Data-driven optimal dynamic pricing strategy for reducing perishable food waste at retailers

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Abstract:	Approximately forty per cent of fresh products are wasted in low and middle-income countries before reaching consumers. Perishable foods have only a certain shelf-life and they need to be sold for consumption before a specific date. When a product is priced incorrectly, it is often disposed of directly or redistributed. Redistribution of surplus food also has an economic impact on food prices. Therefore, setting an optimal pricing strategy is crucial to reduce inventory and surplus food in an environment with volatile demands. In this context, big data analytics can help managers forecast customer behaviour and determine pricing strategies throughout the retail industry. This study focuses on food waste at the retailer stage of food supply chain (FSC). We present a dynamic pricing model that uses real-time Internet of Things (IoT) sensor data as a novel contribution to decide pricing at different stages of a sales season for retailers. The food waste problem at the retail stage of a FSC is investigated in a pilot project for bulk apple sales to address the research question. This study proposes a four-stage data-driven optimal dynamic pricing strategy for bulk produce to reduce food waste for retailers in low and middle-income countries. A multi-stage dynamic programming method is used to decide on a pricing strategy for bulk produce, with real-time IoT sensor data being retrieved to analyse and determine the length of freshness scores. The effect of the sale price, replenishment amount, discount rate, and freshness score on profit and food waste are evaluated. All these analyses assist managers in taking the best possible actions and remedies. Appropriate interventions boost sales, increase profits by reducing waste and determining competitive sales price, while improving customer loyalty and satisfaction by striking the right balance between food quality and price. Our results show the huge potential of using hyperspectral imaging sensors in the FSC of a retailer. The model is demonstrated empirically to test its practicability.

CRediT author statement

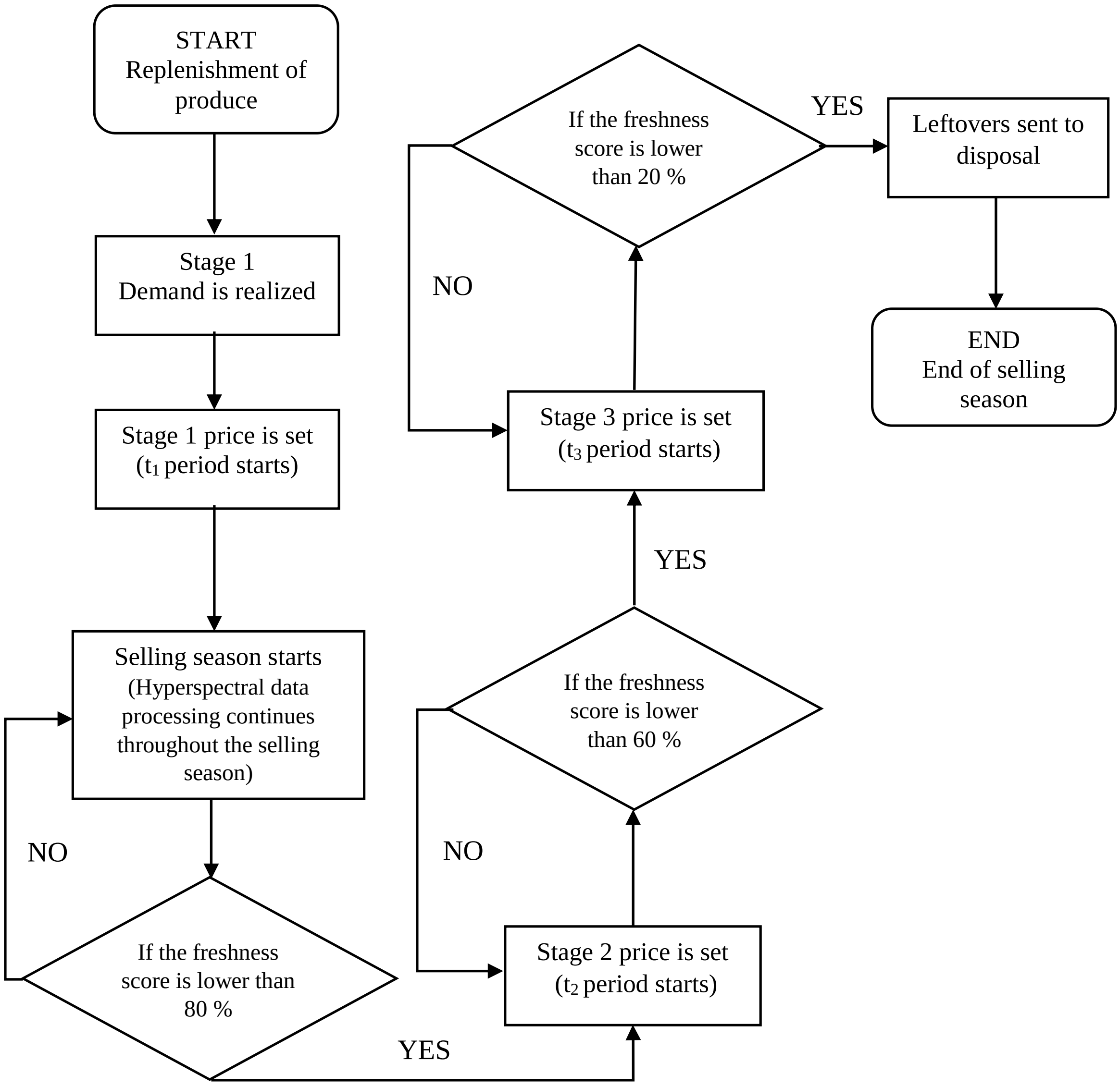
Yaşanur Kayikci: Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Writing- Original draft preparation, Writing- Reviewing and Editing **Sercan Demir:** Methodology, Investigation, Visualisation, Validation, Writing- Original draft preparation **Sachin K. Mangla:** Formal analysis, Investigation, Writing- Reviewing and Editing **Nachiappan Subramanian:** Supervision, Writing- Reviewing and Editing **Basar Koc:** Methodology, Investigation, Visualization, Validation

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Graphical abstract



Highlights

i. Nearly 40% of fresh products get wasted in developing countries.
ii. Redistribution of surplus food has an economic impact on food prices.
iii. Proposes a multi-stage dynamic model for pricing strategy to reduce food wastage.
iv. IoT sensor data is retrieved to analyse and determine the length of freshness scores.
v. The proposed model is illustrated by providing numerical examples.

Data-Driven Optimal Dynamic Pricing Strategy for Reducing Perishable Food Waste at Retailers

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Abstract

Approximately forty per cent of fresh products are wasted in low and middle-income countries before reaching consumers. Perishable foods have only a certain shelf-life and they need to be sold for consumption before a specific date. When a product is priced incorrectly, it is often disposed of directly or redistributed. Redistribution of surplus food also has an economic impact on food prices. Therefore, setting an optimal pricing strategy is crucial to reduce inventory and surplus food in an environment with volatile demands. In this context, big data analytics can help managers forecast customer behaviour and determine pricing strategies throughout the retail industry. This study focuses on food waste at the retailer stage of food supply chain (FSC). We present a dynamic pricing model that uses real-time Internet of Things (IoT) sensor data as a novel contribution to decide pricing at different stages of a sales season for retailers. The food waste problem at the retail stage of a FSC is investigated in a pilot project for bulk apple sales to address the research question. This study proposes a four-stage data-driven optimal dynamic pricing strategy for bulk produce to reduce food waste for retailers in low and middle-income countries. A multi-stage dynamic programming method is used to decide on a pricing strategy for bulk produce, with real-time IoT sensor data being retrieved to analyse and determine the length of freshness scores. The effect of the sale price, replenishment amount, discount rate, and freshness score on profit and food waste are evaluated. All these analyses assist managers in taking the best possible actions and remedies. Appropriate interventions boost sales, increase profits by reducing waste and determining competitive sales price, while improving customer loyalty and satisfaction by striking the right balance between food quality and price. Our results show the huge potential of using hyperspectral imaging sensors in the FSC of a retailer. The model is demonstrated empirically to test its practicability.

Keywords: Dynamic pricing; Data analytics; Food supply chain; Waste management; Perishable products; IoT sensor

1. Introduction

Food Supply Chains (FSCs) are subjected to challenges such as climate change, natural resource scarcity, food insecurity, governance and organisation of the food system (FAO, 2019), population growth (Salehi-Amiri et al., 2022), food loss and food waste as well as food surplus (Papargyropoulou et al., 2014). The term "food loss and waste" (FLW) is commonly used to describe total losses and waste, which can occur from farm to fork within the different stages of the FSC; these include production, post-harvesting, processing, transportation and distribution, storage, retailer and consumption at household, hotel or restaurant (Parfitt et al., 2010; Vilarino et al., 2017). According to the Food and Agriculture Organization (FAO), FLW is defined as (FAO, 2011):

> "*Food loss is a decrease in mass (dry matter) or nutritional value (quality) of food that was originally intended for human consumption, whereas food waste refers to food appropriate for human consumption being discarded, whether or not after it is kept beyond its expiry date or left to spoil. Food wastage refers to any food lost by deterioration or waste. Thus, the term wastage encompasses both food loss and food waste*."

