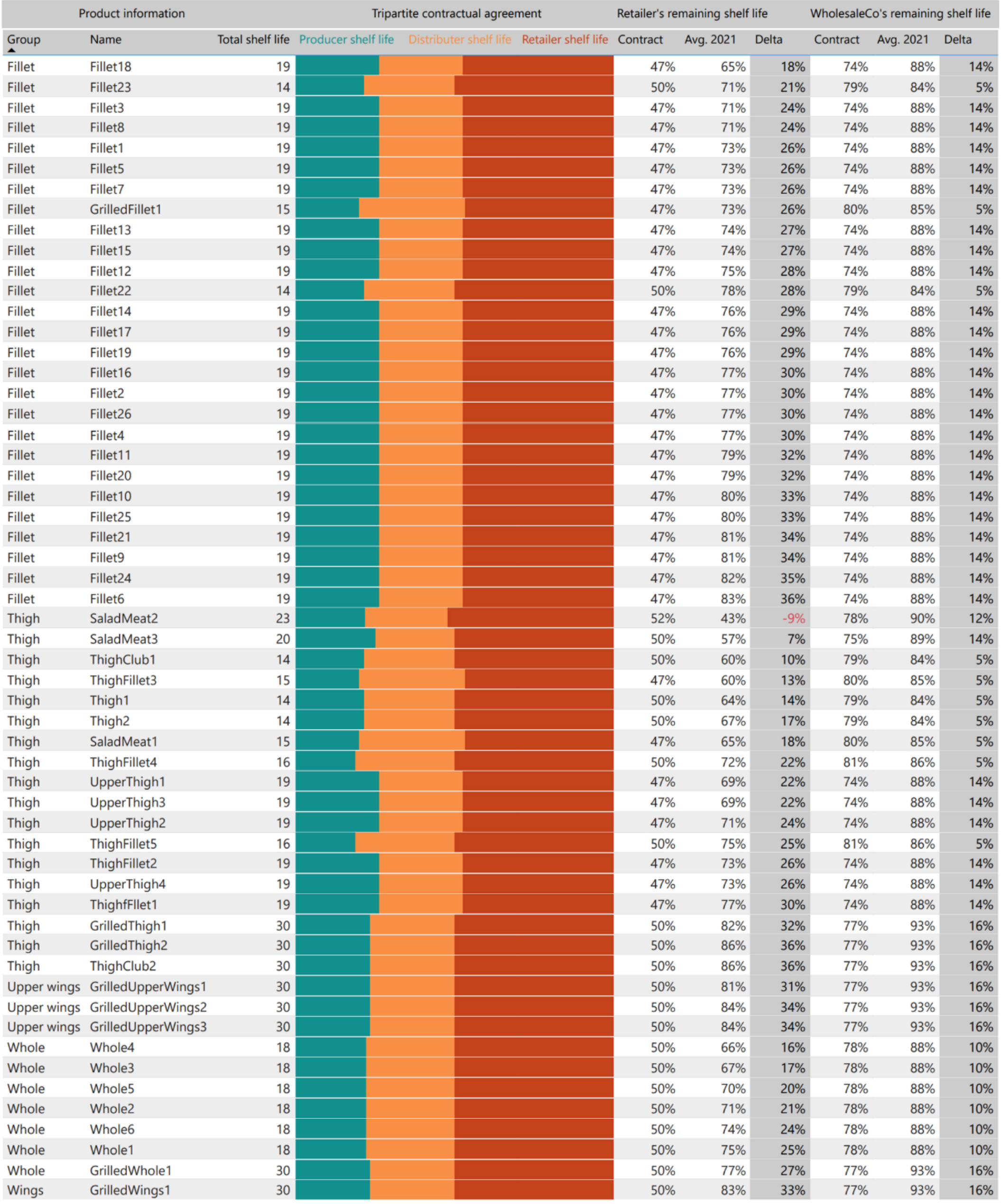
Retailers can institute policies to prevent the expiration of products by imposing minimum shelf life requirements to prevent shipments containing products with little shelf life left (Akkas, 2015, p. 90; Lütke Entrup et al., 2006, p. 1).

There are two main types of practices in the industry: (1) a fixed number of days and (2) a percent of manufactured shelf life. Policy (1) specifies a fixed time per product as the minimum remaining shelf life (in days); policy (2) specifies that the minimum remaining shelf life varies according to the manufactured shelf life (in percentage).

AlphaCo operates on a tripartite contractual agreement following the approach of policy (1). Based on the total shelf life of a product in days defined by the manufacturer, the number of days of total shelf life available to the manufacturer, distributor and retailer are defined (STAND). It acts as a control mechanism for how old a product can be before it latest must be shipped to the next supply chain stage.

The total shelf life and contractual agreement between ChickenCo, WholesaleCo and the retailers for each chicken product in 2021 is captured in Table 5. Additionally, the chart shows how much relatively remaining shelf life the retailer expects from a shipped product from WholesaleCo, the actual rate it received in 2021, and how much the contract was over- or underperformed. Same applies to the remaining shelf life WholesaleCo expects from ChickenCo. The products are organised by product groups and sorted ascendingly by contract performance.

Table 5: Tripartite contractual agreement on remaining shelf life at each supply chain stage per product in 2021 (own figure).



Product information			Tripartite contractual agreement			Retailer's remaining shelf life			WholesaleCo's remaining shelf life		
Group	Name	Total shelf life	Producer shelf life	Distributer shelf life	Retailer shelf life	Contract	Avg. 2021	Delta	Contract	Avg. 2021	Delta
Fillet	Fillet18	19				47%	65%	18%	74%	88%	14%
Fillet	Fillet23	14				50%	71%	21%	79%	84%	5%
Fillet	Fillet3	19				47%	71%	24%	74%	88%	14%
Fillet	Fillet8	19				47%	71%	24%	74%	88%	14%
Fillet	Fillet1	19				47%	73%	26%	74%	88%	14%
Fillet	Fillet5	19				47%	73%	26%	74%	88%	14%
Fillet	Fillet7	19				47%	73%	26%	74%	88%	14%
Fillet	GrilledFillet1	15				47%	73%	26%	80%	85%	5%
Fillet	Fillet13	19				47%	74%	27%	74%	88%	14%
Fillet	Fillet15	19				47%	74%	27%	74%	88%	14%
Fillet	Fillet12	19				47%	75%	28%	74%	88%	14%
Fillet	Fillet22	14				50%	78%	28%	79%	84%	5%
Fillet	Fillet14	19				47%	76%	29%	74%	88%	14%
Fillet	Fillet17	19				47%	76%	29%	74%	88%	14%
Fillet	Fillet19	19				47%	76%	29%	74%	88%	14%
Fillet	Fillet16	19				47%	77%	30%	74%	88%	14%
Fillet	Fillet2	19				47%	77%	30%	74%	88%	14%
Fillet	Fillet26	19				47%	77%	30%	74%	88%	14%
Fillet	Fillet4	19				47%	77%	30%	74%	88%	14%
Fillet	Fillet11	19				47%	79%	32%	74%	88%	14%
Fillet	Fillet20	19				47%	79%	32%	74%	88%	14%
Fillet	Fillet10	19				47%	80%	33%	74%	88%	14%
Fillet	Fillet25	19				47%	80%	33%	74%	88%	14%
Fillet	Fillet21	19				47%	81%	34%	74%	88%	14%
Fillet	Fillet9	19				47%	81%	34%	74%	88%	14%
Fillet	Fillet24	19				47%	82%	35%	74%	88%	14%
Fillet	Fillet6	19				47%	83%	36%	74%	88%	14%
Thigh	SaladMeat2	23				52%	43%	-9%	78%	90%	12%
Thigh	SaladMeat3	20				50%	57%	7%	75%	89%	14%
Thigh	ThighClub1	14				50%	60%	10%	79%	84%	5%
Thigh	ThighFillet3	15				47%	60%	13%	80%	85%	5%
Thigh	Thigh1	14				50%	64%	14%	79%	84%	5%
Thigh	Thigh2	14				50%	67%	17%	79%	84%	5%
Thigh	SaladMeat1	15				47%	65%	18%	80%	85%	5%
Thigh	ThighFillet4	16				50%	72%	22%	81%	86%	5%
Thigh	UpperThigh1	19				47%	69%	22%	74%	88%	14%
Thigh	UpperThigh3	19				47%	69%	22%	74%	88%	14%
Thigh	UpperThigh2	19				47%	71%	24%	74%	88%	14%
Thigh	ThighFillet5	16				50%	75%	25%	81%	86%	5%
Thigh	ThighFillet2	19				47%	73%	26%	74%	88%	14%
Thigh	UpperThigh4	19				47%	73%	26%	74%	88%	14%
Thigh	ThighfFllet1	19				47%	77%	30%	74%	88%	14%
Thigh	GrilledThigh1	30				50%	82%	32%	77%	93%	16%
Thigh	GrilledThigh2	30				50%	86%	36%	77%	93%	16%
Thigh	ThighClub2	30				50%	86%	36%	77%	93%	16%
Upper wings	GrilledUpperWings1	30				50%	81%	31%	77%	93%	16%
Upper wings	GrilledUpperWings2	30				50%	84%	34%	77%	93%	16%
Upper wings	GrilledUpperWings3	30				50%	84%	34%	77%	93%	16%
Whole	Whole4	18				50%	66%	16%	78%	88%	10%
Whole	Whole3	18				50%	67%	17%	78%	88%	10%
Whole	Whole5	18				50%	70%	20%	78%	88%	10%
Whole	Whole2	18				50%	71%	21%	78%	88%	10%
Whole	Whole6	18				50%	74%	24%	78%	88%	10%
Whole	Whole1	18				50%	75%	25%	78%	88%	10%
Whole	GrilledWhole1	30				50%	77%	27%	77%	93%	16%
Wings	GrilledWings1	30				50%	83%	33%	77%	93%	16%

An analysis of the data shows that upper wing- and wing products arriving at the retailers exceed the contractual remaining shelf life agreement on average by 33%, followed by chicken fillets (29%), and chicken thighs and whole chickens (21%). In 2021, there was just one product (thigh – saladmeat2) that did not hold up to the agreement and missed it by 9%. ChickenCo has slightly lower performance than WholesaleCo in the contractual agreement, but it outperforms it across all products. Upper wing- and wing products arriving at WholesaleCo exceed the contractual remaining shelf life agreement on average by 16%, followed by chicken fillets (13%), and chicken thighs and whole chickens (11%).

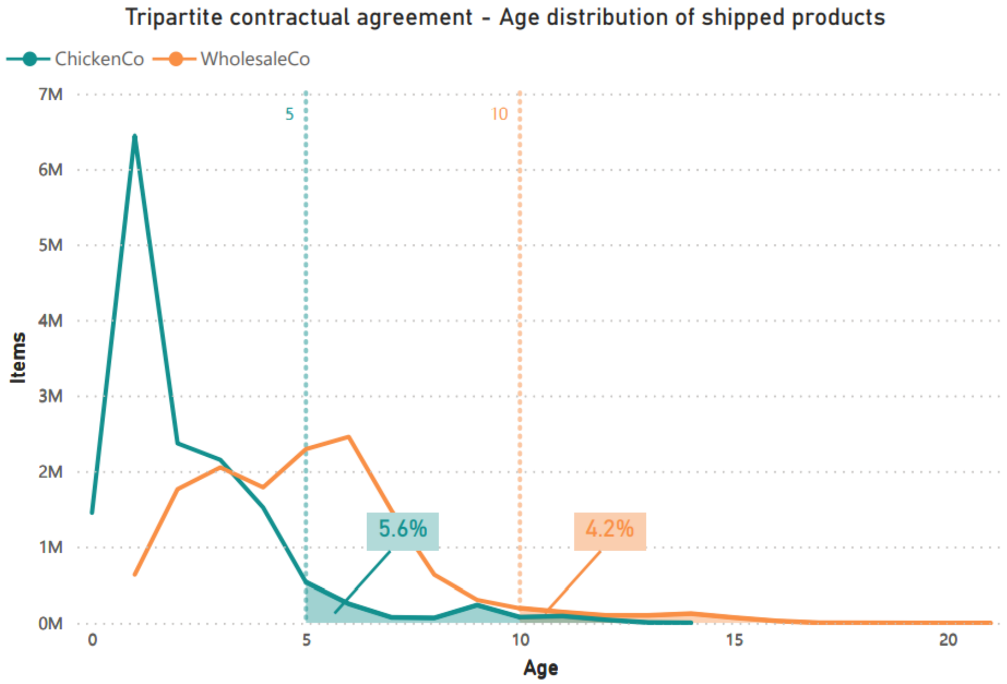


Figure 17: Age distribution of shipped products under the tripartite contractual agreement (own figure).

In almost 96% of the cases, WholesaleCo is in compliance with its remaining shelf life obligations to retailers (see Figure 17). ChickenCo fails to deliver fresh enough products to WholesaleCo around 6% of the time. These analyses draw a solid basis for a starting point with potential for improvement in the remaining shelf life agreements. To provide still fresher products to retailers, it should not just be about fulfilling the expectations of the agreement, but also about exceeding them.

6.2. Optimisation model

We present a mixed-integer linear programming (MILP) model that focuses on the waste and freshness of processed chicken products, while considering the most fundamental business goals and constraints of all supply chain participants in the case study. Although we do not delve into the financial outcome of each actor, we consider satisfying demand one of the most important drivers of our model along with minimizing waste.

6.2.1. Assumptions and limitations

Formulating assumptions and limitations for the model are the following.

