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Development and analysis of static and dynamic pricing models for fresh fruit and vegetable retailers with food waste as a key consideration

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Executive Summary

Fresh fruit and vegetable waste at retail locations is widely prevalent and often accepted as a byproduct of food retailing. To recognize this source of food waste and encourage change, the United Nations has introduced a goal to halve per capita food waste at the retail level by 2030 (‘*United Nations’*, 2020). As retailers begin to turn their focus to an all-encompassing triple bottom line, they have the opportunity to rethink their approach to food waste. This research explores various retailer optimization methods to combat the food waste of highly perishable items by utilizing the mathematical programming technique of decision modelling. The models developed provide evidence that operating under a static product pricing model with a singular objective to minimize waste is not a sustainable approach for retailers as it neglects profits. Further, the inclusion of a financial weight on waste in a profit maximizing business model with static pricing is presented as a more financially effective approach. However, this model is also a likely unsustainable option due to the modelled decrease in profits. Lastly, dynamic pricing by way of markdown management is presented to offer food retailers a more sustainable method to sell fresh fruit and vegetables with less waste. Of the four models presented, the Dynamic Pricing Model appears to be the most applicable model for retailers and should be considered as an approach to reduce waste among perishable items such as fresh fruits and vegetables.

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1. Introduction

The method in which fresh fruits and vegetables are bought and sold has evolved. Early on, people grew their own food. Humans only had access to what they could grow or gather. Over time, the globalization of markets has allowed for the specialization and segmentation between the produce suppliers and consumers (Baldwin, 2016). Until the birth of the modern-day grocery store, humans could only eat what was geographically and seasonally relevant to them (Ruhlman, 2018). Today, retail stores are often filled with every type of fruit or vegetable, no matter the location or time of year. There are avocados in Norway, oranges in Canada, and pineapples in Ireland. But, at what cost does this seemingly unlimited access to produce come with? It is estimated that between 30-40 percent of the food supply ends its life as food wastage; 13 percent of which is attributed to the retail sector (Fritts, 2021). Thus, the question is asked, what can retailers do to sell these highly perishable fruits and vegetables profitably and responsibly with less waste? This paper seeks to answer this question through a discussion, literature review, and the creation and analysis of mathematical decision models. Three static pricing models will be developed leading to the development of one dynamic pricing model. The results obtained in this research will provide fresh fruit and vegetable retailers with information on expected business implications when striving to reduce their negative environmental impact caused by food waste.

1.1 Defining Food Waste

Multiple methods exist to define the non-use of food that is intended for consumption. For example, the terms food waste, food loss, and food wastage each have their respective definition (Gheoldus, 2016). In this paper, the definition of these three terms follows that as outlined by The United Nations Food and Agriculture Organization. Food waste is 'the decrease in the quantity or quality of food resulting from decisions and actions by retailers, food service providers and consumers' (*'Food Waste',* 2021). Whereas food loss is 'the decrease in quantity or quality of food resulting from decisions and actions by food suppliers in the chain, excluding retailers, food services providers and consumers' (*'Food Waste'*, 2021). Food wastage is the term used to encompass both food waste and food loss (Gheoldus, 2016). These definitions are outlined in order to provide a holistic understanding of the focus of this paper, food waste.

1.2 Global Value Chains

The global value chain for fresh fruits and vegetables is undoubtedly complex. Only two-hundred years ago, local farmers were producing food and selling it at local markets (Ruhlman, 2018). In recent years, globalization has revolutionized the fresh food industry. Globalization can be thought of as the unbundling of consumption and production (Baldwin, 2016). Rising incomes, falling transportation costs, improved technology, and evolving international agreements have led to substantial growth in the volume and variety of fruits and vegetables traded globally (Ruhlman, 2018). This globalization of fruit and vegetable trade has afforded consumers with more variety year-round, while overcoming seasonality, and smoothing price fluctuations (Haung et al., 2004). As retailers have begun offering a more accessible and diverse spread of fruits and vegetables, the food consumers eat must now travel long distances, to more retailers, in more markets (Thyberg & Tonjes, 2016). This global value chain means that people are 'more likely to waste food as they do not have a deep connection and understanding of it' (Pretty et al., 2005). The innovation of global value chains has led to a tripling of the global supply of food since 1970, however at the same time the amount of food wastage has also tripled ('*The global food supply chain…'*, 2020).

1.3 Quantifying Food Wastage

Roughly one third of food that is produced globally becomes food wastage (Gustavsson et al., 2011). This amount of food wastage does not only have financial implications but societal and environmental as well. The production of this discarded food costs 2.6 trillion USD globally on an annual basis (*'Food Waste',* 2021). Societally, the United Nations Food and Agriculture Organization estimates that the world could be feeding 2 billion people per year with this wastage (*'United Nations'*, 2020). Additionally, food wastage should not only be thought of in terms of the resources that were produced in vain, but also as the emissions that were produced in vain (Huber, 2017). Considering these emissions, food wastage accounts for 8 percent of annual global greenhouse gasses (Scialabba, 2015). Although these figures can be disheartening, food wastage can be thought of as a global opportunity. Through utilizing the full potential of our food production system, we can simultaneously feed a growing global population, decrease annual global greenhouse gasses by up to 8 percent, and access 2.6 trillion USD of untapped market potential (Huber, 2017).

Reducing food wastage is a vast subject which can and should be addressed from various angles. One category of large food wastage offenders is food waste in the retail sector (Ruhlman, 2018). The increasing food waste in retail stores can be accredited to globalization (Baldwin, 2016). Globalization has not only allowed for a decentralized retail food supply chain, but a diversification in consumer demand (Thyberg & Tonjes, 2016). In the race for profit, retailers have pushed labor intensive food production to areas of cheap labor and expanded product offerings to keep up with new consumer demand (Baldwin, 2016). For example, in the United States in the 1990's a typical grocery store carried around seven-thousand items. Now, that number is pushing fifty thousand (Ruhlman, 2018). This increase in total item count does not come without a cost. The United Nations estimates that retail outlets accounted for 13 percent of global food waste in 2019 (Fritts, 2021). This existing opportunity makes reducing waste at retail stores a seemingly non-controversial way to increase the productivity of the food supply chain and reduce global food wastage (Eriksson, 2005).

Fresh fruits and vegetables account for around 50 percent of retail food sales (Tekin et al., 2017). Additionally, fresh fruits and vegetables have some of the highest profit margins in retail stores, with 74 percent of consumers buying them at least once a week (Renner et al., 2019). This accounts for 40 percent of grocery stores' total revenue (Trimasova, n.d.). Stemming from high levels of sales, the fresh category is a primary driver for consumer store choice (Bacos et al., 2013). It is reported that 'customers who are satisfied with the fresh offer of their store shop more frequently and spend much more each trip, both on fresh products and in the rest of the store' (Bacos et al., 2013, pg. 4). Fresh fruits and vegetables are clearly pivotal products for retailers; however, due to their nature of high perishability and high demand, it is no surprise that they have some of the highest rates of waste in the retail sector. It is estimated that 15 percent of fresh fruits and vegetables are thrown away due to damages and spoilage at retail stores (Tekin et al., 2017). In the United States, the total value of food waste at the retail level was 18.2 billion USD in 2016 (Tieso, 2018), whereas fruits and vegetables have historically accounted for 26 percent of that total (Buzby & Hyman, 2012). Thus, the effects of this high level of fresh fruit and vegetable food waste that retailers experience can be noticed on their bottom line, and the bottom line of the planet's resources.

1.4 Causes of Fresh Fruit & Vegetable Food Retail Waste

Fresh fruit and vegetable retail food waste is over-indexed when compared to other retail categories. This means that fruits and vegetables are wasted more often than other retail products (Buzby & Hyman, 2012). The most common causes of this perishable food waste at retailers are overstocking, consumer behavior, inappropriate quality control and product handling (Wang & Li, 2012).

1.4.1 Overstocking

Overstocking is the phenomenon of having more product than there is consumer demand (Sedicot, 2020). Product that is overstocked, and ultimately unsold, becomes retail food waste. The most common causes of overstocking are misjudgment of customer demand, fear and overcorrection for out-of-stocks, ineffective promotional planning and execution, seasonality, poor inventory management and compensation for supply chain issues (Jenkins, 2020). Overstocking boils down to bad forecasts and poorly controlled supply chains. All food retailers forecast demand, but their forecasts are not typically regarded as accurate or used with confidence (Karolefski, 2017). While exact figures on forecast error rates are tough to find, naive retail forecasts are reported to have average forecast error of 35 percent (‘*Forecasting and Inventory Benchmark Study’*, 2018). Due to their highly perishable nature, fresh fruits and vegetables require more granular daily forecasting and replenishment than their shelf-stable retail counterparts, and thus often report higher levels of forecast errors (Sukhochev, n.d.). When retailers are faced with supply chain uncertainties or inconsistencies, it is standard to increase forecasts and buy into safety stock. The desire to purchase inventory above forecast occurs because ‘on-shelf availability is more critical than waste avoidance from the retailer's point of view’ (Lemaire & Limbourg, 2019, pg. 1226). Any unneeded safety stock leads to overstocks and increased forecast error rates (Jenkins, 2020).

1.4.2 Consumer Behaviour

For fruits and vegetables, product appearance and use-by-date (expiration dates) have significant importance to consumers. “With perishable items, consumers optimize their behavior for freshness” (Sukhochev, n.d.). That freshness is perceived either visually or numerically from the expiration date given. Buyers have traditionally wanted produce that is uniform and appealing to the eye as ‘the more off-spec the fruit or vegetable is, the tougher it can be to move’ (Karolefski, 2017). Products close to the use-by date are perceived as products with lower quality by consumers and are therefore less favorable to purchase (Tsiros et al., 2005). This consumer behavior leads to increased food waste. Fruits and vegetables that are perceived as lower quality due to appearance are more likely to go unsold, especially under uniform pricing methods (Karolefski, 2017). Additionally, the first in first out inventory method commonly used for random weight products such as fruits and vegetables, is highly sensitive to consumer behavior. First in first out assumes that the oldest items will be sold first, but there is no guarantee that this will occur (Shelton, 2017). Some clever consumers who select younger inventory cause inaccuracies of inventory data, increased forecast errors, and increased rates of food waste (*'Forecasting and Inventory Benchmark Study'*, 2018).

1.4.3 Quality control

When compared to other consumer staples, perishable foods such as fresh fruits and vegetables are highly sensitive products (Kilian, 2020). The post-harvest storage conditions of these products 'influence the flavor, firmness, disease incidence, shelf life, and sometimes color of the product' (Neibauer & Maynard, 2011). The transport and storage of fresh foods determines if the product is accepted onto retail shelves. In most countries, all fruits and vegetables are held to retail dating and aesthetic standards (Bilow, 2014). Due to local optimization, retailers require suppliers to provide food with at least 70 percent of shelf life remaining (Lemaire & Limbourg, 2019). Fruits and vegetables that arrive under shelf life requirements are typically rejected and wasted. These standards, determined by both governing bodies and retailers themselves, are in place to reduce liability. If there are zero product defects, there is almost zero liability (Manley, 2014). Products that do not live up to retail standards but remain edible contribute to increased retail food waste.

1.5 Retail Food Waste & Sustainable Development

Image 1: Sustainable Development Goals (‘*United Nations’*, 2020)

In 2015, the United Nations debuted Sustainable Development Goals with the objective “to produce a set of universal goals that meet the urgent environmental, political and economic challenges facing our world’ (‘*Background of the...’*, n.d.). Sustainable Development Goal 12; Responsible Consumption and Production is aimed at doing more with less (‘*United Nations’*, 2020). The United Nations included Goal 12 as they consider reductions in food waste to offer economic benefits, feed additional people, and alleviate pressures on the climate (‘*Target 12.3’*, n.d.). Specifically, the United Nations state that ‘sustainable consumption and production can also contribute substantially to poverty alleviation and the transition towards low-carbon and green economies’ (‘*United Nations’*, 2020). With the increase of global demand for food projected to grow by 70% by 2050 (Gustavsson et al., 2011), combating the consumption and production of high waste categories such as fruits and vegetables is imperative in reaching Goal 12.

Within Sustainable Development Goal 12 lies Target 12.3 which aims 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 (‘*United Nations’*, 2020). Retail food waste is called out specifically here for multiple reasons. First, value is added in every step in a food supply chain, and thus waste at the retail level means a higher value loss (Eriksson, 2005). Second, individual retailers produce a large amount of waste at the same physical location and even a minor percentage reduction can give major reductions in terms of lowering the amount of wasted mass (Mattsson et al., 2018). Lastly, serving as the link between producers and consumers, retailers have the potential to influence consumer consumption patterns through pricing strategies, marketing tactics, and consensus sourcing

(Eriksson, 2005). As fresh fruits and vegetables have such high levels of retail waste, the category has the potential to lead the way in food waste reduction.

The reduction of fresh fruit and vegetable retail waste, while tied most closely to Sustainable Development Goal 12, plays a role in a variety of other goals. For example, Goal 2; Zero Hunger is aimed at increasing food security (‘*United Nations'*, 2020). As stated, nearly one third of the food produced in the world is wasted, while nearly the same percentage, 26 percent, of the world's population is affected by food insecurity (‘*United Nations'*, 2020). Food waste and food security are closely related topics that bring attention to ‘the moral implications of throwing food away while people in parts of the world are starving” (Eriksson, 2005). Additionally; Goal 6 Clean Water and Sanitation focuses on sustainable clean water infrastructure and distribution. Food production accounts for about 70 percent of the global freshwater use (‘*Water in Agriculture'*, n.d.). When 125 liters of water are required to produce one apple (Paddison, 2013), a reduction in retail food waste of fruits and vegetables can mean the water that is allocated to these crops is used in an effective and sustainable manner. Retail waste of fresh fruits and vegetables plays a role in the achievement of many of the 17 UN Sustainable Development Goals and more specifically Goal 12, whereas Goal 2 and 7 have been provided as examples of additional goals to consider.

