Romeo van Adrichem

Increasing the efficiency of the flower inventory management using RFID technology and optimal control

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by

Romeo van Adrichem

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Thesis Committee:	Prof. Dr. R. Negenborn- TU Delft committee Chair, Faculty
	Dr. Ir. Y. Pang- TU Delft committee Member, Faculty
	Ir. A. Pelser - Company Supervisor
	Ir. W. Romijn - Company Supervisor
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Preface

This report has been written to obtain the master's degree in Mechanical Engineering at the Delft University of Technology with a specialization in Multi Machine Engineering. In this report, I present the insight of improvements of efficiency for inventory management of the flower industry. I was engaged in writing this report from March 2021 till November 2021. This report is the final version of my graduation project.

I would like to express my gratitude to my TU supervisor Dr. Ir. Yusong Pang for mentoring me through this project, and to Prof. Dr. Rudy Negenborn for helping me with insights into the academic world. I am also grateful for the supervision of Ir. Anouk Pelser and Ir. Walter Romijn, who helped me by coaching me through the project day by day. Furthermore, I also want to thank Duco Schaefer for his help and previous work that has benefited my project. Next to that, I would also like to thank the companies Mieloo & Alexander and DRF for giving me excess to their resources and facilities, and especially Sander Merkx and Rob Sliedrecht from Mieloo & Alexander for involving me as much as possible at the company.

Finally, I also want to thank my parents, brother, and friends who helped and supported me during my time at the Delft University of Technology.

Romeo van Adrichem Rotterdam, November 2021

Summary

Flowers are a delicate product. They have a very short time for which they have the most sales value. The supply chain of flowers is focused on speed. The post-harvest life of flowers is usually around 9 days. The Netherlands is traditionally a central point between supply and demand of the flowers due to growers and auctions. The supply to external partners in other countries can therefore take several days, leaving fewer days of actual shelf life. This short shelf life leads to difficulties in inventory management. Overstocking can occur (too many flowers are ordered/ replenished). If these flowers are not sold before expiration, they have to be disposed of. However, from a business standpoint, it is of similar importance that there are also not too few flowers replenished (understocking). If this happens, not all demand can be met, sales are missed, and the shelves become empty. The key performance indicators (KPI) of inventory management are disposals for overstocking and out-of-stock (OoS) occasions for understocking. This trade-off in risking over- vs. understocking is relevant for all products, however with the short shelf life and not always daily delivery it is even more important to be efficient.

The goal of this thesis is to make the inventory management of flowers more efficient. The focus for this research within the supply chain of flowers is shown in figure 1. The assumption is made that the auction always has sufficient fresh stock available at the auction
The inefficiency in inventory management can be split up into two main parts: correct inventory information and reactive replenishment. If there is incorrect or delayed information about what is in stock, there is more uncertainty about which amount to replenish. To avoid empty stock, a higher level of inventory should be present. However, with the same demand, this will directly lead to more disposals over a longer period of time. Furthermore, the reactive nature of the replenishment strategy means that the new orders are based on what is earlier sold or disposed to maintain a certain level of sufficient inventory. When approaching from expected sales perspective, it can have a beneficial effect that not always the same level is maintained but only a buffer level. In situations with a high and low season this can have beneficial effects.

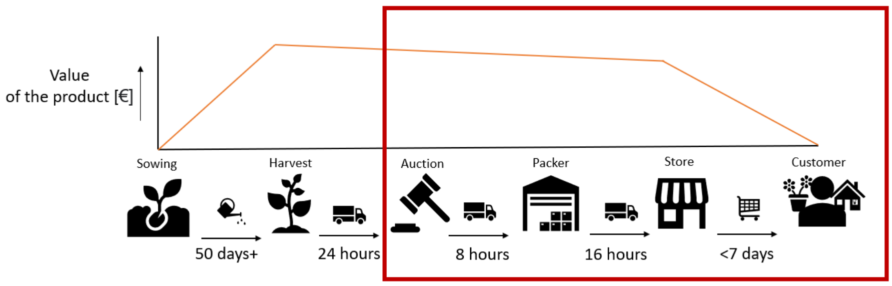

Figure 1: Schematic overview of the supply chain of flowers, with the focus part of this research indicated with the red rectangle

The inventory information can be improved by implementing a radio frequency identification (RFID) technology-based inventory system. This system should be able to measure the inventory without the requirement of manual registration. Over long distances (± 4 meters) passive RFID tags can be read and registered by just being in the scanned area. However, the packing or moist in buckets or the flowers themselves may cause shielding. The water or other material may stop the radio frequency waves that power the tag or are used for reading. After extensive testing it turned out possible for an overhead system that in a store environment with large amounts of flowers can be automatically registered with a performance of 98% in 60 minutes.

Furthermore, different strategies are considered for better replenishment.

- Demand Stock Replenishment (DSR)- The foundation of this replenishment strategy is a standard inventory that works as a buffer for sales. The system works that under normal circumstances the products will not be sold out until the next replenishment moment. However, since the product is perishable and the space is limited there is a limit to this. Every product that is expired or sold a certain day is ordered and will arrive in the store after the lead time.
- Expiration anticipation- This strategy acts similar to DSR strategy, except for one key difference. It does not only replenish what is sold or disposed of, but also looks ahead of how many products are on the verge of expiring. It anticipates already the possibility of partly disposal of these products by ordering a percentage of the remaining ones already.
- Predictive Inventory Replenishment Model (PIRM)- This strategy is based on optimal control that tries to predict what will be demanded. Here a prediction is made concerning predicted demand, taking into account incoming orders, lead time, and expiration for how the inventory will change over time. From this information an optimal order is made. The parameters to emphasize either preventing OoS or disposals can be tweaked to decide how the trade-off will be made, what risks are avoided.

Experiments with simulations were executed to compare the DSR strategy for situations with and without up-to-date information. Then other strategies with good information are simulated to see how they can improve the KPI even more. The scenarios that are simulated are either one single normal distribution with constant mean and large deviation, or a situation with a high and low season, so multiple normal distributions with smaller deviations.

If the demand is distributed in certain ranges and follows seasonal trends, adding good information to the current replenishment strategy has the largest impact. Anticipation of expiration might be a solution if the importance of avoiding OoS, but only if there is a maximum on the largest order. PIRM does not show any improvements if the demand is variable. For the situation with seasonal demand, the better information works even better compared with the current situation. Anticipation of expiration leads only to more disposals in this situation. However, using optimal control with good information can reduce disposals even better if the deviation of demand is not too large and the ratio between high and low season becomes larger.

Contents

List of Figures

Chapter 1

Introduction

Flowers are a delicate matter when it concerns the continuity of the product. As cut flowers only last about nine days after havest, there is no such thing as keeping them in stock, as their value is almost instantly gone compared with regular retail products. In uncertain times, luxury products tend to be avoided, as the previous health crisis demonstrated. When the Covid-19 pandemic started, all not necessary events were cancelled [1]. With weddings postponed, festivals cancelled, and funerals in modest sizes, the demand for flowers dropped. Some luxury markets like fashion or perfumes, can keep in store and relocate resources more easily because these products do not expire within months. It is also possible to improve on webshops and therefore online sales for seasonal products. On the other side was the flower market, which took large hits due to the short life cycle. New York Times reported that 140 million Dutch tulips were disposed of in the spring of 2020 [2]. The EU cut flower market lost €1bn in just the first six weeks of the lockdown. This affected the global supply chain of the flowers. Kenya lost 85% of its flower exports and two million households were affected financially [3]. There is of course to be taken into account that a pandemic impacts everyone, and it is near impossible to provide a robust supply chain system that prepares for situations like this. However, the losses in this market are exemplary for how fragile the product is, how the demand can be erratic and how careful this market should be approached for making large changes. Furthermore, flowers in the current supply chain have a large environmental impact, with the cooled environment and flight transport,[4] so every flower overproduced is a form of waste. To make the supply chain of the flower industry more efficient is to contribute to its sustainability. As said by Sylvie Mamias, secretary-general of Union Fleurs (n continental umbrella organisation for stakeholders active in the floricultural trade): "There have been lessons learned and I think it will make us more sustainable and resilient in the long run[3]."

1.1 Research problem

Just like every other product, it is a waste of resources to deliver flowers which will be thrown away eventually before being purchased/ used. Especially in the category of short shelf-life products where the expiration date is only several days or weeks ahead. Supplying a large quantity at the wrong time will lead to products staying on the shelves for too long and going beyond expiration before a customer can get hold of them. How shorter the shelf-life, the more delicate replenishment should be executed. Otherwise the result is large losses of resources. However, from a business perspective it is of similar importance that there is always stock available to avoid missed sales and for branding purposes, there is a certain availability guarantee [5]. With short shelf-life products such as flowers, the extra problem occurring is that overstocking will lead to unavailability due to products being thrashed and moved from the shelves. The rest of this section covers the problems that occur in Flower Retail, and how they relate to each other.

Uncertainty about inventory levels due to delayed information

Correct information of which stock is available in store is crucial for the performance of a company that acts in a fast market like the flower industry. Independent of the replenishment strategy, to know what is still present for sale, to anticipate any significant changes in demand. More uncertainty leads to bigger risks being taken to secure serving all demand. It is therefore for the sake of efficiency that the inventory should be known in real-time [6].

Lack of efficiency in replenishment strategies

From a business perspective, a company wants to have sufficient products available to the customer at any time. Simultaneously, if there are more flowers available than sold within the expiration time these unsold flowers are disposed of. This overproduction is a waste of resources, as the value of the flowers is reduced to zero after only several days in the store. Finding the balance between having a certain availability and limiting the amount of thrashed flowers can be done more efficiently [7].

1.2 Objective

This research is aiming to make the supply chain of the flower industry more efficient. There is a relation between the two problems of the previous section, as the uncertainty of inventory complicates replenishment strategies anyhow. Therefore solving these will lead to a reduction of waste in the process.
During this process of solving the efficiency problems, the research gaps in this field should be filled. Currently, there is little material available on how auto-ID technology in combination with predictive replenishment improves the efficiency in inventory management for short shelf-life products. Especially one that does not require human assistance and can be placed as overhead construction. Moreover, the effects of inventory management efficiency for this type of products and supply chain has little research done as well. The link between these gaps is that with better information all the strategies should generate better research by reducing uncertainty.

1.3 Scope

To keep the research comprehensible and within the desired time range, the scope is narrowed down to two parts. First of all the focus of efficiency is on one type of flower product, and the lessons learned for this inventory management can be used for similar products. Next, the better information system cannot be designed for all situations but is scoped down to relevant environments.

1.3.1 Inventory management of rose bouquets

The focus for this research will be only on one type of short shelf-life product in one single store. This way the output of the research can be the advised strategy for replenishment of that specific product for that specific store. However, this strategy should also work on other products with other shelf-life and in other stores. The selected flower products are bouquets of roses. Other bouquets or products with short shelf-life are assembled with flowers from different suppliers, all with slightly different shelf-life. In those instances of mixed bouquets could be looked at the flower with the shortest shelf-life. However, as supply is not always constant, any assumption with availability of mixed bouquets becomes less valid. Also, as roses are a type of flowers that symbolise love, they are in demand over the entire year and less of only extreme seasonal popularity [8].

1.3.2 Store environments

The inventory insight will only be applicable for flowers in store environments. This will be the most common location the inventory is relevant to know in the process. In larger quantities or in other situations testing is not feasible within the time of the graduation project. The most relevant information is in store environments, for other places in the supply chain other solutions may be developed later and can use lessons from this research.

1.4 Approach

This research will provide a framework for more efficient inventory management, especially for products with short shelf-life. It covers the physical inventory system description, with digital structure, and decision logic, as well as suited replenishment strategy. A case study will be used to give concrete examples of the problems that occur. By solving this narrow down situation of the lack of efficiency with this specific example, it can imply which improvements are possible and how much they improve for the overall industry. Then, simulations are made to compare the current situation with new, improved situations. The outcome of this research should therefore be a solution for inventory tracking with quantified performance, combined with a new replenishment strategy and measured improvement.

1.5 Research questions

The main research question is: **How can the inventory management of flowers be made more efficient?** To get to the answer of this, the following subquestions need to be answered first. From these, the conclusion can be drawn how much more efficient the process of flower trade can become.

- What are the characteristics of the flower industry and where is it lacking efficiency?
- How can real-time inventory data be acquired?
- How can the inventory management be modelled and optimized?
- How does a real-time inventory system based on RFID perform in a store environment?
- Which strategies exist for replenishment and inventory control?
- What is the effect of predictive replenishment with real-time information on inventory management of flowers?

1.6 Methodologies

To solve the larger problem of inefficiency, the two related problems both need to be solved. First, the inventory issue should be fixed, and with the assurance of real-time data, the improvement replenishment strategy can be researched. Figure 1.1 gives an overview of which type of research methods are used during this project. Both have a foundation of literature study about the flower industry and then follow two paths towards more efficiency. Figure 1.1 shows how each part of the problem is categorized and how it is researched.

1.6.1 Real-time inventory tracking system

The goal of this part is to design build and test a state-of-the-art, fully automated inventory solution. The requirement is that the supplier can have insight of the inventory, independent of any input from third parties. Before the company can replenish anything correctly, it is necessary to have correct inventory data.
For anticipation in fluctuations, the more is uncertain about the levels of inventory, the larger risks are in decision making. This counts both for a time frame in which the data is presented, as well as how precise the inventory for each product can be as a percentage of a whole. Therefore a auto-ID system will be designed and tested to see how well it can with giving automated inventory data for flowers in the shelves.