6.2.1.1. Assumptions

1. Demand forecast is accurate.
2. There is infinite processing capacity at ChickenCo which is only limited by the number of available chickens.
3. All chickens and their processed parts weight the same.
4. All chickens have an average weight of 1.3 kg.
5. Chickens are only cut if they will also be used for fillets.
6. There is infinite inventory capacity at the retailers, WholesaleCo's warehouses and ChickenCo.
7. The warehouses of WholesaleCo are simply pass-through points. Therefore, they are treated as one single warehouse in the model.
8. WholesaleCo is ChickenCo's only customer.
9. There is no other use for unused chickens and their parts and must be wasted.
10. Transportation costs are not relevant. Trucks go according to their schedule regardless of if we need them or not as they transport also other products from WholesaleCo to the retailers aside from our chicken products.
11. Transportation capacity is ignored in this model (see reason in 7.).
12. There is no priority rule among retail stores.
13. All assumptions that are incorporated in the Leadtime parameter $L_{s,p,t}$, are assumed in the model as well (see chapter 6.2.3.2(b)).
14. The waste probability parameter $F_{p,t-k}$ is adequate.
15. The value parameters V_p, WL_i represent the correct financial value.

6.2.1.2. Limitations

1. Production costs are not considered.
2. Case size for shipment is not considered.
3. Safety stock (alternatively, minimum presentation stock at the retailers) can be incorporated only by increasing the forecasted demand.
4. Waste costs are only represented as potential revenue lost.
5. Stock-outs are only penalized by lost revenue.
6. Product campaigns are not considered.
7. Included are only retail stores under OrderCo.

6.2.2. Mathematical model notation

The AMPL script is included in Attachment 4 - AMPL script.

Sets

Chicken part groups *(fillet, whole chicken, thighs, wings…)*	CG
Chicken part subgroups *(thigh fillet, grilled wings…)*	CS
Consumer packed product	P
HappyChicken products	PHC
NormalChicken products	PNC
Retail stores	S
Types of chicken *(HappyChickens or NormalChickens)*	$type$

Parameters

Matches *(chicken part subcategories "CS" to chicken part group "CG")*	$a_{CG,CS}$
Starting period of demand	b
Chicken capacity slaughter *(per chicken type "type", per period "T")*	$Cap_{type,T}$
Demand *(per store "S", per product "P", per period "T")*	$D_{S,P,T}$
Minimum allowed deviation between store's fill rate	dev
Waste probability due to product age *(per product "P", per age "T")*	$F_{P,T}$
Grams of chicken part *(per chicken part group "CG")*	$grams_{CG}$
Lead time *(per store "S", per product "P", per period "T")*	$L_{S,P,T}$
Waste loss per gram *(per chicken part group "CG")*	WL_{CG}
Chicken parts needed *(per product "P", per chicken part subgroup "CS")*	$r_{P,CS}$
Time horizon	T
Value *(per product "P")*	V_P

Variable

Age-inventory *(per period "T")*	$AI_{T,T}$
Fill-rate for the entire period *(per store "S")*	FR_S
Produced product quantity *(per product "P", produced in period k "T")*	$PX_{P,T}$
Required chicken for chicken part groups *(per chicken type "type", per chicken part group "CG", per period "T")*	$ReqCG_{type,CG,T}$
Required chicken for chicken part subgroups *(per chicken type "type", per chicken part subgroup "CS", per period "T")*	$ReqCS_{type,CS,T}$
Chickens to be cut *(per chicken type "type", per period "T")*	$RM_{type,T}$
Waste-inventory *(per chicken part group "CG", per period "T")*	$WI_{CG,T}$
Product quantity *(per store "S", per product "P", produced in period k "T", to satisfy demand in period t "T")*	$X_{S,P,T,T}$

Objective function: *maximise "estimated value"*

$$\begin{aligned}\text{Max}\sum_{s\in S}\sum_{p\in P}\sum_{t=1}^{T}\sum_{k=1;k<t}^{t} \mathrm{V_p}\times \mathrm{X_{s,p,t,k}} - \sum_{s\in S}\sum_{p\in P}\sum_{t=1}^{T}\sum_{k=1;k<t}^{t} \mathrm{V_p}\times X_{\mathrm{s,p,t,k}}\times F_{\mathrm{p,t-k}} \\ - \sum_{i\in CG}\sum_{t=1}^{T}\mathrm{WI_{i,t}}\times \mathrm{WL_i}\end{aligned} \tag{1}$$

Constraints

Sales cannot exceed demand

$$\sum_{k=1}^{t} X_{s,p,t,k} \le D_{s,p,t} \qquad \forall\, s \in S,\ p \in P,\ t \in 1..T \tag{2}$$

Product cannot be produced closer to sale period than the time it takes to deliver it

$$X_{s,p,t,k} = 0 \qquad \forall\, s \in S,\ p \in P,\ t \in b..T,\ k \in t - L_{s,p,t} + 1..t \tag{3}$$

Connect X to the Production variable

$$\mathrm{P}X_{p,k} = \sum_{s\in S}\sum_{t=k}^{T} X_{s,p,t,k} \qquad \forall\, \mathrm{p} \in \mathrm{P},\ \mathrm{k} \in 1..\mathrm{T} \tag{4}$$

Compute age inventory for analysis purposes

$$\mathrm{A}I_{t,t-k} = \sum_{s\in S}\sum_{p\in P} X_{s,p,t,k} \qquad \forall\, \mathrm{t} \in \mathrm{T},\ \mathrm{k} \in 1..\mathrm{t};\ \mathrm{k} < \mathrm{t} \tag{5}$$

Compute the fill rate per store

$$\mathrm{F}R_s = \frac{\sum_{p\in P}\sum_{t=1}^{T}\sum_{k=1}^{t} X_{s,p,t,k}}{\sum_{p\in P}\sum_{t=1}^{T} D_{s,p,t}} \qquad \forall\, \mathrm{s} \in \mathrm{S} \tag{6}$$

Demand must be satisfied equally (with some degree of variation) in each store

$$FR_{s1} \geq FR_{s2} - dev \qquad \forall\, \mathrm{s1} \in \mathrm{S},\ \mathrm{s2} \in \mathrm{S}; \mathrm{s2} \neq s1 \tag{7}$$

$$FR_{s1} \leq FR_{s2} + dev \qquad \forall\, \mathrm{s1} \in \mathrm{S},\ \mathrm{s2} \in \mathrm{S}; \mathrm{s2} \neq s1 \tag{8}$$

Compute the production requirements in terms of HC chicken parts

$$\sum_{p\in PHC} \mathrm{P}X_{p,t} \times r_{p,j} = \mathrm{ReqC}S_{\text{"HC"},j,t} \qquad \forall\, \mathrm{j} \in \mathrm{CS}, \mathrm{t} \in 1..\mathrm{T} \tag{9}$$

Compute the production requirements in terms of NC chicken parts

$$\sum_{p\in PNC} \mathrm{P}X_{p,t} \times r_{p,j} = \mathrm{ReqC}S_{\text{"NC"},j,t} \qquad \forall\, \mathrm{j} \in \mathrm{CS}, \mathrm{t} \in 1..\mathrm{T} \tag{10}$$

Aggregate the requirements over chicken parts groups

$$ReqCG_{y,i,t} = \sum_{j\in CS} a_{i,j} \times ReqCS_{y,j,t} \qquad \forall\, \mathrm{y} \in \mathrm{type},\ \mathrm{i} \in \mathrm{CG}, \mathrm{t} \in 1..\mathrm{T} \tag{11}$$

Chickens required should not exceed the maximum number of chickens to be cut

$$RM_{y,t} \geq ReqCG_{y,i,t} \qquad \forall\, y\ in\ type, t\ in\ T, i\ in\ CG; i \neq \text{"}h\text{"} \tag{12}$$

Chickens to be cut 1

$$RM_{y,t} \geq ReqCG_{y,\text{"f"},t} \qquad \forall\, \mathrm{y} \in \mathrm{type},\ \mathrm{t} \in 1..\mathrm{T} \tag{13}$$

Chickens to be cut 2

$$RM_{y,t} \leq ReqCG_{y,\text{"f"},t} + 0.99 \qquad \forall\, \mathrm{y} \in \mathrm{type},\ \mathrm{t} \in 1..\mathrm{T} \tag{14}$$

Pre-planned HC chicken capacity constraints for production

$$ReqCG_{\text{"}HC\text{"},\text{"}h\text{"},t} + RM_{\text{"}HC\text{"},t} \leq Cap_{\text{"}HC\text{"},t} \qquad \forall\, \mathrm{t} \in 1..\mathrm{T} \tag{15}$$

Pre-planned NC chicken capacity constraints for production

$$ReqCG_{"NC","h",t} + RM_{"NC",t} \\ \leq Cap_{"NC",t} + Cap_{"HC",t} - ReqCG_{"HC","h",t} + RM_{"HC",t} \qquad \forall\, \mathrm{t} \in 1..\mathrm{T} \qquad (16)$$

Compute waste for whole chickens

$$WI_{"h",t} = grams_{"h"} \times \sum_{y \in type} \left(Cap_{y,t} - ReqCG_{y,"h",t} - RM_{y,t}\right) \qquad \forall\, \mathrm{t} \in 1..\mathrm{T} \qquad (17)$$

Compute waste for other chicken part groups

$$WI_{i,t} = grams_{i} \times \sum_{y \in type} \left(RM_{y,t} - ReqCG_{y,i,t}\right) \qquad \forall t \in 1..T, i \in CG; i \neq \text{"h"} \qquad (18)$$

Variable constraints

$$AI_{t,t} \geq 0 \qquad \forall\, t \qquad (19)$$

$$FR_{s} \geq 0 \qquad \forall\, s \qquad (20)$$

$$PX_{p,t} \geq 0 \qquad \forall\, p, t \qquad (21)$$

$$ReqCG_{type,CG,t} \geq 0 \qquad \forall\, type, CG, t \qquad (22)$$

$$ReqCS_{type,CS,t} \geq 0 \qquad \forall\, type, CS, t \qquad (23)$$

$$RM_{type,t} \geq 0 \quad integer \qquad \forall\, type, t \qquad (24)$$

$$WI_{CG,t} \geq 0 \qquad \forall\, CG, t \qquad (25)$$

$$X_{s,p,t,t} \geq 0 \quad integer \qquad \forall\, s, p, t \qquad (26)$$

6.2.3. Model explanation

6.2.3.1. Objective function

The objective function represents an estimated value of the whole process, that we are trying to maximize. The function can be simplified mathematically, but it is written in a way to emphasize the three major parts of the function.

The first component - ($\sum_{s \in S} \sum_{p \in P} \sum_{t=1}^{T} \sum_{k=1;k<t}^{t} V_p \times X_{s,p,t,k}$) – represents the value gained from selling the products at the retailers and satisfying demand. Parameter V_p shows the average selling price of product “p”, and it is multiplied with the decision variable $X_{s,p,t,k}$, which is the quantity of goods “p” in store “s” sold in period “t” that were produced in period “k”. Together they compute the generated sales revenue. This part of the objective function will motivate the model to satisfy as much of the demand as possible. In this thesis, food waste reduction should not be at the expense of stock-outs by simply producing too little. It should be noted

that the decision variable X, has a facility location-based formulation (FAL) (Brahimi et al., 2006, p. 7).

The second part of the objective function promotes fresher products and improve the age inventory - $(-\sum_{s\in S}\sum_{p\in P}\sum_{t=1}^{T}\sum_{k=1;k<t}^{t} V_p \times X_{s,p,t,k} \times F_{p,t-k})$. We introduced a parameter $F_{p,t-k}$ that acts as a probability of waste function that penalizes the revenue according to the age of the product sold. For example, if a given product reaches its expiration date, then the parameter F equals 1, and thus all the sales of that product will be lost, or one can say it will be wasted (more about this parameter in chapter 6.2.4.2). Note that the formulation $t-k$ tells the age of a given product at the moment of sale.

The last part of the objective function - $(-\sum_{i\in CG}\sum_{t=1}^{T} WI_{i,t} \times WL_i)$ – penalises the food waste generated at the producer ChickenCo. The variable $WI_{i,t}$ keeps track of the waste “inventory” (in grams) generated at the producer in each period, and for each chicken part group (whole or fillet/thigh/wing/upper wing). It is multiplied with parameter WL_i, which constitutes the financial value per gram (potential revenue) of a given chicken part group. This will motivate the model to minimize the waste at the producer, given all the constraints, in the most financially optimal way.

Our objective function tries to satisfy as much of the demand as possible with as fresh products as possible while considering the waste generated at the producer level. It maximises "estimated" value due to the fact that the value parameters and waste probability function are estimated. This function is motivated by the desire to focus on the waste and freshness of perishable products, while also considering the business objective of the actors in the supply chain.

Additionally, please note that no economic value is attributed to WholesaleCo. This is due to our assumption that their direct economic circumstances will not change. The model utilizes their existing transportation schedule in the most efficient manner and does not modify it. In reality, though, delivering fresher products would be regarded as an advantage for them – for example less waste, fewer sales on discounts due to outdated products and better business recognition.

6.2.3.2. Constraints

(a) Demand constraints

In *(2)*, the constraint ensures that no more products are sold than there is demand (retailer order) for them. Constraint *(6)* computes the fill rate (percentage of the demand that is being satisfied) for each store, while *(7)* and *(8)* make sure that all the stores get satisfied equally (with some degree of variation). This ensures that in the event of limited production capacity, we do not satisfy some stores entirely, while others get little.

(b) Lead time constraints

Constraint *(3)* makes sure that no products can be sold whose age is smaller than the minimum time it takes from production to the point of sale ($L_{s,p,t}$). This parameter is pre-computed outside of the model and is explained in detail in chapter 6.2.4.1. Constraint *(4)* connects the decision variable $X_{s,p,t,k}$ to the production variable $PX_{p,k}$. This step combines two modelling approaches - production lot sizing and facility location.