1.6 Paper Structure

This paper's goal is to analyze the waste of fresh fruits and vegetables at food retail stores. The discussion presented in the introduction of this paper established the topic of fresh fruit and vegetable retail food waste. Knowledge of retail food waste has been built through the researched synopsis of the origin, delivery of key statistics, and explanation of the drivers. The global importance of fresh fruit and vegetable retail food waste reduction was stressed through the reference of the United Nations Sustainable Development Goals. The importance of the topic of this paper was chosen to be portrayed through the United Nations Sustainable Development Goals as they are a large motivator for current business decisions and are expected to continue to be in the future (*‘United Nations'*, 2020). Following the present discussion, a literature review of previous work pertaining to the topic of this paper is conducted. In the review, literature regarding dynamic pricing is presented first and is followed by a review of supply chain focused work. Through the literature review, gaps in previous research are identified to position this paper's purpose. Thus, the introduction and literature review are included in this paper to provide relevant context, facilitating the formation of a knowledge base that this paper's research is built from.

To begin exploring the ideas introduced, a mathematical analysis of methods to reduce fruit and vegetable retail food waste is explored. In Section 3, essential information that is pertinent to all mathematical models formulated in this research will be outlined. The decision to offer the general model framework was made to eliminate unnecessary repetition and to ensure that all models are presented cohesively. Following, Section 4 introduces three statically priced decision models that are developed to replicate a food retailer selling process. The goal of the statically priced models is to assess the financial, social, and environmental implications of a food retailer deploying different methods to reduce their food waste. The models in Section 4 are then further developed in Section 5 with the inclusion of dynamic pricing. Incorporating dynamic pricing into a mathematical decision model, helps understand its effectiveness in reducing a retailer's food waste, while also improving their financial and social results. The decision models formulated in Sections 4 and 5 are analyzed through a mathematical lens as well as illustrated through a numerical example. This paper will be closed in Section 6 through dialogue regarding research limitations, discussion of future work, and a summary of findings.

The perspective of this paper is guided by the author's personal experiences working inventory and supply chain management for perishable foods at both a national retailer in the United States as well as for a multinational retailer in Norway. These experiences offer a unique perspective as to solutions that could be reasonable for retailers to implement. Additionally, due to the author's history, industry specific knowledge is applied and referred to throughout this paper.

2. Literature Review

Food wastage is a topic of increasing concern. With individuals, corporations, and governments turning their eyes to food wastage, the topic has noted a growth in analytical research interest since the turn of the century. In positioning this paper, a discussion regarding related research literature is required. This paper is specifically focused on reducing food waste at retail food stores through manipulation of pricing strategies. To accurately address the issue, this literature review is segregated between literature centering on dynamic pricing for perishable goods and those with more of a retail level supply and inventory emphasis. Following the review, gaps in the literature are discussed and this paper's intent to fill said gaps is emphasized.

2.1 Literature on Dynamic Pricing

An earlier piece of research literature that has provided a foundation for many of the recent works on retail discount pricing for perishable goods is, "How should a firm manage deteriorating inventory?" by Mark E. Ferguson and Oded Koenisberg published in 2009. The research focused on "items when a firm faces quantity and pricing decisions for products with different quality levels." The specificity of a singular product line, for a singular retailer, allowed the authors to study the interaction between varying degrees of freshness and price from both an operational and marketing perspective. Developing a dynamic, two period, pricing model, they determine that the price of fresh products is not affected by the lower-priced competing, less-fresh, products. Through a numerical study, the authors found that profit is expected to increase by 10 percent if firms choose to carry over an optimal amount of unsold product into the second period and price it strategically (Fergeuson & Koensberg, 2009).

Fergeuson and Koensberg's work has often been expanded upon. In 2012 Xiaojun Wang and Dong Li published a study on the sales of perishable foods based on perceived quality titled, "A dynamic product quality evolution based pricing model for perishable food supply chains." Using a kinetic approach, they calculate product quality for perishable products as a rate of chemical reaction to the product temperature and time. By integrating this kinetic quality into a price dependent linear demand function, they find that price markdowns should ideally occur continuously over the life of a product as it remains unpurchased to maximize total profit (Wang & Li, 2012).

Wang and Li's finding that price and quality should be dynamically integrated for perishable foods in the retail setting was supported in a 2019 publication. Authors M.E. Buisman, R. Haijema, and J.M. Bloemhof-Ruwaard conducted a study titled, "Discounting and dynamic shelf life to reduce fresh food waste at retailers." The focus was on dynamically identifying product shelf life (DSL) based on microbiological conditions and strategically pricing the product based on its DSL. The authors acknowledge that although integrating DSL is highly effective at reducing food waste and increasing profit, it is expensive and extremely difficult to implement. Thus, they offer that simply strategically discounting expiring food based on current product shelf life dating methods is also effective, however not as effective as doing so with DSL (Buisman et al., 2019).

Research conducted by Fergeuson & Koensber, and Wang & Li centered on identifying the quality of a perishable food at a specific point and time and analyzing how customers' perceived value of the product changes with continuous changes in product quality. Both works, while offering key findings, offer methods that are arguably very challenging to implement. Work by Piril Tenkin and Rizvan Erol in a research paper titled, "A new dynamic pricing model for the effective sustainability of perishable product life cycle" offers a simpler dynamic pricing solution. They build a deterministic model that optimizes retailer profit by offering the same product with varying degrees of freshness at different prices. Offering five pricing scenarios for each item type, the research focuses on the relationship between consumer value of items at varying degrees of freshness. As with previous literature, Tenkin & Erol find that the degree of freshness has a significant impact on a consumers' value of the perishable product and that consumers tend to place increased value on items that are more cost-effective (have longer shelf lives). Tenkin & Erol offer a more feasible method to determine product freshness by assuming that product freshness deteriorates linearly from arrival at the retailer. Yet, the feasibility of daily price updates at varying product freshness levels for all perishable goods in a retail setting must be questioned (Tekin & Erol, 2017).

2.2 Literature on Inventory Models

Inventory management models offer an additional angle in which to analyze the waste of perishable food at retail stores. The effect on retail goods of deteriorating quality was studied by Masoud Rabbani, Nadai Pourmohammad Zia, and Hamed Rafiei in a 2006 paper, "Joint optimal dynamic pricing and replenishment policies for items with simultaneous quality and physical quantity deterioration." In their work, they constructed a model to maximize total profit by determining optimal replenishment cycles, inventory holding methods, initial price, and discount rates. In doing so, they used simulation to conclude that if product deterioration rates are slowed though preservation technology, the replenishment cycle can be extended, and profit increased. Alternatively, if deterioration rates cannot be slowed through preservation technology, price can be applied as a level to control demand and optimize replenishment cycles (Rabbani et al., 2016).

An additional study on inventory management models was offered by Larissa Janssen, Jurgen Saur, Thorsten Claus, and Uwe Nehls titled, "Development and simulation analysis of a new perishable inventory model with a closing days constraint under non-stationary stochastic demand," in 2018. The study was unique in that it looked at the effect of retail closing days on perishable foods. In doing so, they develop an inventory model using mixed-integer programming to minimize cost and demonstrate the importance of including closing days. Their work is applicable only in regions where food retailers face closures more often, such as Norway where they close on Sundays. However, the work is not so relevant in other regions such as The United States where large food retailers shut their doors maybe three days out of a year (Janssen et al., 2018).

The papers on inventory models by Rabbani et al. and Janssen et al. have been reviewed due to their efficient and creative inventory models which provided inspiration for the work of this research paper. There exist countless additional published works on retail inventory models to consider and there has been research devoted specifically to analyze these other works. In "Integrating deterioration and lifetime constraints in production and supply chain planning: A survey", authors Julia Pahl and Stefan Voss provide an extensive discussion on literature regarding the mathematical modeling of deterioration and value loss for in production, planning and retailing (Pahl & Voss, 2014). Additionally, "Literature review of deteriorating inventory models by key topics from 2012 to 2015" by Larissa Janssen, Jurgen Saur, and Thorsten Claus does the same. There, they provide classification of nearly four-hundred works of research regarding deteriorating inventory models (Janssen et al., 2016).

2.3 Identifying Research Gaps

The early dynamic pricing work by Ferguson & Kongsberg was focused specifically on profit maximization and makes no reference to waste reduction efforts. However, more recent works on dynamic pricing and inventory management of perishable goods do place some emphasis on waste. This trend be accredited to the light that has been shed on the issue of food waste by organizations such as the United Nations. Although waste is a key topic of discussion in most of the recent research literature, it is commonplace that optimization models are designed to specifically either maximize profit or minimize costs. As the objective function is optimized, waste is analyzed as a result. Thus, a gap in literature regarding optimization models built specifically to minimize waste while studying profit and cost as a tertiary result.

There have been many works published with a focus on dynamically identifying perishable product quality. Similarly, most of the literature reviews above implemented methods to dynamically identify product quality. The current practice in food retail for perishable goods is the use of expiration or best buy dates (Sukhochev, n.d.). Each new lot of inventory arrives with expiration date information. These expiration dates are by no means precise, as they are blanketed based on production date and not quality, however they are implemented for the health and safety of the consumers (Buisman et al., 2019). The inventory arriving with pre-identified expiration dates removes the burden for the retailer to allocate labor to identify the quality of the perishable goods (Dhanalakshmi et al., 2011). Models such as those reviewed above provide an interesting ideology to reinvent the current product dating process, but one must question the feasibility. Implementing dynamic product quality methods would require technological transformations across many locations as well as a high allocation of labor. This new technology and additional labor could be significantly cash-intensive investment for the retailers. Thus, a model focused more on accepting the current process of product dating may prove to be more applicable in a real-life setting.

Further, many of the researched pricing strategies involve frequent price changes. All the inventory and pricing models reviewed above include price changes to deteriorating items. While the literature provides evidence that these dynamic price changes are advantageous for retailers, the research overlooks the feasibility of frequent price changes and its reception by consumers. Dynamically pricing each item based on their level of freshness may contribute to over choice and potentially overwhelm consumers. If a consumer was faced with 100 red apples, each priced individually, it may stifle their decision-making. From the perspective of the retailer, frequent price changes require a significant investment in labor (Mattsson et al., 2018). Some models did include an additional cost to account for the labor when price changes occur, however overlooked potential costs that would be required to hire and train the additional laborers. A model that restricts the number of possible price changes would again be more applicable in a real-life setting.

2.4 Filling the Gaps

The dynamic pricing models in this paper are built with a focus on the author's perspective of applicability in a practical retail food setting. First, the current retail process of item expiration/use-by dates being established for a lot of items by the producer of said item is accepted. This means that in the models developed, all products will have a predetermined shelf life. Furthermore, each product has a set weekly price and will only be able to undergo a price change once, as the process of weekly product pricing is the current standard in the retail industry. Finally, filling a noted gap in the research above, one of the models developed will optimize solely based on food waste minimization, allowing an opportunity to analyze business implications of this shift in priority. While in the reviewed literature, model success was evaluated through the results on revenue/profit or waste, this paper's models will be evaluated through the holistic approach of their financial implications, social result, and effect on food waste.

3. General Model Development

To analyze effective strategies in reducing waste for retail stores, mathematical programming models will be formulated. The term mathematical programming is used to describe the minimization or maximization of an objective function with many variables, subject to constraints on those variables (Fourer, 2009). The chosen mathematical programming method will provide results by way of decision modeling. Decision models reveal relationships which might not have been previously apparent through mathematical analysis and experimentation (Gaujardo, n.d.). Four nonlinear decision models will be developed to analyze methods for retailers to sell fresh fruits and vegetables profitably and responsibly. The chosen price response function gives the models their nonlinear characteristic. The dynamic features of the models stem from key considerations made to replicate a food retailer's sales processes. The results obtained through the prescriptive analytics in decision modeling form the backbone of this paper's findings.

The following section presents essential information consisting of the key elements of each model developed in this research. First, key terms that are utilized in the model formulations are explicitly defined. These key terms are outlined to establish an understanding of some terms that may be considered broad and could be easily muddled. Explicitly defining key terms also ensures continuity of the terminology used in this research. Next, key model assumptions are outlined. These assumptions provide context on current retail processes and references to ensure real-life applicability of the research. The assumptions outlined in this section provide the foundation for the various models that are developed. Additional assumptions will be introduced in the coming sections as they correspond to each model's development. Following, the model indexes and notations are provided. While not all the defined variables are integral in every model developed, they are catalogued in this section for organization and clear understanding. In closing, an instance data set is offered that will be used to provide a numerical representation of the various decision models. In the following sections, models are formulated in stages and studied through mathematical analysis.

3.1 Term Definitions

Term	**Definition**
Product	A lot of like items. Ex: honey crisp apples, organic zucchini, meyer lemons
Item	An individual unit of a product. Ex: *one* honey crisp apple, *an* organic zucchini, *one* meyer lemon
Shelf life	The period of time in which an item remains suitable for consumption.
Deteriorating Inventory	A group of items or products, with fewer than one day of shelf life remaining.
List Price	The non-discounted price for a product.

3.2 Assumptions

Assumption 1: The model lasts seven periods.

The models are developed to replicate one week of retail sales so that one period represents one day. Based on the author of this paper's previous experiences, it is common for retailers to manage prices and analyze key performance indicators such as sales, waste, and profit on a weekly level. Thus, seven-period models are chosen to reflect typical operations.

Assumption 2: A single retailer operating without competition.

This research focuses on the selling of fresh fruits and vegetables at a single retail location. In doing so, the element of competition is removed. This assumption asserts that there are no close product substitutes from either other retailers or the retailer themselves. In practice, fresh fruits and vegetables face competition between both similar products, such as spinach and kale, and the plethora of food retail businesses in an area (Matsa, 2010). However, the interaction between like products and retailers is removed as the complexity of modeling competition is outside the scope of this research.

Assumption 3: Inventory is deterministic.