1.6.2 Forecasting for replenishment strategy

To get a controlled output of how much of a product need to replenished, given previous sales and current situation of the supply chain. The controller should measure sales and inventory, and should use this to give an output of how many products to send to the store. The input for this system information will be: the predicted amount, lead time and replenish moments. The actual sales will be considered disturbances that have effect on the state of the system, namely the age and amounts of the inventory. The controller should take into account age of the products as well, to measure overproduction. The controller should also count the empty situations. The output of this forecasting and replenishment system will be a quantified improvement for these relevant KPI's of the industry. The conclusion of this research will be based on a simulation of actual days in the store, mimicing real-life sales. The simulation will be verified with mock data, seeing if it anticipates decline or incline in sales. This can serve as an advisory report for implementing a controller in the replenishment process. If the controller would be tested straight away in real-life, the company would risk large costs, as well as the time to get to results would be increased from hours or minutes of simulating to real-time duration before sales. Hence is chosen to make a model in python in which an optimal controller (OC) is build. Chapter 7 elaborates on how the forecast and controller work. Later these results may be used for real-life implementation, depending on how significant the improvement is.

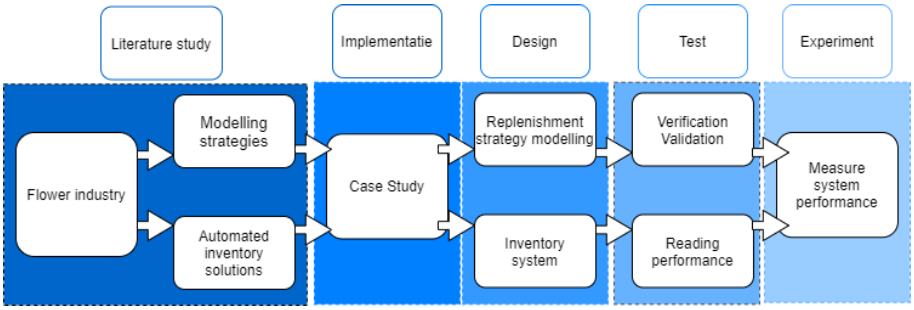

Figure 1.1: Different steps of the research with a specific approach

1.7 Report structure

In this report, the research (sub)questions will be answered to lead up to solving the overall problem of increasing efficiency. The different chapters of this research all help answer one or multiple subquestions. In each chapter is elaborated on how the answer of the subquestion is relevant for the final goal and how it is researched.

Chapter 2 gives an introduction of the flower industry. History, relevant geological locations, biological boundaries and KPI are mentioned. This way the subquestion *What are characteristics of the flower industry?* can be answered.

Chapter 3 gives a literature overview of automatic identification methods as well as the use and benefit of digital twins. The knowledge gap for feasible automated inventory systems in a store environment is explained. Furthermore, the subquestion *How can real-time inventory data be acquired?* is answered here.

Chapter 4 elaborates on what type of programming potentially could simulate and optimize the supply chain. After this explanation, the model requirements are discussed and the model type to use for simulation is chosen. This way the answer to *How can the supply chain be modelled and optimized?* becomes clear.

Chapter 5 zooms in on the situation of the case study. This chapter shows their typical situation in the supply chain of flowers. It explains which specific problems occur in this part of the supply chain. In this chapter also relevant numbers in the company operation are determined. The specific boundary conditions for the inventory design and simulation design will come from this case study. The results of improvement will be based on different relevant situations in this case study. The case is used to verify and quantify the improvements.

Chapter 6 shows how the answer to *How does a real-time inventory system based on RFID perform in a store environment?* is achieved. First, the design process and final design is shown. Then the performance to test specific parameters such as tag type/ orientation or distance to the reader is tested. Finally an experiment is executed to measure the reading percentage in a real-life set up, as expected in the case study to see if it comes close to the required performance.

Chapter 7 explains which relevant replenishment strategies are designed. It shows the relevant mathematical models and flow graphs for each strategy. The answer to *Which strategies exist for replenishment and inventory control?* is then clear. In this chapter the verification and validation are explained.

Chapter 8 shows the experiments that each strategy undergoes. The scenarios and hypothesis are described. The results from the experiments are also shown. This way the answer to *What is the effect of predictive replenishment with real-time information on the inventory management?* will become clear. The simulation output is to compare situations with different strategies or different availability of information.

Chapter 9 contains the conclusion to the research and the answer to the main research question **How can the supply chain of flowers be made more efficient?**. It also discusses the results and evaluates the process of getting to the answers. Finally, recommendations for further research are mentioned.

1.8 Scientific contribution

The benefits of automated measuring of inventory of short shelf-life products ($\pm$ 7 days) at product level have not yet been researched. Furthermore, for a store environment RFID technology has not been verified to be feasible. Also, there is little literature available about the gain of predictive replenishment, optimal control to be exact, for inventory management of this type of products.

Chapter 2

Literature: Insight in the flower industry

This chapter answers the first subquestion of the research: *What are characteristics of the flower industry?* It first explains how the industry has developed over time and how the supply chain currently works physically. Then the latest developments in this field are elaborated on. Finally, the gaps in the literature that lead to efficiency losses are mentioned, to introduce the next chapters.

2.1 History of the flower industry

The trade of flowers is one of the oldest luxury product sectors in the world. It was already in the golden area of the Netherlands that the trade of tulip bulbs reached similar prices of large canal houses, as their beauty and vulnerability had large value as a status symbol [9]. The value of the bulbs reduced over time and became more a ”trade in wind” than one with an actual intrinsic value. Therefore this market imploded as it was a ”bubble” and as the golden age ended, these luxury products were not that high in demand for several centuries. However, this was concerning bulbs, and later flower trade with cut flowers was also considered a very luxurious product, especially given the short shelf life. This is characteristic of the flower trade, which leads to producing more than bought, hence disposals, as one of the biggest risks. The decay happens fast, and the products need to be at the customer's house to guarantee sufficient quality ”in the vase”. This market developed again as the nation underwent the industrial revolution. By the end of the nineteenth-century Dutch farmers started to grow flowers as supplement to their income in the growing economy of the industrial area. However, it was hard to reach the customer in time with quality product, and if demand is lacking, it was easy to overproduce. When the growers decided to sell these flowers from one central point, the efficiency of the market increased as combined demand was able to meet total supply, and flowers sales exploded. During the next decades, growers went over borders and overseas to sell their flowers to explore new markets with their competitive pricing. Delivering more quality products at larger scale than elsewhere possible [10].

This all has led to the present situation, where flowers and plants are examples of the largest export products of the Netherlands, as it covers 2.1 percent of the total Dutch export. In 2010 this market had an export value of eight billion euro [12]. The Dutch auctions are the biggest in the world, as a key turnover point between supply and demand, transferring flowers to all continents in a supply chain where time is key. On a daily basis 3000 trucks filled with flowers come to and leave Aalsmeer Flora Holland. Figure 2.1 shows how the warehouse of the auction looks during operations.

2.2 The supply chain of flowers and plants

This research will be executed in the field of the flower industry. To understand the situation and to determine boundary conditions, this chapter gives a general insight in how this industry works nowadays. It covers physical lay out, seasonal peaks and biological boundary conditions. Next to the working principles of the industry are set out, the state-of-the-art technology developments are discussed and how these may be used for improving the supply chain. The chapter ends with how their current replenish process works, what problems they are specifically dealing with and how these are measured.

2.2.1 Physical and biological characteristics

This subsection will explain how the supply chain of flowers is limited by the biological nature of the product and physical influences. Flowers have a post-harvest life of about 9 to 12 days, depending on how well they are taken care of [13]. As

Figure 2.1: Example of how many flowers are transferred daily at the Flora Holland Aalsmeer Auction [11]

the customers also want a decent product at home, for at least a few days, freshness needs to be guaranteed in the shops. Therefore the emphasis in flower supply chain is speed. Between 48 hours, flowers should go from grower to auction to store, so that the flowers have at least a week left on quality. Figure 2.2 shows how the value of a flower develops over time schematically. First the growth in which the seed develops towards a salable product. After harvest the freshness decreases, so a fast supply chain is critical for the remaining quality when it is in the store for the customers to buy. The 48 hours is also visible, with the times between harvest, auction, packer and store added up.

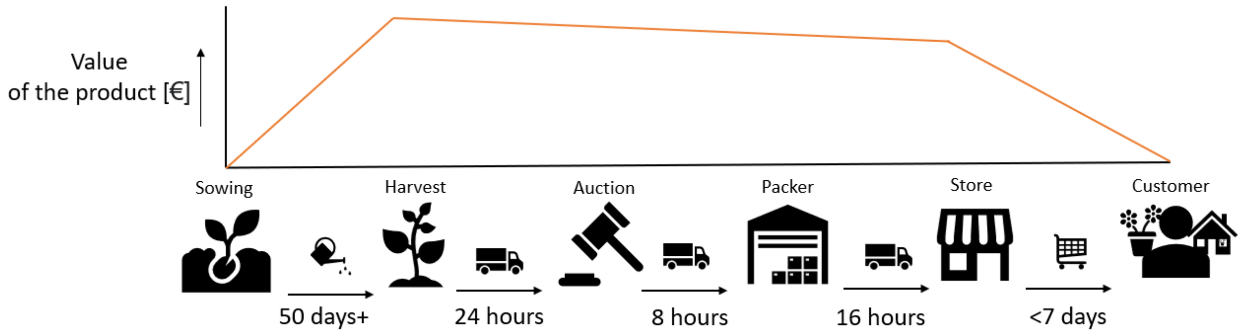

Figure 2.2: Supply chain of flowers

As flowers are very delicate, from the moment of being cut, they require to be handled with care to remain quality product. The flowers are packed together, usually with their stems in buckets with (nutritious) water. These buckets are stacked on cars consisting of multiple levels, this is the most space-efficient set-up without damaging the petals, valuable parts of the flower. These carts are brought to the auction, where they are sold and distributed over all buyers. From here they either go to the local packer in Holland or are transported to the end-user. This can be for example a route over a warehouse towards supermarkets, or direct delivery to smaller florists [10].
Flowers also require more than just regular transportation conditions. They need to be transported in cooled environment (around 15° C), for the cells to maintain their optimal state longer. All the petals should also be in open space as much as possible to avoid damaging of the leaves that define the product. The flowers cannot be put as bulk together, which is limiting capacity of the transporting vehicles. On the other hand, for some stores that sell lower volumes, it is also not viable to replenish more frequent than the flowers shelf life. The costs of transportation, especially cooled and over longer distances, can just not break even elsewise. Therefore replenishment moment occur for international supply less frequent is some occasions. This can be once or twice a week.

2.2.2 Season products and peak moments

Unlike other production industries, it is not possible to speed up production as the growth of flowers is limited by biology. It takes on average at least 50 days to grow from a seed to a flower. It is not directly clear yet what the demand will be, and therefore which price the grower will receive at the auction. However, in this market, demand can follow supply, as overproduction from growers usually leads to purchase at lower prices of leftovers. This way the growers do not have to trash their overproduction, and the customer can have bouquets at lower prices, at which they are more likely tend to buy. Historically is the flower market one with seasonal products. Some flowers (bolls) already blossom during spring, and others later in the year. This has led to availability only during these biological dependent times. Nowadays, with greenhouses able to simulate environmental conditions as desired, every crop or flower can be produced year-round. However, with the popularity linked with historical seasons, the demand still changes over the year. Spring is still associated with bulb type of flowers, like daffodils [14]. This market also heavily relies on some peak moments, with special flowers associated with certain holidays. Valentine's and Mothers-day are examples of moments of the year when respectively roses and pink tulips are in high demand.

2.2.3 Key Performance Indicator

In this supply chain, certain indicators are relevant for how well the supply chain is performing. To quantify progress and compare the situation before and after the implementation of this research, Key Performance Indicators (KPI's) are looked into for the supply chain as whole. It is important to make the correct decision between risking over- and understocking. Understocking can lead to not having sufficient products for the demand. This equals empty shelves and missed sales. This is very undesirable as it has downsides in both branding and financial aspect. There should therefore always be sufficient stock, to have always (under normal circumstances) the right amounts amount for the customer. On the other hand, it is also undesired to do the opposite and maximize the replenishment amounts, more than will be sold: overstocking [15]. Overstocking can be measured in the number of flowers that are longer than their expiration date (exclusive vase life at home) in the store. After this time the product will not be sold anymore and needs to be trashed. The KPI for this research in this industry are therefore the number of flowers disposed of (overstocked) and the amount of out of stock moments (understocked).

2.3 Technological developments

In a fast-paced industry as with flowers, companies are required to follow innovations, to stay competitive and to guarantee high-quality products. This section presents recent technological developments in the flower industry and how they have improved the processes.

2.3.1 Automation of processes

The flower industry is a labour intensive industry (sow, feed, water, harvest, bind etc.) that also requires high pace in the supply chain. With the growing economy, more is expected with the same manual resources. The fragile nature of flowers is a cause of lack of automation so far. The picking of the flowers still has to be done manually as affordable and accessible robots are currently unable to correctly handle flower harvest without damaging them. However steps are made to work around this problem.

Moving of the flowers

While robots are in general quite able to cut brittle and soft tissues like flower stalks, the downsides of this cutting is the value drop that happens when a flower is damaged. It can either not hold the flower or smoothly pass through a field without harming them. The grabbing may be done by robots with a more delicate touch, so called soft robotics. These machines have actuators made of soft and elastic material and adapt to the brittle object that is being grabbed, as is currently already done with fruit picking [16]. Furthermore there is the possibility to move the fields to the pickers instead of the other way around. Moving flower tables, conveyor belts for bouquets or vertical farming (multiple layers of crops with lights illuminating lower levels) are all examples of how technology helps agriculture or flower industry get more out of the same or fewer resources [17].

Figure 2.3: Automatically moving tables minimize movements required for the working force, which lead to a more efficient process [18].