(c) Production constraints

From this point forward, the constraints focus on the production's side. Constraints *(9)* and *(10)* compute the number of chickens required, for each chicken part subgroup, to satisfy the production plan. Constraint *(9)* for HappyChickens, and constraint *(10)* for NormalChickens. The parameter $r_{p,j}$ provides how many chickens, and what subgroup of them, are needed to produce one item of product "p". For instance, to create a product that contains 10 grilled chicken wings, it needs to be made from the grilled chicken wings of 5 chickens.

By constraint *(11)* the chicken part subgroups are grouped into respective chicken part groups, and the chickens required are summed accordingly. The goal of the constraints *(12)*, *(13)* and *(14)* is to figure out the number of chickens to be cut into chicken parts. The basis of these constraints is that ChickenCo cuts a chicken only if they need the fillet. And this is represented in constraint *(13)* and *(14)*. Since $RM_{y,t}$ is an integer, constraint *(14)* sets the upper bound of this integer and constraint *(13)* the lower bound. With the number of chickens to be cut, constraint *(12)* limits the production for products that uses other chicken parts than "fillet", so that we do not cut more chickens unless we need the "fillet".

Constraint *(15)* and *(16)* apply the production constraints. Constraint *(15)* specifies that, for HappyChickens, the number of chickens required for products that uses whole chickens, and the number of chickens required to be cut shall not exceed the pre-planned number of HappyChickens to be slaughtered. As for constraint *(16),* it is similar, however, since ChickenCo can use HappyChickens for NormalChicken products, but not the other way around, it allows unused HappyChickens to be used for that purpose.

Constraints *(17)* and *(18)* calculate the waste inventory (in grams) in each period for each chicken part group – constraint *(17)* is for whole chickens, and constraint *(18)* for the rest of the chicken part group.

(d) Analytical constraints

Constraint (5) computes the age-inventory for each period. It indicates how many products of which age have been sold in each period.

6.2.4. Parameter description

6.2.4.1. Lead time $L_{s,p,t}$ (pre-computed)

The model uses a parameter defined as $L_{s,p,t}$ – lead time. It represents, for each of the store “s” and for each of the product “p”, the number of days before the demand period “t” in which the product can be produced. For example, if $L_{s1,p1,10} = 4$, this means that, for store “s1”, to satisfy the demand in period “10”, product “p1” must be produced in period 6 (10 – 4) or earlier. Thus, period 6 is the closest period to the demand period the product can be produced.

This parameter is computed outside of the model to reduce the computation load of the model. In order to include this step into our optimisation model, we would have needed to change the variable $X_{s,p,t,k}$ to $X_{s,p,t,k,l,g}$ (Brahimi et al., 2006; Gruson et al., 2019). This refers to the amount of product “p”, sold in store “s”, in period “t”, produced in period “k”, delivered to the appropriate warehouse in period “l”, arriving to the store in period “g”. Taking 100 stores, 10 products, and a 14-day planning horizon as an example, X would have 100 x 10 x 14 x 14 x 14 = 38,416,000 variables. Moreover, it can quickly increase to unfeasible levels. In this case, it is better to outsource this complexity to a pre-processing step.

(a) Computation parameters

Parameter $L_{s,p,t}$ is based on the following parameters:

- $TS_{s,p,t}$: 1 - if store “s” can receive product “p” in period “t”, 0 - otherwise.
- T$F_{s,p,t}$: 1 - if the warehouse supplying store “s” can receive product “p” in period “t”, 0 - otherwise.
- T$P_{p,t}$: 1 - if the producer can produce product “p” in period “t”, 0 - otherwise.
- $tS_{s,p}$: time (in days) it takes to deliver product “p” from the relevant warehouse to the store “s”.
- $tF_{s,p}$: time (in days) it takes to deliver product “p” from the producer to the relevant warehouse.

(b) Assumptions

With this pre-processing step, and ultimately with the model, the following assumptions arise:

1. As the central warehouse only delivers to the outbound areas of the regional warehouses, where products stay for just a few hours before being delivered to the stores, it is reasonable for simplifying purposes to assume that the central warehouse delivers directly to the stores.
2. Warehouses follow a pick-to-zero policy. In other words, the warehouse receives the product on the same day that it sends it to the store.
3. It is impossible for a store to receive and sell a product on the same day. For instance, if it arrives in the store in period 5, it can be sold (satisfy demand) in period 6 or later.
4. The delivery times act only as a minimum. For example, if a product is scheduled to arrive on Monday, and it takes 1 day to deliver, but the warehouse can send it the earliest on Friday, then it will be considered in transit for 2 days.
5. It is impossible to produce and deliver a product on the same day. If the item is produced in period 5, it can be delivered in period 6 or later.
6. Parameter $TS_{s,p,t}$ is a hard constraint. In reality, it is possible for stores to receive certain products outside of their normal delivery schedule. This option (and its consequences) will not be considered in our model or pre-processing steps.

(c) Computation steps

The following steps are required for the algorithm to calculate the parameter $L_{s,p,t}$:

1. Find the closest period to the demand period "t" (but not "t" itself) when the store "s" can receive product "p". Let us call it "x". Here the algorithm looks at the $TS_{s,p,t}$ parameter.
2. Find the closest period to "$x - \mathrm{tS}_{\mathrm{s,p}}$" when the warehouse satisfying store "s" with product "p", can receive product "p" from the producer. Call this period "y". Here the algorithm looks at the $\mathrm{T}F_{s,p,t}$ parameter.
3. Find the closest period to "$y - \mathrm{tF}_{\mathrm{s,p}} - 1$" when the producer can produce product "p". Here the algorithm looks at the $\mathrm{T}P_{p,t}$ parameter. Call this "z".
4. Finally, $L_{s,p,t} = t - z$.

The pseudo-code can be found in Attachment 3 – Pseudo-code for computing $\boldsymbol{L_{s,p,t}}$

(d) Remarks

- It is important to note that there is only one warehouse (path) that can satisfy the demand for any given store and product combination. Hence, there is no need for a decision that determines which path a product must take to reach the demand point.
- It is enough to know the lead time for the 7 days in a week. Based on the computed 7 days, the rest periods of the planning horizon can be replicated.
- The negative days we loop through in the pseudo code represent days before the 1st to 7th period we are interested in. These are there to account for the fact that products might need to be produced a week (or more) in advance. The parameters $\mathrm{TS}, TF, TP, tS, tF$ are adjusted so that they can be indexed accordingly.

6.2.4.2. Probability of waste function $F_{p,t-k}$

In the explanation of the model's objective function, we have introduced the parameter $F_{p,t-k}$. It represents the probability that product "p" with age "t-k" (t – current period, k – period in which it was produced) is wasted at the retail store.

The main goal of this parameter is to drive the model to satisfy demand with fresher products. Thus, as age increases, the probability of food waste increases. This parameter is part of the pre-processing steps and is given to the model as an input.

It can also be interpreted as the probability that a given product of a certain age/with a certain remaining shelf lifetime will not be sold. A product with a small age has more time to be sold until it expires and thus a greater chance of not being discarded. Furthermore, even if a product is purchased, it may still become waste in the household. Consequently, if someone buys a product that has 2 days to expiration, there is a greater chance that it will end up in the rubbish than a product that has 15 days to expiration. Parameter $F_{p,t-k}$ tries to incorporate these reasons why fresher products result in less waste. Figure 18 demonstrates this discrete function for a product with a total shelf life of 19 days.

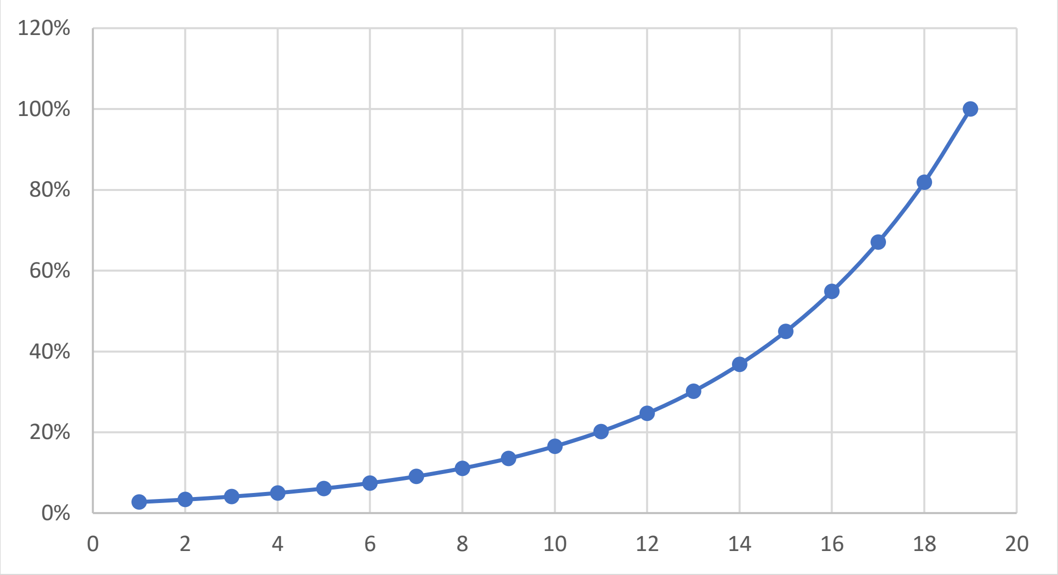


Figure 18: Probability of waste given age of the product (own figure).

One might observe that it is similar to an exponential growth function, which it actually is. To be more precise, it is:

$$f(x) = \begin{cases} 0.022373e^{0.2(t-k)}, & t-k <= \mathit{Total\ shelf\ life} \\ 1, & t-k > \mathit{Total\ shelf\ life} \end{cases}.$$

This constant varies based on the product's shelf life, such that when it reaches its expiration age, its probability of being thrown away is 100%.

(a) Formula reasoning

The age-related waste probability could have been incorporated into many other functions like:

- linear: $(f(x) = a + b \cdot Age)$,
- exponential decay: $f(x) = a(1 - e^{-b \cdot Age}), b > 0$,
- logistic growth: $f(x) = \frac{a}{1 - C \cdot e^{-b \cdot Age}}$,
- logarithmic: $f(x) = a + b \cdot ln(Age)$

We chose exponential growth: $f(x) = a \cdot e^{b \cdot Age}$. This argument is based on the statement made by *Tsiros and Heilman* that “WTP [willingness to pay] decreases linearly for produce and dairy and exponentially for beef and chicken as the number of days left before the product’s expiration decreases” (Tsiros & Heilman, 2005, p. 121). Hence, it is reasonable to assume that the probability of a product not being bought and thus wasted increases exponentially with age.

Even though we do not have further empirical evidence to support our decision, it is sensible to set up the function in this manner. It is not expected that if a product has an age of 3 as opposed to an age of 4, the buyer will act differently regarding his decision whether to purchase it or not. But when it expires in one day instead of two days, especially with chicken products, this could be a game changer.

(b) Assumptions

The following assumptions arise:

1. There are no discounts and product offers, as the age of the product approaches its expiration date.
2. The coefficient of the function is selected arbitrarily.

6.2.5. Application possibility

The model can be used by ChickenCo to decide on their production planning based on transparent forecasts throughout the whole supply chain. This way allows more efficient planning. The lead time computation generates valuable planning data for WholesaleCo. Knowing when certain demands must be met and knowing all the delivery times and transportation schedules, the output of this algorithm will tell WholesaleCo the pickup and distribution plan that yields the shortest possible delivery time. Using the model, retailers can get information about the arrival plans and product ages of the arriving products. Retailers can then adjust their strategy accordingly (e.g., discounts or shelf placement). It is important to note that the model requires a transparent food supply chain and the sharing of information between participants.

7. Results and discussion

In this section, we examine the effectiveness of our model on different food waste aspects along AlphaCo's supply chain and its robustness (see Figure 19). By modifying ChickenCo's capacity input to produce chicken products, chapter 7.1 describes how the food waste situation may change. In chapter 7.2, we perform a sensitivity analysis of the demand rate using the optimal results from our model.

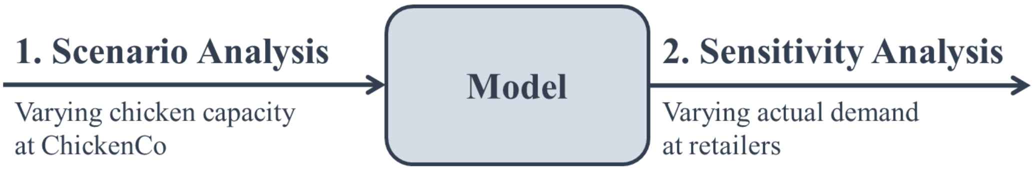


Figure 19: Analysis strategy (own figure).

7.1. Scenario analysis – Chicken capacity input

The production at ChickenCo can be affected by three situations: (1) receiving exactly the number of chickens for slaughter necessary to meet demand, (2) having more chickens than required, or (3) not having enough chickens. Scenarios 1, 2 and 3 are defined as such:

- *Scenario 1 – Exact capacity:* For each planning period and each chicken type (HappyChicken, NormalChicken), we run the model with the exact number of chickens required.
- *Scenario 2 – Additional capacity (+10%):* For each planning period and each chicken type (HappyChicken, NormalChicken), we increased the exact capacity from Scenario 1 by 10%.
- *Scenario 3 – Insufficient capacity (-10%):* For each planning period and each chicken type (HappyChicken, NormalChicken), we decreased the exact capacity from Scenario 1 by 10%.

To ensure a reasonable computational time, the scenarios are run on a sample dataset containing orders from 100 retail outlets for 25 different products. Because these 100 stores do not require all available products, there is a decrease in product variety. In these scenario datasets, the time period ranges from 03.01. – 23.01.2022. Unless otherwise defined, "current" analyses refer to this time period.