FAO estimates that nearly one-third of all food produced for human consumption worldwide is lost or wasted. In addition, fruits and vegetables have the highest wastage rates of any food products with nearly half of all fruit and vegetable production being wasted (Kayikci et al., 2019). Based on producer prices, the direct economic cost of food wastage of agricultural products (excluding fish and seafood) is roughly USD 750 billion, equivalent to Switzerland's GDP (FAO, 2013). Food loss significantly occurs in the early and middle stages of the FSC (close to the farm), whereas later stages of FSC mostly witness food waste at the retail and post-consumer stages (close to the fork) (Kayikci et al., 2019). This wastage mainly occurs due to lack of awareness and education among stakeholders across enterprises especially small-scale firms (Kayikci et al., 2019, Kayikci et al., 2021a). In this context, the circular economy has been suggested as an important pathway to reduce and manage food wastage among actors such as farmers, distributors and retailers in the food chain (Kusumowardani et al., 2022). Food waste is a global problem and causes difficulties in feeding the growing world population allied with inefficient use of scarce resources such as land, water, and energy. Food waste can be seen in almost all stages of a FSC, but the value-added loss is highest when consumers waste food i.e., household waste (Aktas et al., 2018). Food waste refers to unsaleable products that need to be disposed of or recycled in the retail sector (i.e., markets, groceries, bakeries, supermarkets) (Kayikci et al., 2021a). The retail stage may involve various sub-stages, including primary processing (cleaning, classification, pounding, grinding, packaging, soaking), secondary processing (mixing, cooking, frying, cutting), product evaluation (quality control), packaging (weighing, labelling, sealing), and marketing (publicity, selling, distribution). Perishable food waste at the retail stage occurs due to different reasons (Parfitt et al., 2010; Buisman et al., 2019) such as process losses, contamination in the process causing quality loss, inappropriate quality control, overstocking, inaccurate forecasting, product discarded/out-grades, improper packaging damage, grain spillage from sacks, rodent attack, damage during transport, poor infrastructure or consumer behaviour.

Some researchers (Li et al., 2021; Gustavo et al., 2021) propose several models for the FSC's retailer-level food waste problem based on data collection and digital solutions to reduce this waste. These studies present a great potential to provide food waste information and help companies to deal with surplus food (Martin-Rios et al., 2021). Knowledge hiding and lack of information-sharing among stakeholders (distributors, producers, consumers, retailers**,** suppliers and farmers) has also been highlighted as a significant area in reducing food wastage and improving overall performance within the perishable food (Kayikci et al., 2020).

Meeting customer expectations on the demand side of the FSC through the delivery of good quality products in the right quantities with an optimal cost is the primary objective for FSCs (Validi et al., 2014). Other groups of researchers focus on the theoretical framework to build sustainable FSCs. Martin-Rios et al. (2018) published a recent paper that addresses food waste from the innovation management perspective. The authors employ innovation management and social constructionism approaches to evaluate food waste solutions and innovations that merge strategic dimensions of waste management, such as incremental and radical innovations.

Hennchen (2019) applies practice theory to build a theoretical framework that helps address food waste in professional kitchen work. Messner et al. (2020) coined the term "Prevention Paradox", proposing a holistic framework to analyse food waste prevention. The authors investigated unsustainability issues in the food industry by focusing on food waste prevention and overproduction. As the volume of product flow grows and supply chain processes become more complex, the need for tracking and sensory technologies increases in FSCs. A huge amount of generated data related to distribution centres, transportation modes, retail stores, and storage conditions (e.g., temperatures) must be collected. Food companies use this data to make optimal decisions for performance improvement. (Li and Wang, 2017). Management of perishable food has a significant impact on supermarket revenues in today's competitive markets. While many retailers apply a price-cutting strategy as the products approach their expiration dates, some employ a single price strategy on fresh produce. In addition, dynamic pricing also has an impact on food waste. Notably, food waste at the retail stage of an FSC imposes a high cost on retail stores since the operating cost is usually high while the overall margins on food products are lower (Teller et al., 2018).

Retailers' pricing strategies manage food waste generation upstream of the FSC (Chen et al., 2019). Therefore, there is also a need to apply an optimal dynamic pricing strategy with real-time data monitoring at retailers. Data-driven innovation (DDI) technologies such as Internet of Things (IoT) make it easy for retailers and consumers to generate big data to monitor the precise freshness level of bulk produce (Kayikci et al., 2021a). Data-driven decision-making and big data techniques present a huge performance improvement for many businesses (Provost and Fawcett, 2013; Sorescu, 2017), including food producers. In addition, an IoT-driven pricing model realises a level of service (e.g., price level according to freshness) that aggregates data from several sources, including sensors, and mobile apps (Al-Turjman, 2017). Thus, retailers with IoT sensor data-driven pricing strategies can better monitor and manage the merchandising of perishable produce on the shelves and its remaining saleable life while reducing food waste (Kayikci et al., 2021a). In addition, an IoT sensor data-driven optimal dynamic pricing strategy can enable edge computing analytics, where data is generated in real-time and facilitate issuing work orders automatically to advanced ERP systems (Kayikci et al., 2021a; Kayikci et al., 2021b). Thus, regardless of central decision-making, stores can independently decide on the pricing of any product in terms of the freshness score. Therefore, this research aims to answer the following research question:

- RQ: What is the role of the data-driven optimal dynamic pricing strategy in reducing food waste at the retailer's end?

This study focuses on food waste at the retailer stage of FSCs. We present a dynamic pricing model that uses real-time IoT sensor data as a novel contribution to decide pricing at different stages of a sales season for retailers. The food waste problem at the retail stage of an FSC is investigated in a pilot project for bulk apple sales to address the research question. This research proposes a four-stage data-driven optimal dynamic pricing strategy using real-time IoT sensor data to reduce food waste in Turkey; this gives a perspective from a middle-income country. The novelty of this paper is to present a real-time IoT sensor data-driven optimal dynamic pricing strategy to decide pricing at different stages of a sales season at retailers in the perishable food supply chain. Both large and small companies have recognised the value associated with effectively utilising big data. Data-driven businesses have delivered 5-6% higher performance than similar organisations that do not utilise data-driven processes (Brownlow et al., 2015). Additionally, the practical applicability of the model is tested using a case study. The results are discussed with the company to check the rigour of the model.

The remainder of this paper is structured as follows. Section 2 provides a brief overview of the food waste challenge and the effect of data-driven dynamic pricing with the usage of IoT sensor devices on food waste. Section 3 presents the proposed methodology. Section 4 performs a numerical analysis to obtain quantitative results. Finally, the conclusions of this study are presented in Section 5, along with implications and future research opportunities.

2. Research background

2.1. Reduction of food waste at the retail stage

The reduction of food waste at the retail stage of the FSC has gained enormous attention from practitioners and academicians globally in the past decades. In a recent study conducted by Dora et al. (2021a), the root causes of food waste in low, middle and high-income economies are identified. In addition, their study has also proposed a conceptual framework along with strategies to contribute to sustainable food eco-systems. Some researchers have further focused on food waste at the retail stage. For instance, Aktas et al. (2018) study consumer-generated food waste and consumer food waste behaviour by using the theory of planned behaviour to incorporate contextual factors such as motives, financial attitudes, planning routines, food surplus, social relationships, and Ramadan. Eriksson et al. (2012) analyse the flow of fruit and vegetables at six Swedish retail stores using recorded data by taking, physical measurements then evaluating waste patterns to reduce retail food waste.

Wang and Li (2012) present a model to reduce food waste and maximise retail profit. Their model introduces a pricing strategy based on dynamically identified food shelf-life via tracking and tracing technologies such as a radio frequency identification device (RFID) and time-temperature indicators. La Scalia et al. (2016) study a predictive shelf-life model based on RFID technology that leads to better management of FSC. The food industry is becoming more customer-focused and now provides faster customer response time in today's competitive markets. Food traceability systems minimise the possibility of poor-quality food production and distribution, helping FSCs to improve customer service levels (Aung and Chang, 2014). As technological solutions carry FSCs to a new level, public awareness of food waste increases. According to Kumar et al. (2020), perishable food supply chains are characterised by rising food quality and safety concerns, alarming food wastages and losses plus poor economic sustainability. Information sharing and traceability technologies improve the efficiency of perishable food supply chain efficiency, leading to effective demand management and eliminating supply uncertainty. Kaur and Singh (2018) introduce a joint procurement and logistics model that simultaneously minimises procurement and carbon emission costs in a sustainable supply chain. Li and Wang (2017) investigate the potential benefits of sensor data-driven pricing decisions on chilled food chain management and quantitatively analyse the effects of dynamic pricing strategy to reduce food waste.