Identification of products

It is already possible for automated systems to recognise flower species based on digital pictures [19]. This way a machine can identify which parts of the flower are to be protected during picking or transport. Also, blooming can be recognised [20] so the life phase of this flower can be determined for sales value reasons. Right now this is still done by humans, as the picking still requires manual handling. However, once the correct automated hold, cut and transport are developed, the technology is available to recognise flowers to keep intact and to decide whether or not to harvest.

2.3.2 Quality management

Next to the physical brittleness of agricultural products such as flowers, is a consideration in how to remain in the best biological condition. With the right additions to its water, they may survive already days longer [13]. As the flower is also a gift suitable for celebration, holidays result in a large increase in demand, and these periodical scale-ups require the right approach to maintain the right quality. Next to this is there also the decreasing effect on expiration of some variables in the supply chain. These affect how long the products still can be sold, and therefore may form a waste of resources.

Delivery issues

To act upon seasonal peaks and their downsides, Mieloo & Alexander has experience with this phenomenon in the flower business. In their Butters group case the peaks from holidays was given more insight using RFID technology [21]. As these peaks (Valentine's, Mothers day and Christmas) require a lot of temporary working force, there is an increased risk of not delivering the right quality or quantity. By integrating RFID tags into the gift cards, visibility in which delivery required which products, and also with correct location within the supply chain. This way Butters group was able to control quality of the assembly without making it too complex for the temp workers, and prove correct sending towards customers.

Measurement of transport impact

As the flowers are moved through the supply chain, one of the main physical factors in the biological quality of the flowers is temperature. With the temperature too high the structural integrity of the plant cells declines rapidly. If this is measured along the supply chain the remaining shelf life can be determined and this information to better anticipate changes in inventory [22]. This can be done for example by having an active RFID tag that tracks the temperature during transport, as currently already done with perishable food distribution [23].

2.3.3 Inventory management

In order to serve demand, all of the actors of the supply chain want to have sufficient in stock to avoid backlog. However, too much stock can lead to spoilage, as inventory space and decrease of value are wasteful factors. If any actor solely orders for his own, a phenomenon called the bullwhip effect occurs. With daily delivery moments it is possible to optimise over multi-agent supply chain for cut roses [24].

2.4 Literature gap

Although the industry is developing towards more automated and optimised processes, certain situations still are lacking efficiency. This section points out what these literature gaps are, which will be elaborated more on in the next chapters.

2.4.1 Automated inventory information

As the Netherlands is one of the largest exporters of flowers, multiple external partners work with Dutch companies in the supply chain. Not all partners have a good working inventory system. They might be not automated or not up to date. A consequence of this is that for the Dutch suppliers it is regularly unclear what amount to replenish. A solution for this would be an automated inventory system. One that requires no input from the external party and can be placed at the desired location for real-time information about the inventory. However, such a system is not yet researched and developed for the flower industry. Chapter 3 shows the options for inventory systems and what is most suited for this application to design and build later.

2.4.2 Predictive strategies

Although the industry is innovating, the ordering remains manually in a lot of occurrences. Predictive technologies developed for replenishment of branches such as fashion retail may be useful for the flower industry as well. However, as overstocking on the long-term can lead to fewer products available due to expiration, and because delivery is only once or twice a week in some situations, long term inventory strategies are not useful. With direct replenishment, without to many wholesalers and warehouses, this effect can already be reduced, but the demand of the products is a disturbance on inventory that is hard to truly predict. Chapter 4 shows the options for decision making and how to model the real world to develop and measure strategies, to find better improvements.

Chapter 3

Literature: Inventory identification

To design a system that digitally registers products on a individual level, literature has to be reviewed to determine options for identification. This chapter answers the question *How can real-time inventory data be acquired?* First is elaborated on what type of identification systems exist and how each of these technologies is used. Which is most suited for specific parts in the flower industry and what missing in the literature of which this can be a solution.

3.1 Auto ID systems

Improvement of efficiency in this supply chain requires accuracy and cost-efficiency. The new system should avoid any noise or delay in the communication stream, the inventory should be automatically registered. An employee that counts or manually scans on a daily basis is not only expensive, but also does not track real time and moreover, human error is also not avoided. As the bar code systems of Casino have proven to be inadequate, DRF requires an independent, automated solution, that can be implemented for any store. Different Auto-ID technologies have been developed to make a digital twin of each product for better tracking of inventory.

- Bar or QR code. This is the system similar to regular bar codes as in the store. The product has a code consisting of colored bars on it, with a unique spacing between and width of bars for each specific product type. With a light sensor the bar code is scanned and recognised. However, these can only specify down to product type level, EAN13 or EAN8 [25]. As these work with international standards, they can not be identified on a individual level. This method only suites regular inventory counting. It also requires active scanning, for at least the sales of products, which makes it only a better connected version of the current systems at Casino supermarkets.

- Magnetic stripe. This technology is used in for example in credit cards. It works due to a magnetic strip that is divided into smaller strips, al with different size and North-South orientation. If this bar is moved passed a gap in magnetic coil, a magnetic flux difference will result in an electric signal. Due to every bar having a unique order of smaller strips and orientation, the flux difference over a swipe will be different for each strip [26]. Downside of this technology is the close distance range in which it needs to operate. Furthermore, the products have to move past the magnetic reader, at the right speed, to be registered. Similar to the previous identification of bar codes, the actual inventory is not measured. It has to be determined from the difference between replenished product and check-out. This way the thrashed flowers also have to be checked out. If the replenished amount also needs checking to ensure everything arrives, than the products require a check in as well.

- Optical character recognition. With this identification method, the actual product is identified and not a code that contains information about what item is put onto. This technology is based on cameras being able to recognize flowers based on shape and color [19]. This way each seen flower is registered and if it leaves this departure is instantly measured as well. However state of the art image recognition technology is expensive. It also needs to differentiate between items of the same product type.

These technologies all does not seem to be a realistic option for solving the problems at DRF. Bar codes are already used and would not only require manual registration but multiple bar codes on the same price label is also undesirable. Magnetic stripe would be possible if the items would all be in close range to a reading system. With the overhead system requirement, this technology is also unsuited. Optimal character recognition is a technology that potentially could fit all the physical requirements. However from a financial perspective this is also not feasible. One technology that can function as automated inventory solution, does not require human assisting, and can be used relatively cheap is Radio Frequency IDentification (RFID).

3.2 RFID

RFID is a technology that can identify, track, and trace an object. The foundation for this data acquisition is having a receiver communicating with a sender attached to it, using radio waves. RFID has multiple benefits in logistic tracking, as it can serialize data (this comes in hand with shelf life tracking), does not require any human intervention,
The objects can be tracked using the attachment of tags. Tags that consist out of chip with integrated circuit for storing a unique serial number and an antenna to receive external power and exchange the data from the chip to a reader system. Tags can be either active, with an own power supply (for example a battery) or passive, that require energy from the transmitted radio signal waves of the reader. Active tags continuously send out information, can communicate with other tags and are suited for large distances of reading and in large quantities. However these tags only last as long as their power source lasts, and are more expensive than the passive tags. Passive tags only send a modulated data stream with the tag's information after being charged by the Radio frequency waves from the reader. Once the reader receives the information (send through both antennas) the object is registered and the data is communicated to the host. The radio frequency fields can be send in different type of polarization. Vertical, horizontal, left handed circular or right handed circular polarization (shown in Figure 3.1) all consist of radio frequency waves. However due to the different nature of the waves, different locations can be reached with a better signal, and tags can be read by overcoming obstructions [27]. Figure 3.2 shows how passive tags are powered and read. In case active tags are used, the reader is only sending information and no charging is required, the rest remains.

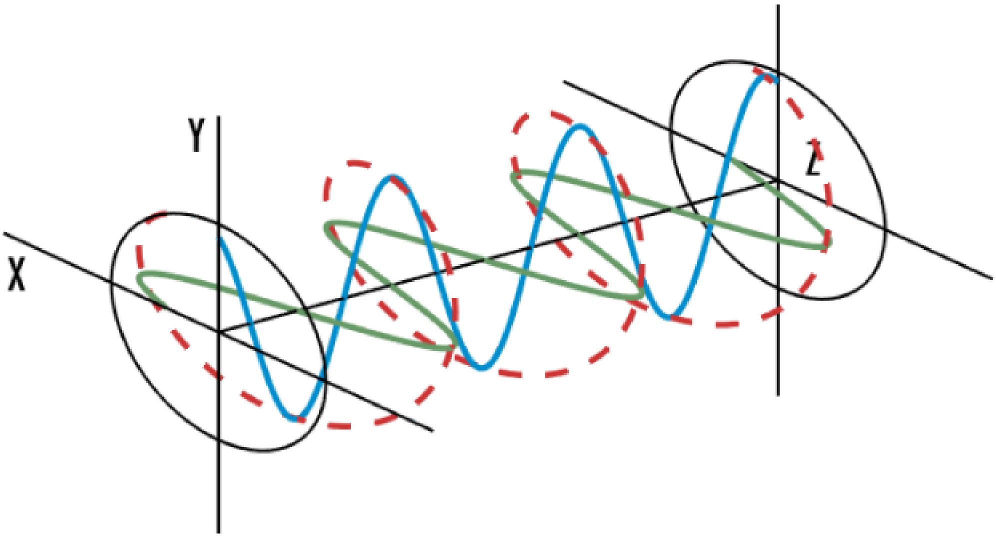

Figure 3.1: Different polarization for radio frequency waves [28]

Each chip has unique information that consists out of an EPC, a code that is build up out of the international standard European Article Number (EAN, this can be EAN13 or EAN8 a difference based on how long the company pre fix is) and a serial number. This way the inventory can be counted per product type, but also the time it has been on the shelf is possible to register.

3.2.1 Applications

Known applications of this technology are the usage in Near Field (NFC), which is used in identification for public transport or payments [29]. Either with cards, that act as passive tags, or with phones which can send and receive actively [30]. Identification of persons within public transport or other networks already quite integrated into the society. With products it is done less often due to larger number of products to identify and the increase in costs compared with regular bar codes. However, in larger logistical organisations it is also already used. Mieloo & Alexander have assisted PostNL in their cost efficient switch from active to passive tags in their logistical processes. Also in the fashion retail industry some companies as Suit Supply or Bon Prix track their clothes using passive RFID tags. Furthermore, RFID has been

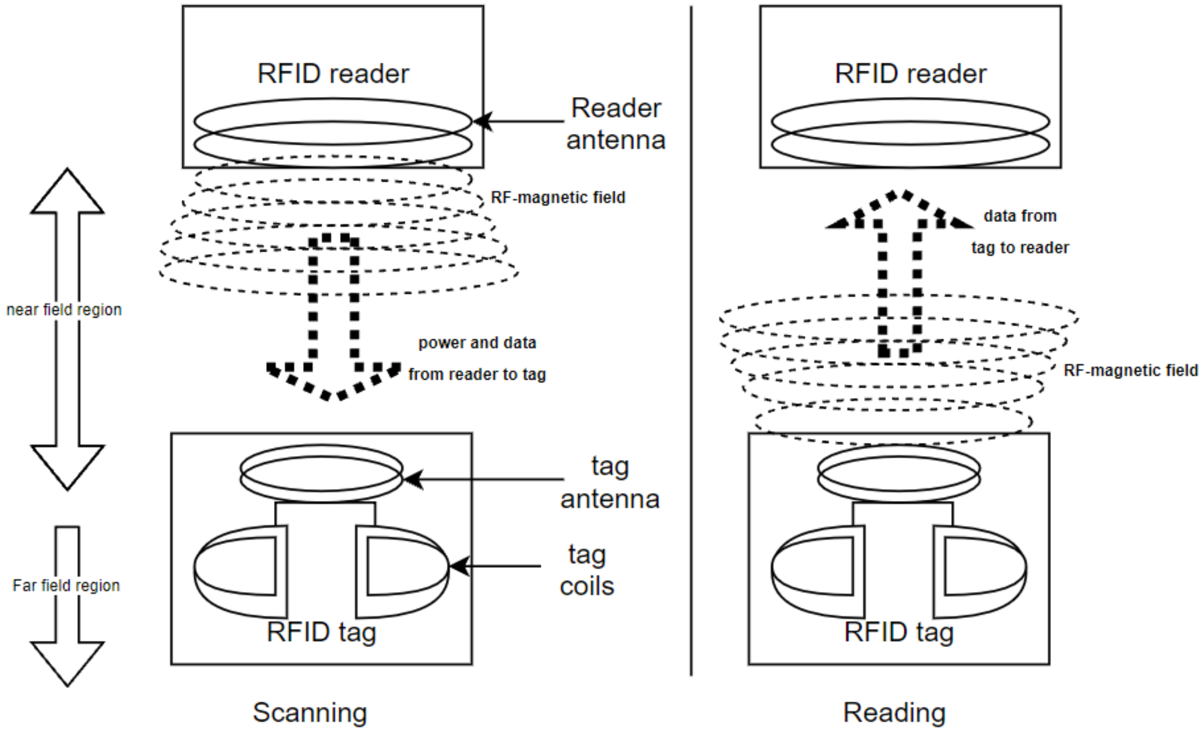

Figure 3.2: How passive tags are charged and read by RFID readers

implemented in food applications [31]. Especially to determine quality decay due to temperature active tags can be used to assign quality to batches and deliveries. RFID is on the relatively long range up to 5 meters proven, however, reflection due to liquid in the flowers, in customers, or due to metal frames/ black surfaces can lead to double or no readings. The double reading part can be filtered out digitally, and reflection can work also beneficial, that hard to read tags are powered and read by reflected waves. Passive tags have already proven to be useful in RFID application in the flower industry. On warehouse level in combination with E-commerce, complex flower pieces could be assemble better and the moist in the environment did not cause the readings to be faulty [21].