The target of this scenario analysis is not just to show the differences in waste numbers between various scenarios, but to also compare them with the actual situation at AlphaCo. The analysis investigates the effect of the optimisation model on direct food waste numbers, supply chain aging, and remaining shelf life statistics.

7.1.1. Food waste

In this section, we discuss the amount of waste generated by ChickenCo, WholesaleCo and the retailers, in each scenario (addressing Research Question (1)). It describes how and why the distribution of waste-generating companies along their supply chain has changed, as well as what impact this has on total food waste.

Considering the structure of our model, it is evident that there will be no waste at the wholesale- and retail levels. WholesaleCo is simply considered a pass-through point in the computation of lead time and the forecasted demand in retail stores represents actual sales in our model and cannot be exceeded. This will allow for the maximum amount to be delivered from ChickenCo without resulting in food waste at any of these two stages (see Figure 20).

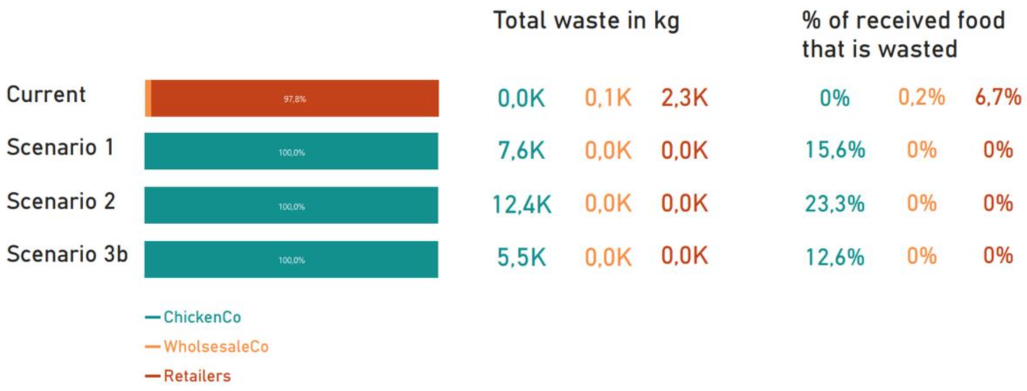


Figure 20: Food waste numbers per scenario (own figure).

Consequently, all chicken waste can just be generated at the level of the producer. A first insight can therefore be gained from examining the waste from ChickenCo's production site - to determine how much waste was generated by which part of the chicken.

7.1.1.1. Chicken capacities and fill rates

Before elaborating more about these waste numbers, the analysis reveals something very contradictory: Scenario 3 generates the most food waste, despite the fact that there are not enough chickens to meet all demand. Further, entire chickens are wasted, despite there not being enough chickens. This observation points to the presence of some semi-optimal behaviour within the model, which is most likely due to a constraint (compare Scenario 1, 2 and 3 in Figure 21).

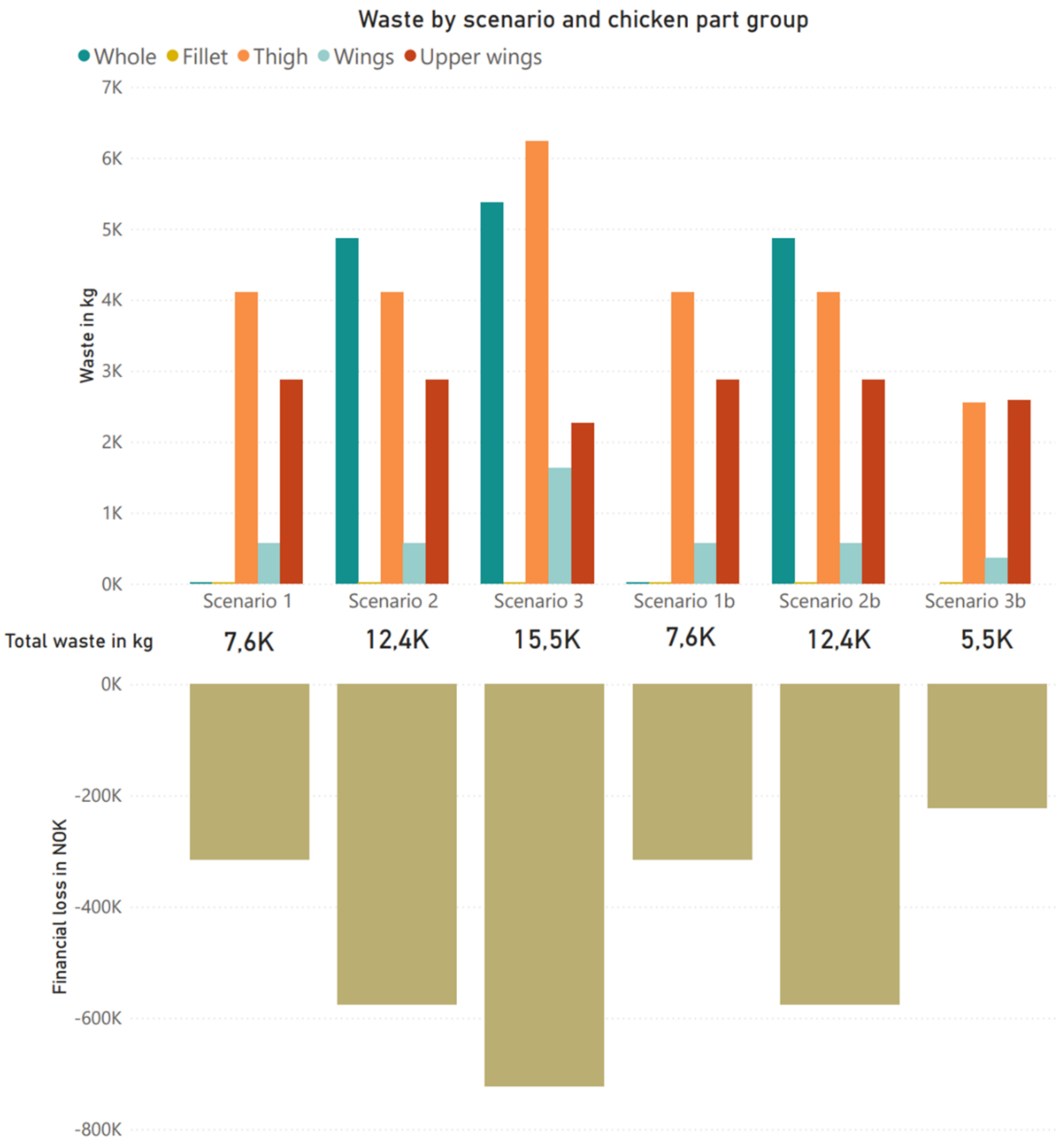


Figure 21: Chicken waste per scenario and chicken part group (own figure).

This abnormal result can be traced back to a constraint on fill rate (constraint (7) and (8), see 6.2.3.2(a) Demand constraints). These constraints make certain that all the stores are treated equally (with some degree of variation). Especially in the event of insufficient production capacity, it was intended to ensure that some stores are not entirely satisfied while others are only partially satisfied. However, this logic ended up backfiring.

Table 6 illustrates that in Scenario 3 the average fill rate fell to 54%. This enormous drop is due to a single small store with a demand for just two products over the entire planning period. There are only three ways to satisfy this store's demand: 100% (two products), 50% (one product), or 0% (no product). In Scenario 3, because of insufficient chicken capacity, this store could only get one product, which forced all other stores (as a result of the fill rate constraint) to a fill rate around 50% as well.

Table 6: Fill rates (own table).

		Average fill rate	**Share under 94.5% fill rate**
Fill rate constraint	**Scenario 1**	96%	0%
	Scenario 2	96%	0%
	Scenario 3	54%	100%
No fill rate constraint	**Scenario 1b**	94%	33%
	Scenario 2b	94%	30%
	Scenario 3b	92%	47%

The assumption was confirmed by running the model again without fill rate constraints for all three scenarios (scenarios without fill rate constraints: Scenario 1b, 2b and 3b). Without the fill rate constraint, Scenario 3b satisfies on average 92% of the demand (see Table 6) and creates the least amount of food waste over all scenarios (see Figure 21). But it also shows that in the case of exact capacity (Scenario 1) and additional capacity (Scenario 2), constraining the fill rate improved the demand satisfaction by 2%, while holding the food waste almost identical (deviations on gram-level). Despite Scenario 1b and 2b maintaining quite high average fill rates of 94%, they are below WholesaleCo's minimum targeted fill rate of 94.5%. More precisely, 33% of the stores in Scenario 1b have a fill rate below this threshold; 30% of the stores in Scenario 2b do.

This suggests that keeping fill rates comparable across stores may not be efficient for reducing food waste if there are too few chickens available and if there are stores with low demand during the planning period. Scenario 3 wastes almost three times as much food as Scenario 3b. It even exceeds the waste amount in Scenario 2, which has more chickens than demand, by 25% (see Figure 21).

Currently, the fill rate is coded as a hard constraint, meaning it must always be fulfilled. To resolve this issue, it can be coded as a soft constraint within the objective function. It is possible to violate a soft constraint, but this incurs a penalty on the objective function. The model must determine whether it should follow the constraint or accept the penalty. We do not intend to change the current model in this way at the moment. In all subsequent analyses, Scenario 1, 2 and 3b will thus be used as they represent the best outcomes as far as food waste and fill rates are concerned.

A closer look at Scenario 3b provides another interesting insight. 10% less available chickens for slaughtered do not resemble to a 10% decrease in demand satisfaction.

The fill rate drops by just 4% compared to Scenario 1 with "optimal" capacity while generating 28% less food waste, equivalent to around NOK 92,000, resulting in 29% less financial loss due to waste. The reason is that ChickenCo receives whole chickens to process and not just chicken parts. Even in an optimal capacity scenario, this leads to leftovers that are of little use, because they either cannot fill another product with them or there is no further demand - assuming ChickenCo only has one customer. When capacity is insufficient, it appears that the whole chicken is used more effectively to fulfil as much demand as possible.

There is a possibility that having too few chickens is in the end more profitable - not just from a food waste perspective, but also economically. To verify this bold hypothesis, further research is needed to evaluate the value of saving actual food waste (in kg) and financial losses associated with it versus missed profit of selling less chicken product than possible. Additionally, it has to be evaluated in an environment with more than one customer.

7.1.1.2. Food loss and waste generator

A close examination of the total waste numbers in Figure 21 reveals two important points. At present, AlphaCo's poultry supply chain generates almost 98% of its food waste from retailers, and 2% from wholesalers, while ChickenCo produces no waste. However, the model reverses the situation in every scenario. As explained earlier, given the structure of our model, there is no possibility of waste at the wholesale and retail levels. All food waste is now generated at the production stage.

Furthermore, the amount of waste generated by ChickenCo under each scenario is higher than the current amount of waste generated by WholesaleCo and the retailers combined. Within these three weeks WholesaleCo had in total approximately 760 kg of chicken waste and the retailers had 31,700 kg. In terms of our sample size, this amounts to 2,400 kg of waste together at both stages. Compared to this Scenario 1 (7,600kg), Scenario 2 (12,400kg), and Scenario 3b (5,500 kg) seem to generate between 130% to 420% more waste than before. Moreover, between 13% and 23% of the chickens they receive are discarded.

On the surface it appears that our optimisation model exacerbates the problem of food waste. Previously, we noted that our model throws away food parts in ChickenCo either because there is an excess of slaughtered chicken to meet demand or because there are insufficient cut leftovers to make another product. It is due to the design of the model in an isolated environment - ChickenCo produces exclusively for WholesaleCo and they do not produce any other products.

However, this does not reflect reality. In reality, ChickenCo has more than one customer, a wider product variety and the option to freeze surplus chickens. Thus, the leftovers that are currently wasted in our model could be used to produce similar CPG for different customers, to produce raw material for subsequent industry production (e.g., sausages), or to freeze excess chickens to produce certain products[13] later. The food waste that accumulates at the production stage right now is therefore not respectively actual food waste at the end of the day. For the same reason, we also anticipate that by including more stores and correspondingly more products in our sample dataset to run the model on, these waste numbers will decrease.

7.1.2. Supply chain aging and remaining shelf life

In this chapter, we discuss the changing age distribution of shipped products from ChickenCo and WholesaleCo in each scenario and which effect it has on AlphaCo's value chain (addressing Research Question (2)). It describes how and why the supply chain aging along the FSC has shifted, as well as what impact this has on the remaining shelf life at the retailers and subsequently on product expiration and food waste.

The second component of our model's objective function attempts to improve the age distribution across the supply chain by encouraging fresh products. Parameter $F_{p,t-k}$ acts as a probability of waste function that penalizes revenue based on how old the product is. In essence, the older a product is when it arrives at a retail store, the less likely it is to be sold and the more likely it will be discarded.

7.1.2.1. Age distribution

Figure 22 illustrates in this respect the results of that logic on the age distribution of shipped products at the production- and wholesale level. Comparing our model to the actual supply chain aging in 2021[14] (see Figure 15), we see a strong, overall shift to younger products.

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[13] It is clearly defined and regulated by ChickenCo which products can be produced with frozen chickens.

[14] Since the scenarios take place in the beginning of 2022 and we do not anticipate a sudden change in shipment patterns to 2021, we are referring to the average supply chain ageing of 2021 and not the respective three weeks' time period. It is also possible that this particular period was influenced

In 2021, ChickenCo shipped items of an average age of 2.2 days to WholesaleCo, and WholesaleCo shipped items of an average age of 5.0 days to retailers. In comparison to that, each shipment in every scenario is approximately 22% younger when it leaves ChickenCo and 60% younger when it leaves WholesaleCo (see Table 7). In all scenarios, ChickenCo ships items with an average age of 1.7 days to WholesaleCo, and WholesaleCo ships items with an average age of 2.0 days to retailers - Scenario 3b is just marginally older.