Eriksson et al. (2016) investigate the net effect of food waste reduction in Swedish supermarkets by reducing the storage temperature. Their findings suggest that a significant reduction of food waste can be achieved by decreasing storage temperature in many supermarket departments such as cheese, dairy, deli, and meat. Eriksson et al. (2017) examine the impact of food rejection practices such as take-back agreements (TBAs) on FSCs by focusing on different types of food chains such as bread, fresh fruit, vegetables, and milk. Their study aims to understand the impact of TBAs on FSCs and investigates whether these agreements contribute to food wastage by leading to a sub-optimal solution in FSCs. Buisman et al. (2019) investigate the effect of discounting and dynamic shelf life (DSL) on the replenishment policy of a retailer by developing a simulation-based model. The researchers conclude that applying DSL and discounting strategies reduces food waste in FSCs. Combining the two strategies is proved to be more effective than separate applications. Cuellar and Webber (2010) estimate the energy embedded in wasted food annually in the United States and conclude that wasted food represents nearly two percent of annual energy consumption. Huang et al. (2021) reported that retailers have an important role in a five-tier food waste framework. In retail food waste problems, retailers mainly focus on reducing food waste and avoiding food surplus at the customer end. Some of the important measures in retail food waste management that could be taken are repositioning, reallocating, reacting, re-engineering and relating.

Paam et al. (2016) present a comprehensive literature review on research papers aiming to minimise food loss (fruits and vegetables) in the agri-fresh food supply chain. The authors assert that food loss should be considered a priority dimension and that a profit increase will arise in developing an agri-fresh food supply chain. This must address many factors including population growth, climate change, and food safety. Annosi et al. (2021) conducted qualitative research to investigate the role of digitalization in a food supply chain context. Their findings highlighted the importance of collaboration in overcoming challenges associated with adoption of digitalization in the food value chain. Hermsdorf et al. (2017) investigate German food retailers' food waste reduction strategies by taking two practices into account - redistribution of non-marketable food items and lowering quality standards for fresh produce. Otrodi et al. (2019) study a joint pricing and lot-sizing problem for a perishable item to determine the lot-size quantity and selling prices in multiple demands. Li et al. (2021) investigated a single-cycle food chain with one supplier and one retailer to evaluate the festival food waste problem. They proposed an optimal production and pricing strategy; as a result, forward contracts were suggested for centralized and decentralized supply chains. Some of the parameters evaluated in their study are optimal strike price, wholesale price, retail price, food deterioration rate, demand risk, and relevant cost. Huge amounts of data are generated from the myriad of daily transactions. These large data streams are generated through information and communication technologies, including the internet, sensors, cameras, and healthcare devices. DDI refers to big data and analytics implemented to improve or introduce new products, services, processes and organisational methods. DDI is considered a new source of growth, offering the potential to increase productivity, resource efficiency, and economic competitiveness. The utilisation of DDI in business processes has already created value-added benefits as more firms adapt their processes to this way of working (OECD, 2015).

Businesses tend to invest in new models that create additional value by extracting, refining, and effectively utilising data (Brownlow et al., 2015). Since companies incur a cost to generate, compile, collect, secure and utilise data, these organisations make huge investments in data management. As these investments increase, many enterprises in various industries understand the importance of data-driven decisions and adjust their processes to use data to drive innovation (Hemerly, 2013).

Chien et al. (2016) propose a data-driven product design framework that integrates the decision elements of product forms and features to identify useful design concepts based on customer expectation. Jetzek et al. (2013) develop a conceptual model that explains how open government data can generate data-driven innovative solutions and how an enterprise creates economic and social value by adopting this mechanism. Kusiak (2009) proposes a data-driven approach that evaluates innovative products and services, selecting the most promising ventures for future markets.

In developing digital applications, it is also important to list food waste reduction approaches throughout the value chain. Some of them are specified as forecasting, waste analysis, redistribution, and measure catalogues (Strotmann et al., 2021). These approaches also help food service firms to manage food waste during crisis events. Big data analytics is used to forecast customer behaviour and determine pricing strategies in the retail industry. Big data can be characterised by three features; volume, velocity, and variety (Belarbi et al., 2016). The FSC is one of the first industries to embrace IoT and use this technology to track shipments in the distribution network. Monitoring and evaluating food quality and ensuring authenticity by integrating spectral cameras into the process have gained increasing attention in recent years. Blockchain is another emerging technology in FSCs to ensure food safety (Kayikci et al., 2021b; Kayikci et al., 2020). Furthermore, a great volume of social media data becomes a new source for consumer behaviour analysis and decision-making (Misra et al., 2020). With business intelligence tools, big data helps an organisation to make optimised decisions. Enterprises have to capture, filter, store, and analyse a huge volume of data to gain meaningful information. Filtering and analysing data is a complicated task; hence, business intelligence tools are necessary. Santoro et al. (2018) investigate the role of big data in transforming business practices and gaining a competitive edge for retail companies. Carolan (2018) investigates how food retailers benefit from big data and use data analytics techniques such as predictive analytics and artificial intelligence.

Verma et al. (2020) propose an intelligent retail mining tool that helps retailers to discover the buying pattern-based purchase history of customers and provide managerial implications leading to increased sales performance (Verma et al., 2020). Big data analytics and data-driven decision-making techniques impact an organisation’s performance, such as increased sales volume, reduced costs, and higher customer service levels (Ying et al., 2020). The next section discusses the use of DDI technologies on the pricing strategy of retailers within the context of food waste.

2.2. Effect of data-driven dynamic pricing strategy on food waste

Technology can enable greater transparency and traceability from farm to fork in FSCs. However, the adoption of technology especially artificial intelligence in food chain management, is not well established. Dora et al. (2021b) explored the key success factors to AI adoption in Indian food chains. They suggested a TOEH (Technology–Organisation–Environment–Human) framework. The use of food traceability systems can significantly improve supply chain visibility and accuracy of product shelf-life information of fresh foods. Real-time product quality and shelf-life information affect consumers' buying decisions. This information helps retailers update product pricing dynamically based on identified quality features; this helps to minimise food waste due to spoilage (Wang and Li, 2012).

Kappelman and Sinha (2021) studied a dynamic food chain problem. They formulated an integrated approach using big data mining methods to evaluate the quality level of the product. In their study, stochastic optimization techniques are employed to derive an optimal policy for the process for different actors, including retailers.

Food chains can be severely affected by disasters such as an earthquake, COVID-19 etc. (Kayikci et al., 2021b). In this context, it becomes more important to address the issues of food waste and design an optimal inventory policy. Ekren et al. (2021) proposed a lateral inventory share-based business concept to reduce food waste for online grocery stores, where e-grocery stores were connected through IoT in an Industry 4.0 context.

Data-driven tracking systems provide helpful information for stakeholders in the up-and downstream supply chain to make better decisions and create more revenue benefits. Therefore, many companies use IoT. These IoT devices are connected digitally via sensors, actuators or network communication technologies to interconnect supply chain parties (Sangeetha et al., 2020). Connecting physical objects helps streamline operations and information flow while enabling real-time monitoring. Most importantly, IoT devices collect and analyse data that gives users an insight into the processes employed and business operations. Several technologies can be operated with IoT sensors (e.g., light, humidity, temperature, and image). They can be used in the retail industry to monitor and predict the shelf-life of produce and reduce food waste. Table 1 lists the sensor types most used in the retail stage of an FSC. These sensors can differ in terms of capabilities and architecture. They can be utilised during retail phases to prevent food spoilage (i.e., biological and chemical contamination) and dumping.

Table 1 - Sensor types and technologies in the retail stage of FSC.

Sensor type	Determination	Source
Light sensors/colour sensors: RGB camera	Colour sensing or machine vision inspections; recording produce images	Holm (2005); Sangeetha et al. (2020)
Temperature sensors: near-infrared (NIR) spectrometry	quality inspection and temperature measurement, ripeness	Holm (2005); Sangeetha et al. (2020)
Electromagnetic sensors: X-Ray, microwave imaging	Foreign body detection on produce, measurement of an entire component of produce (i.e., measurement of water content)	Holm (2005); Sangeetha et al. (2020)
Biosensor: Electrochemical Ion sensitive field-effect transistor (ISFET)	Portable for ethylene detection	Sangeetha et al. (2020)
Ultrasonic sensors: ultrasonic cavity ring-down spectroscopy, Photoacoustic imaging: Photoacoustic spectroscopy	Ultrasonic sensing, quality inspection, freshness spotting	Sangeetha et al. (2020)
Optical sensor: biospeckle laser, hyperspectral imaging, terahertz imaging, chlorophyll fluorescence	Biological sensing detects the edible nature of fruits and vegetables to provide a better shelf-life. Freshness, continuous monitoring	Holm (2005); Sangeetha et al. (2020); Pieczywek et al. (2018)
Gas sensor: micro-gas chromatography, electronic nose (E-Nose)	Crop health and diseases, electronic sensing, freshness, ripeness, decaying	Sangeetha et al. (2020)

A freshness sensor senses and informs users regarding the status of a food item in terms of its quality (e.g., its freshness score) and safety standards. Increasing demand for fresh, high-quality, safe foods with longer shelf-life encouraged retailers to use freshness sensors in their grocery sections. Consumer interest in the ingredients and components of products, packing information and storage conditions increases the need for freshness sensors during food packing operations (Kuswandi, 2007). Both retailers and customers can monitor the quality of a fresh product through food sensors used in smart packaging. A time-temperature indicator is a smart label that shows the accumulated time-temperature history of a product, and is the simplest form of smart packaging. Food quality can be analysed using more sophisticated indicator sensors by monitoring different organic compounds such as ethanol, glucose, or gas molecules, and by measuring bacterial content, contamination, texture or colour degradation, and bruising (Pal and Kant, 2018). The sensors form different case technologies for detection of edible produce where a better shelf-life can be produced (Holm, 2005; Sangeetha et al., 2020). Monitoring the level of freshness can increase the availability of fresh, high quality and safe foods with a longer shelf-life. For instance, one of the optical sensors, hyperspectral imaging, has a better capability to access more information about freshness and demands higher storage requirements to monitor produce frequently (Sangeetha et al., 2020). Hyperspectral imaging is an emerging technology that can obtain optimal filters for a multispectral imaging system. These systems can analyse spectral data of various food products and the possible presence of contaminations (Mehl et al., 2004). Hyperspectral imaging technology can flawlessly identify early bruises and determine the degree of bruising of apples; this provides a new method for online, non-destructive detection and grading of early bruises in apples (Tan et al., 2018).