3.3 Filling the research gap

With the research known so far, it seems that the overall system requirements should not be a deal breaker for an RFID systems. However this system can not only be designed and deemed successful from only the available. This were all systems with small range recognition, not with the liquid containing flowers, active tags and/or in a warehouse setting. To have a solution that can be placed at any partner an overhead system should be designed and tested in the specific conditions to get a good idea of how useful RFID can work as a cost-efficient solution. Chapter 6 shows the design process, the experiments, and the results for this project to fill the research gap of automated inventory solution in the flower industry.

Chapter 4

Literature: Modelling strategies

This chapter provides insight in which modeling methods are possible and the (dis)advantages of each. The goal is to find a way to simulate the sales, to simulate a strategy and to have basic modelling principles to generate results. It gives an There is also a decision made which method suits the application of replenishment and RFID in the supply chain best. The question: *How can the supply chain be modelled and optimized?* will be answered here.

4.1 Modelling

The main reason to model a system is to calculate and test a certain process change without having to deal with the real life consequences. Any replenishment strategy can be tested to see how much it performs compared with others. The simulation method should be able to compute a model that has improvements or is optimised, it should be able to adapt to changes in demand, and work with the limited amount of historical data. The next list of various modelling methods that could be chosen from.

4.2 Prediction and optimization methods

- Continuous simulation- This type of simulation measures continuously what the state of the system is and acts upon it. This can be used for example in system that handles the flow of fluids, like a vat that has an altering inflow and outflow. In this situation there is happening filling and releasing happening all the time. This can require a lot of processing time and as the system only works with changes that happen on a daily basis, in discreet arrive and leave moments, this does not seem necessary [32]. Also it does not easily implement predictions and optimizing itself, it requires mostly statistic input on what to base the decisions in replenishment on.
- Discreet Event Simulation (DES)- This type of simulation can be used to measure events that happens at an exact time step. For example the arrival of customers at a airport terminal or when appointing people from a queue to a check out. DRF works with a replenishment that only delivers on fixed times of the week, and only the daily sales matter for this restocking. The fixed moments in time make DES a better simulation option than continuous. It saves computing time that is irrelevant for the current application [33]. It also helps to get insight in how systems work over longer period of time. However, DES still requires some extra tools to enable optimization and better decision making [34].
- Linear Programming (LP)- LP is principle of finding the minimum of a linear objective function, while still holding to constraints of linear (in)equality [35]. This can be used for example with assigning heaps of iron orb to certain factories or solving a assignment problem with trucks having to restock bars. This method is able to find the optimal for a problem but it requires perfect information up front. With the unknown and altering demand LP cannot predict an optimal amount to replenish at each time step.
- Machine Learning (ML)- Machine learning can forecast demand based on large amount of data, with which accuracy compared with traditional statistical techniques [36]. If implemented correctly this method has already proven to increase efficiency in short shelf life supply chain by reducing disposals by circa 40%. However, since there is limited sales data available, as well as limited data for the weather at those days, the temperature of transport etc. there might not be sufficient information for correct usage.

- Optimal control (OC)- Optimal control is a closed loop controller that uses measurements to predict system behaviour and works towards a preliminary determined ideal state. It is only required this one step, to calculate what input it should deliver to reach that state pased on the predicted value that is a consequence of a moving horizon estimation (MHE). This MHE uses historical data to recognise paterns and to generate a predicted value for the system in the next discreet or continuous moment.

- Model Predictive Control (MPC)- MPC is a closed loop controller that measures the system it acts upon. It has the possibility to function both in continuous and discreet systems. MPC determines the output on the measured input. MPC uses historic input as foundation for predicting the next disturbances. In a self driving car this can be the route to an ideal trajectory, but with inventory this is to find a optimal amount to replenish. It seems a bit like optimal control, however model predictive control calculates for future state was is expected, and anticipates these steps as well. This anticipation will be based on an objective function that measures how well the system performs, giving a penalty if certain undesirable events happen. This way it will work towards a target value that may change over time, depending on what the historic sales indicate. The reason MPC is considered robust is that it requires little data to form a foundation to start forecasting. Every new time step of information is used, and as it only predicts until a prediction horizon. If the information is different from what is predicted the system can adapt to it at the next time step already with little computation time. There will also be boundary conditions, that the inventory can not become negative for example. Figure 4.1 shows how the system predicts, calculates and decided what to deliver from now until the prediction horizon, and there is demonstrated how this differs from OC.

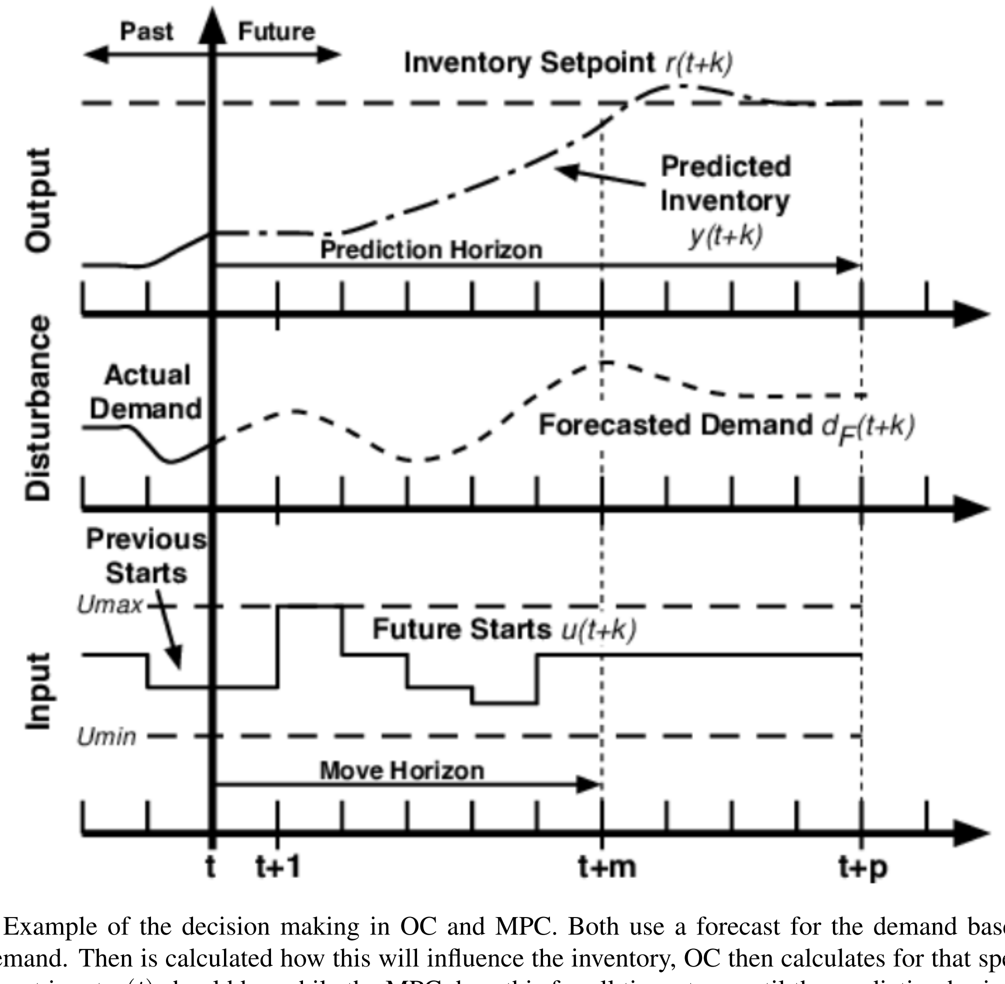

Figure 4.1: Example of the decision making in OC and MPC. Both use a forecast for the demand based on historic measured demand. Then is calculated how this will influence the inventory, OC then calculates for that specific moment what the correct input $u(t)$ should be, while the MPC does this for all time steps until the prediction horizon t+m before it generates the input action [37].

4.2.1 Selecting the suited method

As the disadvantages of continuous simulation, DES, LP, and ML were already mentioned it is mainly a choice between OC and MPC as foundation for the replenishment strategies. Model predictive control is usually more precise as it can anticipate for disturbances itself. However, the demand can be quite unpredictable, especially if it is direct replenishment, and no buffer zone with multiple nodes over which the inconsistency of the demand can be spread out. With the limited shelf life of only a few times steps, looking ahead further than the next time step is not rewarding. Figure 4.2 and 4.3 show how long replenish goods remain and for what window a decision is made. In the case of one delivery each week (/shelf life) the starting inventory will be zero each time, and everything left at the next delivery will be disposed of. In the case of two deliveries each week (/shelf life) one can predict how much will be sold in the window until the next delivery moment, however, it is easier to aim at a small overestimation, since what is left can still be sold. However, this means that for the next time step the non-zero starting inventory needs to be considered as well.

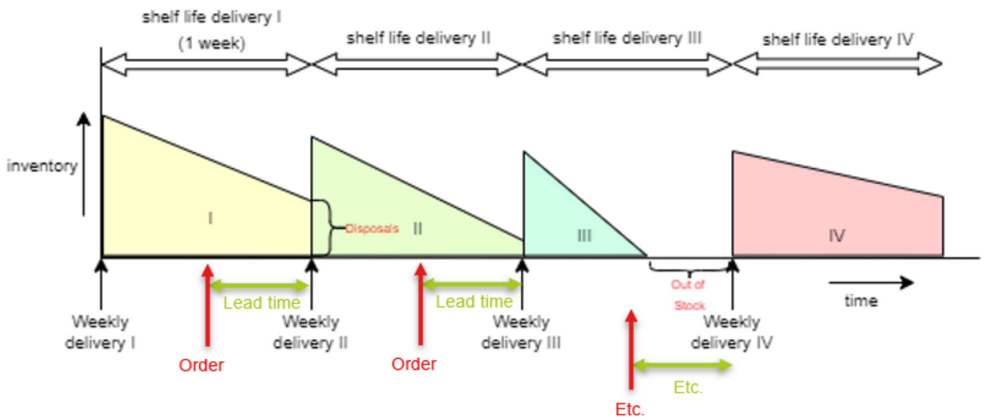

Figure 4.2: Schematic overview example of inventory of short shelf life products over time, with weekly replenishment. If the shelf life matches the delivery interval, the goal of replenishment is to meet all the demand until the next delivery moment. Everything left will be disposed of regardless.The order decision is done the lead time before arrival.

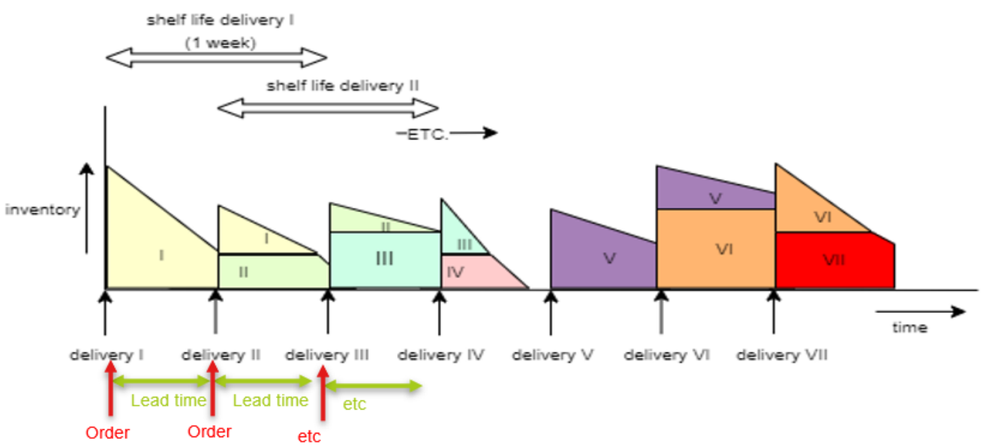

Figure 4.3: Schematic overview example of inventory of short shelf life products over time, with replenishment twice a week. The goal of replenishment is to replenish enough until the next delivery moment, and using what remains from last time as well in this decision. Only at the next delivery products expire. Each time an order is delivered, the decision for the next order is made. (Required for this system is FIFO selection by customers)

Furthermore there is no trend in disturbance due to the random nature of human demand so to look further ahead than the first prediction is only adding uncertainty of inaccurate predicting. Model predictive control can therefore do nothing more than optimal control in only recognising mayor trends. By tweaking an objective function to anticipate for possible larger disturbances or turn stochastic demand into probabilistic constraints MPC can create an optimal situation for replenishment [38]. However this requires a lot of calculation time, the tweaking might be harder due to the large deviation compared with physical processes, it is also harder to program correctly and to verify the correctness. Moreover an ideal reference level with buffer inventory can be defined in front for optimal control, can lead to a situation that performs equally well. The relative robustness, ability to make decisions and the limited information that is required for a (local) optimum makes this optimal control a suited method to improve the supply chain of flowers [39].

4.3 Programming

The model will be written in the open source program Python. This program has the possibility to add packages/modules like numpy, GEKKO, GUROBI or salabim. All of these enable simulation opportunities, compatible amongst other for LR, MPC, OC and DES. The benefit of this program is that follow up research can be done easier due to the open source nature of the program, it does not require a license before the information can be used. From the aforementioned modules. especially GEKKO can be used for predicting application, for which is pre-existing work available [40]. This section explains how this module calculates the predicted demand point and how the control loops works for optimal control.

4.3.1 Moving Horizon Estimation

GEKKO programming helps with calculating the forecasted demand. This tool contains preprogrammed moving horizon estimation (MHE). This tool is used in other researches with dynamic modelling in (non-)linear systems, also occurring in MPC programming [41] [42] .This type of observer demonstrates optimality properties. Because minimization problem is solved directly at each time instant [43] [44].