Table 7: Average age of shipments in 2021 and per scenario (own table).

	2021	**Scenario 1**	**Scenario 2**	**Scenario 3b**
ChickenCo	2.19	1.71	1.71	1.73
WholesaleCo	5.04	1.99	1.99	2.01

In contrast to the situation in 2021, it is not possible to produce and ship products on the same day in our model (see 6.2.4.1(b) Assumptions). Therefore, there are no items of age 0 in Figure 22. Additionally, no product shipped is older than 7 days in Scenario 1 and 2 and no older than 11 days in Scenario 3b. The proportion of items older than 7 days is, however, just 0.1% in the latter scenario. In 2021 though, a total of 3.5% of ChickenCo's shipped products and 12% of WholesaleCo's shipped products were older than 7 days (see Figure 15). Consequently, the backlog of older products seen in 2021 was reduced by the model in all scenarios.

Moreover, half of the products shipped by ChickenCo as well as WholesaleCo are 1 day or younger in almost each scenario. Under Scenario 3b, only 49% of the products shipped by WholesaleCo are 1 day or younger. Meanwhile, in 2021 half of WholesaleCo's shipments were 5 days old or younger.

As a result of the model, aging of products along the supply chain was shifted towards younger products. These changes will impact the remaining shelf life of products at retailers, where the majority of food waste arises from expired consumer products (see Figure 14).

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by Christmas- and New Year's holidays, therefore, it would be more prudent to rely on the average of 2021 for the comparison.

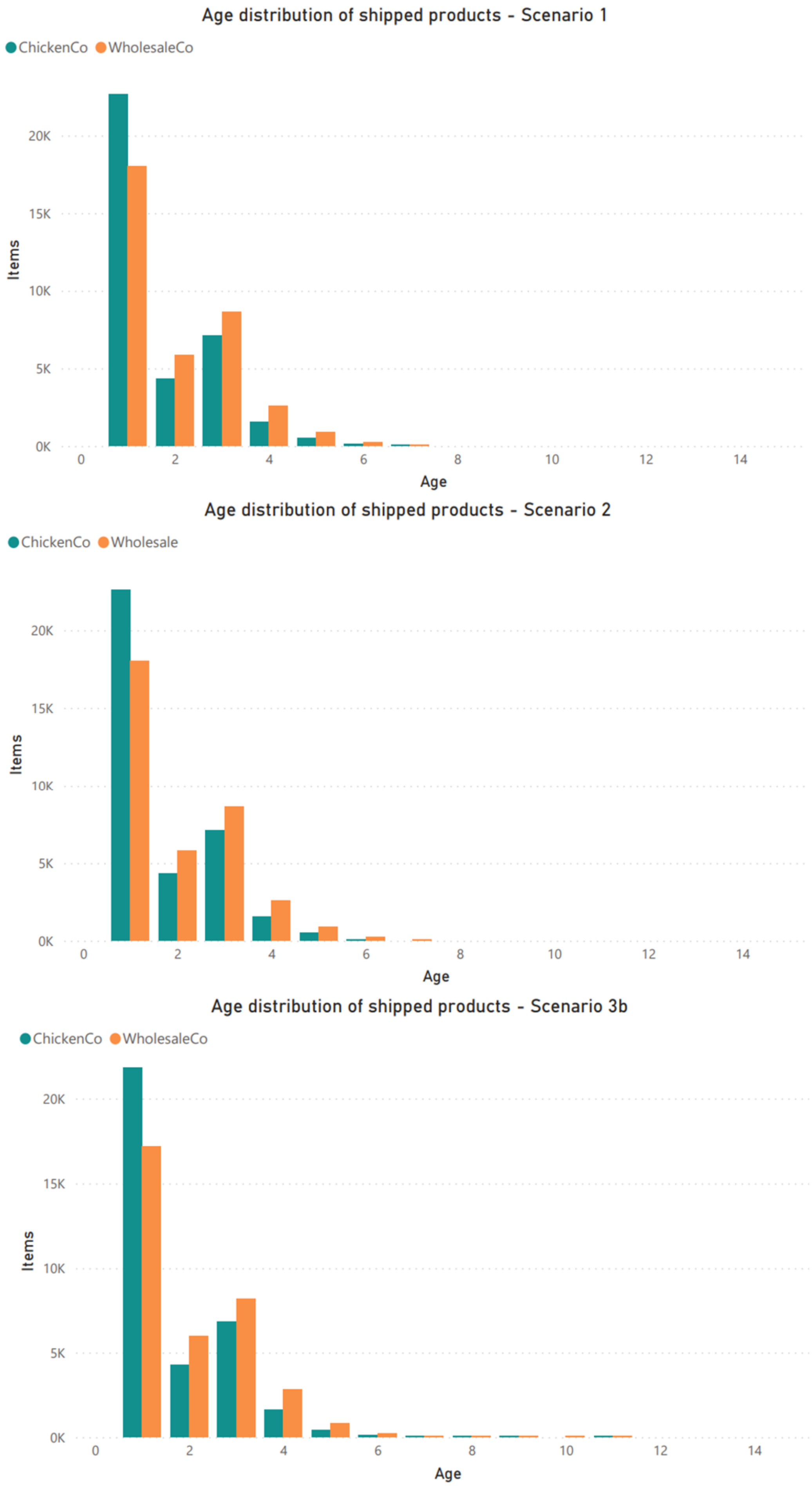


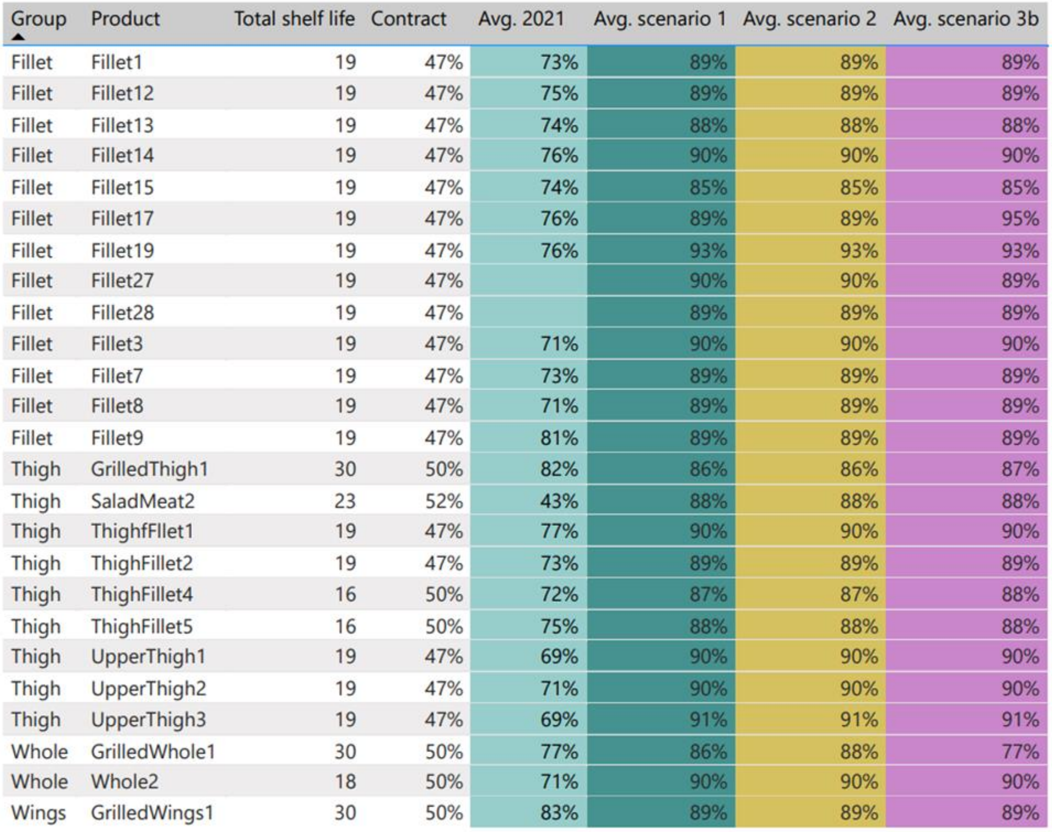
Figure 22: Product age when shipped from ChickenCo and WholesaleCo per scenario (own figure).

7.1.2.2. Remaining shelf life

The shorter time a good spends throughout the FSC, the less effective shelf life is diminished at the retailer's end and the less likely the probability of product expiration/food waste is. Taking a close look at Table 8 from this perspective, it illustrates exactly this impact on remaining shelf life at the retailers in each of the three scenarios.

The average remaining shelf life in 2021 was already exceeding the tripartite agreement terms, but due to the tapering of the supply chain in our model, the remaining shelf life in each scenario increased even more overall. An analysis of the data indicates that the sample products in 2021 arriving at the retailers exceed the contractual remaining shelf life agreement on average by 25 percentage points; however, Scenario 1, 2 and 3b exceed it by 41 percentage points on average. Thus, our model improved the existing remaining shelf life of 2021 by 16 more percentage points on average. In terms of actual days, this accounts for an average of 15 days before expiration in 2021 and 18 days left in each scenario – increasing the product lifespan at the retailers by 20%.

Table 8: Tripartite contractual agreement on remaining shelf life at the retail stage per product in 2021 and per scenario (own figure).



Group ▲	Product	Total shelf life	Contract	Avg. 2021	Avg. scenario 1	Avg. scenario 2	Avg. scenario 3b
Fillet	Fillet1	19	47%	73%	89%	89%	89%
Fillet	Fillet12	19	47%	75%	89%	89%	89%
Fillet	Fillet13	19	47%	74%	88%	88%	88%
Fillet	Fillet14	19	47%	76%	90%	90%	90%
Fillet	Fillet15	19	47%	74%	85%	85%	85%
Fillet	Fillet17	19	47%	76%	89%	89%	95%
Fillet	Fillet19	19	47%	76%	93%	93%	93%
Fillet	Fillet27	19	47%		90%	90%	89%
Fillet	Fillet28	19	47%		89%	89%	89%
Fillet	Fillet3	19	47%	71%	90%	90%	90%
Fillet	Fillet7	19	47%	73%	89%	89%	89%
Fillet	Fillet8	19	47%	71%	89%	89%	89%
Fillet	Fillet9	19	47%	81%	89%	89%	89%
Thigh	GrilledThigh1	30	50%	82%	86%	86%	87%
Thigh	SaladMeat2	23	52%	43%	88%	88%	88%
Thigh	ThighfFllet1	19	47%	77%	90%	90%	90%
Thigh	ThighFillet2	19	47%	73%	89%	89%	89%
Thigh	ThighFillet4	16	50%	72%	87%	87%	88%
Thigh	ThighFillet5	16	50%	75%	88%	88%	88%
Thigh	UpperThigh1	19	47%	69%	90%	90%	90%
Thigh	UpperThigh2	19	47%	71%	90%	90%	90%
Thigh	UpperThigh3	19	47%	69%	91%	91%	91%
Whole	GrilledWhole1	30	50%	77%	86%	88%	77%
Whole	Whole2	18	50%	71%	90%	90%	90%
Wings	GrilledWings1	30	50%	83%	89%	89%	89%

Figure 23 illustrates these results by comparing the distribution of remaining shelf life in 2021 to that of each scenario. There is a noticeable shift towards a longer shelf life in the modelling results with just little backlog. Most products in 2021 have a remaining shelf life 70% - 75%, whereas in Scenario 1, 2 and 3b it is 90% - 95%.

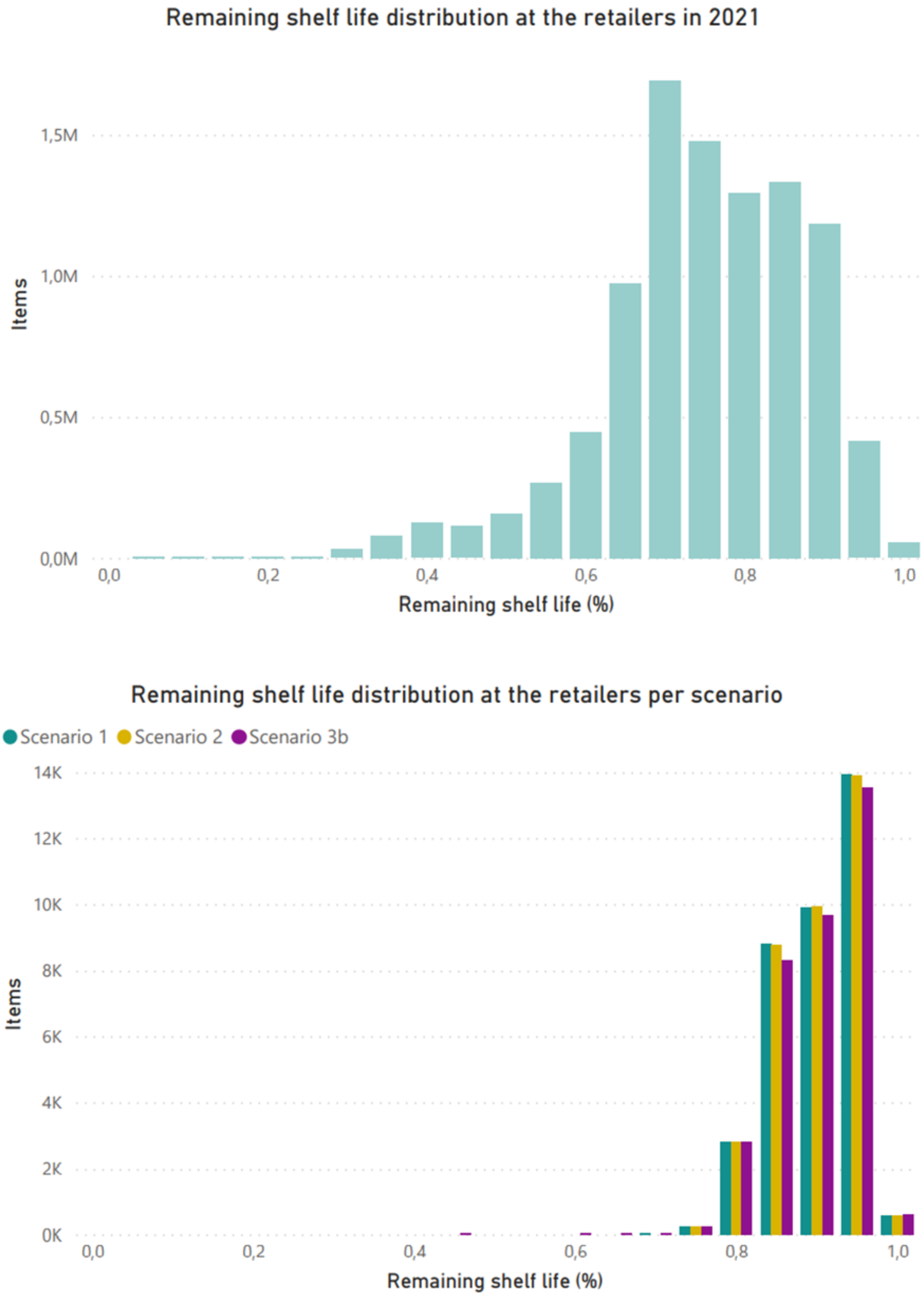


Figure 23: Remaining shelf life distribution at the retailer in 2021 and per scenario (5%-bins) (own figure).