This study considers hyperspectral imaging, an emerging technology that integrates image information and spectral information to visualise and analyse the internal and external characteristics of objects. Hyperspectral imaging technology is widely used in the quality inspection of agricultural products, such as identifying hidden bruises on kiwi fruit, internal injury in almond nuts, common defects in jujube, and black spots in potatoes (Tan et al., 2018). Hyperspectral imaging has special cameras that see wavelengths (400-1000 nm) not visible to the human eye; it can detect molecular changes in produce, indicating its freshness score (freshness level) or whether it was previously frozen (Hagen, 2018). It can help determine how soon it takes to reach a store shelf-life before spoiling. Figure 1 illustrates the hyperspectral imaging for fresh food.

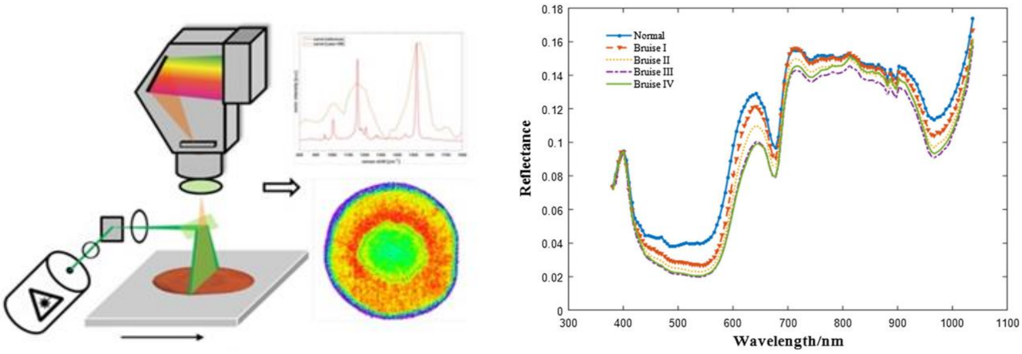


Figure 1 - Hyperspectral imaging for fresh food (Source: Gruber et al., 2018 and Tan et al., 2018)

After reviewing existing literature on FSCs and food waste, no research has been conducted to propose a pricing model that uses real-time IoT sensor data to apply dynamic pricing strategy and reduce food waste by retailers. In addition, there is a dearth of studies that employ real-time IoT data concerned with the shelf-life of fresh products in terms of outside factors such as temperature, humidity, contamination, bacterial content, etc. Furthermore, no papers analyse the shelf-life by considering the freshness score of produce under a multi-stage setting. This paper introduces a multi-stage dynamic programming method to decide on a dynamic pricing strategy for bulk production by integrating real-time sensor data to analyse and determine the length of the freshness stages in the model.

3. A Four-Stage Data-Driven Optimal Dynamic Pricing Strategy Model at the Retailer

In this study, a four-stage data-driven optimal dynamic pricing strategy model using hyperspectral imaging sensor data for freshness score is proposed to solve the food waste problem at retailers in Turkey. Because of the habitual consumption in Turkey, consumers mainly prefer to buy quantities of fresh foods in bulk. Therefore, packaged fresh foods are not routinely sold to consumers.

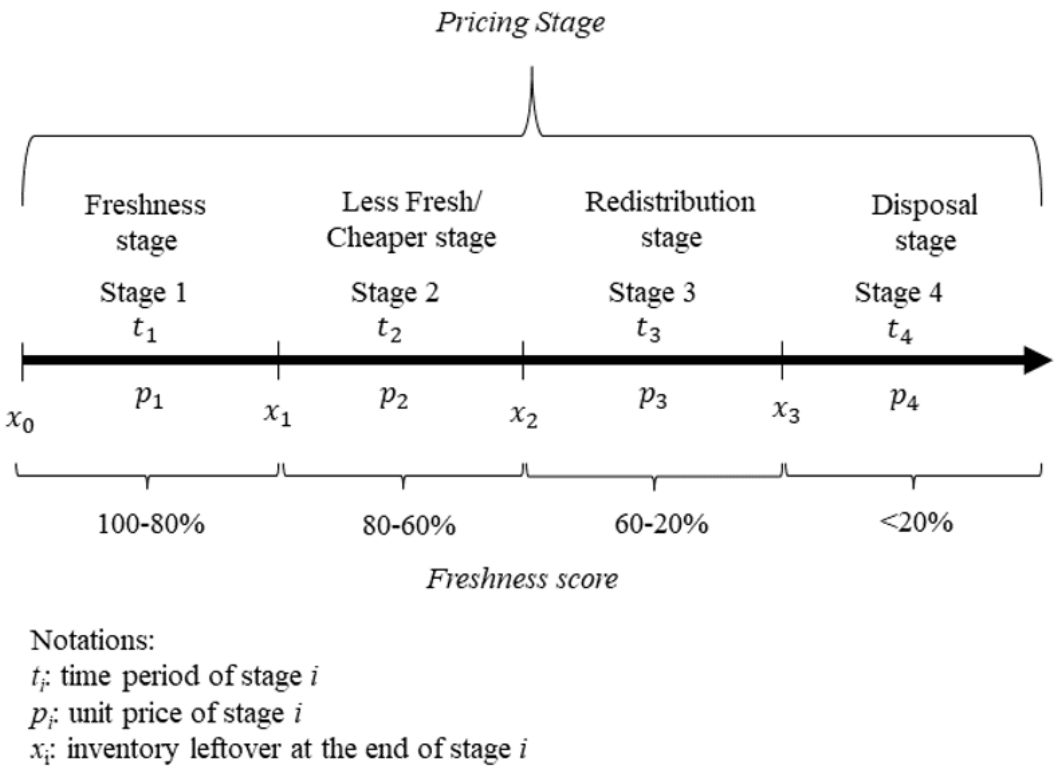


Figure 2 - Timeline and Freshness Scores of the Pricing Model at the Retailer

Stage 1 – Freshness Stage: We assume that the demand (D) for the product is based on the freshness score of the produce. In the multi-stage dynamic pricing model under study, the selling season starts with the replenishment of the produce (Stage 1). At this stage, the grocery receives a demand signal (D) based on the freshness score of produce and sets the initial selling price, p_1, under the unit purchase price c_0. During this and subsequent stages, which are not necessarily equal in length, the store can update the unit price of the product as it becomes necessary. We assume the length of each period depends on the rate of decay of the produce, with the grocery updating the unit price dynamically based on the freshness of the produce.

Stage 2 – Less Fresh/Cheaper Stage: As the product becomes less fresh, the grocery reduces the unit price to make it more appealing. At the beginning of Stage 2, the store updates the unit price based on the on-hand inventory since this is the last chance to sell the remaining produce in the store before the redistribution stage. During this stage, the produce is less fresh but still edible. Since only t_2 periods are left to the redistribution stage, the grocery is expected to set a unit selling price, $p_2 (p_2 < p_1)$ to deplete stocks. Since produce quality will be lower, and the grocery will incur an additional distribution cost in the next stage, the profit margin will diminish significantly. Hence, this stage is the last opportunity for the store to sell the remaining inventories with a relatively high margin.

Stage 3 – Redistribution Stage: Stage 3 marks the end of the sales of produce in the grocery due to the lack of required standards. From this point, the leftover produce needs to be redistributed by incurring an additional cost, namely redistribution cost, c_R. We assume the unit price at this stage, p_3, is relatively lower than previous stages, $c_0 \leq p_3 < p_2 < p_1$, since $p_3 = p_2 - c_R$.

Stage 4 – Disposal Stage: Finally, the remaining inventory is disposed of at Stage 4. The store incurs a unit disposal cost, $c_D (c_0 < c_D)$ if disposal is necessary. Thus, any leftover produce at the disposal stage (Stage 4) will be sold with a negative profit; the grocery will generate a net loss from this produce. Figure 2 summarises the timeline and stages of the model. The freshness score is considered in each stage, with the hyperspectral imaging sensors measuring this rate.