Using the model equation (formula for change of inventory over time) and with historical data the objective function of a MHE can be defined [45].

$$\min_{x,y,p} \Phi = (y_x - y)^T W_m (y_x - y) + \Delta p^T c_{\Delta p} + (y - \hat{y})^T W_p (y - \hat{y}) \tag{4.1}$$

In this function, x is the state variable, the inventory, y is the measured state variable, and p are the disturbances. For this system those are orders, sales and disposals, and with orders actually being a variable that can be manipulated. In the equation, the difference between the measure value and the actual state y and y_x is squared with a weighting factor W_m, also a forgiving factor W_p is multiplied with estimations $\hat{y}$ and actual measurements. $\Delta p^T c_{\Delta p}$ can be used as a penalty factor for changing variables. The result will be an estimation of the next demand curve. At every time step this is repeated for the new horizon, leaving one measurement out, and taking the previous measurement and comparing it with the MHE. Figure 4.4 shows an example of how measurements and earlier estimations in a certain window lead to a new estimation.

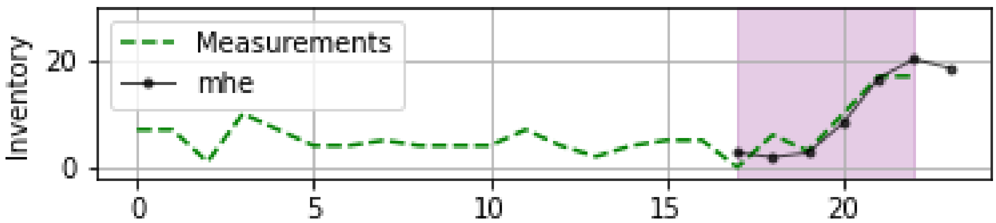

Figure 4.4: Example of the working principle of a Moving Horizon Estimator. In

4.3.2 Optimal Control

Using this expected demand the optimal control can order the ideal amount given the current inventory and expected sales. These can lead to expected inventory and forecasted disposals, if this is calculated up until the expected arrivals of the products, the optimal amount can be replenished.

$$IdealInventory = Buffer + ExpectedDemand \tag{4.2}$$

Because the order arrives at the next time step, the order to reach that ideal state can be calculated using:

$$Order = IdealInventory - ExpectedInventory \tag{4.3}$$

These can also be described in variable form:

$$x(k+1) = h_{ref} + \hat{p}(k+1) \tag{4.4}$$

$$u(k) = x(k+1) - \hat{x}(k+1) \tag{4.5}$$

In this case the variable h_{ref} is the reference amount, or predetermined buffer amount above the expected demand. $\hat{p}$ is the estimated demand and u is the action the controller takes.

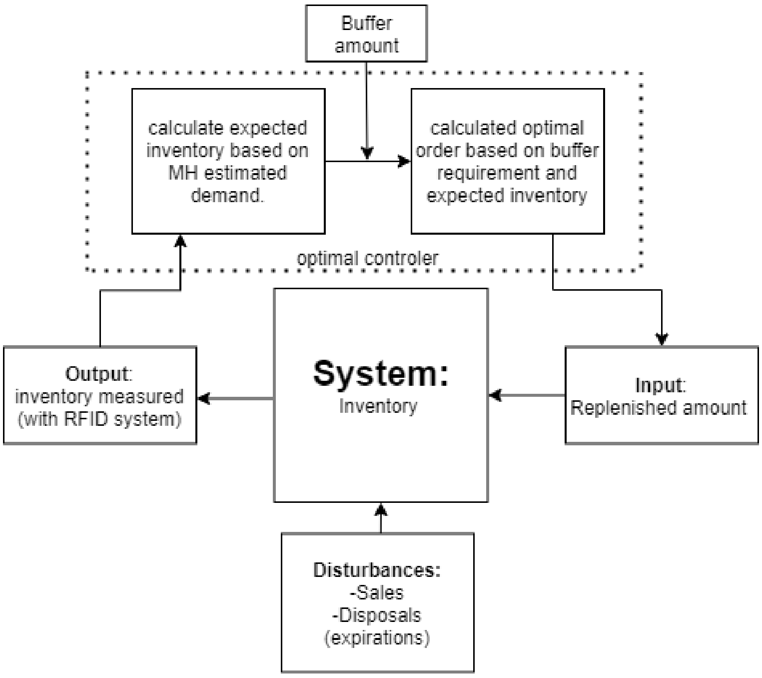

Figure 4.5: The inventory control system with the optimal controller, including the description for each part

A longer prediction horizon is not necessary since the demand can be quite inconsistent, and a large difference between expected sales and actual sales will effect the forecasted disposals. After two delivery moments, the flowers will be either thrashed or sold, therefore looking further ahead does not seem necessary as the range of variables is too wide and random for better accuracy. Figure4.5 shows the closed loop diagram for the inventory, including the optimal controller.

4.4 Filling the research gap

Predictive replenishment can be the key for more efficient inventory management. If the replenishment uses optimal control, opportunities exist that inventory management is handled better. It is possible to design such a system with the open source program python, and has build in options for optimisation using optimal control. Chapter 7 shows the design of strategies, and how one of these is based on optimal control.

Chapter 5

Case Study: DRF

This chapter points out how the research problem occurs in real life with consequences. A case study of Direct Retail France is used. This chapter will show specific and relevant problems that require solving

Direct Retail France is a supply chain director, located in Honselersdijk, in the municipality Westland, heart of the greenhouse industry. They collaborate with (their own) growers and the auction to get supply and operate at Casino Supermarkets in France. Their way to service demand is with store-in-store flower shops, a stand that they place inside of the supermarket. These store-in-store concepts do not require any additional checkout or maintenance, as this is included in the fee they pay to casino for these services and the rent of the store space.

Figure 5.1: Frame filled with flowers at one of their stores in store.

5.1 Case study: Direct Retail France

Direct Retail France (DRF) is a supply chain director and customer of Mieloo & Alexander. They are exporter of flower bouquets, flower bulbs, plants and vases. These flowers are sold in supermarkets in France under the name of La Reve Nature. They buy flowers at the auctions in the Netherlands and have them transported to the packer**location to be announced**. Here bouquets are composed, price tags are added to the products and the wrapping is executed. Next the trays with products for each store are assembled and shipped to the stores in France. Currently DRF operates with a store-in-store concept in cooperation with Casino Supermarkets. Figure 5.1 shows an example of how the products can be presented to the customer. The check-out and money transfer is done by Casino supermarkets and DRF pays for these services, as well as for renting the places in the stores and cleaning around the frames.

Mieloo & Alexander

This research is performed in cooperation with Mieloo & Alexander (M&A) and is focused on the flower industry, and specified on one supply chain director in this field. This section gives a short introduction about Mieloo & Alexander and their relevance to improving supply chain systems. ”Mieloo & Alexander Business Integrators is specialised in delivering ”technology-enabled supply chain improvement”[46]. One of the industries they excel is creating customized solutions using Auto-ID technologies, especially RFID. One of the focus areas of M&A is RFID solutions for insight in supply chain, as they have worked out improvements in for example postal logistics and fashion retail. Logistically systems increasingly acknowledging the benefits of RFID-deployments, and this knowledge is useful for the efficiency problems in the flower industry. They have offer standardised, modular supply chain solutions for Horticulture (ScanGreen), Asset Tracking (ScanTrack), biometric Time & Attendance registration (ScanTime), Linen Management (ScanBlue) and Apparel (TracEye). Mieloo & Alexander is based in Amsterdam and has a sales office in Düsseldorf, Germany.

5.2 Supply Chain of DRF

Like for every company active in this industry, with the limited time the flowers have value, it is key for DRF to keep the supply chain as fast as possible. Every intermediate station takes time so should be avoided if not deemed necessary. They do not produce themselves (or at least only a small amount) so they do not risk producing too many or not enough flowers. They pay for this risk reduction by going to the market and buy from other parties. Figure 5.2 shows which parts of the supply to demand path are in the business model of DRF. Given this business model as a supply chain director, DRF

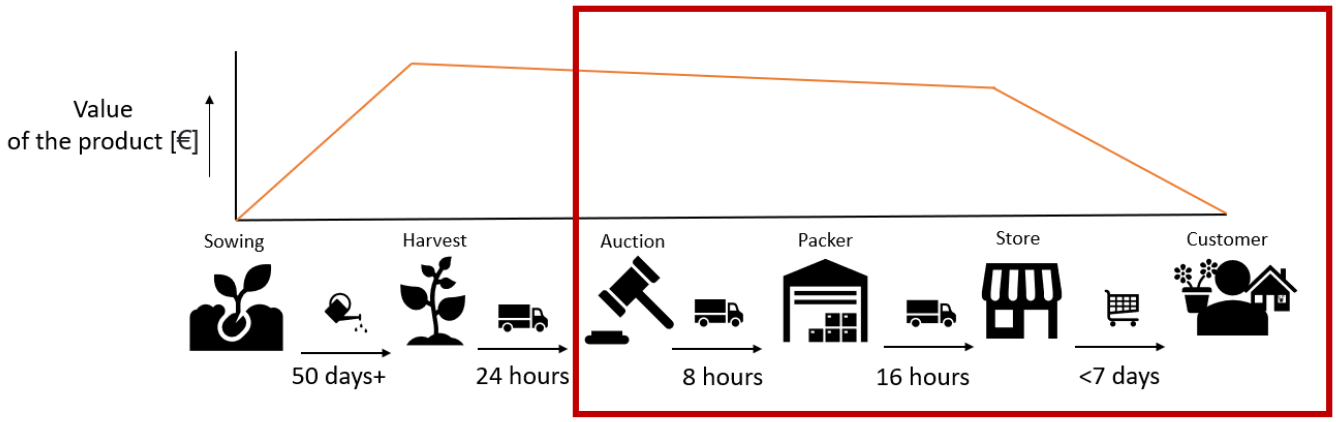

Figure 5.2: The focus of DRF in the supply chain of flowers

oversees the whole process, and is capable of having near complete information along the supply chain, which consist of three actors: Source (grower or packer), distribution (packer) and retailer for customer access (Casino Supermarket). Figure 5.3 shows which parts of the world are in their focus of the supply chain of flowers.

5.2.1 Auction to packer

Once DRF has decided how many flowers or plants they want to get delivered to each store, there are two options for acquiring product. They either communicate this to the growers they collaborate with and order directly, or go to the Flora Holland auction in Aalsmeer to purchase the correct total amounts of each product. The first option may be more desired as it cuts out a middle man in the form of the auction. However, the growers can not always deliver the exact quantities, which forces DRF to go to the auction. Auction is considered more robust than the direct delivery, as the higher supply can anticipate fluctuation in demand better. Once they are bought the suppliers deliver the products to their packer in Leiden. The lead time time to packer is shorter when direct retail succeeds as they skip one station in the supply chain.

Figure 5.3: The locations relevant for DRF operations on a continental scale

Looking at freshness this is preferred, as long as the suppliers can handle the demand. Figure 5.4 shows this journey of the flowers.
Over here all the flowers are assembled in the desired quantities and mixed for the diverse bouquets. They are packed in the correct wrap, foil or paper and given the correct price labels. Thereafter they are put on pallets for delivery, already divided per store. However, if one pallet has not reached full capacity, more products are placed on here to save transportation costs. These products come from margins in the quantity ordered, to create this flexibility in delivery. DRF also sells plants, and with those having a longer lifetime than flowers/ bouquets, they can be added without risking thrashing more on short term.

5.2.2 Packer to store

The pallets are then put on transport to France. The transport is done by truck driving with flower friendly cooled conditions. In the current situation only Paris is a destination for the trucks, but DRF is aiming to expand towards other larger French cities still in 2021. The trucks bring the flowers and plants to a central transfer station in Paris. Here the pallets are distributed again and put onto smaller, city friendly delivery trucks. These deliver the plants and flowers along with other fresh products to the designated stores, so the flowers have to wait until the total truck is filled. Figure 5.5 shows how this part of the flower distribution on the map of North West Europe. With the distribution and packing time, the waiting for full at the packer and at the smaller distribution centres in France, the total lead time is usually 48 hours between purchase at the auction and arrival at the store.

5.2.3 The stores

In the stores the flowers and plants are stocked on the DRF-owned displays, ready to get pick up by the customers. Every display consist out of the same pieces. There are two stairs-shape flower frames, with in the middle a multi level plant frame. Figure 5.6 shows an empty display. All have surface measures of 80 by 120 cm, giving a floor coverage of 2.88 m^2. So it differs from the one displayed in figure 5.1 as that is the previous set up in operation.

5.3 Current replenishment process

Replenishing means restoration of a stock to a desired level or condition. The decision of many flowers this delivery handles is a delicate one. Currently they are building a brand, so they should have sufficient flowers available at all times. Especially with the uncertainty of what in store, a large buffer is a solution to guarantee inventory.