Regardless of chicken capacity, these results indicate that optimising the supply of fresher chicken products throughout the entire FSC extends the shelf life at retailers and can thus reduce the amount of expired products (reduce FLW) at the retail stage. Because as mentioned in chapter 6.1 a consumer tends to purchase the product with the longest shelf life - especially for fresh meat products. With the optimisation approach, products are on average 3 days younger than they were before.

As explained earlier, since our model treats forecasted demand as actual sales, there is no food wasted at the retailers. In order to evaluate the true impact of a longer shelf life on waste - beside customer purchasing behaviour - it is necessary to consider uncertainty and variation in demand. Because the effect of supply chain aging on expiration is likely to vary depending on the demand rate. In the following section, we present therefore a sensitivity analysis to complement our current findings.

7.2. Sensitivity analysis

As the model assumes deterministic demand, it is pertinent to investigate the sensitivity of the results to varying demand and assess the robustness of our model. For this purpose, we developed a Monte Carlo model that simulates retail inventory levels based on age. The simulation was run over 100 various demand rates. The python code for the simulation can be found in Attachment 5 - Simulation python code for sensitivity analysis.

This simulation has two main components:

(1) Arriving products:	The arriving products at the retailers represent the output of the model under Scenario 1 (exact capacity). It indicates the number of products each store receives in each time period and their age.
(2) *Demand rate:*	The demand rate represents a random variation of the forecasted demand used in the model. It is calculated as follows: $DR_{s,p,t} = RANDOM.POISSON(FD_{s,p,t})$, where $FD_{s,p,t}$ is the forecasted demand, and $DR_{s,p,t}$ is the demand rate. The right-hand side of the formula

gives a random sample from a Poisson distribution with $\lambda = FD_{s,p,t}$.

The reason for choosing the Poisson distribution is that, just like our demand, it is discrete, non-negative, and the variance is based on the magnitude of the demand.

The target of this sensitivity analysis is to set and evaluate the food waste outcomes of our model in a more realistic setting of demand uncertainty considering the impact of supply chain aging on it (addressing Research Question (1) and (2)). We expect that demand variations will impact the amount of waste generated at retailers and the age of their inventories.

7.2.1. Expired products and food waste

In this section, we explore the amount of food waste generated by retailers as a result of expired products due deviating demand patterns from forecasted demands. It describes how demand uncertainty influences food waste numbers at retailers that previously did not produce any food waste in the model.

Due to the varying demand scenarios in the simulation, it is possible that more ChickenCo products will be delivered than are actually purchased. Consequently, an inventory is built up, and if the products within the inventory have exceeded their expiration date, they are discarded. Figure 24 illustrates the food waste distribution in number of wasted chicken products.

For 33% of the demand scenarios, the amount of food waste is equal to zero items. Overall, the waste numbers are vanishingly small – despite the variations in demand. On average, the 5%-worst cases in terms of wasted kilograms throw away 3.8 products equivalent to 2.3 kg. In 50% of the scenarios, food waste accounts for only one item or less.

The results of this analysis indicate that the food waste outcomes at retailer level are not increasing significantly with varying demand - they still tend toward zero – supporting the robustness of our model. But the model runs over a short time period of three weeks. This implies some implications to consider. Some products have a total shelf life of over 21 days (see Table 8), which means they will not expire during the simulation anyway. Following this thought, it is conceivable that the food waste problem has possibly only shifted beyond the timeframe of our model. Therefore, it is necessary to review the inventory at the end of the three weeks.

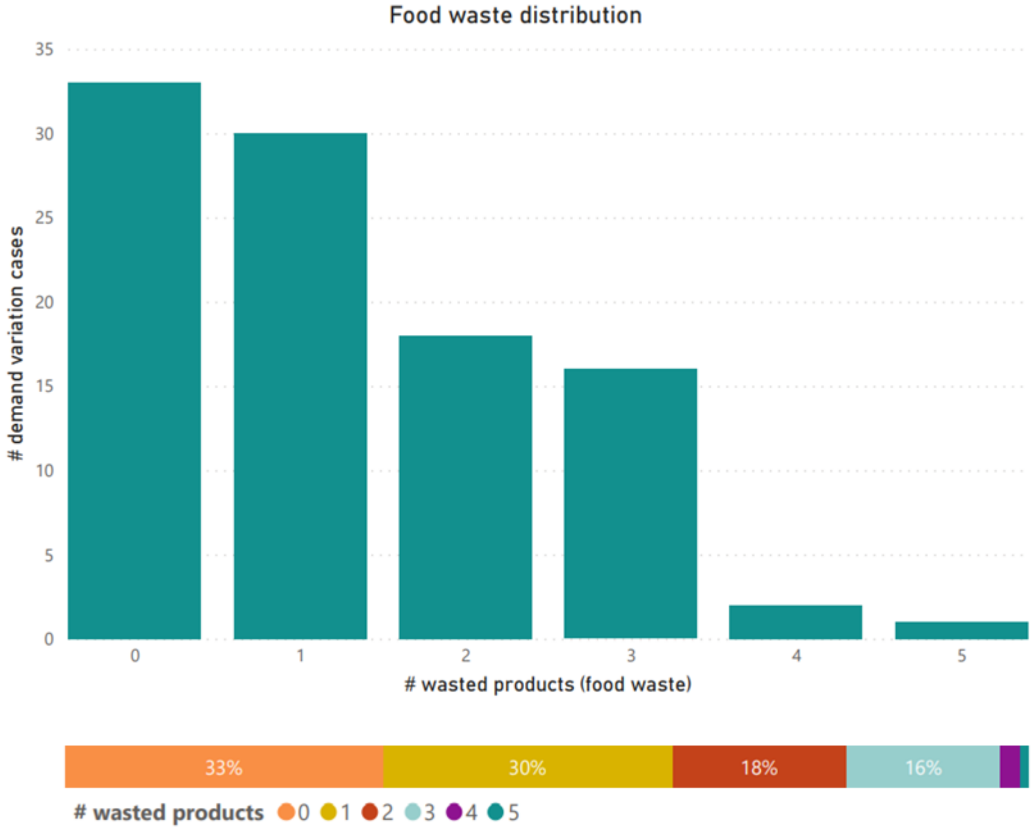


Figure 24: Food waste distribution of varying demand (own figure).

7.2.2. Inventory aging

An in-depth analysis of the inventory levels and aging characteristics of the inventory allows for extrapolation and speculation about what might happen after the modelling period is over. It aims to describe whether or not the simulated demand uncertainty over a longer time horizon could lead to more food waste than shown within these three weeks.

Figure 25 illustrates the distribution of inventory levels over all scenarios at the end of week three. It ranges from 180 to 310 items in stock and resembles a normal distribution with a peak at 240 items. In light of the estimated daily demand of about 1,700 chicken products[15], it seems reasonable to expect to be able to sell these leftover items within a few days if no unexpected events occur. Additionally, all of these products still have an average of 71% of their shelf life left (see Figure 26). This indicates that they will not expire for another 14 days approximately.

However, taking a closer look at the average inventory age over time and the remaining shelf life over time (see Figure 27), we are left with a somewhat concerning picture. It states that over time the products stay constantly longer in the warehouse/shelves before they get sold. Starting off with just 1 day, since products arriving at retailers can be sold earliest the next day, the average inventory age increases up to 5 days. Accordingly, the remaining shelf life shows a steady decline, from 95% in the beginning down to 69% in the end.

Considering these numbers, we can expect higher food waste amounts beyond the modelling period at some point, but not to significant levels shortly after. Nevertheless, if the trend of aging inventories and diminishing shelf life over time, shown in Figure 27, is not interrupted by for example forecasts adjustments, it will lead back to a food waste problem triggered by more product expiration.

Therefore, it would be pertinent to evaluate the model over a longer planning horizon. Furthermore, it would also be interesting to have a closer look into the relationship between forecast qualities and remaining shelf life regarding food waste.

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[15] This number is based on the forecasted demand of 36,000 products over the three weeks.

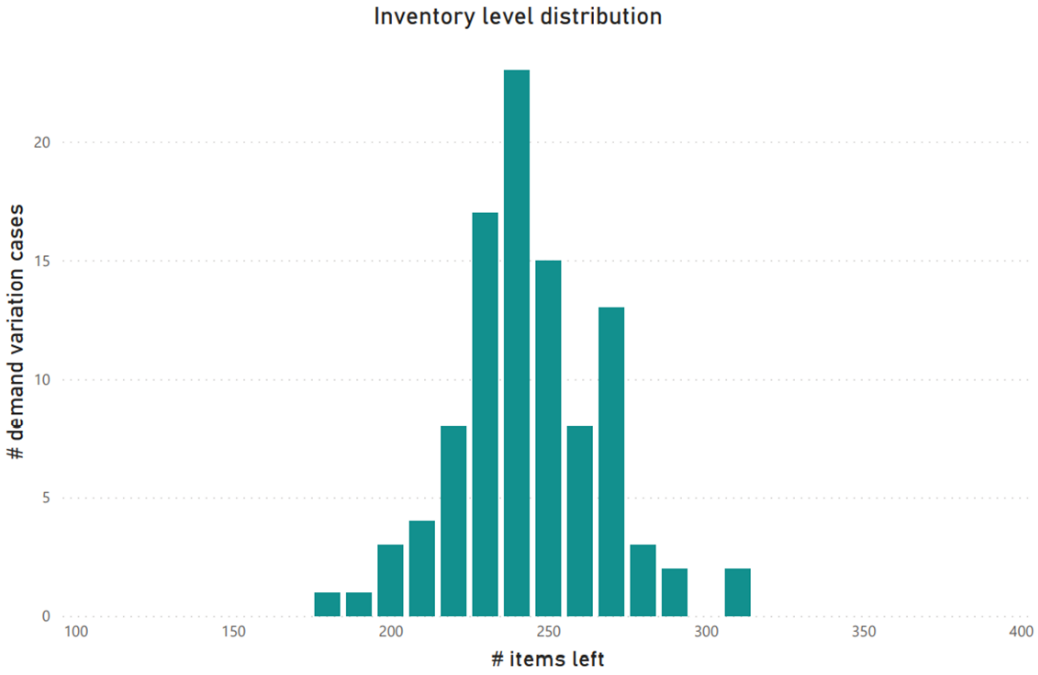

Figure 25: Inventory level distribution at the end of the simulation (own figure).

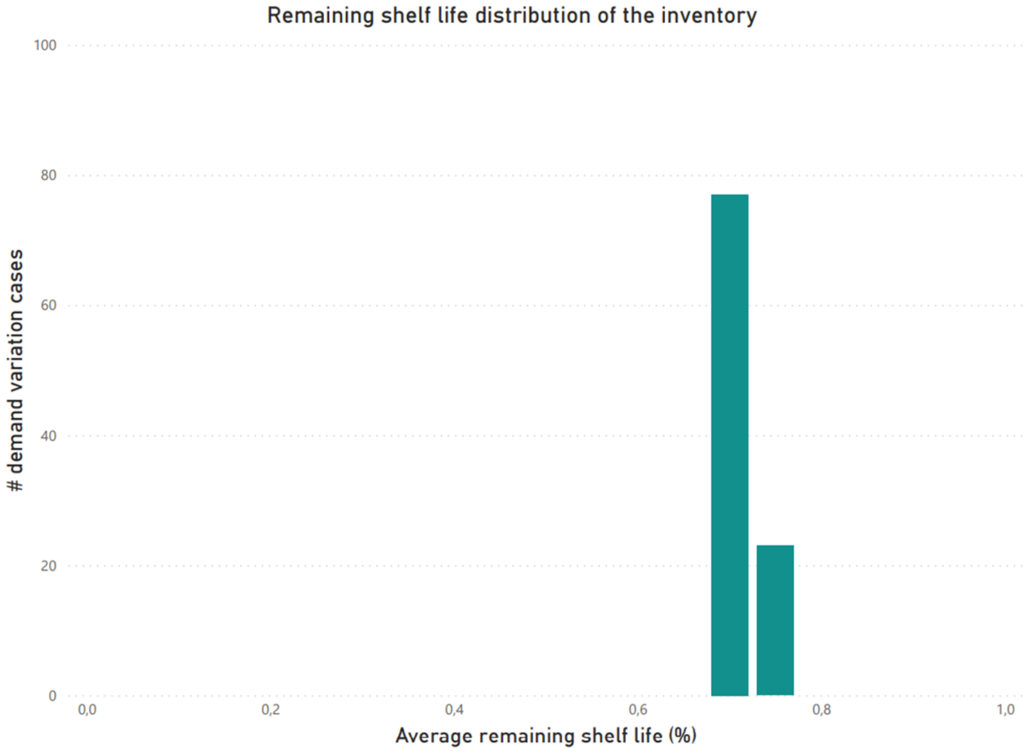

Figure 26: Remaining shelf life distribution of the inventory at the end of the simulation (own figure).