It is no longer common for food retailers to function as stand-alone stores as the food retail market is dominated by large multi-location or national/multinational corporations (Ruhlman, 2018). The models in this paper are developed from the perspective of an individual retail location that is part of a greater retail network. For multi-location or national/multinational food retailers, it is typical that the individual retail locations do not make decisions regarding the assortment of products and the inventory levels they receive (Ruhlman, 2018). Based on the author of this paper's previous work experience, it is common for a headquarters location to work on behalf of the retail network and make store-level strategic decisions including those pertaining to inventory. For multi store retailers, centralized inventory decision making occurs due to the efficiencies gain through utilizing a central warehousing network (Lin et al., 2021). Individuals working at a headquarters can exploit economies of scale while negotiating, strategizing, and ordering inventory from vendors. Additionally, headquarters locations utilize complex software tools that aid in efficiently extrapolating inventory decisions across many locations in a retail network (*'Forecasting and Inventory Benchmark Study'*, 2018). The decisions made by business leaders at central headquarters locations are strategically done with the objective of profit maximization across all sectors of the business (Maverick, 2020). These employees purchase the inventory from vendors, manage the inventory through the various nodes of the supply chain, and ultimately ensure it is delivered to individual retail locations. Thus, the author's industry experience suggests that individual retail locations typically have insight into their expected weekly allocated inventory, however they have little to no discretion on the inventory amounts they receive. To reflect the processes outlined above, the models in this research assume deterministic inventory

Assumption 4: Demand is a function of price.

Demand in the models is calculated by the linear price-response function. The general formula for the linear price response function is,

$$d(p) = z - mp$$

Where $m > 0, z > 0$ and $z = d(0)$ (Phillips, 2011). The linear price-response function is 'a convenient and easily traceable model of market response' (Phillips, 2011, pg. 49). Each product is assigned predetermined values for demand at price zero, z, and change in demand resulting from a change in price, -m. The models then evaluate optimal values for demand, $d(p)$, and price, p, for each product provided the objective function and included constraints. Thus, each product will consider its own linear price-response function.

Assumption 5: A single list price is assigned to each product.

There is only one non-discounted list price per product for the entirety of the seven-period model. At a single retail location, frequent price changes would require high levels of manual labor as well as risk confusing and overwhelming consumers (Berk et al., 2009). Thus, restricting list price changes lends itself to more applicability in a practical setting as retailers do not have access to unlimited manual laborers.

Assumption 6: All new inventory has a sunk cost.

The inventory that arrives at a retail location has an associated cost, regardless of if the products are sold or not.

3.3 Notation

Below the standard notation for the models developed in this research are provided.

Sets

F: set of product, f … ∞
T: set of periods, $t = 1 \dots 7$

Parameters

$ni_{f,t}$: amount of units of product f arriving in period t *
c_f : cost of obtaining one unit of product f
m_f : slope of the linear price response function for product f
z_f : demand at zero price for product f
mo_f : slope of the linear price response function for deteriorating product f
zo_f : demand at zero price for deteriorating product f
wc_f : the cost of disposing of one unit of waste for product f

* *Product can be sold in the period it arrives*

Variables

D_f : demand in units of product f

W_f : total waste in units of product f

P_f : list price of one unit of product f

$S_{f,t}$: sales in units of product f in period t

$OI_{f,t}$: units of deteriorating inventory of product f in period t

$OD_{f,t}$: demand in units of deteriorating inventory of product f in period t

$OS_{f,t}$: sales in units of deteriorating inventory of product f in period t

$disc_f$: the discount percent for product f

3.4 Instance Data

To support the analysis of the models, instance data is created using Microsoft Excel to replicate the data from a food retailer's fresh fruits and vegetables department for one week. Detailed sales and inventory data is commonly classified information and was unobtainable for this research. Thus, the instance data, visible in Table 1 below, is created using Microsoft Excel's tools for randomization. For each product, seven days of new inventory amounts are created using the NORMINV(RAND(),mean,sd) function. Values for means are generated from the random function, RANDBETWEEN(1,700) while values for standard deviations are created using the function, RANDBETWEEN(1,0.5*mean). The normal function is used so that new inventory variations are included. Similarly, values required to model linear price response functions, m_f and z_f are again obtained through the RANDBETWEEN function. RANDBETWEEN(-500,-100) is used for generating values for m_f and RANDBETWEEN(1500,2500) is applied for producing values for z_f. Doing so ensures that each product has a unique price response function that can be studied. Finally, item costs are also randomly generated using RANDBETWEEN(1,20). In total, data for 30 unique items are created to simulate a retail assortment. The names given to each line of data are only presented as an example and do not contain actual data regarding said food product. This instance data is created to provide a numerical example of the decision models.

Table 1: Instance Data

Product	New Inventory							Total Inventory	Mean Inventory	SD Inventory	m	z	c
	1	2	3	4	5	6	7						
Lime	42	38	44	46	40	44	44	298	43	3	-128	1857	6
Carrot	46	66	74	60	70	72	66	454	65	9	-276	2050	4
Broccoli	208	358	248	388	374	356	242	2174	311	69	-101	2458	15
Cucumber	482	472	530	434	456	552	488	3414	488	38	-143	2233	6
Cauliflower	124	98	116	140	90	112	122	802	115	15	-333	2383	4
Grapefruit	382	396	458	274	354	428	358	2650	379	55	-444	2315	3
Spinach	18	24	20	24	24	24	20	154	22	2	-346	2242	4
Kiwi	294	330	412	344	474	280	434	2568	367	68	-277	1875	5
Red Pepper	28	26	34	28	40	30	42	228	33	6	-288	1633	3
Cherries	626	596	538	640	580	656	640	4276	611	39	-146	2370	11
Red Grape	38	38	48	56	60	52	58	350	50	8	-152	2333	13
Organic Spinach	458	474	440	428	446	446	468	3160	451	15	-199	2245	7
Plums	106	120	102	144	142	118	114	846	121	15	-270	1350	3
Green Grape	26	28	26	28	22	24	28	182	26	2	-108	2265	17
Clementine	386	408	348	412	400	390	366	2710	387	21	-224	1868	6
Blueberry	142	176	156	184	208	182	168	1216	174	20	-178	1637	7
Strawberry	124	98	76	130	98	88	62	676	97	23	-392	2065	3
Raspberry	276	326	262	342	264	246	226	1942	277	39	-374	2033	4
Green Pepper	668	484	422	492	538	498	698	3800	543	94	-184	1341	3
Zucchini	306	328	250	228	286	318	284	2000	286	33	-184	1641	6
Asparagus	266	224	216	290	184	148	186	1514	216	46	-160	1617	8
Kale	152	136	144	150	162	140	176	1060	151	13	-162	2255	11
Brussel Sprouts	172	288	340	168	230	234	220	1652	236	57	-311	1921	3
Sprouts	82	64	70	102	50	72	84	524	75	15	-466	2364	3
Avocado	14	16	28	26	14	24	30	152	22	6	-413	1926	3
Apple	254	266	328	288	430	256	512	2334	333	93	-319	2186	5
Banana	694	358	708	684	700	360	510	4014	573	150	-198	1531	3
Tomato	568	506	424	510	510	524	590	3632	519	49	-380	2340	4
Orange	542	392	634	458	438	418	448	3330	476	78	-183	2466	10
Watermelon	560	176	256	336	326	372	400	2426	347	111	-468	2129	3

4. Static Pricing Profit & Waste Decision Modeling

Food retailers exist all over the world in various fashions. From large multinationals to family-owned markets, in big cities and remote lands, there are places to buy groceries (Ruhlman, 2018). The market need for food retail is undeniable and with that there exists a lucrative financial market (Campbell, 2020). Most businesses are financially motivated, and food retailing is no different (Maverick, 2020). The challenge though, is that food retailers have extremely low profit margins, requiring high sales volumes, efficient supply chains, and strategic pricing (Campbell, 2020). Every item that goes unsold can have a negative impact on an already tight margin. Focusing on the financial implications of reducing waste is important. However, initiatives such as those presented by the United Nations Sustainable

Development Goals, are holding retailers to a higher standard in which quantifying success should no longer solely be financially based (Lemaire & Limbourg, 2019).

Retail focus on the triple bottom line seems to be growing in importance. The triple bottom line is an approach for measuring success within the financial accounting of a business (‘*A Simple Explanation of the Triple Bottom Line’,* 2021). The approach ‘evaluates a company’s degree of social responsibility, its environmental impact, and its economic value’ (*‘Refrigerants and the 'Triple Bottom Line'',* 2018). Measuring success beyond a retailer’s economic results is explicitly stated in the United Nations Sustainable Development Target 12.3 (‘*United Nations’*, 2020). The research included serves to explore the effects of profit maximization and waste minimization on a retailer’s triple bottom line. Using price and demand as levers, models are developed to replicate the process of food retailing where supply is deterministic. In these models, product prices are static throughout the duration of each specific model optimization instance. Static pricing is the characteristic difference between these models and the model that will be formulated in Section 5. Both a mathematical analysis and numerical example of the decision models’ results are presented. The goal is to understand the financial, social, and waste related implications of a food retailer opting to utilize optimization methods that promote sustainable consumption.

4.1 Optimizing for Profit vs. Optimizing for Waste

To assess the financial, social, and environmental implications of a food retailer waste, two initial static pricing models are created. These opposing models, a profit maximizing model and a waste minimizing model, are formulated, and compared. The information obtained from the profit maximizing model is used to compare the financial, social, and environmental implications of the alternative waste minimizing model. In these models an emphasis is placed on Assumption 3 to outline the challenge of managing incoming product with little decision-making power in advance. Assumption 3 states that inventory is deterministic, meaning stores have no control. If retailers were able to accurately forecast supply with demand, while perfectly managing product through a supply chain, there would be no waste and profit would be maximized (Fildes et al., 2019). However, this is rarely the case in practical operations. In the formulation of these profit and waste focused models, Assumption 7 is added.

Assumption 7: Each item has a one-period lifespan.

Inventory is available for sale in the period that inventory arrives at the retailer. If the item is not sold on the period it arrives, the item is considered waste.

4.1.1 Pure Profit Model Mathematical Formulation

Objective Function

The objective function is to maximize total profit. Total profit is calculated as sales times profit minus costs.
MAXIMIZE

$$\sum_{f\in F}\sum_{t\in T} S_{f,t} * P_f - \sum_{f\in F}\sum_{t\in T} ni_{f,t} * c_f$$

With constraints

A. Price and demand are determined by the linear price response function.

$$D_f = z_f - (m_f * P_f) \qquad \forall f \in F$$

B. Sales must be less than or equal to demand.

$$S_{f,t} \leq D_f \qquad \forall f \in F, t \in T$$

C. Sales must be less than or equal to total inventory.

$$S_{f,t} \leq ni_{f,t} \qquad \forall f \in F, t \in T$$

D. Non-negativity of all variables.

$$D_f, P_f, S_{f,t}, \geq 0 \qquad \forall f \in F, t \in T$$

4.1.2 Pure Profit Model Numerical Example

The Pure Profit Model developed above is coded into AMPL, a computer language used to describe many types of problems known generally as mathematical programming (Fourer, 2009). The model is solved using the BARON solver, a global optimization solver that uses a brand-and-reduce algorithm to solve mixed-integer nonlinear optimization problems ("*BARON*", n.d.). A table of the AMPL code for this model is provided in Appendix

A. The instance data is then applied to the model and the results of the numerical example are presented below.

Table 2: Pure Profit Model instance data results

Product	Price	Profit	Waste
Lime	14.15	2428.23	0
Carrot	7.16	1434.38	0
Broccoli	20.63	11958.71	14
Cucumber	11.91	19911.64	22
Cauliflower	6.74	2194.06	0
Grapefruit	4.25	3185	30
Spinach	6.41	371.2	0
Kiwi	5.2	311.08	40
Red Pepper	5.52	575.54	0
Cherries	11.85	3442.08	16
Red Grape	14.95	683.88	0
Organic Spinach	8.93	6044.11	6
Plums	4.47	1240.8	0
Green Grape	20.71	675.76	0
Clementine	6.52	1377.32	4
Blueberry	8.03	1250.16	0
Strawberry	4.94	1308.89	0
Raspberry	4.56	1022.59	16
Green Pepper	4.59	4131.47	419
Zucchini	7.19	2308.53	10
Asparagus	8.44	469.19	24
Kale	12.83	1943.33	0
Brussel Sprouts	5.2	3446.16	35
Sprouts	4.85	971.54	0
Avocado	4.59	241.8	0
Apple	5.5	726.59	82
Banana	4.64	5019.84	338
Tomato	4.71	2307.43	55
Orange	10.51	743.23	92
Watermelon	3.69	1093.61	160
		82818.16	**1364**

4.1.3 Waste Model Mathematical Formulation

The Pure Profit Model developed in Section 4.1.2 is altered so that the objective function is no longer to maximize profit but to minimize waste. All previously listed assumptions are maintained in the formulation of this model. The alterations to the objective function from the previously developed Pure Profit Model are provided below along with additional model constraints.

Objective Function

The objective function is changed so that minimizing waste is now the priority. It is calculated as total inventory minus sales.

$$MINIMIZE \quad \sum_{f\,\in F}\sum_{t\,\in T} ni_{f,t} - S_{f,t}$$

With constraints

E. Total profit is equal to sales times price minus total inventory costs. Total profit according to this constraint must be positive. *There is no incentive for a retailer to remain in business if they are losing money with their pricing strategies. If this constraint is not included in the model, each product will be sold for zero price, ensuring there is zero waste.*

$$total\,profit = \sum_{f\,\in F}\sum_{t\,\in T} S_{f,t} * P_f \; - \; \sum_{f\,\in F}\sum_{t\,\in T} ni_{f,t} * c_f \; - \quad \geq 0$$

F. Profit per item is equal to sales times price minus total inventory costs. Item profit according to this constraint must be positive. *Once again, there lacks incentive for a retailer to sell a product if it is negatively impacting their financial balance sheet. It is noted that this constraint could be considered redundant however it is included because it can be relaxed for specific products if the product is a driver of traffic to the store where product profit is negligible.*

$$item\,profit_f \; = \sum_{t\,\in T} S_{f,t} * P_f - \sum_{t\,\in T} ni_{f,t} * c_f \;\geq 0 \qquad \forall\, f \in F$$

4.1.4 Waste Model Simulation

The Waste Model is coded into the AMPL software system and solved using the BARON solver. This AMPL code is provided in Appendix B. The instance data outlined in Section 3.4 is applied to the newly developed Waste Model. The numerical results are provided in the table below.