3.1. Problem Formulation

The multi-stage inventory model in this study is based on the model proposed by Demir (2017), where the author investigates a finite horizon multi-period inventory control problem of a cruise liner. A stochastic dynamic programming method is used to analyse a cruise liner's pricing strategy to maximise profit while eliminating food waste on the ship. The system updates the product's unit price at the beginning of every stage based on the remaining inventory throughout the selling period. This study has extended the model by adding the freshness score of a perishable product and dynamic pricing strategy and then analysed the model with simulation tests. We will use the following notations for the four-stage dynamic pricing problem:

<u>*Parameters*</u>

D: market (demand) signal

ξ_n: random variable representing the total demand for period n $(n > 0)$

t_n: total time for the n^{th} period of the selling season $(n > 0)$

$\varphi^{t_n}(\xi_n|D)$: probabilistic density function of demand over t_n given D $(n > 0)$

$\Phi^{t_n}(\xi_n|D)$: cumulative probability function for demand over t_n given D $(n > 0)$

x_n: inventory level at the end of stage n $(n > 0)$

x_0: Inventory level at the beginning of the selling season (The initial purchased inventory level; all bulk items are at the freshness stage)

x_1: Inventory leftover at the end of stage 1 (The level of unsold inventory at the beginning of Stage 2; all remaining items are at the less fresh stage – discounted products)

x_2: Inventory leftover at the end of stage 2 (The level of inventory items to be sent to redistribution due to the lack of quality standards – need to be consumed within hours)

x_3: Inventory leftover at the end of stage 3 (The level of remaining inventory that will be disposed of - spoiled, do not consume)

$\mu(D)$: expected demand rate per unit time in any period of given D

p_{i} : the price of the product at i^{th} stage

c_0: unit purchase price at stage 1

c_D: disposal cost

$f_{N-n}(x_n|D)$: expected cost over the remaining $N-n$ stages, starting with an initial inventory of x_n given D

N: total stage number of the selling period ($N > 0$)

n: current selling period ($0 \leq n \leq N$)

$Z_{N-n}\,(p_n; x_{n-1}|D)$: profit of the grocery at stage n, given the market signal and inventory leftovers at stage $n-1$

Assumptions

The following assumptions hold for the proposed model:

- No replenishment is possible during the selling season
- Shortage penalty in case of stock-outs is neglected
- The strategy under consideration is bulk purchasing

– Holding cost during/between stages is neglected

– Disposal cost, c_D, is assumed to be exogenous

– Redistribution cost is neglected

We write the recursive function starting from the last stage (Stage 4) and continue until Stage 1. In the end, starting from the last stage, the optimal policy for each stage can be determined one by one by using the backward induction method.

3.1.1. Stage 4 Problem (Disposal Stage)

This stage finalises the selling season; the remaining inventory at this period will be disposed of with a unit disposal penalty fee, c_D. Since, $c_D < c_0$, this stage generates a net loss of $c_0 - c_D$ for each unit of produce. The grocery intends to minimise the net loss in this period, which equals zero. No leftovers at this stage indicate that the food waste is zero. The optimal expected profit for the disposal stage can be written as:

$$f_0(x_3|D) = \max Z_0(c_D; x_3|D) \tag{1}$$

where

$$Z_0(c_D; x_3|D) = -c_D\, x_3 \tag{2}$$

This function is the total profit function for the last stage. Any unsold inventory during the redistribution stage is disposed of with an additional penalty cost. Hence any positive value of x_3 (e.g., $x_3 > 0$) generates a loss for the grocery. To exclude the unrelated cases, we make the following assumption in our model, $c_D > c_0$. The retailer keeps the inventory at the lowest level due to the zero-waste goal. The rest of the inventory can be sold to food waste producers with negative profit to turn food into a nutrient-rich animal feed and organic fertiliser, instead of disposing of waste via landfill or incineration. The disposal stage indicates that the product is unsuitable for human consumption and should be disposed of due to the low level of freshness. Typically, the freshness score is lower than 20% in this stage.

3.1.2. Stage 3 Problem (Redistribution Stage)

At this stage, there are only t_3 periods left to the disposal stage and given the inventory remaining at the end of the second stage and the market signal, optimal expected profit for the remaining period of time can be written as:

$$f_1(x_2|D) = \max_{p_3 \geq c_D} Z_1(p_3; x_2|D) \tag{3}$$

where

$$Z_1(p_3; x_2|D) = p_3 \int_0^{x_2 - x_3} \xi_3 \varphi^{t_3}(\xi_3|D) d\xi_3 \ + (-c_D\, x_3) \tag{4}$$

This function is the total profit function for any continuous demand distribution at the third stage. The first integral in (4) represents the portion of the profit function where the market signal (D) falls between 0 to $(x_2 - x_3)$ and the grocery charges a unit price of p_3. The second part of the function in (4) represents the expected profit (loss) function of Stage 4. If the total demand during t_3 is less than x_2, the grocery redistributes the leftovers with a relatively low unit price (p_3) compared to previous stages; the remaining inventory will be sent to the disposal stage. If the total demand during t_3 is greater than x_2, then the grocery experiences a shortage with no additional cost. We assume that the selling season is reached at the redistribution stage when the freshness score is less than 60%. At this stage, unsold produce will be distributed to discount markets within the retailing operation, and the monitoring process continues there. The sensors monitor the product freshness score to trace compliance with all determined standards at this stage.

3.1.3. Stage 2 Problem (Less Fresh / Cheaper Stage)

This stage marks the beginning of the first discounted stage (Stage 2) of the selling season. At this stage, the grocery breaks down the unit price to deplete stocks. The objective of this stage is to determine a selling price to maximise profit while selling as much as possible before the redistribution stage. The grocery needs to determine a unit price, p_2, to maximise the expected total profit through the end of Stage 3. The expected cost for the remaining period can be written as:

$$f_2(x_1|D) = \max_{p_2 \geq p_3} Z_2(p_2; x_1|D) \tag{5}$$

where

$$Z_2(p_2; x_1|D) = p_2 \int_0^{x_1 - x_2} \xi_2 \varphi^{t_2}(\xi_2|D) d\xi_2 + \int_0^{x_1 - x_2} f_1(x_1 - x_2 - \xi_2|D)\, \varphi^{t_2}(\xi_2|D) d\xi_2 \tag{6}$$

This function is the total profit function for any continuous demand distribution at the second stage. It is clear to see that in addition to the profit from sales, Stage 3's and Stage 4's expected profit functions are also included in the expected profit function of Stage 2. The first integral in (6) represents the portion of the profit function where the market signal (D) falls between 0 to $(x_1 - x_2)$ and the grocery charges a unit price of p_2. The second integral in (6) represents the expected cost function of the last two stages (Stage 3 and Stage 4) after expected customer demand is deducted from the on-hand inventory at the beginning of Stage 2. We assume that Stage 2 is characterised by a 60-80% freshness score for produce, meaning 60-80% of the produce is still fresh and edible.

3.1.4. Stage 1 Problem (Freshness Stage)

Since demand signal (D) is revealed at the beginning of this stage, we assume that the store orders an initial inventory level, (x_0), equal to cover the random demand throughout the selling period. The unit cost, p_1, at this stage is higher than all other stages since the shelf-life of the produce is still long enough to sell it. Hence, an optimal pricing strategy is to maximise the overall profit in this stage. Expected profit starting from Stage 1 through to the end of the time frame can be stated as:

$$f_3(x_0|D) = \max_{p_1 \geq p_2} Z_3(p_1; x_0|D) \tag{7}$$

where

$$Z_3(p_1; x_0|D) = p_1 \int_0^{x_0 - x_1} \xi_1 \varphi^{t_1} | d\xi_1 + \int_0^{x_0 - x_1} f_2\,(x_0 - x_1 - \xi_1|D) \varphi^{t_1}(\xi_1|D) d\xi_1 \tag{8}$$

This function is the total profit function for any continuous demand distribution at the first stage. In addition to the profit from sales, the profits from the next three stages are included in the function. The first integral in (8) represents the portion of the profit function where the market signal (D) falls between 0 to $(x_0 - x_1)$ and the grocery charges the highest unit price of the selling season, p_1. The second integral in (8) represents the expected cost function of the last three stages (Stage 2, Stage 3, and Stage 4) after the expected customer demand is deducted from the initial inventory at the beginning of Stage 1. We assume that Stage 1 is characterised by an 80-100% freshness score of the product which means the price will not be updated; and the product will be categorised in the freshness stage unless its freshness score is less than 80%.

3.2. Evaluation of streamlined data by using hyperspectral imaging sensors

- Instant real-time data analytics with edge control at stores to analyse the product and to determine the length of freshness scores
- Instant decisions, sensors collect data, instant data analytics performed by edge computing
- Hyperspectral imaging sensors are used to scan the bulks at stores to detect the real-time freshness of produce
- Rule setting according to freshness score of the produce (food freshness level): 100-80% represents freshness stage, 80-60% represents the less fresh but still saleable stage, 60-20% represents redistribution stage, < 20% is disposal stage.