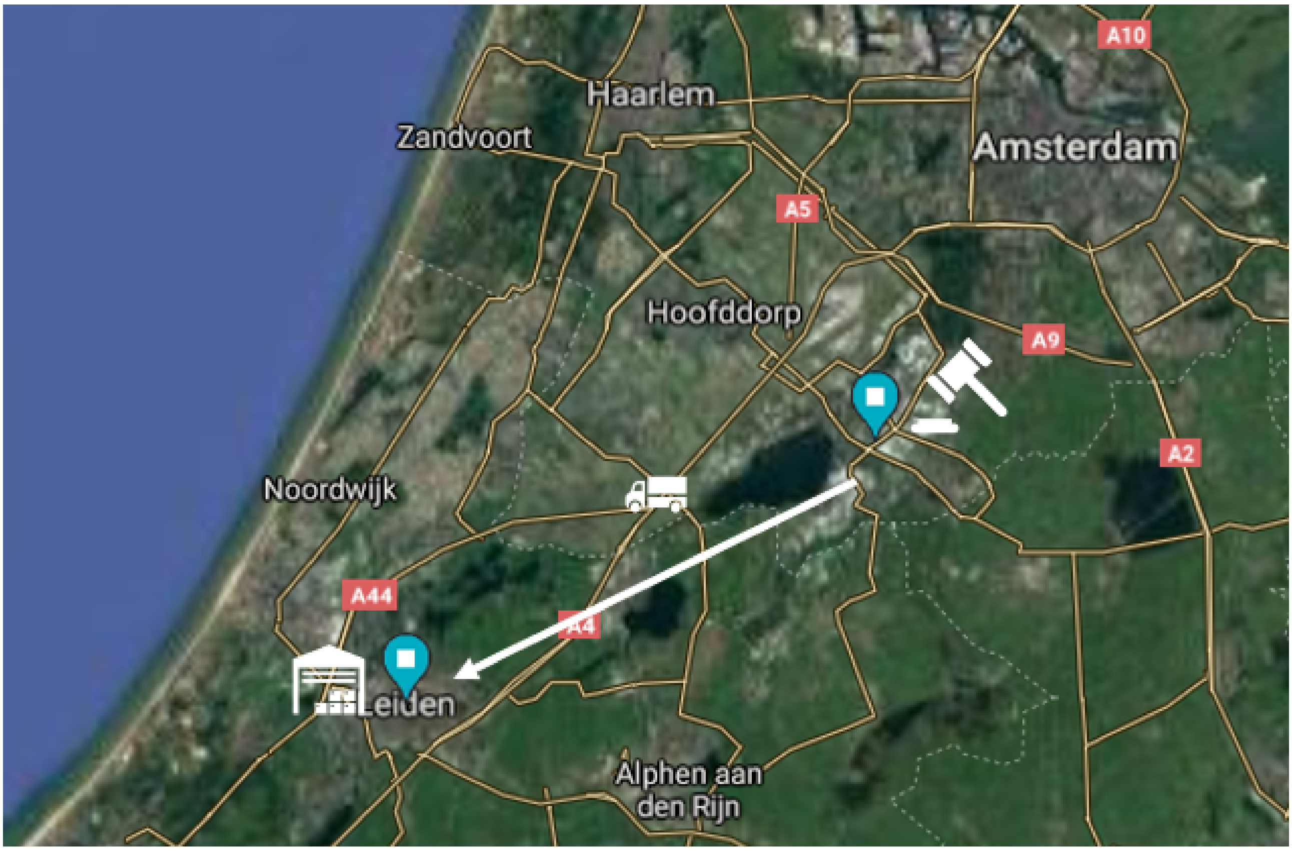

Figure 5.4: The first part of the supply chain relevant for DRF, from auction in Aalsmeer to packer in Leiden

5.3.1 Ordering strategy

As in section 5.2.1 is mentioned, this replenishment process starts when DRF orders flowers for their stores. Right now the replenishment strategy is based on refilling the sold products. This way a minimum of products should always be present. If the buffer is sufficiently large that it can last until the next replenishment moment, given the largest sales, there is always inventory in store for the customer to purchase. Currently this is all done manually and based of the sales that arrive from the casino stores.

5.3.2 Lead time and delivery moments

Between ordering and arrival of flowers in France is a lead time of about 48 hours total. Usually it takes about 20 hours for the flowers to reach the packer after harvest. Then it takes a packing time of a few hours. Thereafter they are transported to the French transfer station, and after a short break for transportation to the correct city truck, they are filled at the shelves in the Casino supermarkets. This lead time is necessary for correct replenishment. The amount that needs to be delivered must take into consideration the changes in inventory during the operation of delivery itself.

5.4 Waste in the process

There are inefficiencies in the process of replenishment at DRF that waste a lot of resources. These are the four largest challenges to overcome. These forms of waste is what the KPI are based on.

5.4.1 Understocking

To ensure sufficient products to meet demand, without an exactly known inventory, is to prevent understocking. This means that there are fewer products replenished than demanded so the shelves become empty. The inventory is out of stock. No products available for demand leads to missing sales. To avoid understocking, is to ensure sufficient available

Figure 5.5: Second part of DRF's supply chain, from packer Leiden to store in France.

Figure 5.6: Empty display of DRF

products by supplying more than is expected to sell. This is not only to not miss out on revenue, also for branding purposes, to be renowned as a constant source for flowers. Finally, with always available product, the demand can be measured, contrary to the situation with empty shelves, as there is no insight in what more could have been sold. This increase in uncertainty leads to worse forecasting.

5.4.2 Overstocking

However, if there is replenished too much overstocking occurs. By producing too large of a quantity, products are at risk to decay or lose value, especially these with the short shelf life. This will lead to disposals which are also undesired as it is a loss of resources.
The goal is therefore to find a trade off between not risking out of stock scenario's and not having more products than necessary to avoid wasting due to overproduction. This is for more common non-perishable products already the case, as inventory costs time, space, and money, but backlog is also not desired. In the case of little information known between different agents in the supply chain, and the order is done manually, the bullwhip effect can occur [47].

5.4.3 Information

Looking from a information perspective, the inventory data provided by Casino supermarket is limited. Both in real time service and in depth of the information, this is necessary to tackle in an inventory solution to get any starting point to replenish from.

Delay

First of all, there is a large delay between sales and inventory update to DRF. It can take up to two days before it becomes clear what is sold and what is left. This means that the uncertainty range in time that the replenishment need to cover doubles. Also the delay can cause a blind spot for certain peaks in sales and therefore lead to out of stock scenario's. A reduction in sales on the other hand can lead to overstocking and therefore a trashing. Uncertainty in inventory information due to delay leads to increase in waste when the demand differs from what is expected.

Differentiation of products

Another problem in the data provided from Casino is the limited amount of product unique EAN codes that can be scanned at the check-out. DRF wants to offer more products than EAN codes are available, and is therefore forced to sell products under the same "group" EAN with the same price. This leads to more unknowns, as the next example shows: DRF wants to sell both cacti and ferns for €5,- each. However they only receive one unique barcode with EAN referring to "Plante

Verte €5" (green plant of five euro). Once they receive the sales it only shows the total amounts of this group, but not whether or not this concerned cacti or ferns. To summerize, one can say that the better perfect information is available the better the supply chain can function.

5.4.4 Allocation and scaling

DRF has the ambition to scale up and deliver flowers also to more stores that will be further away from the current packer. Larger quantities will require more resources and coordinating the allocation of , and to deliver them in time to the correct location needs to be decided in time, as it takes time to grow the correct amounts of each flower. This is problem in the long term for production, as demand can currently be met easily. Furthermore, the further the distance the flowers are delivered from the Netherlands, the shorter the flowers have value in the store. There should be a temporal maximum from which flight transportation or local suppliers is more efficient than through Flora Holland. As the distance is related to the lead time, this is still within the scope of this research, however, the long term communication on large quantities is too broadening to include in this research.

5.5 Information stream

As DRF acts as a supply chain director, all information is available at the relevant places. The third parties (Casino, packers and transporters) act upon whatever DRF tells them to, making sure the information is known from supply (auction) to demand (store). However, this only occurs on the time of ordering. For long term more efficient growing, it might be possible to involve growers in desired amounts that will be required over months time. However for this research it is assumed that the orders that DRF makes can always be fulfilled. In real life they may change products if the price for certain products is too high, but that is outside of the scope of this research.

5.6 DRF in numbers

This section gives insight in what the size of the company DRF actually is. It states in how many stores is operated, what the price range is in which the flowers are sold, what the goal is for expansion and how the KPI are currently.

5.6.1 Stores, products and prices

DRF started early in 2021 with a display in 10 stores in the region of Paris. By the time of this writing (October 2021) an addition 12 stores have been opened in the same region. The plan is to expand towards 400 stores all around France. However, before such large scale distribution can be realised, a standard inventory insight is required. DRF sales about 80 different products over five different categories. Single flowers, single type of bouquet, mix bouquet, green plant and colored plant. The assortment is all in the price range of €2,99 for a single flower to €14,99 for the largest mixed flower bouquets.

5.6.2 Financial situation and KPI

No exact data of the total sales and profit were made available for this research. However, some sales of the week with several stores where given. For several stores this ranged from 300 to 600 euros a week. With the current number of 22 stores open this would result in €350.000 to €700.000 annually.
As is common in the flower industry [48] DRF has have a mark-up of about a factor three for buy-in from the auction. This should cover other expenses like transport, packing, labour etc. as well. The exact profit margin in this revenue was also classified. In general the gross profit margin of flowers is around 40% [49]. However, there are still other costs to reach the net profit, operating expenses and others, taxes for example. Given taxes for profit in the Netherlands of 16%, VAT of France at 20% of the overal product and unknown operating costs the actual profit margin can be approximated. The profit margin is therefore assumed around 15% of the retailer price. This will be used for the calculation on return on investment.
Due to the inadequate information from Casino, there is no exact data available about the current situation of the KPI. It is not sure when the store is empty, when the products are replenished or when they are disposed. The only available information is on total arrivals and sales, but this does not correlate directly to disposals due to theft. Furthermore, with different type of products under the same category name it is not possible to distinguish the different disposals level for

individual products. To still get a quantified insight of how much the situation could improve, chapter 8 also simulates the current situation from which is improved.

5.7 Use of the case study

The case study can be used to determine the boundary conditions and to measure the success rate of the improvements. The physical boundaries/ environment for the inventory solutions are based on the situations in the store, and the other requirements are also derived from the actual situation at store level. Furthermore, the current strategy can be compared with the one based on optimal control. Moreover, the specific lead time, expiration time and historical sales data can be used as a foundation for modelling specific situations. Also with the costs per flower and the savings can be approximated, and therefore a break even point in efficiency can be calculated.

Chapter 6

Design I: Real-time inventory solution

DRF is experiencing problems for their inventory due to the communication by Casino Supermarkets. Both exact sales per specific product and the time when these sales occur are uncertain. This effect has effects upstraim in the supply chain, as DRF is forced to blindly replenish product, for branding and availability purposes. Hence a solution should be found for what is still in the stores, and what is leaving at that time. This chapter explains what system is designed for this issue. It explains how the technology works, how well it performs and how the data is communicated to DRF. This all will lead to the answer of the question: *How does a real-time inventory system based on RFID perform in a store environment?*

6.1 Digital structure

Each reader is connected with a 4G connection, and the aforementioned host is in this case an inventory database in the cloud. Each tag can be charged due to the RF waves, and give back the information stream to show its presence. As every individual tag is part of the inventory until the threshold of time is passed, the information of this individual is combined with the information of the other tags for each EAN group to give insights in what is there by aforementioned logic. Figure 6.1 shows how this automated inventory system works. This is registered by the reader, and the information is passed over from reader to centralized system. Appendix B shows how the whole information chain of DRF is, from hardware to user interface.

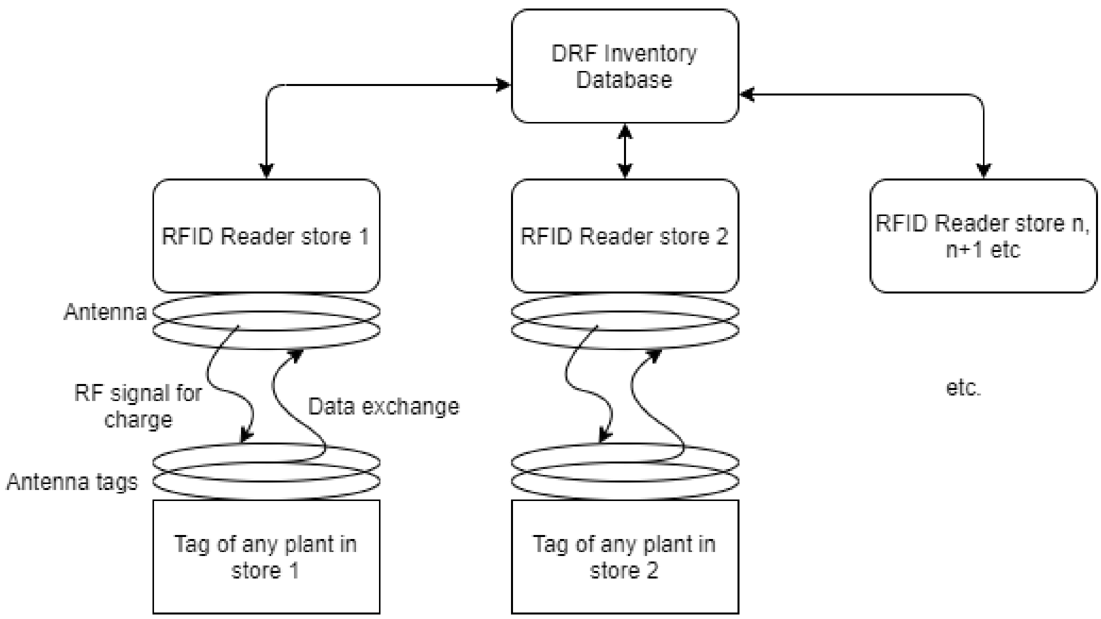

Figure 6.1: Schematical overview of how one tag communicates with their designated store's reader

Area	Store Code	Product Type	Designation	Gencode	Date	Time	Inventory	New Items	Items Departed
Paris	CS167	plante	Plante verte 5€	8720364248666	4-6-2021	15:30	10	8	5
Paris	CS167	plante	Plante verte 8€	8720364240004	4-6-2021	15:30	17	10	13
Paris	CS167	bouquette	ouquet unifleur 3	8720364245719	4-6-2021	15:30	17	6	4
Paris	CS167	bouquette	ouquet unifleur 5	8720364246990	4-6-2021	15:30	17	11	0
Paris	CS167	bouquette	ouquet unifleur 7	8720364248024	4-6-2021	15:30	17	9	2
Paris	CS369	plante	Plante verte 5€	8720364248666	4-6-2021	15:30	11	11	19
Paris	CS369	plante	Plante verte 8€	8720364240004	4-6-2021	15:30	10	15	10
Paris	CS369	bouquette	ouquet unifleur 3	8720364245719	4-6-2021	15:30	16	11	4
Paris	CS369	bouquette	ouquet unifleur 5	8720364246990	4-6-2021	15:30	19	12	4
Paris	CS369	bouquette	ouquet unifleur 7	8720364248024	4-6-2021	15:30	9	7	5
Paris-Nord	CS494	plante	Plante verte 5€	8720364248666	4-6-2021	15:30	25	21	17
Paris-Nord	CS494	plante	Plante verte 8€	8720364240004	4-6-2021	15:30	28	21	12
Paris-Nord	CS494	bouquette	ouquet unifleur 3	8720364245719	4-6-2021	15:30	7	8	1
Paris-Nord	CS494	bouquette	ouquet unifleur 5	8720364246990	4-6-2021	15:30	3	10	10
Paris-Nord	CS494	bouquette	ouquet unifleur 7	8720364248024	4-6-2021	15:30	12	8	8

Figure 6.2: Raw inventory data example

Figure 6.2 shows an example of a snapshot on how this data will be received per store per EAN (in French: Gencode). Every day will start with a current inventory, the tags that are being read at that moment, so including new arrivals. These new arrivals will be shown for that day, also for DRF to see if their replenished goods arrive at the location. The items that are not being read for sufficient time are counted in the departed list, and the inventory is updated. (This helps DRF to also have insight in theft or removal of broken items.)