Table 3: Waste Model instance data results

Product	List Price	Profit	Waste
Lime	6	0	0
Carrot	4	0	0
Broccoli	15	0	0
Cucumber	6	0	0
Cauliflower	4	0	0
Grapefruit	3	0	0
Spinach	4	0	0
Kiwi	5	0	0
Red Pepper	3	0	0
Cherries	11	0	0
Red Grape	13	0	0
Organic Spinach	7	0	0
Plums	3	0	0
Green Grape	17	0	0
Clementine	6	0	0
Blueberry	7	0	0
Strawberry	3	0	0
Raspberry	4	0	0
Green Pepper	3	0	0
Zucchini	6	0	0
Asparagus	8	0	0
Kale	11	0	0
Brussel Sprouts	3	0	0
Sprouts	3	0	0
Avocado	3	0	0
Apple	5	0	0
Banana	3	0	0
Tomato	4	0	0
Orange	10	0	0
Watermelon	3	0	0
		0	**0**

4.1.5 Pure Profit Model & Waste Model Analysis

If a retailer's data is run through the Pure Profit Model and Waste Model, contrasting results are expected. The Pure Profit Model is formulated to maximize profit for a set of products F, across a set of periods T. Profit is calculated as the sum of product sales times list price minus product inventory costs. In doing so, values which lend themselves the largest total profit for the variables of demand, D_f, and list price, P_f, are obtained. Sales, $S_{f,t}$, are then calculated by Constraint B and Constraint C, ensuring that product sales for a period are less than or equal to demand and available inventory. Due to the profit maximizing objective, $S_{f,t}$ will be maximized to the largest possible values that fit within Constraint B and Constraint C. A product's decision model optimization will result in zero waste if demand at the profit maximizing list price is greater than or equal to the demand in the period with the greatest amount of new inventory, e.g., $if \;\; D_f \geq max\, ni_{f,t}\, ,\; then\;\; ni_{f,t} - S_{f,t} \; = \; 0 \;\; \forall\, f \in F\; t \in T$. However, the Pure Profit Model only considers product waste as the sunk cost of the product inventory.

Alternatively, the Waste Model is defined to minimize waste. Waste is calculated as the sum of all products' new inventory minus the sum of their sales in each period. While Constraints A through D remain the same for both the Pure Profit Model and the Waste Model, the constraints are expanded. Without the addition of Constraint E and Constraint F, the most effective way for the model to minimize waste is by obtaining the largest demand through selling each product for a list price of 0 kroner. With the addition of Constraint E and Constraint F, the most effective method for the model to minimize waste is through equalizing product list price with product cost, $P_f = c_f$, resulting in zero profit. With this pricing method, waste is eliminated so long as demand is greater than or equal to new inventory across all periods, e.g., $if \;\; d(P_f = c_f) - max\, ni_{f,t} \geq 0 \;\; \forall \; t \in T$. If the previous equation does not hold true for a product, waste will occur in periods where demand is less than new inventory, e.g., $if \;\; d(P_f = c_f) < ni_{f,t}, \; then \quad ni_{f,t} - S_{f,t} = W_f \; \forall \, f \in F \; t \in T$. Due to the waste minimizing objective, $S_{f,t}$ is maximized to be the largest possible value that fits within Constraint B and Constraint C. This allows for the sale of the most amount of product possible rendering the least amount of waste. Thus, the Waste Model focuses on waste and only considers profit through the inclusion Constraint E and Constraint F.

Turning to the numerical example as an illustration of possible outcomes, the Pure Profit Model realized 82,818 kroner in additional profits when compared to the Waste Model. In contrast, the Waste Model successfully reduced waste to 0 units, whereas the Pure Profit Model resulted in 1,364 units of waste. As expected from the mathematical analysis, the Waste Model reduced waste by selling all products at cost. Limes noted the largest price decrease of nearly 59 percent, whereas kiwis had the least at only 4 percent. The decrease of each product's list price yielded an increase in demand, contributing to the removal of waste. In this numerical example the Waste Model successfully eliminated total waste by reducing each product's price and removing profit altogether.

In conclusion, the analysis suggests that a retailers' profit will be eliminated when their operating model is shifted to only focus on eliminating waste. The profit elimination is caused by product list prices being reduced to equal the product costs. A lower product list price opens access to more potential buyers, yielding a positive benefit to society. The analysis also provides evidence that a retailer can drastically reduce waste through shifting focus away from profit. If a food retailer is to shift their store level focus from maximizing profit to minimizing waste it will positively benefit the planet and people but plague their profitability. The complete elimination of profit is not a feasible option for a retailer as no business can survive for a significant amount of time without making any profit (Maverick, 2020). Due to the expected financial results, implementing a waste minimization model, as formulated in Section 4.1.3, is not an adequate method for a retailer to improve their triple bottom line. Next, an alternative decision model is presented that will provide an improvement in the impact of reducing waste on a retailer's triple bottom line.

4.2 Weighted Waste Model

An operating model focused purely on profit maximization or purely on waste minimization provides conflicting results. The Pure Profit Model suggests high profits and high waste while the Waste Model cuts out both waste and profit entirely. Thus, a new model is created with the ability to both maximize profit and reduce waste. While standard mathematical programming involves finding an optimal solution for one decision, techniques from multi-objective mathematical programing can be used to develop a combination model (Baky, 2010). "In multi-objective programming there are multiple conflicting objectives whereby improving one objective will reduce the value of others, leading to a trade-off between solutions" (Yap, 2014). The challenge with standard multi-objective mathematical programming is that there is no single solution that will optimize all objectives ('*Multiple Objectives'*, 2019). Various methods and approaches that replicate multi-objective mathematical programing have been developed (Yap, 2014), and a pseudo multi-objective decision model is utilized in this research.

A decision modeling technique that allows for both retailer profit maximization and waste reduction is through the application of weights on the waste variable. In statistical analysis, a common method to either increase or decrease the importance of a factor is through the application of a weight (Stephanie, 2020). The application of variable weighting in statistical methods is commonly deployed through sampling techniques such as weighted least squares regression, weighted linear regression, decision trees or k-nearest neighbors (James et al., 2021). The statistical weight quantifies the significance of an observation in terms of the population it represents ('*Value Weighted Analysis'*, n.d.). In this analysis, a weight in the form of a financial penalty is applied to the amount of product waste resulting from the Pure Profit Model. Statistical theory suggests that this weight on resulting waste will incentivize the decision model to reduce total waste. The amount of product waste reduction in the optimization model is expected to correlate to the financial value of the weight.

The Pure Profit Model, as developed in Section 4.1.2, is altered to include a weight parameter. The value that the weight carries is financial, as the optimization model's objective is to maximize profit. While in traditional statistics, programming languages aid in optimizing the value of the weights (James et al., 2021), in this research the value of the weight will be a predetermined model parameter. This weight on waste is represented through a waste cost, which simulates the cost of disposing unsold products. The implications of the inclusion of a weight applied to the Pure Profit Model are analyzed through both a mathematical analysis and numerical example under which various values of the financial weight on waste will be contrasted.

4.2.1 Weighted Waste Model Formulation

The objective function from the Pure Profit Model is altered to include a financial weight on resulting waste. The weight on waste, given by parameter, wc_f, is a cost in kroner of an unsold unit of inventory. Note, that the weight on waste can take on unique values for each product. The constraints and assumptions for the model formulated in this section remain unchanged from those in the Pure Profit Model. The model developed in this section is referred to as the Weighted Waste Model.

Objective Function

The objective function is to maximize total profit. Total profit is calculated as sales revenue minus costs, minus unsold inventory times waste cost.

MAXIMIZE

$$\sum_{f\,\in F}\sum_{t\,\in T} S_{f,t} * P_f \;-\; \sum_{f\,\in F}\sum_{t\,\in T} ni_{f,t} * c_f \;-\; \sum_{f\,\in F}\sum_{t\,\in T} ((ni_{f,t} - S_{f,t}) * wc_f)$$

4.2.2 Weighted Waste Model Numerical Example

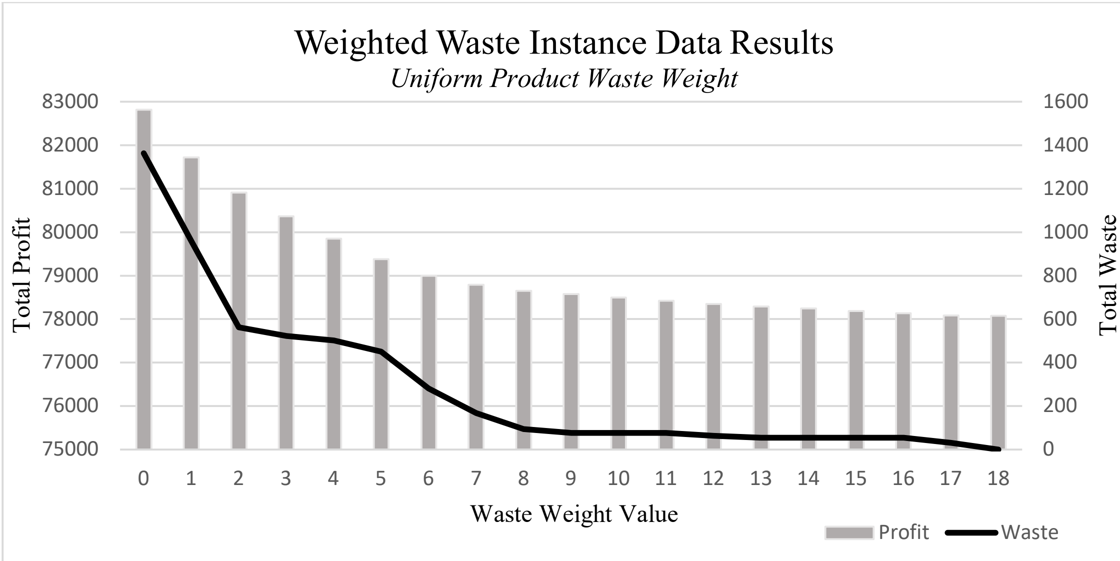
To offer an example of the effectiveness of the application of a weight on waste, the instance data outlined in Section 3.4 is applied again. The Weighted Waste Model is coded into the AMPL software and solved using the BARON solver. The code can be found in Appendix C. The model is run first, with no weight on waste. Next, a universal waste weight of 1 kroner is applied to all products. Following, the weight for each product is increased to the lowest possible value that results in zero waste. The results from this numerical example are provided below.

Table 4: Weighted Waste Model instance data numerical results

	WC = 0			WC = 1			WC = Min w/0			
Product	**List Price**	**Profit**	**Waste**	**List Price**	**Profit**	**Waste**	**WC**	**List Price**	**Profit**	**Waste**
Lime	14.15	2428.23	0	14.15	2428.23	0	0	14.15	2428.23	0
Carrot	7.16	1434.38	0	7.16	1434.38	0	0	7.16	1434.38	0
Broccoli	20.63	11958.71	14	20.51	11946.26	2	2	20.5	11946.24	0
Cucumber	11.91	19911.64	22	11.91	19889.64	22	13	11.76	19648.41	0
Cauliflower	6.74	2194.06	0	6.74	2194.06	0	0	6.74	2194.06	0
Grapefruit	4.25	3185	30	4.25	3155	30	2	4.18	3133.45	0
Spinach	6.41	371.2	0	6.41	371.2	0	0	6.41	371.2	0
Kiwi	5.2	311.08	40	5.2	271.08	40	5	5.06	148.33	0
Red Pepper	5.52	575.54	0	5.52	575.54	0	0	5.52	575.54	0
Cherries	11.85	3442.08	16	11.85	3426.08	16	18	11.74	3163.07	0
Red Grape	14.95	683.88	0	14.95	683.88	0	0	14.95	683.88	0
Organic Spinach	8.93	6044.11	6	8.93	6038.11	6	7	8.9	6002.41	0
Plums	4.47	1240.8	0	4.47	1240.8	0	0	4.47	1240.8	0
Green Grape	20.71	675.76	0	20.71	675.76	0	0	20.71	675.76	0
Clementine	6.52	1377.32	4	6.52	1373.32	4	6	6.5	1355	0
Blueberry	8.03	1250.16	0	8.03	1250.16	0	0	8.03	1250.16	0
Strawberry	4.94	1308.89	0	4.94	1308.89	0	0	4.94	1308.89	0
Raspberry	4.56	1022.59	16	4.52	1012.54	0	1	4.52	1012.54	0
Green Pepper	4.59	4131.47	419	4.58	3721.36	410	18	3.49	1879.35	0
Zucchini	7.19	2308.53	10	7.19	2298.53	10	4	7.14	2271.74	0
Asparagus	8.44	469.19	24	8.38	445.88	14	2	8.29	444.74	0
Kale	12.83	1943.33	0	12.83	1943.33	0	0	12.83	1943.33	0
Brussel Sprouts	5.2	3446.16	35	5.08	3442.11	0	1	5.08	3442.11	0
Sprouts	4.85	971.54	0	4.85	971.54	0	0	4.85	971.54	0
Avocado	4.59	241.8	0	4.59	241.8	0	0	4.59	241.8	0
Apple	5.5	726.59	82	5.5	644.59	82	3	5.25	578.01	0
Banana	4.64	5019.84	338	4.28	4865.11	50	17	4.16	4642.45	0
Tomato	4.71	2307.43	55	4.66	2284	22	5	4.61	2198.32	0
Orange	10.51	743.23	92	10.51	651.23	92	9	10.01	36.39	0
Watermelon	3.69	1093.61	160	3.69	933.61	160	2	3.35	855.32	0
		82818.16	**1364**		**81718.02**	**959**			**78077.44**	**0**

The results obtained in Table 4 provide a numerical example of an application of the Weighted Waste Model. In addition, a visual representation of the models results under various waste weights is also helpful in evaluating the results. A uniform weight on waste value is applied to all products in the instance data. The value of the weight on waste again begins at zero and is increased incrementally until all waste is eliminated. The instance data total results for profit and waste under each uniform waste weight are provided in the graph below.