3.3. Solution Approach

Figure 3 presents a flowchart illustrating the proposed four-stage optimal dynamic pricing strategy model with steps.

The first stage is the replenishment of the product conducted only once at the beginning of the sales period; no replenishment is allowed during this period. Demand is realised at Stage 1, and the grocery sets the selling price of the freshness stage. As soon as the selling season starts, hyperspectral imaging sensors continuously monitor the freshness of the products and reveal the freshness scores. Based on the defined freshness scores (100-80% freshness stage, 80-60% less fresh, 60-20% redistribution stage, <20% disposal stage), the system decides the length of each stage by updating the selling price. The selling process continues under different pricing strategies until the freshness score of the produce goes below 20%. The selling season ends after leftovers are disposed of with penalty cost.

The pseudo-code of our model is given in Appendix 1 based on optimal pricing strategy, in Appendix 2 based on the optimal initial replenishment amount and in Appendix 3 based on the optimal discount rates between stages.

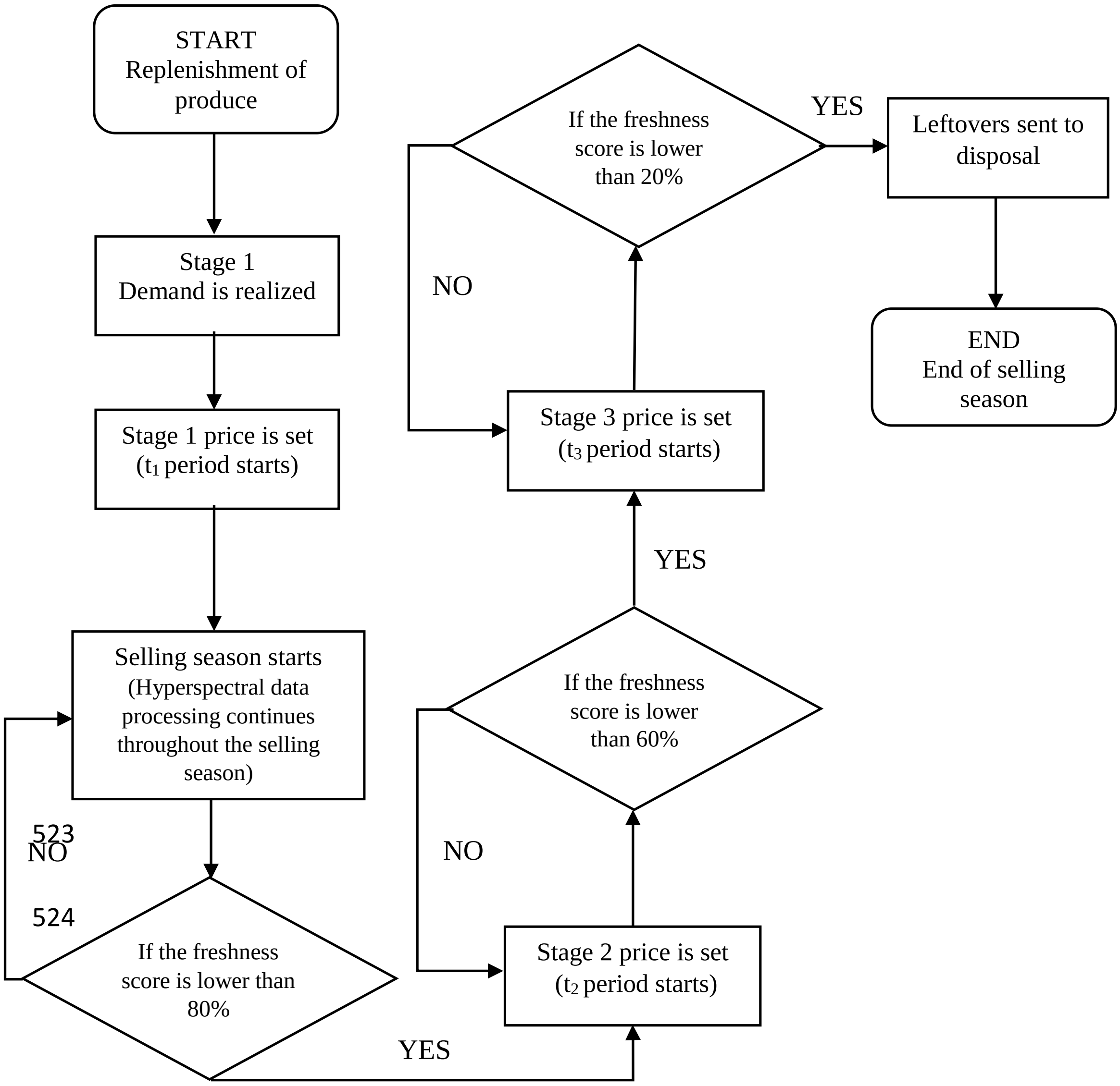


Figure 3 - Flowchart of the solution approach

4. Numerical Analysis

This study examines a grocery store that carries perishable produce whose shelf quality is continuously measured using hyperspectral imaging sensors. We simulate the sales process of this perishable produce where the price is being dynamically updated based on the quality condition of the product. Our goal in this simulation study is to meet customer quality and price requirements while minimising food waste (disposal of produce) and increasing the retailer's profit. The quality loss of a perishable item occurs naturally, and eventually becomes unacceptable to customers as it stays on the shelves. Computational logistics applications such as hyperspectral imaging sensors can help grocery stores to reduce food waste and increase profit by continuously inspecting food quality and sending signals to a computer that updates the unit price based on the freshness score and the remaining quantity of the product. To simulate the operations of a grocery chain, we generate real-time IoT sensor data and use this data in our simulation. We use the random function of Python with Gaussian distribution to simulate the real-life application (Pseudo-random numbers, 2021). The number of daily customers is regenerated based on the parameters given in Table 2. For each customer, individual demand, preference priority (price vs quality), perception of the product value, and quality preference are generated. The simulation covers 30-days of a sales period. The algorithm dynamically adjusts the selling price based on the product quality and on-hand inventory with the objective of minimising food waste while maximising profit.

Table 2 – Used Simulation Event Parameters

Simulation Event	Distribution Parameters
Customer Arrivals (person)	N ~ (30,4)
Each Individual's Demand (kg)	N ~ (5,2)
Customer Price Expectation	N ~ (120,5)
Quality Decay Rate (%)	Real-time hyperspectral imaging sensors data

4.1 Scenario-based and Parameter Effect Analysis

This section provides numerical examples for a grocery store's real-time IoT sensor data-driven four-stage optimal dynamic pricing strategy to solve the inventory control problem. Simulation experiments are performed to analyse the effect of the sales price (p_{i}), initial replenishment amount (x_0) and discount rate (d_{i}) on profit and food waste. Our goal is to find the optimal sales price, initial amount to purchase and discount rate that maximise profit while minimising food waste under the different scenarios with the parameters given in Table 3. Simulation runs imitate the 30-day operation of a grocery store where customer arrivals, each customer's demand and price expectations are distributed with a normal distribution whose parameters are given in Table 2. In the early sales period, it is challenging to identify any damage with the naked eye; however, hyperspectral imaging sensors can detect the decay rate.

Table 3 – Analysed and Target Simulation Parameters

Analysed Parameter	Target Parameters Estimated
Sales prices (p_i)	Profit (Z) Food waste (x_3)
Initial amount (x_0)	
Discount rate (d_i)	

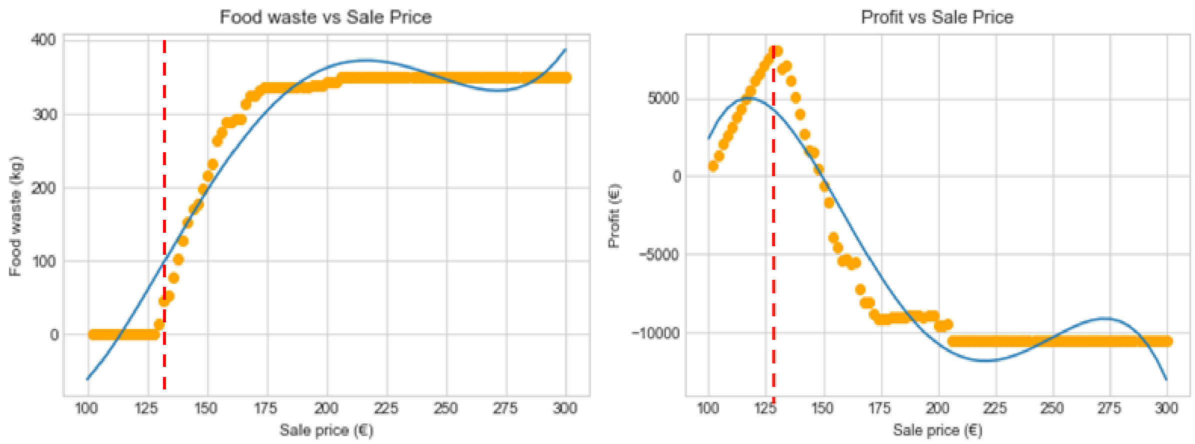
4.1.1. Effect of Sale Price on Profit and Food Waste