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Inventory overview per Gencode

Date > Time

		Jun 3, 2021			Jun 2, 2021			Jun 1, 2021			May 31, 2021		
		22:00			22:00			22:00			22:00		
Designation	Gencode	Inventory	New Items	Items Depart...	Inventory	New Items	Items Depart...	Inventory	New Items	Items Depart...	Inventory	New Items	Items Depart...
Plante verte 8€	8720364240004	44	0	31	75	69	33	39	0	16	55	59	17
Plante verte 5€	8720364248666	47	0	25	72	57	29	44	0	13	57	55	17
Bouquet unifl...	8720364248024	29	0	13	42	27	9	24	0	6	30	23	10
Bouquet unifl...	8720364246990	20	0	11	31	28	8	11	0	3	14	31	26
Bouquet unifl...	8720364245719	24	0	10	34	26	9	17	0	9	26	23	20

Figure 6.3: Overview per product

Figure 6.3 shows how the combined totals of all their different products over all stores over the past days. This can help them get an idea of revenue and desired order amounts. Figure 6.4 show how this overview per store per day. DRF can use this insight to decide what to distribute per store. However, this is what based on mock data, so this is what should be worked towards with and what the reader should deliver

Inventory overview per store

Date > Time

					Jun 3, 2021			Jun 2, 2021			Jun 1, 2021		
					22:00			22:00			22:00		
Area	Store Code	Product Type	Designation	Gencode	Inventory	New Items	Items Depart...	Inventory	New Items	Items Depart...	Inventory	New Items	Items Depart...
Paris	CS167	plante	Plante verte 5€	8720364248666	7	0	3	10	10	2	2	0	4
			Plante verte 8€	8720364240004	20	0	8	28	28	10	10	0	6
		bouquette	Bouquet unifle...	8720364245719	15	0	2	17	6	4	15	0	4
			Bouquet unifle...	8720364246990	6	0	2	8	8	2	2	0	3
			Bouquet unifle...	8720364248024	10	0	6	16	12	1	5	0	2
	CS369	plante	Plante verte 5€	8720364248666	19	0	12	31	26	16	21	0	5
			Plante verte 8€	8720364240004	5	0	15	20	20	10	10	0	6
		bouquette	Bouquet unifle...	8720364245719	9	0	5	14	12	0	2	0	1
			Bouquet unifle...	8720364246990	11	0	5	16	10	0	6	0	0
			Bouquet unifle...	8720364248024	7	0	3	10	7	4	7	0	3
Paris-Nord	CS494	plante	Plante verte 5€	8720364248666	21	0	10	31	21	11	21	0	4
			Plante verte 8€	8720364240004	19	0	8	27	21	13	19	0	4
		bouquette	Bouquet unifle...	8720364245719	0	0	3	3	8	5	0	0	4
			Bouquet unifle...	8720364246990	3	0	4	7	10	6	3	0	0
			Bouquet unifle...	8720364248024	12	0	4	16	8	4	12	0	1

Figure 6.4: Overview per store

6.1.1 Decision logic

Every tag contains an EPC, that contains unique information of the product it is put on. Which general EAN it has and which more further down selected product it is. Another benefit from its uniqueness is the knowledge of how long a product there is. Regular inventories with just EAN from supermarkets do not differentiate between individual products and their arrival dates. However, the tags could disappear out of the reading field and reappear later. For example due to a tag being to shielded in an orientation to be charged enough with a polarization cycle. So before a tag can be registered as departed, their should be a time threshold sufficiently high. Otherwise the inventory would continuously depart and re-enter, which results in superfluous updates to the inventory database. As communication goes over 4G network, the data stream should consider only sending true departures to keep down costs in this area. If the products happen to re-enter despite the threshold this will only effect the inventory in a small way, as this should only occur in a desired 2% of the readings. This amounts of re-enter can be listed separately to tune the RFID system even further, but to get this 2% allowance even lower is out of scope.

6.2 Design boundary conditions

The reader and antennas system should be delivered to the supermarkets and implemented in the existing set-up for the flowers. As the location for the frame is modular and the system cannot connect to the frame due to crime prevention reasons, the system should be hanging from the ceiling. Furthermore, the design of this reader system should take into account other criteria as well, this section will cover this, to enable designing concepts and selection final concept.

6.2.1 Flower set-up variables

The flower set-up has a fixed size and only two variation of this are possible. However, the orientation from the center of the reading system may differ. There is no 100% guarantee that the frames will be perfectly underneath the reader/ antenna's. Therefore the design should be designed and tested for reading the tags over a larger area, with different configuration of the frames relative to the reader. Furthermore, as the stores do not all have the same ceiling height, the distance between tags and antenna/ reader is in the range of 2.5 till 4 meter.

6.2.2 Environment

RFID has one big downside in this reading of flower purpose. Radio frequency waves are not able to easily surpass environments with a lot of water and moist. As flowers are put in buckets with water for a longer shelf life, and the flowers still hold water inside their cells, this may shield the tags. The idea is to put the tags inside the pricing labels, and these on the foil or paper packing. Therefore they may end up in a mixture of packing material and leaves, and it is important to consider multiple ways to energise the tag and receive its data. Furthermore it is important that the tags are able to energise with the surface they are put on. As the antennas of the tag are charged by how the RF waves pass through, the tags should be able to work when attached to packing paper or foil.

6.2.3 Antennas

For these type of applications two type of antenna's can be selected from, either standard, cheaper antenna's, that can only cover left handed circular polarization (LHCP). The other choice is the KRAI antenna, which covers all 4 types of polarization. This option costs more but increases the reading possibilities within the reading field. For both antenna's the radio waves leave at an angle of 30-35 degree circular relative to the normal. This has a consequence that one antenna on a low ceiling of 2.5 meter high can only cover a circular surface with a 1.75 m radius.

6.3 Concept designs

From all these criteria three concepts were developed. Given these situational, environmental and technical circumstances, two conclusion were be made regarding the reader system. The selected antenna's should have the optimal possibility of energizing the tags, so first the limits of KRAI should be tested. As these antennas register what type of polarization activated the tag, there can be seen whether or not all tags are seen with only LHCP. Moreover, there should be a sufficient amount of antennas to cover enough ground surface. To read tags in different orientations of the set-up relative to the center of the reader, the two horizontal dimensions should have redundant surface covered. In case of movement of the

reader system or potential enlargement of displays. So at least three antenna's are required. From this the dimensions are determined for designs with either 3 or 4 antennas. As the reader system should also not weight to heavy, should be able to connect to cables or hooks on the ceiling, and the construction should not be made to complicated, two main foundations for frames are designed. With these boundary conditions and requirements three concepts were designed. From this one will be selected for testing, and further iterations will be made if necessary. For all designs is also the same connection to the ceiling applied. Two chains will be connected to the ceiling, and carabiner with cable attached to the reader can be hooked into at the desired height. This way a more or less constant height is achieved and therefore a constant distance between antennas and tags.
The first design is made with 40* 40 aluminium IBS profile in a cross shape (Figure 6.5). It allows space for a central reader and minimal material reaching the corners. The diagonal distances of the system are 1800 mm, with the angle of the RF waves known this gives a theoretical ground area coverage of about **check this 15 m^2**. The cross section is connected with bolt and IBS nut corner joints. The mounts that were used for the antennas and readers are standard monitor vesa mounts. Cables will be lead from the antennas to the central reader through the profile of the beams. The carabiner can be connected to eyes that can be bolted to IBS nuts in the profile. These can be moved along the beams if the situation requires different configuration. Big advantage of this material is the ability to assemble, disassemble and adjust the parts. Downside of this is how well all parts are protected. During transport this may cause damage, although this is a bit out of scope as the design concern more of the store environment and the digital structure. However it is still a design requirement to take into account.

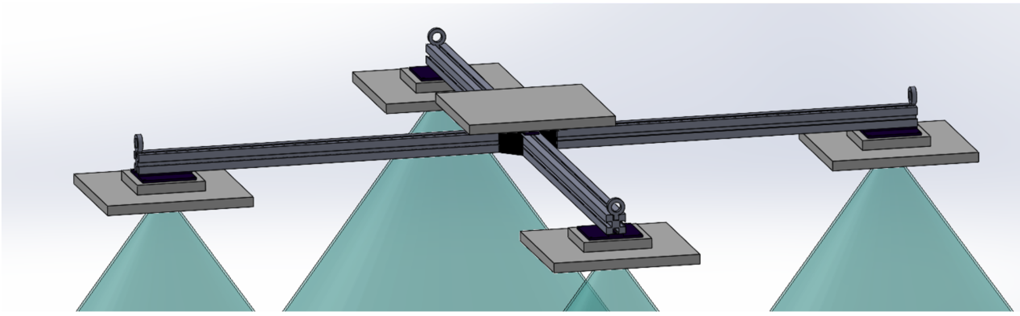


Figure 6.5: Beam construction, containing 4 KRAI antennas

The second design is made from a multiplex plates, with the antenna mounts screwed into the frame (Figure 6.6). The top plate will be square with sides of 1350 mm and 15 mm thick. Under the reader will be another multiplex plate with a cross shape. This allows the antennas free space between them and the tags but also offers a stronger frame for transport. The ground coverage is the same as the previous concept since the antennas are at the same distance. The cables can be hidden between the frames so these are out of sight. The plates will be connected through wooden beams of 40*40*200 mm with screws for attachment. Transport wise this concept has an advantage, as it contains already protection for the antennas and is overall quite stable. On the downside, multiple square meter plates of wood have a significant mass. Also, adjusting configuration is harder in a rigid plate, so if any changes must be made this will take time and damage the system.

Figure 6.6: Wooden plate construction, containing 4 KRAI antennas

The third design is the only one concept with three antennas (Figure 6.7). These are put on the corners of a triangular shaped plate. The design principle is similar to the previous one, as it already has a rigid frame for its own protection during transport. The distances between the antennas remains 1350 mm, but the ground area cover is reduced to**check this 15 m^2**. The benefit of an antenna fewer is cost effectiveness, especially if 400+ stores require one fewer antenna for sufficient performance this option should be investigated. Another downside is the different balance of the frame, it is harder to hang it stable and horizontal from the roof.

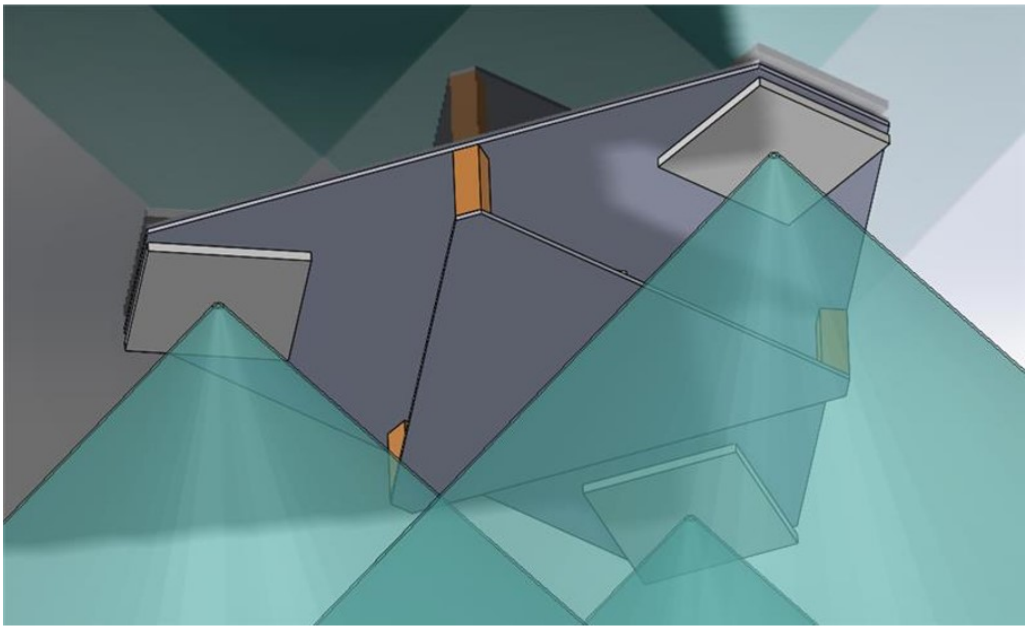


Figure 6.7: Triangular plate construction, containing 3 KRAI antennas

6.3.1 Design selection

As the IBS profile system had the possibility to change dimensions to different distances from the center to test multiple configurations, this concept would first be build. Next to the benefit of agility during testing, this concept is lighter than both of the concept with the dense plates. If testing suggested an antenna fewer could be feasible the concept could be redesigned to a Y shaped construction, similar to the current favorite. Protection during transport can be done by using correct packaging. If these transport units can be reused the extra costs can be a worthy investment. However, the design for these transport units will be out of scope.