Graph 1: Weighted Waste Model instance data visual results



4.2.3 Weighted Waste Model Analysis

The Weighted Waste Model has a similar mathematical structure to the Pure Profit Model formulated in Section 4.1.2. The distinction between these two models is that the Weighted Waste Model considers an additional financial penalty on unsold inventory in its objective to maximize profit. In this model profit is calculated as the sum of product sales, times product price, minus the cost of inventory, minus the sum of unsold inventory, times the financial weight on unsold inventory. If a product does not have waste in the Pure Profit Model, the addition of a weight on waste will have no impact. However, if a product has waste in the Pure Profit Model, e.g., $ni_{f,t} - S_{f,t} > 0 \quad \forall\, t \in T$, then the addition of a weight on waste impacts that products optimization results. As the weight on waste, wc_f, increases the model is incentivized to reduce waste and does so by decreasing product list price, thus increasing demand. Once a product's weight on waste, wc_f , is increased to the point in which the model results in zero waste, $ni_{f,t} - S_{f,t} \ = \ 0 \quad \forall\, t \in T$, any increase in the weight's value will have no effect on the profitability of the product. If the Pure Profit Model for a product has waste, depending on the size of the waste weight, this model results in a lower product list price. This reduction in list price increases product demand and results in less product waste while also decreasing profitability.

Table 4 provides a numerical outline of possible results from the Weighted Waste Model. In this example, when the weight on waste is 0 kroner, the model provides identical results to that of the Pure Profit Model. However, when applying a uniform weight on waste of 1 kroner across all products in the instance data, total waste decreases by 29.7 percent, or 405 units, when compared to the previous results with no weight on waste. Additionally, the financial implications are such that total profit decreases by 1.3 percent when the same 1 kroner weight is included. Similar to the numerical example results from the Waste Model, waste is reduced through a decrease in product list prices, increasing product demand. However, the Weighted Waste Model only reduces the list price of a product if the Pure Profit Model resulted in waste. When the weight on waste is set to the lowest possible value that yields zero waste, total profit notes a 5.72 percent decrease when compared to the Pure Profit Model. While eliminating waste, the Weighted Waste Model reduces 13 of the products' list prices, with the greatest price reduction occurring with green peppers, a nearly 24 percent reduction. The impact of the weight in this model can be visually analyzed in Graph 1. The graph shows that as the value of the uniform weight increases, both total waste and total profit decrease. When the weight on waste is the smallest, either 1 or 2 kroner, its impact on both total profit and total waste is most significant. As the value of the weight increases, the financial and environmental impact stemming from an increase in the weights value became lesser. However, under a weight of 18 kroner, all waste is eliminated at the expense of the retailers' total profits.

Analysis of the Weighted Waste Model suggests that adapting the theory of statistical weighting can be advantageous for food retailers who wish to shift their optimization models to have a more multi-objective focus. Under this model, considering multiple variables in its objective, retailers can improve their triple bottom line without sacrificing financial performance. Unlike in the Waste Model, the Weighted Waste Model suggests only a 5.72 percent decrease in total profits. As the weight on waste increases, waste is reduced, and profits are lowered. The analysis shows that when a weight is applied to eliminate all product waste, the negative financial implications are significantly less than compared to the Waste Model. As stated previously, any reduction in profits for a significant amount of time can be detrimental to a retailer (Maverick, 2020). While the weight on waste in this analysis represents the financial cost to dispose of the expiring product, it can be used to represent other costs in future applications of the model. For example, one may choose to apply the weight on waste to represent the social or environmental cost of wasting food items that may have otherwise been consumed. Thus, economic research regarding the ramifications of including a food waste weight, whether theoretical or practical in nature, into a retailer's operating model should be studied further before deploying the strategy in practice.

4.3 Concluding Analysis

The three static pricing models constructed in this section are formulated to analyze varying methods in combating store level retail food waste of fresh fruits and vegetables. Through the formulation of these models, and with support of numerical examples, evidence suggests that shifting from a sole focus on profit to a consideration of waste reduction can positively impact the elements of planet and people in a retailer's triple bottom line. However, each of these models also suggests a decrease in profit alongside the waste reductions. Additionally, the Weighted Waste Model suggests that it is possible to increase waste considerations without completely abandoning profits. In closing, focusing on waste in a statically priced operating model will likely have negative ramifications for a retailer's profit, making these strategies unattractive and unsustainable in the long run. To further close the priority gap between profits and waste reduction, the following section explores a dynamic pricing model. This model analyzes whether dynamic pricing may be a more sustainable method for businesses on the pursuit of fresh fruits and vegetables waste reduction.

5. Dynamic Pricing Decision Modeling

The conventional food retail pricing strategy for fresh fruits and vegetables is to offer a single price for each product per sales week (Berk et al., 2009). The models constructed in Section 4 exemplify this pricing strategy. Pricing each item similarly assumes that buyers place the same value on all items of an individual product. While this ideology may hold true for less perishable goods such as condiments or canned goods, it is not necessarily true for highly perishable goods such as fresh fruits and vegetables. These items are strongly impacted by quality deterioration. In most retail situations, buyers have a lower willingness to pay for items of lesser quality, e.g., deteriorating food items (Tekin et al., 2017). Due to consumers' preconceived notions of price versus quality, a 'decline in freshness of fresh fruits and vegetables induces a decline in sales if the product is sold at the same price as that of the fresh product' (Banerjee et al., 2017, pg. 54). Thus, the commonly used singular product list price strategy for fresh fruit and vegetable retail sales is not an efficient method to match product price with consumer demand. Dynamic pricing, otherwise referred to as price differentiation, ‘refers to the ways that additional profits can be extracted from a marketplace by charging different prices’ (Tekin et al., 2017, pg. 74). As mentioned in the literature review, various ideas on price differentiation in fresh fruit and vegetable retailing have been widely researched. In this previous research, dynamic pricing has been introduced as a powerful method for sellers to increase profits. To contrast, dynamic pricing in this research is deployed as a tool for waste reduction and is evaluated by its effect on a retailer’s triple bottom line.

The dynamic pricing method of markdown management is a tool used to combat consumers’ lower willingness to pay for food that is deteriorating. A markdown is a permanent reduction in price, commonly used ‘to clear inventory before it becomes obsolete or needs to be removed to make way for new stock’ (Tekin et al., 2017, pg. 240). Markdowns allow for market segmentation and price discrimination offering a powerful method for retailers to increase revenue (Tekin et al., 2017). However, traditional markdown optimization relies on the fact that ‘a seller has a fixed inventory without the opportunity to reorder’ (Tekin et al., 2017, pg. 250). In fresh fruit and vegetable retail, there is constant replenishment where fresh and deteriorating inventory of a product may be offered simultaneously. Despite this variation from traditional markdown theory, as of 2021 food retailers have begun to experiment with markdown methods for highly perishable products. In Norway, small shelves of marked down deteriorating items that would have previously been discarded can be found in most food retailers. These shelves feature items donning bright stickers offering a universal discount percentage across all items (Meland, 2019). In the United States, Target Corporation offers discounts on a limited number of deteriorating items, featuring assorted dollar amounts off the list price (Tigar, 2020). These retail methods are deployed because some consumers are willing to pay for fruits and vegetables that are nearing their expiration dates although those consumers would not have previously purchased the product without the price reduction (Tekin et al., 2017). Unfortunately, data regarding the success of these retailers’ markdown programs has not been made publicly available.

In the following section the business implications of a dynamic pricing strategy of markdown management for fresh fruits and vegetables are studied through mathematical decision modelling. The model seeks to answer the question: can dynamic pricing through way of markdown management be an effective tactic to improve a retailer’s triple bottom line? Traditionally, markdown management relies on the assumption that a seller’s inventory is fixed (Tekin et al., 2017). In the case of fresh fruit and vegetable retail sales, inventory is constantly replenished (Fildes et al., 2019), introducing a deviation from traditional markdown management theory. Gaining an understanding of the possible effectiveness of the inclusion of a markdown strategy is done by studying the impact of an optimized markdown percentage under variations of the consumer linear price response function. Effectiveness is again considered through the holistic approach of the triple bottom line. First, an optimization model that includes dynamic pricing following those developed in Section 4 is constructed. Next, this Dynamic Pricing Model is mathematically defined. Following, the instance data, also developed in Section 3.4, is applied to the formulated Dynamic Pricing Model. The instance data provides a numerical example of the model developed in this research. Finally, the results are discussed and analyzed.

5.1 Dynamic Pricing Model Formulation

The Dynamic Pricing Model is formulated to replicate a fresh food retailer's weekly business processes while introducing dynamic pricing. The model assumptions outlined previously, Assumptions 1-6, are again applied in this model. Assumption 3 is stressed to focus this research on individual locations of food retail chains, where it is accepted that individual stores do not have discretion over the inventory that arrives. If retailers were able to accurately forecast supply with demand at an individual store level and perfectly manage inventory through an advanced supply chain, profit would be maximized, and food waste eliminated (Fildes et al., 2019). However, this is never the case in practical operations, suggesting that opportunities exist for alternative solutions. Assumption 7, which states that each item has a one-period life span, is disregarded in the Dynamic Pricing Model. However, four additional assumptions presented in detail below are included in the formulation of this model. Following the delineation of assumptions, the Dynamic Pricing Model is provided in mathematical notation.

5.1.1 Assumptions

Assumption 8: A multi-period model lasting seven periods.

A multi-period model is advantageous in that it allows for the carry of unsold inventory and more closely reflects day to day grocery operations (Dhanalakshmi et al., 2011). In this Dynamic Pricing Model, each item has a two-period shelf-life. Items not sold in the first period will be carried over and sold in the second. If the items remain unsold at the end of the second period, it is discarded as waste. In a traditional setting, most retail food items have a shelf-life longer than two days (Sukhochev, n.d.). To allow for inventory traceability, the Dynamic Pricing Model assumes a two-period product shelf-life. Retail models for fresh fruits and vegetables traditionally assume a first-in-first-out inventory model. However, this assumption rarely holds up in practice as it does not reflect true consumer habits (Tekin & Erol, 2017). When items have multi-period shelf lives, modeling inventory tracking becomes increasingly complex and reliant on assumptions. Thus, assigning each item a two-period shelf-life helps maintain item traceability while sustaining the integrity of a dynamic model.

Assumption 9: Fresh and deteriorating items have differing sets of buyers and face differing price response functions where $z \geq zo$ *and* $m \leq mo$.

Deteriorating items that are marked down can face a differing linear price response function to the same food items that are considered fresh and not discounted. The formula for the linear price response function for a deteriorating item is (Tekin et al., 2017);

$$d(p) = zo - mo\ (p\ (1 - disc)).$$

The set of buyers willing to purchase the expiring items is different from the set of buyers with demand for the fresh version. Thus, there exist two sets of potential buyers. z, is the number of buyers who have demand for fresh items at price zero. Whereas zo, is the number of buyers who have demand for deteriorating items at price zero. The model assumes that the number of buyers who have demand at price zero for deteriorating items is less than or equal to the number of buyers who have demand for the fresh items, $z \geq zo$. This indicates that there will never exist more demand for the deteriorating version of an item than the fresh version. This assumption is made to reflect consumer preferences as it is unlikely demand for a deteriorating item would be greater than demand for fresher version when list prices are equal (Pahl & Voss, 2014).

Additionally, buyers with a willingness to pay for fresh items and buyers with a willingness to pay for deteriorating versions of the same items have differing slopes in their linear price response functions. The slope of the linear price response function for fresh items is less than or equal to the slope of the linear price response function for deteriorating items, $m \leq mo$. Recall that the slope of a linear price response function represents the expected change in consumer demand due to a price change. The steeper the slope of a linear price response function, the more sensitive the buyers' demand is to a price change (Tekin et al., 2017). Buyers of top-quality goods, such as fresh fruits and vegetables, are commonly less price sensitive than those who typically purchase diminishing goods, including deteriorating produce (Kagan, 2020). Therefore, the linear price response function for fresh items is less than or equal to the slope of the linear price response function for deteriorating items.

Assumption 10: Expiring items are discounted once.

Dynamic pricing's markdown management involves items being discounted as they arrive at the end of their freshness in order to attract possible buyers (Tekin et al., 2017). The model developed allows for one markdown per an item's life cycle on a retailer's selling floor. As outlined in Assumption 8, each item has a two-period lifespan. In the first period, the item is priced at its non-discounted list price. If the item is not sold in the first period, it is considered expiring and is carried over to the second where it can be marked down. There is one markdown percentage per type of product for the entirety of the seven-period model. A deteriorating item's markdown percentage is determined by the decision model optimization. The decision variable, $disc_f$, is applied in the linear price response function for deteriorating items and represents the optimized product markdown value. Note, the optimization provides a unique markdown percentage for each type of product. The application of a markdown in an items second period, where it is considered deteriorating, is applied to replicate a retail store discounting expiring items.

Assumption 11: The retailer has space to offer the sale of deteriorating items and no costs exist in discounting the items.

Traditional food retailers offer thousands of products within the confines of their sales floor (Ruhlman, 2018). Thus, many retailers do not have access to additional shelf space to offer the sale of deteriorating products. However, the assessment of limited space is disregarded in this research as space constraints are unique to specific retail locations. Additionally, the model assumes no additional costs to markdown an item. There may be an increase in required labor to markdown the price of an item, however the cost of this labor is challenging to quantify (Berk, 2009). By only allowing one markdown per item and one markdown percentage per product, the magnitude of possible additional labor costs is reduced (Mattsson et al., 2018) and assumed to be negligible.