In this subsection, we conduct experiments to identify the effects of the sales price on profit and food waste while keeping other parameters constant. Our purpose is to analyse the effect of the initial sales price (p_i) on the grocery's profit and the amount of wasted food at the end of the selling season under different scenarios. The graphics in Figure 4 are obtained from the simulation. Figure 4a depicts the effect of the sales price on food waste, while Figure 4b illustrates the effect of the sales price on profit. The sales price is determined at the beginning of the first sales stage. We assume that the initial price is 120 of the unit cost and it is updated based on the freshness score of the produce given in the ruleset. We obtained an optimal initial price point based on our simulation results that maximise profit while minimising food waste. The dashed lines in Figures 4a and Figure 4b show the retailer's minimum waste and maximum profit, respectively. The point ($p_\mathrm{i} = 130$) shows the first stage selling price of the produce decreased by the discount rate at the beginning of each stage. This discount rate is applied when the freshness score of the produce goes below-assumed limits defined in the ruleset. The dashed lines in both figures overlap at the point at which profit is maximised and waste is minimised. The grocery manager should set the initial selling price to meet both objectives.

4.1.2. Effect of Replenishment Amount on Profit and Food Waste

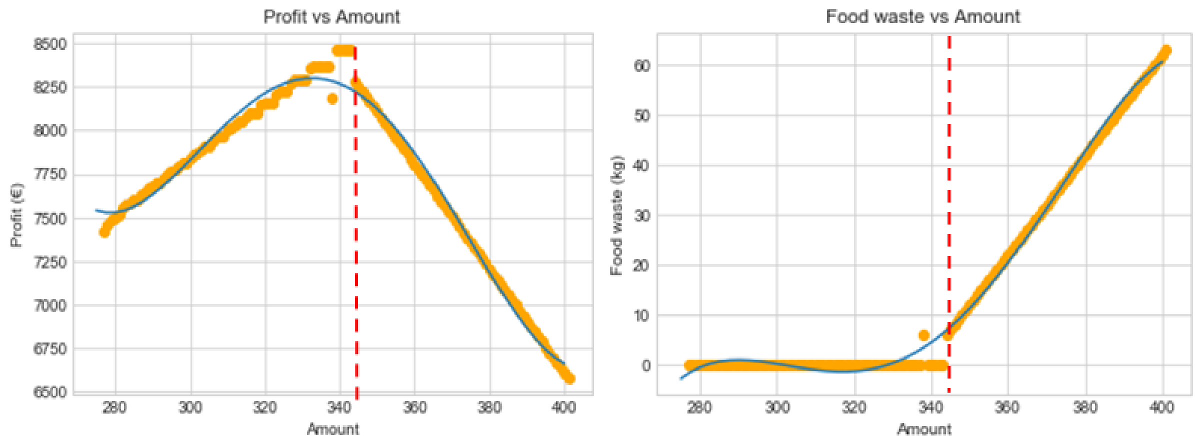
Replenishment is one of the most important operational parts of FSCs due to its ability to balance availability and food waste. In our model, replenishment is allowed only at the beginning of the sales season; the grocery is not able to replenish produce during the sales period. If the initial replenishment quantity is not high enough, the risk of stock-out may occur, resulting in customer dissatisfaction. On the other side, an excessive order quantity may result in the disposal of produce at the end of the sales period due to the loss in quality.

Here, we analyse the effect of the initial replenishment amount on profit and food waste. We conduct experiments to test profit and food waste based on the on-hand inventory under different customer arrivals, demands and purchasing habits. Figures 5a and Figure 5b illustrate the simulation results based on a grocery's selling season scenarios during a 30-day period. We prove that there is an optimal replenishment quantity that maximises profit. The grocery achieves maximum profit with zero food waste in this run, when 345 kg of apples are purchased at the beginning of the selling season. After this point, for each additional purchase, the grocery lowers its profit due to the unsold products that are disposed of at the end of the selling season.



(a) *(b)*

Figure 4 - The effect of the sale price on food waste profit



(a) *(b)*

Figure 5 - The effect of initial replenishment on food waste and profit

4.1.3. Effect of Discount Rate on Profit and Food Waste

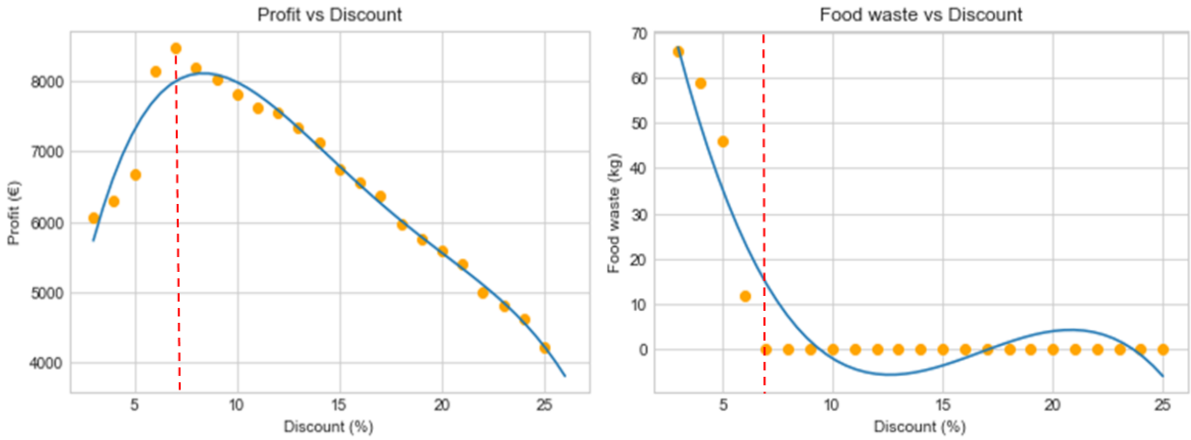
The retailer can balance the inventory on-hand and the turnover rate by applying variable discount rates during the selling season. Product price is one of the most prominent factors together with quality, for customers. During the selling season, retailers might need to update product pricing in the right manner to fulfil customer needs, recover investment for the next sales season, and generate revenue. A prudent discount price is an important factor for the retailer to fight possible food waste. An effective pricing strategy leads to depleting on-hand inventory before perishable products reach their best-before date. As the selling season continues, retailers might need to lower product prices based on their on-hand quantity and freshness score. Selling produce with a quality loss at a discounted price can help to reduce food waste. Any price reduction must be aligned with the product and its defects.

Here, the effects of the discount rate on the retailer's profit and food waste are investigated through the 30-days of the selling period. Figures 6a and Figure 6b show the effects of different discount rates on profit and food waste, respectively. As seen in Figure 6a, the discount rate increases the retailer's profit due to its direct effect on sales. When the retailer sells the product at a discounted price, revenue increases because the price becomes lower than the customers' expectation and encourages them to purchase in large quantities. At the same time, food waste diminishes, as shown in Figure 6b. In our example, a 7% discount rate maximises the retailer's profit and reduces food waste to zero. After this point, the retailer's profit margin declines, and food waste remains at zero. Hence, there is no advantage for the retailer to provide more than 7% discount in this example because any bigger discount reduces profit.

4.1.4. Effect of Freshness Score on Profit and Inventory Level

In this subsection, we examine the whole selling period to see the effect of the freshness score of produce on the retailer's profit and inventory level. Our purpose in this analysis is to understand how freshness score affects profit and inventory level. As expected, the inventory level decreases while the profit accumulates as product sales continue throughout the selling season.

Figure 7 shows four freshness scores of the selling season, each characterised by different freshness scores measured and reported by hyperspectral imaging sensors. At each transition between stages, the grocery updates the produce's unit price, aiming to achieve maximum profit and no food waste at the end of the selling season. Each price update changes the profit and food waste amount since price affects customer buying decisions. Sales depend on the price and quality expectations of the customer in our simulation. The results show that price breaks accelerate sales while product deterioration does the opposite. The retailer aims to reach zero inventory before the sales period ends (redistribution stage) while keeping food waste low at a marginal cost.