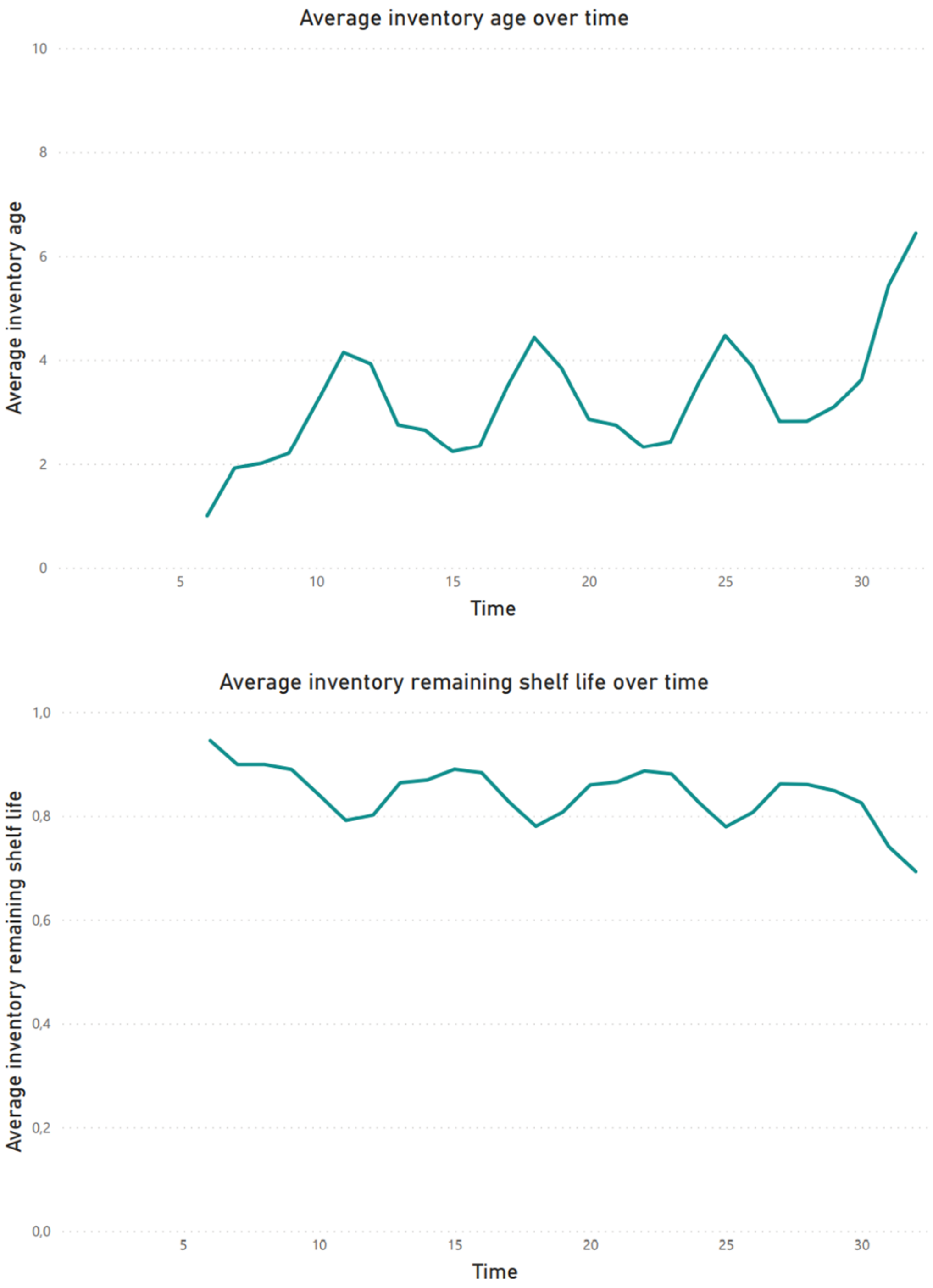

Figure 27: Average inventory age and remaining shelf life over time in the simulation (own figure).

8. Conclusion

This chapter will conclude the study by summarising the key research findings in relation to the research aims and research questions, as well as the value and contribution thereof. It will also review the limitations of the study and propose opportunities for future research.

The purpose of this thesis was to identify an effective optimisation approach that would reduce FLW within the poultry supply chain of our research collaborators. Based on quantitative analyses, all food waste at AlphaCo is generated at the retail- and wholesale levels - in particular, at the retailers. The primary cause of their food waste is the expiration of products. The results indicate that reducing the product aging within the supply chain leading to fresher products increases the remaining shelf lives and can reduce food waste due to expiration.

This research developed a framework to satisfy as much of the demand as possible with as fresh products as possible while generating the least possible amount of food waste. We built a mixed-integer optimisation model that produces the maximum "estimated value” taking into account food waste amounts, remaining shelf life and economic value.

We examined the effect of our model on direct food waste numbers and found that waste generating companies along the supply chain had changed. Even when demand uncertainty is taken into account, the results show that there is almost no food waste in retail anymore, and that all food waste is generated at the chicken producer. Further findings demonstrate that the amount of waste generated by ChickenCo is higher than the previous waste amount by the wholesaler and retailers together – irrespective of the initial situation whether there were too less/too many/adequate chicken available for production.

In a truly isolated environment – like in our model design – this would mean that the optimisation exacerbates the problem of food waste. Due to the fact that ChickenCo has more than one customer and a wider selection of products, excess chickens or cut leftovers can be used for other purposes reducing the food waste numbers. ChickenCo's production is flexible in that sense and retailers contribute at the moment by far the most food waste in AlphaCo's supply chain, so we view the result positively that with the optimisation almost no food waste occurs at retailers anymore, but at the producer level.

The reduction of food waste at the retailers can be attributed to a younger supply chain and consequently more remaining shelf life at the stores. These results indicate that optimising the supply of fresher chicken products throughout the entire FSC extends the product lifespan at the retailers - since the products spend a shorter time in the value chain - and thus reduces food waste.

However, by including demand uncertainty, further findings illustrate that overtime products start to stay slowly longer in the warehouse/store shelves before they are sold. If this is an ongoing trend beyond our model’s planning horizon, we expect higher food waste numbers at the retailers. It indicates that the effects of supply chain aging on product expiration are depending on demand variations and sequentially forecast quality and accuracy.

So, to resolve the poultry food waste problem at AlphaCo effectively, we gained a solid understanding of the reasons for and the scale of food waste generation along their FSC. Based on this we developed a practical optimisation model that reduces food waste in their poultry industry by addressing the challenges of supply chain aging.

Through this study, we added to the growing literature of addressing FLW by considering logistics associated with it and discovering possible solutions to mitigate it. As of yet, there has not been as much research on the manufacturer and producer side regarding food waste reduction as there has been on the retailer side. We can fill this gap as we combine data from the producer, wholesaler, and retailer in order to gain a more comprehensive understanding of how food waste occurs and the mechanisms and logistics involved - especially in the early stages. Also, our research paper examines the often neglected production planning as well as the integration of the distribution lead time and the effects they have on the products' remaining shelf life.

In doing so, our research is related to existing theories about effective shelf life management, which is often overlooked in similar operation studies. It contributes to this line of research by examining how supply chain aging and remaining shelf life affect product expiration and including a penalty for older products reaching retailers in our model objective.

This approach was developed, based on AlphaCo's supply chain and the characteristics of poultry products. The underlying idea and processes, however, can be implemented and modified to other companies, perishable products, or industries to attack similar issues. Combining the formulation of facility location models to calculate the aging of the products throughout the supply chain with production lot-sizing, is applicable to any supply chain dealing with perishable goods.

Nevertheless, our model is subject to certain limitations. Due to the general complexity of the food system and of AlphaCo's processes, it was necessary to put our model into a carefully selected framework. Thus, we do not consider any other valorisation of wasted food – like circular economies or discount policies. Expired or unused chickens can just be wasted. By doing so, we also focus on addressing food waste generation directly and not how to minimize it when it becomes unpreventable. In addition to that, our model focuses on reducing total food waste in terms of weight without considering in detail all-encompassing financial benefits or consequences of it. Moreover, we did not question every single business set-up at our case companies (e.g., transportation schedules from WholesaleCo). Besides that, our model assumes that ChickenCo only has one customer. Our results are therefore based on waste numbers produced in an isolated environment that was promising to process feasible and extendable results. A few more tangible restrictions arising from computational limitations and data availability are the short planning period of three weeks and the sample data on the model.

Therefore, it would be interesting to confirm the results of our study over a longer planning period and including more customers from ChickenCo. The former could evaluate the detected overtime aging trend of the average inventory at the retail stores. The latter to ascertain if the food waste that accumulates at the production stage right now would decrease with more customers and respectively more processing possibilities.

To better understand the implications of these results, future studies could also address the relationship between supply chain aging and demand forecasting accuracy. Can additional shelf life offset deviated demand and poor forecasting? If so, to what extent? If supply chain aging and demand forecasts are optimised and harmonised, how much food waste can be reduced?

Another enrichment would be to examine the exact value of extending the expiry date by 1 day in terms of food waste and profit. While our research gives an overall effect of increasing additional shelf life, this research could break it down to a specific optimisation target. Further, it could contribute to our model approach by adding a financial dimension. Not least, it would be interesting to apply our study to other fresh food industries, such as vegetables, to see if the results are similar and whether generalisation is possible.

Considering our model results and these conclusions, AlphaCo should in general ensure that shelf life management and product aging tracking are integrated throughout their entire supply chain. Creating a transparent supply chain with appropriate information sharing is key to the success of our model. In order to prevent food waste by addressing the challenges associated with aging products within the supply chain, all actors within the value chain need to coordinate their various activities. Without collaboration, and especially without aligning forecasts, our model cannot perform effectively.

We do not claim that our study will solve all food waste issues at our case companies in an instant. But we see our research as a starting point that underlines the importance of shelf life integrated planning of the entire supply chain and as an actionable suggested solution to address the core issue of their food waste generation – product expiration.

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Attachments

Attachment 1 – Dataset overview

The following section presents and describes the datasets collected from our industry collaborators. It is divided into three sections: datasets related to the producer, wholesaler, and retailer.

Table 9: Dataset overview (own table).