5.1.2 Mathematical Model Formulation

Objective Function

The objective function is to maximize total profit. Profit is determined by the total sale of fresh items times their list price, plus the total sale of deteriorating items times their markdown price, minus the total costs of inventory. Although traditional markdown optimization assumes that costs are zero (Tekin et al., 2017), costs have been included in this model for continuity as they are included in the previous models developed in Section 4.

MAXIMIZE

$$\sum_{f \in F} \sum_{t \in T} S_{f,t} * P_f \; + \sum_{f \in F} \sum_{t \in T} OS_{f,t} * \; (P_{f,t} \; * \; (1 \; - disc_f)) \; - \sum_{f \in F} \sum_{t \in T} ni_{f,t} * \; c_f$$

Constraints

A. Price and demand of fresh items are determined by the linear price response function.

$$D_f \; = \; z_f \; - \left(m_f \; * \; P_f \;\right) \qquad\qquad \forall \, f \in F, t \in T$$

B. Sales of fresh items must be less than or equal to daily inventory.

$$S_{f,t} \; = \begin{cases} ni_{f,t} \; , ni_{f,t} \; - \; D_f \; \leq \; 0 \\ \qquad D_f \; otherwise \end{cases}$$

C. Price and demand of deteriorating items are determined by their own linear price response function, with the inclusion of a markdown provided by the decision variable, $disc_f$.

$$OD_f \; = \; zo_f \; - \; mo_f \; * \left(P_f \; * \left(1 - disc_f\,\right)\right) \qquad \forall \, f \in F, t \in T$$

D. Deteriorating inventory of a product in period *t* is equal to the previous period's, *t-1,* new inventory minus sales.

$$OI_{f,t} \; = \; ni_{f,t-1} \; - \; S_{f,t-1} \qquad \forall \, f \in F, t \in T$$

E. Sales of deteriorating item must be less than or equal to daily inventory of deteriorating items.

$$OS_{f,t} \; = \begin{cases} OI_{f,t} \; , OI_{f,t} \; - \; OD_f \; \leq \; 0 \\ \qquad OD_f \; otherwise \end{cases}$$

F. Waste is calculated by the total of deteriorating inventory minus sales, plus fresh inventory minus sales in the final period. This constraint is included for results and does not impact the objective function.

$$W_f = \sum_{t \in T} (OI_{f,t} - OS_{f,t}) + (ni_{f,7} - S_{f,7}) \quad \forall f \in F$$

G. The markdown percentage cannot exceed 100%.

$$disc_f \leq 1 \qquad \forall f \in F$$

H. Non-negativity of all variables.

$$D_f, W_f, P_f, S_{f,t}, OI_{f,t}, OD_f, OS_{f,t}, disc_f \geq 0 \qquad \forall f \in F, t \in T$$

5.2 Mathematical Anlaysis of the Dynamic Pricing Model

The Dynamic Pricing Model builds from the Pure Profit Model formulated in Section 4.1.1. In doing so, it introduces the carry of expiring items through a two-period model, incorporates a linear price response function for deteriorating items, and applies a discount on the deteriorating items. The objective function for the Dynamic Pricing Model is to maximize total profit for a set of products F, across a set of periods T. Total profit is calculated by the total sale of fresh items times their list price, plus the total sale of deteriorating items times their markdown price, minus the total costs of inventory. In meeting the model's objective function, values which lend themselves to the largest total profit for the decision variables for fresh demand, D_f, fresh sales, $S_{f,t}$, deteriorating demand, OD_f, deteriorating sales, $OS_{f,t}$, list price, P_f , and markdown percentage value, $disc_f$,are calculated. These variables are determined by both the objective function and the included constraints.

Profit maximizing fresh product price and demand are calculated through the linear price response function, $D_f = z_f - (m_f * P_f) \ \forall f \in F$, defined in Constraint A. Each fresh product faces a unique price response function through which the model obtains an optimal list price, P_f , and associated total buyer demand, D_f. A fresh product's single period sales, $S_{f,t}$, are determined through Constraint B, ensuring that the sales amount is less than or equal to demand and available inventory. Due to the profit maximizing objective, the variable for fresh sales is maximized to the largest possible value that fits within Constraint B. As outlined in Constraint D, for each period, the fresh items that are not sold, $ni_{f,t} - S_{f,t} \quad \forall f \in F, t \in T$, are carried over to the next period as deteriorating inventory, $OI_{f,t}$.

Assumption 8 resolves that for each type of product the fresh and deteriorating items face differing linear demand functions where $z \geq zo$ and $m \leq mo$. Assumption 9 states that there exists a variable which represents a price markdown applied to deteriorating items, $disc_f$. The model adjusts the value of the variable $disc_f$ to maximize the profit for both fresh and deteriorating products. The value of $disc_f$ is decided by the non discounted product list price P_f, the amount of buyer demand for the deteriorating items

$d\left(P_f * \left(1 - disc_f\right)\right)$, and the amount of deteriorating inventory for a product that is available across all periods, $OI_{f,t}$. In general, when a markdown, $disc_f$, is applied to price, P_f, in a linear price response function, the demand for the product is increased. This phenomenon is shown in Figure 1 below.

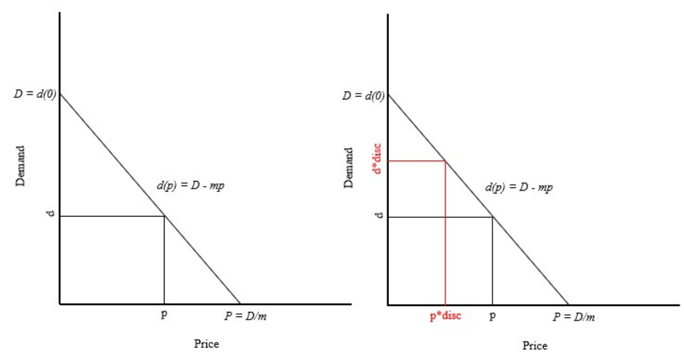


Figure 1: Illustration of a markdowns effect on demand.

Figure 1 shows that a markdown can increase buyer demand from $d(P_f)$ to $d(P_f \times (1 - disc_f))$. The extent to which a markdown stimulates additional buyer demand is related to the slope of the deteriorating products linear price response function. The steeper the slope of a product's demand curve, the greater the impact a markdown will have on demand and vice-versa. Thus, as the slope of a deteriorating product's demand curve increases, the more sensitive a product's demand is to a markdown, e.g., $as\ mo_f \uparrow, d\left(P_f \times \left(1 - disc_f\right)\right) - d(P_f) \uparrow \forall f \in F$. This means that as the difference between a fresh and deteriorating product's price responsiveness increases $(mo_f - m_f)$, the size of a $disc_f$ required to stimulate additional buyer demand decreases. This phenomenon is illustrated in Figure 2 below.

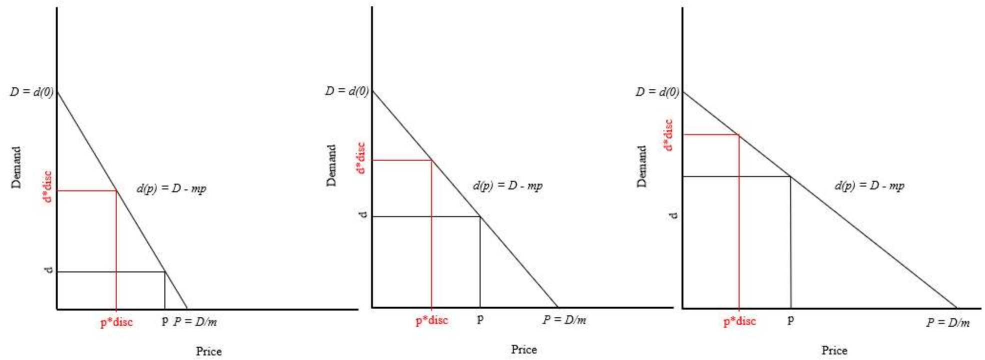


Figure 2: Impact of slope on change in demand when a markdown is applied.

Alternatively, the extent to which a markdown stimulates additional buyer demand is not correlated with the size of the population of a product's potential buyers. When a uniform $disc_f$ is applied to a product's list price, the increase in demand is equal regardless of the size of the population of potential buyers, e.g., $z_f - zo_f = d\left(P_f \times \left(1 - disc_f\right)\right) - d(P_f)\ \forall f \in F$. This is displayed in Figure 3 below.

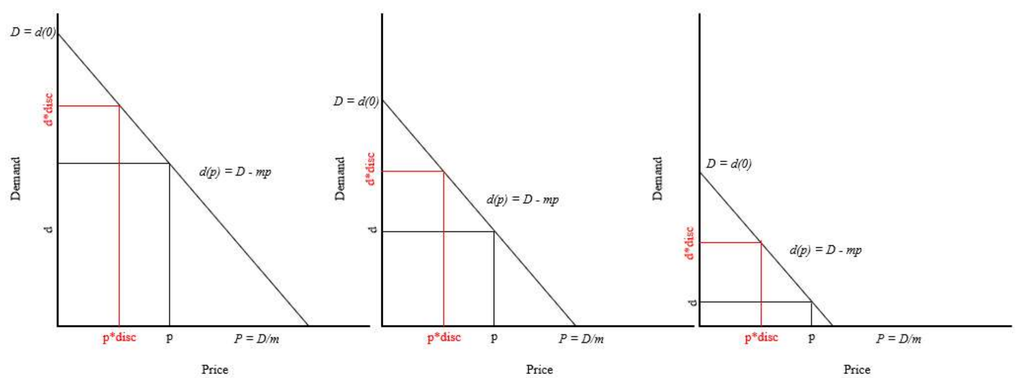


Figure 3: Impact of potential buyer size on change in demand when a markdown is applied.

The Dynamic Pricing Model is motivated to inflate a product's $disc_f$ as a method to increase profit, e.g., $d(P_f) \leq d\left(P_f \times \left(1 - disc_f\right)\right)$. However, the model does not increase or apply the $disc_f$ value in all scenarios. For example, a product will not receive a markdown, $disc_f$, if demand at the list price is greater than or equal to available deteriorating inventory in any one period, e.g., $disc_f = 0\ if\ d(P_f)\ \geq\ max\ OI_{f,t}\ \forall f \in F, t \in T$. So, if demand already exists to consume the available deteriorating inventory, a markdown will not generate any additional sales or profits. Meanwhile, when the demand at a product's list price is less than any one period's available deteriorating inventory ($d(P_f) \leq OI_{f,t}$), the product's optimized $disc_f$ may increase to encourage additional sales. As the difference between price responsiveness for fresh and deteriorating products grows, ($om_f - m_f$), the model is inclined to apply a more significant markdown, $disc_f$. This dynamic pricing effect is outlined in Figure 2. The model treats a growing difference between demand for fresh and deteriorating product, ($z_f - zo_f$), similarly by considering a more significant markdown, $disc_f$, to account for the difference. Thus, if a product has identical linear price response functions for both fresh and deteriorating product, a markdown will not be applied. Sales for deteriorating product, $OS_{f,t}$ is calculated through Constraint E, ensuring that sales of deteriorating items in a period are less than or equal to demand and available inventory. Again, due to the profit maximizing objective of the model, deteriorating sales are maximized to the largest possible value that meets Constraint E.

Additionally, a product's waste is determined by sales of deteriorating products through all periods and sales of fresh products in the final period. A product will have zero waste if two objectives are true. First, if demand at the marked down price is greater than or equal to inventory of deteriorating products in all periods, e.g., $if\ d\left(P_f \times \left(1 - disc_f\right)\right) \geq OI_{f,t}, then\ OI_{f,t} - OS_{f,t} = 0 \ \forall f \in F\ t \in T$. Second, if demand for the fresh product is greater than or equal to the inventory of the fresh product in the final period, e.g., $if\ D_f \geq ni_{f,last}, then\ ni_{f,last} - S_{f,last} = 0 \ \forall f \in F$. If a product had zero waste when optimized under the Pure Profit Model as developed in Section 4.1.1, it will also have zero waste when optimized under this model. However, if a product has waste when optimized using the Pure Profit Model, this model will result in equal or less product waste. In sum, the Dynamic Pricing Model has no explicit incentive to minimize waste, as it is solely motivated to maximize profit. Any reduction in waste that occurs through the application of markdown management in the model is financially motivated.

For the Dynamic Pricing Model, products may note an increase in their list price when compared to results obtained through the Pure Profit Model. The possible increase in list price relates to the extension of a two-period model and the additional population of potential buyers for deteriorating products. Because the model is financially motivated, additional profits can be obtained through the increase of a fresh product's list price, reducing total demand and sales for the fresh product and increasing the amount of deteriorating inventory carried into the second period, e.g., $if\ P_{standard} \leq P_{dynamic}$, $then\ D_{standard} \geq D_{dynamic}$, $OI_{f,t}$ $and\ \pi_{dynamic}$ ↑. An increase in a product's list price only occurs when the demand for a deteriorating product is sufficiently large and the model results in a minimal or non-existent markdown value. Alternatively, the list price of a product will never decrease between the Pure Profit Model and the Dynamic Pricing Model, $P_{standard} \leq P_{dynamic}$. A decrease in a product's list price will always result in less profit which goes against the model's key objective to maximize profit. Considering these expected changes to list price from the inclusion of a markdown management program, the Dynamic Pricing Model will only provide equal or increased product profits when compared to the Pure Profit Model.

5.3 Dynamic Pricing Numerical Example

To offer a numerical example of the effectiveness of a Dynamic Pricing Model on a retailer's total profit, waste, and prices, the instance data outlined in Section 3.4 is applied. The decision model is coded into the AMPL software, and each data instance is solved using the BARON solver. The code can be found in Appendix D. The instance data provides a numerical example of a retailer selling expiring products under various deteriorating product linear price response functions. Thus, three situations where alterations in the linear price response function for deteriorating products are studied. These examples illustrate whether the dynamic pricing of deteriorating food through markdowns is an effective method when compared to the traditional profit maximizing method to improve a retailer's triple bottom line.