(a) *(b)*

Figure 6 - The effect of discount rate on food waste and profit

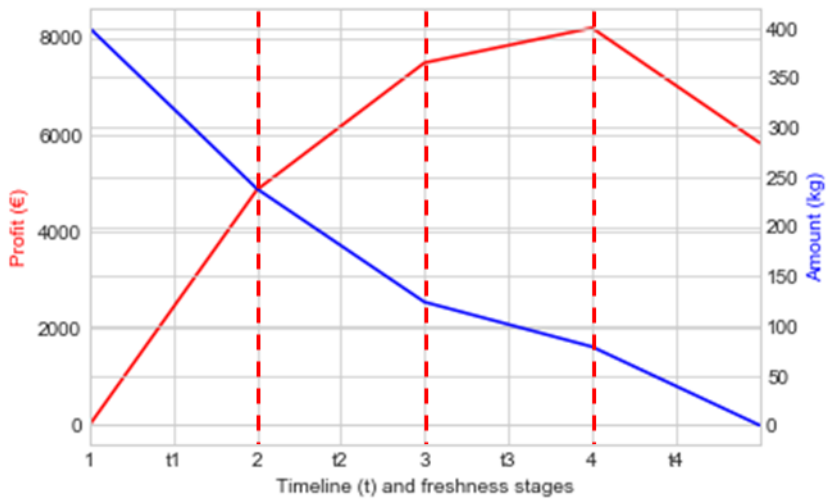


Figure 7 – Profit and amount distribution according to freshness scores

5. Conclusions

High market prices may result in food surplus that needs to be redistributed or disposed of, while low market prices mean a lower profit margin. Hence optimal pricing strategy will help retailers maximise profit while avoiding food waste. The novelty of this paper is to present a real-time IoT sensor data-driven optimal dynamic pricing strategy to decide pricing at different stages of a sales season at the retail stage in the perishable food supply chain. Dynamic pricing strategy in which the unit price of produce is continuously updated in response to the real-time data of the produce shelf-life (i.e., state of freshness or decay), is an effective way for retailers to make quick decisions regarding the inventory on-hand. Machine vision sensor systems such as hyperspectral imaging devices can perform quality inspection of perishable produce and transmit real-time information via sensor systems.

Sensors generate large amounts of data to be used for decision-making. This information can instantly update product pricing based on the remaining quantity and shelf-life of produce. Our model is built on a four-stage selling period where the length of each stage is determined based on real-time information about the freshness score of bulk produce. The hyperspectral imaging sensors determine the freshness state of the produce on the shelves. A numeric example given in this paper shows the practicability of the proposed pricing strategy.

5.1 Theoretical implications of the research

This research has the following theoretical research implications

1. Food waste can occur in different stages of an FSC, such as production, processing, transportation, distribution, marketing, and consumption; its economic consequences affect both retailers and consumers. This research draws up an agenda to address the issue of food waste at the retailer end in the value chain context.
2. Considering the economic impacts of food waste, setting an optimal pricing strategy is important. An appropriate pricing strategy would also contribute to reduced inventory and surplus food in a dynamic world. This research contributes to the literature of food waste by discussing a dynamic pricing model from a retailer’s perspective.
3. This research uses real-time IoT sensor data to decide pricing at different stages of a sales season of a retailer. Real-time IoT sensor data is retrieved to analyse and determine the length of freshness scores of the product. The effect of the sale price, replenishment amount, discount rate, and freshness score on profit and food waste are studied as a contribution to the literature. Finally, considering the use of the data-driven concept in this domain, the research also contributes to the literature of digitalized food supply chain initiatives.

5.2 Managerial implications of the research

The managerial implications of this study lie in explaining those situations where scenario-based and parameter effects analysing the proposed model can make maximum profits and the minimum waste. Our proposed model can be used for data-driven decision-making in the retail stage of FSCs. The effect of the sale price, replenishment amount, discount rate, and freshness score on profit and food waste can be evaluated. All these analyses assist managers in taking the important actions and remedies that boost sales, increase profits by reducing waste and determine the most effective sales prices; customer loyalty and satisfaction can be enhanced by striking the right balance between food quality and price. IoT and hyperspectral imaging technology to monitor food safety and quality is a relatively new trend in FSCs. Our results show the great potential of using hyperspectral imaging sensors in the retailer end of an FSC. Climate change, pandemics and regional conflicts have caused global food crises in recent years. Therefore, food waste prevention becomes an important issue for all FSCs. Integrating new generation technologies into the FSC plays a prominent role in preventing future food crises.

5.3 Limitations and future works

This study can be further extended by including lot-sizing constraints into the model. Moving from bulk purchasing to a small lot will reduce food waste by urging consumers to buy only what and how much they need. In addition, packaging fresh foods can prevent customers from touching the products directly. In this sense, the real-time IoT sensor data might be integrated into the inventory system to forecast consumer demand and buying behaviour. Various sensor technologies (e.g., temperature, sensors, and ultrasonic sensors) can be added to a future model to monitor food freshness. These sensor technologies can monitor the use of chemicals and CO_2 emissions on food packaging to meet the demand for safe and high-quality food. Besides, “no-touch” fresh food packaging might be necessary for human health and safety hazards to prevent recent pandemics such as COVID-19 by reducing the infection risk. Lastly, we could also investigate food waste issues at the retailer end from the perspective of a circular economy.

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Appendix 1 – The pseudo-code of the proposed model based on the optimal pricing strategy

1. Procedure OptimalSalesPrice ($\Delta_{\mathrm{p}}, p_0, x_0, d_{\mathrm{i}}$)
2. **for** $p_{\mathrm{i}} \in \{1, \ldots, \Delta_{\mathrm{p}}\}$ **do**
3.   **for** $indexDay \in \{1, \ldots, number\ of\ days\}$ **do**
4.   Set CustomersList for $indexDay$
5.   Set q_{i} for $indexDay$
6.   Set p_{i} for $indexDay$ using q_{i} and d_{i}
7.   **if** $remainingAmount \geq 0$ **then**
8.   **for** $indexCustomer \in$ {1, …, CustomersList} **do**
9.   **if** $indexCustomer.price \leq p_{\mathrm{i}}$ **and** $indexCustomer.quality \geq q_{\mathrm{i}}$ **then**
10. $remainingAmount \leftarrow x_0 - indexCustomer.x$
11. $profit \longleftarrow p_{\mathrm{i}} - p_0$
12.   **end if**
13.   **end for**
14.   **end if**
15.   **end for**
16.   **if** $remainingAmount \geq 0$ **then**
17. $loss \leftarrow remainingAmount \times$ disposal cost c_D
18.   **end if**
19. $profit_{\mathrm{i}} \leftarrow profit - loss$
20. **end for**
21. $p_{\mathrm{optimal}} \leftarrow \max(profit_1, profit_2, \ldots, profit_{\mathrm{i}})$
22. return p_{optimal}

Appendix 2 – The pseudo-code of the proposed model based on initial replenishment amount

1. Procedure OptimalInitialProductAmount ($\Delta_{\mathrm{x}}, p, p_0, d_{\mathrm{i}}$)
2. **for** $x_{\mathrm{i}} \in \{1, \ldots, \Delta_{\mathrm{x}}\}$ **do**
3.   **for** $indexDay \in \{1, \ldots, number\ of\ days\}$ **do**
4.   Set CustomersList for $indexDay$
5.   Set q_{i} for $indexDay$
6.   Set p for $indexDay$ using q_{i} and d_{i}
7.   **if** $remainingAmount \geq 0$ **then**
8.   **for** $indexCustomer \in$ {1, …, CustomersList} **do**
9.   **if** $indexCustomer.price \leq \mathrm{p}$ **and** $indexCustomer.quality \geq q_{\mathrm{i}}$ **then**
10. $remainingAmount \leftarrow x_0 - indexCustomer.x$
11. $profit \longleftarrow \mathrm{p} - p_0$
12.   **end if**
13.   **end for**
14.   **end if**
15.   **end for**
16.   **if** $remainingAmount \geq 0$ **then**
17. $loss \leftarrow remainingAmount \times$ disposal cost c_D
18.   **end if**
19. $profit_{\mathrm{i}} \leftarrow profit - loss$

```
20. end for
21. x_optimal ← max(profit_1, profit_2, … , profit_i )
22. return x_optimal
```

Appendix 3 – The pseudo code of proposed model based on optimal discount strategy

```
1.  Procedure OptimalDiscountRate (Δ_d, x_0, p, p_0)
2.  for d_i ∈ {1, … , Δ_d} do
3.    for indexDay ∈ {1, … , number of days} do
4.      Set CustomersList for indexDay
5.      Set q_i for indexDay
6.      Set p for indexDay using q_i and d_i
7.      if remainingAmount ≥ 0 then
8.        for indexCustomer ∈ {1, …, CustomersList} do
9.          if indexCustomer.price ≤ p and indexCustomer.quality ≥ q_i then
10.           remainingAmount ← x_0 − indexCustomer.x
11.           profit ⟵ p − p_0
12.         end if
13.       end for
14.     end if
15.   end for
16.   if remainingAmount ≥ 0 then
17.       loss ← remainingAmount × disposal cost c_D
18.   end if
19.   profit_i ← profit − loss
20. end for
21. d_optimal ← max(profit_1, profit_2, … , profit_i )
22. return d_optimal
```

Respond Sheet

Dear Editor,

Thank you for giving us an opportunity to revise our manuscript. We are grateful to the reviewers, both for their positive comments to improve the quality of our manuscript. We have addressed all the comments raised by the reviewers. As suggested by the reviewer we have proofread the manuscript carefully and corrected grammatical errors.

We hope that the revised version of the manuscript meets the review requirements appropriately.

Sincerely,
-Autors