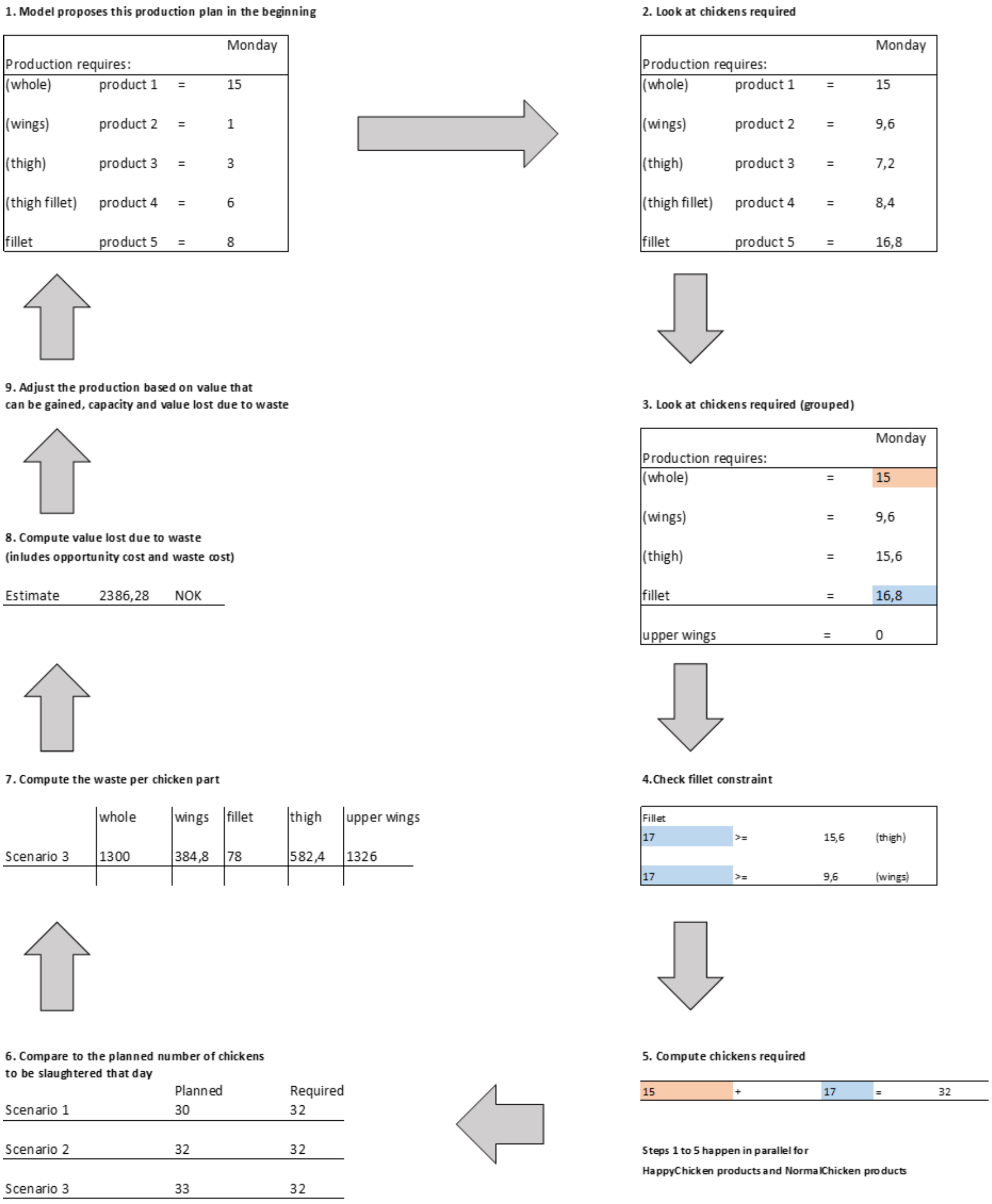
	Datasets	Size [rows]	Dimensions	Description
Producer	**Production plan**	2,646	Per day (03/01/2022 – 23/01/2022) Per product (63)	The planned production (in kg) and the actual production.
	Production capacity	22	Per day (03/01/2022 – 23/01/2022)	Number of chickens (HappyChickens and NormalChickens) planned for slaughter for given period.
	Product information	63	Per product (63)	Detailed description of each product. Such as their total shelf life, the chicken part that is used to produce the product, the weekdays the product can be produced, the average selling price, weight, etc.
Wholesaler	**Goods flow**	63	Per product (63)	The case size they distribute given product, the number of items in each case, and the path it takes to fulfil the demand (in-bound/out-bound).
	Transportation constraints	52	Per warehouse (11) Per day of week	The weekday, warehouses can receive goods from the producer and the transportation duration. ➔ Not all warehouses are listed because they do not receive goods from the producer directly.
	Received goods	115,575	Per day (02/01/2021 – 25/03/2022) Per warehouse (9) Per product (63)	Entries of products received by the majority of distribution warehouses from the producer.
	Shipped goods	3,026,628	Per day (02/01/2021 – 11/05/2022) Per warehouse (9) Per store (1,616) Per product (63)	Entries of products sent to the stores by the majority of distribution warehouses.

	Ordered vs. received	44,924	Per day (02/01/2021 – 25/03/2022) Per warehouse (9) Per product (63)	Product orders placed by the wholesaler to the producer versus what they received.
Retailer	**Sales**	4,835,752	Per day (01/01/2021 – 12/03/2022) Per store (1,616) Per product (63)	Entries of sales quantities.
	Waste	518,582	Per day (01/01/2021 – 05/04/2022) Per store (1,616) Per product (63)	Entries of waste quantities and their reasons (e.g.: due to expiration, mistake, etc.).
	Inventory	9,350,306	Per day (01/01/2021 – 19/04/2022) Per store (1,616) Per product (63)	Inventory quantities.
	Weekly forecasts	1,142,350	Per week (Y2021W01 – Y2022W17) Per store (1,616) Per product (63)	Forecasted amounts.
	Transportation schedule	88,066	Per store (1,616) Per product (63)	Time and day when stores can receive certain products by the relevant warehouse, and by when they must place specific orders.
	Minimum presentation stock	101,808	Snapshot on 19/04/2022 Per store (1,616) Per product (63)	The minimum amount of a given product each store needs to have on display.

Important notes:

- Not all stores sell all the products.
- As entries are created by humans, they can contain errors and mistakes.
- Some data represents snapshots in time. In other words, things may have been different in the past.
- Regular data cleaning and filtering has been performed on the data presented above. However, further pre-processing steps were taken later for analysis and modelling.

Attachment 2 – Calculation of required number of chickens



1. Model proposes this production plan in the beginning

			Monday
Production requires:			
(whole)	product 1	=	15
(wings)	product 2	=	1
(thigh)	product 3	=	3
(thigh fillet)	product 4	=	6
fillet	product 5	=	8

2. Look at chickens required

			Monday
Production requires:			
(whole)	product 1	=	15
(wings)	product 2	=	9,6
(thigh)	product 3	=	7,2
(thigh fillet)	product 4	=	8,4
fillet	product 5	=	16,8

3. Look at chickens required (grouped)

		Monday
Production requires:		
(whole)	=	15
(wings)	=	9,6
(thigh)	=	15,6
fillet	=	16,8
upper wings	=	0

4.Check fillet constraint

Fillet			
17	>=	15,6	(thigh)
17	>=	9,6	(wings)

5. Compute chickens required

15 + 17 = 32

Steps 1 to 5 happen in parallel for HappyChicken products and NormalChicken products

6. Compare to the planned number of chickens to be slaughtered that day

	Planned	Required
Scenario 1	30	32
Scenario 2	32	32
Scenario 3	33	32

7. Compute the waste per chicken part

	whole	wings	fillet	thigh	upper wings
Scenario 3	1300	384,8	78	582,4	1326

8. Compute value lost due to waste (inludes opportunity cost and waste cost)

Estimate	2386,28	NOK

9. Adjust the production based on value that can be gained, capacity and value lost due to waste

Figure 28: Explanation of calculating required chickens (own figure).

Attachment 3 – Pseudo-code for computing $L_{s,p,t}$

```
for each s and p in stores and products:
    for each t from 1 to 7 :  # representing Monday to Friday
        x = 0
        for each i from -10 to t - 1:
            if TS[s,p,i] == 1 then x = i
        y = 0
        for each j from -10 to y – tS[s,p]:
            if TF[s,p,j] == 1 then y = j
        z = 0
        for each k from -10 to y – tF[s,p] – 1:
            if TP[p,k] == 1 then z = k
        L[s,p,t] = t – z
```

Attachment 4 - AMPL script

```
set P        ;
set PHC      ;
set PNC      ;
set type     ;
set S        ;
set CG       ;
set CS       ;

param T             ;
param b             ;
param dev           ;
param D  {S,P,1..T} ;
param L  {S,P,1..T} ;
param Cap{type,1..T};
param V  {P}        ;
param F  {P,1..T}   ;
param r  {P,CS}     ;
param WL {CG}       ;
param grams {CG}    ;
param a  {CG,CS}    ;

var X  {S,P,1..T,1..T}    >=0 integer  ;
var PX {P,1..T}           >=0          ;
var AI {1..T,1..T}        >=0          ;
var FR {S}                >=0          ;
var WI {CG,1..T}          >=0          ;
var ReqCS{type,CS,1..T}   >=0          ;
var ReqCG{type,CG,1..T}   >=0          ;
var RM {type,1..T}        >=0 integer  ;

maximize total_est_val:
sum{s in S, p in P, t in 1..T, k in 1..t: k<t}V[p]*X[s,p,t,k]
- sum{s in S, p in P, t in 1..T, k in 1..t: k<t}V[p]*X[s,p,t,k]*F[p,t-k]
- sum{i in CG,t in 1..T}(WL[i]*WI[i,t]);

s.t. demand{s in S, p in P, t in 1..T}:
sum{k in 1..t}X[s,p,t,k] <= D[s,p,t];

s.t. lead_time{s in S, p in P, t in b..T, k in t-L[s,p,t]+1..t}:
X[s,p,t,k] = 0;

s.t. production{p in P, k in 1..T}:
PX[p,k] = sum{s in S, t in k..T} X[s,p,t,k];

s.t. age_inv{t in 1..T,k in 1..t:k<t}:
AI[t,t-k] = sum{s in S, p in P} X[s,p,t,k];

s.t. fill_rate{s in S}:
FR[s] = (sum{p in P, t in 1..T, k in 1..t}X[s,p,t,k])/(sum{p in P, t in
1..T}D[s,p,t]);

s.t. equal_fill1{s1 in S, s2 in S: s2 != s1}:
FR[s1] >= FR[s2]-dev;

s.t. equal_fill2{s1 in S, s2 in S: s2 != s1}:
FR[s1] <= FR[s2]+dev;

s.t. prod_req1{j in CS, t in 1..T}:
sum{p in PHC}PX[p,t]*r[p,j] = ReqCS["HC",j,t];
```

```
s.t. prod_req2{j in CS, t in 1..T}:
sum{p in PNC}PX[p,t]*r[p,j] = ReqCS["NC",j,t];

s.t. prod_req3{y in type, i in CG,t in 1..T}:
ReqCG[y,i,t] = sum{j in CS}a[i,j]*ReqCS[y,j,t];

s.t. prod_cap1{y in type, t in 1..T, i in CG:i != "h"}:
RM[y,t] >= ReqCG[y,i,t];

s.t. prod_cap2{y in type, t in 1..T}:
RM[y,t] >= ReqCG[y,"f",t];

s.t. prod_cap3{y in type, t in 1..T}:
RM[y,t] <= ReqCG[y,"f",t] + 0.99;

s.t. capacity1{t in 1..T}:
ReqCG["HC","h",t] + RM["HC",t] <= Cap["HC",t];

s.t. capacity2{t in 1..T}:
ReqCG["NC","h",t] + RM["NC",t] <= Cap["NC",t] + (Cap["HC",t]
- ReqCG["HC","h",t] + RM["HC",t]);

s.t. prod_waste1{t in 1..T}:
WI["h",t] = grams["h"] * sum{y in type}(Cap[y,t] - ReqCG[y,"h",t]
- RM[y,t]);

s.t. prod_waste2{t in 1..T,i in CG:i != "h"}:

WI[i,t] = grams[i] * sum{y in type}(RM[y,t] - ReqCG[y,i,t]);
```

Attachment 5 - Simulation python code for sensitivity analysis

```
# make scenarios, demand_scenarios is a dataframe with the
forecasted demand
idxs = demand_scenarios[demand_scenarios.Original_fd != 0.0].index
for sc in range(scenarios):

demand_scenarios.iloc[idxs,demand_scenarios.columns.get_loc("scena
rio "+str(sc+1))] = \

demand_scenarios.iloc[idxs,demand_scenarios.columns.get_loc("Origi
nal_fd")].apply(lambda x: np.random.poisson(x))


# initialise inventory for all cases [sc,s,p,t,a]
InvT = np.reshape(np.zeros((100*100*25*32*32)),(100,100,25,32,32))
# average age at the end of the planning period
AAI = np.reshape(np.zeros((100*100*25)),(100,100,25))
# products left at the end of the planning period
PL = np.reshape(np.zeros((100*100*25)),(100,100,25))
# waste inventory [s,p,t]
WIT = np.reshape(np.zeros((100*100*25*32)),(100,100,25,32))
# product arrivals [s,p,t,a]. Here dataX is the output dataset from
the model
AP = np.reshape(np.zeros((100*25*32*32)),(100,25,32,32))
for row in range(len(dataX)):
    s = stores_[dataX.iloc[row,0]]
    p = prods_[dataX.iloc[row,1]]
    t = time_[dataX.iloc[row,6]]
    a = age_[dataX.iloc[row,7]]
    x = dataX.iloc[row,4]

    AP[s,p,t,a] += x
```

```
# start simulation
for sc in range(scenarios):

    # inventory [s,p,t,a]
    Inv = np.reshape(np.zeros((100*25*32*32)),(100,25,32,32))
    # waste inventory [s,p,t]
    WI = np.reshape(np.zeros((100*25*32)),(100,25,32))
    # demand [s,p,t]
    D = demand_scenarios["scenario
"+str(sc+1)].to_numpy().reshape((100,25,32)).copy()
    # arrivals [s,p,t,a]
    A = AP.copy()

    for s in range(100):
        for p in range(25):
            for t in range(32):
                for a in range(31):
                    v = Inv[s,p,t,a].copy()
                    d = D[s,p,t].copy()
                    if t == 0:
                        # 1 - IN
                        Inv[s,p,t,a] = v + A[s,p,t,a].copy()
                        # 2 - OUT
                        if np.sum(Inv[s,p,t,a+1:]) >= d:
                            pass
                        else:
                            Inv[s,p,t,a] =
max([0.0,np.sum(Inv[s,p,t,a:]).copy()-d])
                    elif t > 0:
                        # 1 - IN
                        if a == 0:
                            Inv[s,p,t,a] = v + A[s,p,t,a].copy()
```

```
                        elif a > 0:
                            Inv[s,p,t,a] = v + Inv[s,p,t-1,a-1].copy() + A[s,p,t,a].copy()
                        # 2 - OUT
                        if np.sum(Inv[s,p,t,a+1:]) >= d:
                            pass
                        else:
                            Inv[s,p,t,a] = max([0.0,np.sum(Inv[s,p,t,a:]).copy()-d])
                    else: pass

                    # 5 - INVENTORY TOTAL
                    InvT[sc,s,p,t,a] = Inv[s,p,t,a].copy()
                # 3 - WASTE
                WI[s,p,t] = np.sum(Inv[s,p,t,max_sf[_prods[p]]+1:])
                Inv[s,p,t,max_sf[_prods[p]]+1:] = 0.0
                WIT[sc,s,p,t] = WI[s,p,t].copy()

            # 4 - AVERAGE AGE END PERIOD
            sumproduct = sum([x*y for (x, y) in zip(list(Inv[s,p,31,:]), list(range(32)))])
            total = np.sum(Inv[s,p,31,:])
            PL[sc,s,p] = total
            if total != 0.0:
                AAI[sc,s,p] = round(sumproduct/total,4)

    print(str(sc+1)+"%",end=", ")
```