5.3.1 Numerical Example Results

In keeping with the instance data model comparisons made in Section 4.2 and 4.3, the results obtained through the Dynamic Pricing Model are compared to those obtained through the Pure Profit Model. Thus, the results from the Pure Profit Model are provided with additional detail. In that model, only a product's fresh linear price response function is considered. Recall that the Pure Profit Model does not allow for the sale of expiring inventory or product price changes. After the first period, if an item is unsold, it is discarded as food waste. The results are provided in Table 5 below.

Table 5: Detailed Pure Profit Model numerical example results

Product	Fresh Demand	Fresh Sales	List Price	Profit	Waste
Lime	46	298	14.15	2428.23	0
Carrot	74	454	7.16	1434.38	0
Broccoli	374	2160	20.63	11958.71	14
Cucumber	530	3392	11.91	19911.64	22
Cauliflower	140	802	6.74	2194.06	0
Grapefruit	428	2620	4.25	3185.00	30
Spinach	24	154	6.41	371.20	0
Kiwi	434	2528	5.20	311.08	40
Red Pepper	42	228	5.52	575.54	0
Cherries	640	4260	11.85	3442.08	16
Red Grape	60	350	14.95	683.88	0
Organic Spinach	468	3154	8.93	6044.11	6
Plums	144	846	4.47	1240.80	0
Green Grape	28	182	20.71	675.76	0
Clementine	408	2706	6.52	1377.32	4
Blueberry	208	1216	8.03	1250.16	0
Strawberry	130	676	4.94	1308.89	0
Raspberry	326	1926	4.56	1022.59	16
Green Pepper	496	3381	4.59	4131.47	419
Zucchini	318	1990	7.19	2308.53	10
Asparagus	266	1490	8.44	469.19	24
Kale	176	1060	12.83	1943.33	0
Brussel Sprouts	305	1617	5.20	3446.16	35
Sprouts	102	524	4.85	971.54	0
Avocado	30	152	4.59	241.80	0
Apple	430	2252	5.50	726.59	82
Banana	612	3676	4.64	5019.84	338
Tomato	551	3577	4.71	2307.43	55
Orange	542	3238	10.51	743.23	92
Watermelon	400	2266	3.69	1093.61	160
Total				**82818.16**	**1364**

The instance data is applied to the Dynamic Pricing Model developed in this section. The parameters for linear price response function for deteriorating product are set at $zo = z$ and $mo = 1.5 \times m$. These parameters are interpreted as a population of potential buyers for a deteriorating version of a product that is the same size as the population of potential buyers of the same fresh product. Additionally, the slope of the linear price response function for the deteriorating version of the product is 50 percent steeper than that of the fresh. The results of this numerical example are offered in Table 6.

Table 6: Dynamic Pricing Model numerical example, where $zo = z$ and $mo = 1.5 \times m$.

Product	Markdown	Fresh Demand	Deteriorating Demand	Fresh Sales	Deteriorating Sales	List Price	Product Profit	Waste
Lime	59.06%	46	745	298	0	14.15	2428.23	0
Carrot	55.62%	74	735	454	0	7.16	1434.38	0
Broccoli	23.82%	345	43	2077	97	20.92	12393.7	0
Cucumber	18.97%	466	86	3221	171	12.35	21026	0
Cauliflower	38.52%	140	314	802	0	6.74	2194.06	0
Grapefruit	24.54%	358	100	2418	232	4.41	3479.31	0
Spinach	61.03%	24	945	154	0	6.41	371.2	0
Kiwi	22.73%	358	116	2321	171	5.48	596.2	0
Red Pepper	62.02%	42	727	228	0	5.52	575.54	0
Cherries	18.05%	538	118	3766	408	12.55	4415.07	0
Red Grape	59.46%	60	951	350	0	14.95	683.88	0
Organic Spinach	17.84%	446	28	3098	40	9.04	6183.63	0
Plums	28.13%	120	24	800	46	4.56	1257.05	0
Green Grape	62.47%	28	1006	182	0	20.71	675.76	0
Clementine	19.13%	366	46	2544	166	6.71	1698.58	0
Blueberry	26.44%	179	29	1180	36	8.19	1368.04	0
Strawberry	29.28%	124	6	670	6	4.95	1310.54	0
Raspberry	26.32%	264	78	1790	152	4.73	1228.3	0
Green Pepper	24.24%	398	270	2788	712	5.12	5648.89	0
Zucchini	21.54%	284	44	1898	102	7.37	2587.95	0
Asparagus	26.58%	216	74	1382	132	8.76	837.79	0
Kale	58.51%	176	961	1060	0	12.83	1943.33	0
Brussel Sprouts	28.28%	234	106	1492	160	5.42	3759.77	0
Sprouts	55.55%	102	856	524	0	4.85	971.54	0
Avocado	60.95%	30	815	152	0	4.59	241.8	0
Apple	20.10%	393	37	2178	37	5.62	738.03	0
Banana	24.08%	430	278	2870	1064	5.56	8403.12	0
Tomato	17.19%	506	62	3460	88	4.83	2522.74	0
Orange	24.68%	448	186	3040	290	11.03	2631.8	0
Watermelon	24.30%	397	163	2261	163	3.7	1542.43	0
Total							**95148.67**	**0**

The instance data is again applied to the Dynamic Pricing Model with an alteration to the inputs for deteriorating products' linear price response functions. The parameters for the linear price response function for deteriorating products are set at $zo = 0.5 \times z$ and $mo = 1.5 \times m$. These parameters can be interpreted as an independent population of potential buyers for a deteriorating version of a product that is half the size of the population of potential buyers of the same fresh product. Additionally, the slope of the linear price response function for the deteriorating version of the product is 50 precent steeper than that of the fresh. The results from this instance data application can be found in Table 7.

Table 7: Dynamic Pricing Model numerical example, where $zo = 0.5 \times z$ and $mo = 1.5 \times m$.

Product	Markdown	Fresh Demand	Deteriorating Demand	Fresh Sales	Deteriorating Sales	List Price	Product Profit	Waste
Lime	65.82%	46	0	298	0	14.15	2428.23	0
Carrot	65.42%	74	0	454	0	7.16	1434.38	0
Broccoli	61.13%	374	14	2160	14	20.63	12070.99	0
Cucumber	59.79%	488	64	3308	106	12.2	20402.97	0
Cauliflower	64.59%	140	0	802	0	6.74	2194.06	0
Grapefruit	61.94%	396	62	2556	94	4.32	3251.84	0
Spinach	66.31%	24	0	154	0	6.41	371.2	0
Kiwi	60.10%	412	62	2484	62	5.28	410.11	0
Red Pepper	65.83%	42	1	228	0	5.52	575.54	0
Cherries	55.85%	626	30	4218	44	11.95	3580.93	0
Red Grape	65.79%	60	0	350	0	14.95	683.88	0
Organic Spinach	58.72%	458	16	3134	16	8.98	6082.31	0
Plums	62.86%	142	2	844	2	4.47	1241.44	0
Green Grape	66.26%	28	0	182	0	20.71	675.76	0
Clementine	58.86%	390	22	2660	50	6.6	1426.96	0
Blueberry	63.55%	184	24	1192	24	8.16	1289.62	0
Strawberry	64.43%	130	0	676	0	4.94	1308.89	0
Raspberry	60.93%	326	16	1926	16	4.56	1051.13	0
Green Pepper	62.15%	484	184	3326	260	4.66	4549.5	0
Zucchini	60.12%	306	22	1966	34	7.26	2362.55	0
Asparagus	61.29%	266	24	1490	24	8.44	547.64	0
Kale	63.90%	176	2	1060	0	12.83	1943.33	0
Brussel Sprouts	62.91%	288	52	1600	52	5.25	3546.56	0
Sprouts	65.16%	102	0	524	0	4.85	971.54	0
Avocado	66.15%	30	0	152	0	4.59	241.8	0
Apple	58.50%	430	0	2252	0	5.5	726.59	0
Banana	62.42%	510	190	3268	738	5.16	6239.69	8
Tomato	58.66%	524	44	3522	44	4.78	2390.37	0
Orange	64.91%	458	176	3070	260	10.97	1387.29	0
Watermelon	65.12%	400	160	2266	160	3.69	1299.76	0
Total							**86686.86**	**8**

Lastly, the instance data is run through the Dynamic Pricing Model with differing parameters for the size of the population of potential deteriorating product buyers. The parameters for linear price response function for deteriorating product are set at $zo = 0.05 \times z$ and $mo = 1.5 \times m$. These parameters can be interpreted as, the population of potential buyers of the deteriorating version of a product is 95 percent smaller than the population of potential buyers of the same fresh product. Additionally, the slope of a linear price response function for deteriorating product is 50 percent steeper than that of fresh product. The numerical results are listed below in Table 8.

Table 8: Dynamic Pricing Model numerical example, where $zo = 0.05 \times z$ and $mo = 1.5 \times m$.

Product	Markdown	Fresh Demand	Deteriorating Demand	Fresh Sales	Deteriorating Sales	List Price	Product Profit	Waste
Lime	99.97%	46	17	298	0	14.15	2428.23	0
Carrot	100.00%	74	21	454	0	7.16	1434.38	0
Broccoli	99.70%	374	12	2160	12	20.63	11959.46	2
Cucumber	99.67%	530	11	3392	11	11.91	19912.07	11
Cauliflower	99.60%	140	6	802	0	6.74	2194.06	0
Grapefruit	99.69%	428	12	2620	12	4.25	3185.15	18
Spinach	99.99%	24	22	154	0	6.41	371.2	0
Kiwi	99.67%	434	9	2528	9	5.2	311.24	31
Red Pepper	99.97%	42	15	228	0	5.52	575.54	0
Cherries	99.66%	640	12	4260	12	11.85	3442.57	4
Red Grape	100.00%	60	23	350	0	14.95	683.88	0
Organic Spinach	99.53%	468	6	3154	6	8.93	6044.36	0
Plums	99.44%	144	0	846	0	4.47	1240.8	0
Green Grape	99.99%	28	22	182	0	20.71	675.76	0
Clementine	99.49%	408	4	2706	4	6.52	1377.45	0
Blueberry	99.42%	208	0	1216	0	8.03	1250.16	0
Strawberry	99.54%	130	3	676	0	4.94	1308.89	0
Raspberry	99.70%	326	10	1926	10	4.56	1022.73	6
Green Pepper	99.56%	495	6	3379	15	4.6	4131.76	203
Zucchini	99.69%	318	8	1990	8	7.19	2308.72	2
Asparagus	99.70%	266	8	1490	8	8.44	469.39	16
Kale	99.49%	176	1	1060	0	12.83	1943.33	0
Brussel Sprouts	99.70%	305	10	1617	10	5.2	3446.31	26
Sprouts	99.68%	102	9	524	0	4.85	971.54	0
Avocado	99.99%	30	19	152	0	4.59	241.8	0
Apple	99.37%	430	0	2252	0	5.5	726.59	0
Banana	99.58%	612	8	3676	31	4.64	5020.43	307
Tomato	99.67%	551	12	3577	12	4.71	2307.61	5
Orange	99.68%	542	12	3238	12	10.51	743.65	80
Watermelon	99.69%	400	11	2266	11	3.69	1093.73	149
Total							**82822.81**	**860**

5.3.2 Numerical Results Analysis

To better understand the effect of dynamic pricing on the instance data, results are compared among the different models. The results from the Pure Profit Model, located in Table 5, serve as comparison data for the various Dynamic Pricing Model results located in Tables 6 through 8. The Dynamic Pricing Model's instance data had the largest number of potential buyers for deteriorating product in Table 6, a lesser amount in Table 7, and the smallest number of potential buyers in Table 8. In the instance data results from Tables 6 through 8, the slope of the deteriorating products' linear demand curves is unchanged. The analysis centers around four key elements. First, the impact of dynamic pricing on retailer profit is discuss. Next, its impact on product price and optimized markdown percentages are discussed. Lastly, overall item waste is discussed.

As shown in Tables 6 through 8, the Dynamic Pricing Model always results in greater product profits when compared to the Pure Profit Model in Table 5. Additionally, in Table 6 when the amount of potential buyers for deteriorating products is greatest, so is total profit. As the potential buyer market decreases so do the additional profits obtained by the Dynamic Pricing Model as seen in the product profits column in Tables 7 and 8. However even in Table 8, when the total profits from the instance data were the least, they remained greater than the results from Table 5. These results support the fact that a product's profit will never be less when comparing data from the Dynamic Pricing Model to the Pure Profit Model. This numerical example provides additional evidence that if there exists a set of potential buyers of deteriorating product and inventory to offer them, profit will always be greater in the two-period Dynamic Pricing Model due to the increase in total potential buyers. It can also be recognized that product profit in the Dynamic Pricing Model and the Pure Profit Model will be equal when there is either no demand for deteriorating products or no deteriorating inventory to offer buyers.

In Tables 6 and 7, the Dynamic Pricing Model instance data results in equal or higher product list prices when compared to the instance data results under the Pure Profit Model in Table 5. The results show that when the number of potential buyers for deteriorating products is greater, so are product list prices. In Table 6, 20 products noted an increase in list price, with the greatest change in list price occurring for bananas at a nearly 20 percent increase in list price. In Table 7, 13 products noted an increase in list price. These price increases occur as the model is motivated to capitalize on second period sales to increase total profit. However, all products that do not have waste under the Pure Profit Model do not note a price increase when compared to the Dynamic Pricing Model’s results. Alternatively, in Table 8, product prices are the same between the two models due to the number of potential buyers of deteriorating product being the lowest of all three examples. Thus, this numerical example shows that a product’s list may be greater in the Dynamic Pricing Model if the demand for deteriorating product is sufficiently large.

In the numerical example the value of the deteriorating product’s optimized markdown percentage increases as the number of potential buyers of the deteriorating product decreases. In Table 6, the required markdown percentage to maximize profit is the least. However, as the difference between the fresh and deteriorating product's price response functions grew, so did the need for a markdown. The change can be seen in the markdown column in Table 7 and Table 8. The results show an interesting phenomenon for products that do not have waste in the Pure Profit Model instance data results. When a product's profit optimization does not result in waste in the Pure Profit Model, the Dynamic Pricing Model still offers a markdown. This occurrence is a result of the chosen solver and is not an expected result. To conclude, in this instance data the required markdown value increases as the population of buyers for deteriorating products decreases.

The Dynamic Pricing Model instance data results consistently present less product waste when compared to the results under the Pure Profit Model. Similar to the findings regarding the optimized markdown percentage, product waste increases as the number of potential buyers of the deteriorating product decreases. In Table 6, when the product demand for deteriorating products is the same size as the demand for fresh products, the Dynamic Pricing Model completely eliminates product waste. Tables 7 and 8 demonstrate that as the set of buyers for deteriorating products decreases waste increases. In Table 7, the instance data optimization results in 8 units of food waste. In Table 8, when the number of potential buyers for a deteriorating product is 5 percent of the amount for the fresh product, the optimization results in 860 units of waste. Even when the number of potential buyers for deteriorating product is smallest, the Dynamic Pricing Model produces a 40 percent decrease in waste. Overall, if a product does not have waste in the Pure Profit Model, it also does have waste in the Dynamic Pricing Model. This occurs because if the model sells through all of a product's available inventory in maximizing profit without a markdown, it will also do so under the presence of a possible markdown. In conclusion, the instance data shows that the Dynamic Pricing Model does not result in more waste when compared to the Pure Profit Model.

5.4 Dynamic Pricing Model Conclusion

A Dynamic Pricing Model was constructed and analyzed with the goal of answering the question: can dynamic pricing through way of markdown management be an effective tactic to improve a retailer's triple bottom line? The hypothesis was tested through the development and analysis of a profit maximizing mathematical decision model that included the offering and marking down of deteriorating food products. The following results were concluded through both a mathematical interpretation and numerical exercise.

The analysis found that offering the sale of deteriorating products will increase a retailer’s profits so long as an independent set of possible buyers with a willingness to pay for the deteriorating product exists. Additionally, the model suggests that there is not situation in which offering deteriorating products with a possible markdown will reduce retailer profits. The Dynamic Pricing Model provides evidence that implementing markdown management can increase a retailer's profit.

The growth of a retailer's profit resulted from either an increase in product list prices, or the sale of what would have been wasted product. When the list price of a product is increased, it restricts a set of possible buyers from accessing the product. If the list price of a fresh fruit or vegetable increases, the buyers that no longer have the product within their willingness to pay may not have demand for similar products, rendering them without access to any product. Thus, this paper’s Dynamic Pricing Model provides evidence that introducing markdown management can lead to an increase in a product’s list price, resulting in negative social effects.

This analysis of dynamic pricing through markdown management also suggests that its application will never lead to an increase in food waste. When a market of buyers with demand for a deteriorating product exists, offering the sale of the deteriorating product will most commonly decrease waste. A food waste decrease will only occur if demand exists for the deteriorating product. This model analysis provides evidence to conclude that when dynamic pricing is included in fresh fruit and vegetable retailing, a markdown management program can only positively impact the planet by decreasing food waste.

6. Discussion

6.1 Limitations & Further Research

The design of this paper’s research is subject to some limitations. Addressing these limitations is done not to undermine the value of the research, but to offer insight into how limitations may affect the conclusions drawn. To provide a comprehensive analysis, both methodological and situational limitations are discussed.

The methodological limitations in this research were imposed onto the models in the form of assumptions. While all assumptions were applied to enhance the focus of the mathematical model and solidify the credibility of the results, only those that were believed to have the greatest impact on the results will be discussed. First, this work did not consider the duration of each product's individual shelf life. The shelf life of a product in this analysis was constricted to one period of freshness. This limitation to the model was imposed to simplify the complexity of the decision models. In contrast, if product shelf lives had been extended beyond a single period, strong assumptions regarding inventory flow would have been required. In practice, inventory does not arrive at stores with uniform shelf lives, nor is product selected from store shelves by consumers in a standardized method (Tekin & Erol, 2017). Thus, successful on-shelf inventory tracking for fresh fruit and vegetable tracking by freshness date is an issue that has yet to be solved and warrants its own additional research (Pahl & Voss, 2014). Second, inventory was considered deterministic in the mathematical decision models formulated in this paper. In practice, store level inventory is forecasted, however deviations are common under market uncertainties (‘Forecasting and Inventory Benchmark Study’, 2018). Thus, future work could be completed by deploying the models developed in this work to forecast price and demand based on expected inventory and later compare the forecasts with the actuals to analyze the efficacy of the model. Finally, internal and external competition between similar products or tertiary retailers was not considered. The absence of competition is a key assumption used to validate the linear price response function. In this absence, a price increase is expected to change demand uniformly across the entirety of the function by disregarding competition (Tekin et al., 2017). The proposed models have the potential to be extended through electing alternative price response functions that adhere more to the element of competition such as the constant-elasticity price response function or logit price response function (Tekin et al., 2017).

Alternatively, some of the limitations relate to the situation in which the research and analysis was conducted. Many of the methodological limitations exist due to a lack of publicly available data on the effects of dynamic pricing through markdown management at food retailers. As stated previously, the concept of offering the sale of deteriorating fresh fruits and vegetables is relatively new (Meland, 2019 & Tigar, 2020). Many retailers are now in the process of figuring out the best way to address food waste while trying to be mindful of their triple bottom line. Future research can be completed utilizing the models developed in this research through the application of historical store level retailer data. Additionally, various solver software packages perform optimizations using alternative methods. This means that the same model and data could see a different result when studied under an alternative solver software. Future work can be completed using alternative software systems and solvers and comparing the results. Finally, although the author of this paper has previous work experience in retail food supply chain, they no longer had access to actual data. An instance data set was created to provide an example of possible results that could be obtained from the decision models. Therefore, the instance data results must be interpreted with caution.

In sum, thoroughly considering the impact of this research's weaknesses allows for an honest interpretation of the results. The limitations addressed above should be seen as an opportunity for further research. Additionally, research extensions were presented in response to the limitations. The benefit of mathematical decision modelling is that it allows for simple model adaptations and extensions (Gaujardo, n.d.). For example, the models developed in this paper could easily be studied from various angles such as studying the effects of markdown percentages as a parameter instead of a decision variable or situations in which list prices were predetermined parameters and inventory as the decision variable. Additionally, the models developed in this paper may be applied to other products and industries in future research studies.

6.2 Conclusion

Food wastage is a topic that plays a pivotal role in the financial, social, and environmental health of the world. Financially, it has been calculated that globally 2.6 trillion USD worth of food is discarded every year (*'Food Waste',* 2021). Socially, it is estimated that 2 billion people a year can be fed with the amount of un-utilized food, ('*United Nations'*, 2020). Environmentally, food wastage is shown to account for 8 percent of annual global greenhouse gasses (Scialabba, 2015). Based on these ramifications, food wastage is a topic that can and should be analyzed from various angles. In this paper, fresh fruit and vegetable retail food waste was specifically studied. The topic is important as 13 percent of food waste is attributed to the retail sector (Fritts, 2021), where fresh fruit and vegetable waste is an over indexed category at a reported food waste rate of 15 percent (Tekin et al., 2017). Thus, this research aims to provide retailers with helpful information regarding the sale of highly perishable fruits and vegetables profitably and responsibly with less waste.

The financial and social consequences of retail fresh fruit and vegetable waste reduction methods were studied through mathematical programing and the creation of decision models. Overall, the evidence shows the superiority of dynamic pricing over static pricing methods for fresh food retailers. Under static pricing methods, food waste will be reduced, and more buyers will have access to the products. However, these static pricing models also provide evidence that reducing food waste also means significantly reducing retailer profit. The structure of the static pricing models was then adapted to include the element of dynamic pricing through a markdown on deteriorating inventory. The analysis of the Dynamic Pricing Model determines that offering deteriorating fresh fruits and vegetables will reduce product waste, increase the access of potential buyers, while bolstering a retailer's profits. Additionally, the value of financial and environmental improvements from the implementation of dynamic pricing positively correlate to the number of potential buyers for deteriorating product. Thus, as the number of potential buyers for deteriorating products increase, so do the benefits from dynamic pricing. In closing, the findings of this research paper should motivate food retailers to see that there exist viable techniques that will increase sustainable consumption of the fresh fruits and vegetables they sell.

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8. Appendix

A.

```
set F; #different food types
set T; #set of days

param ni{F,T};
param c{F};
param x{F};
param z{F};
param disc{F};
param wc{F};


var D{F,T}  >= 0 ;
var total_waste >= 0 ;
var P{F}  >= 0 ;
var S{F,T}  >=0 ;
var item_profit{F};
var wi{F};


#################### objective function ######################################

maximize total_profit:
    sum{f in F,t in T} ((S[f,t] * P[f]) -(ni[f,t] * c[f]))
    ;

subject to

price{f in F,t in T}:
    D[f,t] = z[f] + (x[f]*P[f]);

waste:
    total_waste = sum{f in F}wi[f];

sales_check{f in F,t in T}:
    S[f,t] <= D[f,t];

sales_checkb{f in F,t in T}:
    S[f,t] <= ni[f,t];

profit_calc{f in F}:
    item_profit[f] = sum{t in T}((S[f,t]*P[f]) - (ni[f,t] * c[f]));

item_Waste{f in F}:
    wi[f] = sum{t in T}(ni[f,t] - S[f,t]);



reset;
model profit.mod;
data simulation2.dat;
option solver baron;
solve;
display total_profit,wi;
```

B.

```
set F;
set T;

param ni{F,T};
param c{F};
param x{F};
param z{F};
param wc{F};
param disc{F};


var D{F,T} >= 0;
var P{F} >= 0;
var total_profit >= 0;
var S{F,T} >=0 ;
var item_profit{F} >= 0;
var item_waste{F};
var item_day_profit{F,T};
var wi{F};

#################### objective function ##################################

minimize total_waste:
    sum {f in F, t in T}(ni[f,t] - S[f,t]);

subject to

price{f in F,t in T}:
    D[f,t] = z[f] + (x[f]*P[f]);


sales_check_a{f in F,t in T}:
    S[f,t] <= D[f,t];

sales_check_b{f in F,t in T}:
    S[f,t] <= ni[f,t];

profit:
    total_profit = sum{f in F,t in T} (S[f,t]*P[f] -ni[f,t] * c[f] );

profit_calc{f in F}:
    item_profit[f] = sum{t in T} (S[f,t]*P[f] -  ni[f,t] * c[f]) ;

item_Waste{f in F}:
    wi[f] = sum{t in T}(ni[f,t] - S[f,t]);
```

```
reset;
model waste.mod;
data simulation2.dat;
option solver baron;
solve;
display total_profit,wi;
```

C.

```
set F;
set T; #set of days

param ni{F,T};
param c{F};
param x{F};
param z{F};
param wc{F};
param disc{F};


var D{F,T} >= 0 ;
var total_waste >= 0 ;
var P{F} >= 0 ;
var S{F,T} >=0 ;
var item_profit{F};
var wi{F};

#################### objective function ####################################################

maximize total_profit:
    sum{f in F,t in T} (S[f,t]*P[f] - ni[f,t]*c[f])
    - sum{f in F,t in T} (ni[f,t] - S[f,t]) * wc[f]
    ;

subject to

price{f in F,t in T}:
    D[f,t] = z[f] + (x[f]*P[f]);

waste:
    total_waste = sum{f in F, t in T}(ni[f,t] - S[f,t]);

sales_check{f in F,t in T}:
    S[f,t] <= D[f,t];

sales_checkb{f in F,t in T}:
    S[f,t] <= ni[f,t];

profit_calc{f in F}:
    item_profit[f] = sum{t in T} ((S[f,t]*P[f])-((ni[f,t] - S[f,t])*wc[f])-(ni[f,t]*c[f]));

item_Waste{f in F}:
    wi[f] = sum{t in T}(ni[f,t] - S[f,t]);


reset;
model profit.wc.mod;
data simulation2.dat;
option solver baron;
solve;
display total_profit,wi;
```

D.

```
set F; #different food types
set T; #set of days

param ni{F,T};
param c{F};
param x{F};      #need to change to m
param z{F};
param zo{F};
param xo{F};


var D{F,T} >= 0 ;
var W{F} >= 0 ;
var P{F} >= 0 ;
var S{F,T} >=0 ;
var OI{F,T} >= 0;
var OD{F,T} >= 0;
var OS{F,T} >= 0;
var disc{F} >= 0;
#######for output
var itp{F} ;


#################### objective function ################################################

maximize total_profit:
    sum{f in F,t in T} S[f,t]*P[f] +
    sum{f in F,t in T} OS[f,t]*(P[f]*(1-disc[f])) -
    sum{f in F,t in T} ni[f,t]*c[f];

subject to

price{f in F,t in T}:
    D[f,t] = z[f] + (x[f]*P[f]);

waste{f in F}:
    W[f] = sum{t in T}(OI[f,t]-OS[f,t]);

sales_check_a{f in F,t in T}:
    S[f,t] <= D[f,t];

sales_check_b{f in F,t in T}:
    S[f,t] <= ni[f,t];

sales_check_c{f in F,t in T}:
    OD[f,t] = zo[f] + (xo[f]*P[f]*(1-disc[f]));

old_inventory_start{f in F,t in T:t==1}:
    OI[f,t] = 0;

old_inventory{f in F,t in T:t>1}:
    OI[f,t] = ni[f,t-1] - S[f,t-1];

sales_check_a_old{f in F,t in T}:
    OS[f,t] <= OD[f,t];

sales_check_b_old{f in F,t in T}:
    OS[f,t] <= OI[f,t];

discountunder{f in F}:
    disc[f] <= 1;


#########for output
item_total_profit{f in F}:
    itp[f] = sum{t in T} (S[f,t]*P[f] + OS[f,t]*(P[f]*(1-disc[f])) - ni[f,t]*c[f]);
```

```
reset;
model dynamic.mod;
data simulation2.dat;
option solver baron;
solve;
display total_profit,sum{f in F}W[f];
```