6.4 Tests for Performance

To check whether or not this system is able to read the flags for the flowers, multiple tests were executed, with the system first having its (considered) optimal configuration, the largest field covering. Furthermore to ensure the company has the right quality of tags, two brands with different price classes are measured next to each other for a cost-benefit comparison. Also, as tags are not constantly being seen, there should be a threshold of time before the tag is registered as departed. This threshold will also be determined with testing and discussing with DRF concerning also the time frame they want real-time inventory.

6.4.1 Tag selection

To ensure the right tags were selected, two different brands of tags were used during set-up testing. The tags from one brand were numbered 1 through 100 and the other brand had number 201 through 300. Every tag from the first brand was put on the cardboard plant alternatives, next to the same number +200 on it from the other brand. These were distributed over the different levels of the plant frame, where buckets also were changed in number to see how much the water would have an impact on performance. The tags were also orientated differently during all set up tests, so either vertical or

Figure 6.8: The distance testing in two vertical configuration.

Tag Numbers (also +200)	Location
1-20	Central, top of the table
21-40	Central, under the table
41-55	1 m from center, top of the table
56-70	1 m from center, under the table
71-85	2 m from center, top of the display
86-100	2 m from center, bottom of the display

Table 6.1: Location of the tags during Test 1

horizontal, and facing the center or perpendicular to this. These different configuration of tags should be used to see whether or not the tags should be on attached to the package in a certain way to function as desired. These results can be useful for the threshold testing where the best tags and set-up can be used to get the optimal performance.

6.4.2 Set-up and environment

Since there is no guarantee that the reader system will be perfectly centered above the flower and plant frames, the boundary edges should be determined. Furthermore, the amount and location of water buckets and eventually real life plants should be used for final testing. For the position tests, the tags were placed on six different locations. Either on the height of 1 m on a table or rack, and a distance 0, 1 or 2 meter away from from the center of the reader. Also two bucket for reflection are added halfway the location on the table. Figure 6.8 shows two configuration of the testing set-up, the other two had the tags at the same location and only rotated to horizontal facing upwards.
The second test will be on the actual plant frame with buckets added to it, and with the back edge of the frame 0.65 from the center (direct between two antennas) and the frame pointing outwards. With this configuration the outer tags are at a distance of 1,85 meter from the center of the reader. The top layer has two buckets of water, and the middle layer has 4 buckets. Figure 6.9 shows this set up and table 6.2 shows which tags were located where.

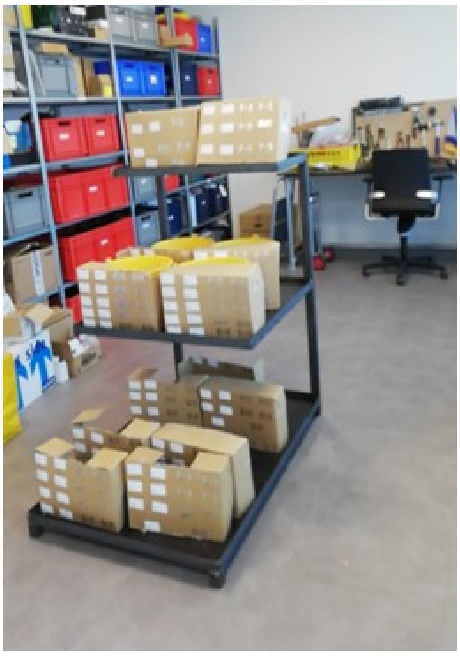


Figure 6.9: Label and set-up testing 2

Tags Numbers (also nr +200):	Location
1-10	Top layer of plant frame
11-50	Middle layer of the plant frame
51-100	Bottom layer of the frame

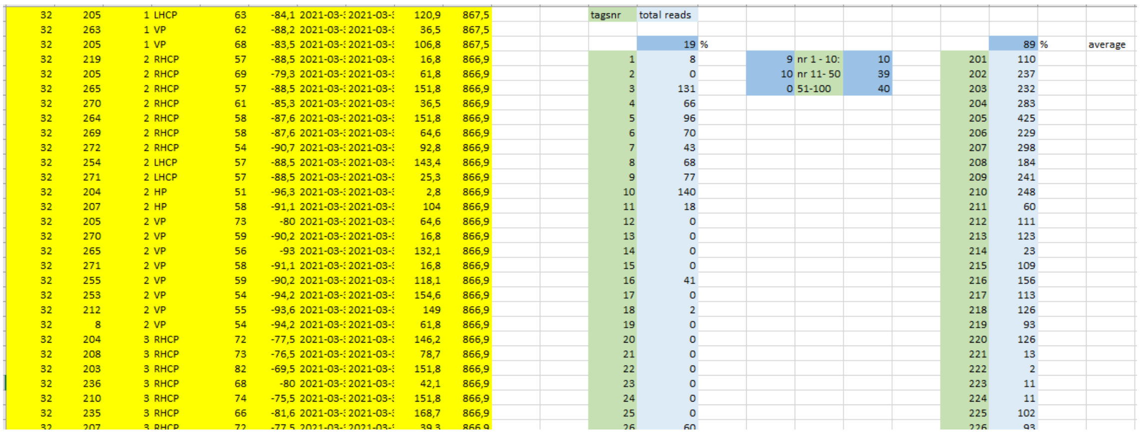
Table 6.2: Location tags test 2

6.4.3 Constant settings

For this testing the Readerstart program from Kathrein is used. This program allows the user to (de)active polarization types or entire antennas and set power levels. This to tweak the conditions for registering tags in the reading field with their EPC. In preliminary testing the power level is determined at 30dB, as well as zero cable attenuation. The scores are presented at whether or not a tag is seen during the test. Every time a tag is seen this is registered and this information is transfered to and counted in an excel. Figure 6.10 shows this data, with in yellow the readers of a tag, in light blue the amount of times the specific tag number in green in read, and dark blue the actual percentage of readings per brand for location and overall. Furthermore, the set-up testing will take 2 minutes per repetition in the first test and 5 minutes for the second test. Each test will be repeated three times to filter out outliers. The average of these will be presented in the results part, and possible outliers may be evaluated.

6.4.4 Departure threshold

After the right tags are selected and the best performing configuration of the set-up with respect to the reader system is determined, the threshold for leaving should be determined. From DRF any improvements is welcome. However, from a performance standpoint, Mieloo & Alexander aim for a level of around 98%. With this desired output should be made the choice when a tag that has not been read for a certain period is actually departed from the store. The trade-off in this section is real-time insight versus accuracy. After the correct set-up and actual real and plants arrived, the selected tags were placed. These tags would mimick different products with actual EPC written on them, similar to the once that eventually would be in the store. The test consists out of measuring how many tags have been read over time intervals. Every 20 minutes the total amount of tags read is counted, and once 98% of all tags are read. This number is used to determine what performance is acceptable compared with the duration of the window a tag before is determined to be departed.



32	205	1	LHCP	63	-84,1	2021-03-	2021-03-	120,9	867,5	tagsnr	total reads									
32	263	1	VP	62	-88,2	2021-03-	2021-03-	36,5	867,5											
32	205	1	VP	68	-83,5	2021-03-	2021-03-	106,8	867,5		19	%						89	%	average
32	219	2	RHCP	57	-88,5	2021-03-	2021-03-	16,8	866,9	1	8		9	nr 1 - 10:	10		201	110		
32	205	2	RHCP	69	-79,3	2021-03-	2021-03-	61,8	866,9	2	0		10	nr 11- 50	39		202	237		
32	265	2	RHCP	57	-88,5	2021-03-	2021-03-	151,8	866,9	3	131		0	51-100	40		203	232		
32	270	2	RHCP	61	-85,3	2021-03-	2021-03-	36,5	866,9	4	66						204	283		
32	264	2	RHCP	58	-87,6	2021-03-	2021-03-	151,8	866,9	5	96						205	425		
32	269	2	RHCP	58	-87,6	2021-03-	2021-03-	64,6	866,9	6	70						206	229		
32	272	2	RHCP	54	-90,7	2021-03-	2021-03-	92,8	866,9	7	43						207	298		
32	254	2	LHCP	57	-88,5	2021-03-	2021-03-	143,4	866,9	8	68						208	184		
32	271	2	LHCP	57	-88,5	2021-03-	2021-03-	25,3	866,9	9	77						209	241		
32	204	2	HP	51	-96,3	2021-03-	2021-03-	2,8	866,9	10	140						210	248		
32	207	2	HP	58	-91,1	2021-03-	2021-03-	104	866,9	11	18						211	60		
32	205	2	VP	73	-80	2021-03-	2021-03-	64,6	866,9	12	0						212	111		
32	270	2	VP	59	-90,2	2021-03-	2021-03-	16,8	866,9	13	0						213	123		
32	265	2	VP	56	-93	2021-03-	2021-03-	132,1	866,9	14	0						214	23		
32	271	2	VP	58	-91,1	2021-03-	2021-03-	16,8	866,9	15	0						215	109		
32	255	2	VP	59	-90,2	2021-03-	2021-03-	118,1	866,9	16	41						216	156		
32	253	2	VP	54	-94,2	2021-03-	2021-03-	154,6	866,9	17	0						217	113		
32	212	2	VP	55	-93,6	2021-03-	2021-03-	149	866,9	18	2						218	126		
32	8	2	VP	54	-94,2	2021-03-	2021-03-	61,8	866,9	19	0						219	93		
32	204	3	RHCP	72	-77,5	2021-03-	2021-03-	146,2	866,9	20	0						220	126		
32	208	3	RHCP	73	-76,5	2021-03-	2021-03-	78,7	866,9	21	0						221	13		
32	203	3	RHCP	82	-69,5	2021-03-	2021-03-	151,8	866,9	22	0						222	2		
32	236	3	RHCP	68	-80	2021-03-	2021-03-	42,1	866,9	23	0						223	11		
32	210	3	RHCP	74	-75,5	2021-03-	2021-03-	151,8	866,9	24	0						224	11		
32	235	3	RHCP	66	-81,6	2021-03-	2021-03-	168,7	866,9	25	0						225	102		
32	207	3	RHCP	72	-77,5	2021-03-	2021-03-	39,3	866,9	26	60						226	93		

Figure 6.10: The raw data from Readerstart, example for experiment 1a of test 1

6.5 Results

The results from this testing show how accurate the system will be during operation, given the boundary conditions (acceptable surface of operation, tag type, usage of water buckets) determined in testing.

6.5.1 Performance of tags

The tags were compared for performance in orientation, and over distance relative to the center of the reader system. Tables 6.3 shows how one competitor outperforms the other by at least at least a factor of two depending on average, independent of the orientation. Table 6.4 shows that the tags from the top performing brand also have a larger field in which they can be read. They also show in close by range promising performance for amount of tags read. In test

	Brand A average read %	Brand B average read %
Test 1: Vertical tags, facing center	34	82,33333
Test 2: Vertical tags, perpendicular facing	33	76,66667
Test 3: Horizontal tags, facing center	35,66667	87,66667
Test 4: Horizontal tags, perpendicular facing	38	77,33333

Table 6.3: The performance of tags based on orientation in test 1

Tag nr. (also +200)	Tags of brand A read %	Tags of Brand B read %
1 - 20	85	100
21-40	37,08333	99,58333
41-55	47,77778	100
56-70	20	76,11111
71-85	0	52,22222
86-100	2,777778	45,55556

Table 6.4: The performance of both brands at different locations, (see Table 6.1) in test 1

6.5.2 Set-up and environment

Directly under and within a meter at top level, close to all tags were seen in a window of 2 minutes. This is also in an environment with buckets being placed in the most obstructing way. These results indicate that

	Brand A average read %	Brand B average read %
Test 1: Vertical tags, facing center	19,33333	89
Test 2: Vertical tags, perpendicular facing	29	94,66667
Test 3: Horizontal tags, facing center	26,66667	61,66667
Test 4: Horizontal tags, perpendicular facing	38	87

Table 6.5: The performance of brand based on orientation in test 2

Tagnr. (also +200)	Tags of Brand A read%	Tags of Brand B read%
nr 1 - 10	97,5	100
nr 11-41	41,66667	92,29167
nr 41-100	3,666667	72,33333

Table 6.6: The performance of brands at different location in test 2

6.5.3 Threshold

Figure 6.11 shows the final set-up, with a table as alternative for the flower display. However, as that only considered a stair shaped display, putting bouquets next to it on the ground will be acceptable alternative. With this test set-up, the environment is the most realistic compared with store condition. Shielding of tags by water in flowers is now like the real life situation, with flowers in their relevant buckets separated from the plants. The buckets are positioned in such a way that they may shield the tags in lower standing bouquets buckets in some way.

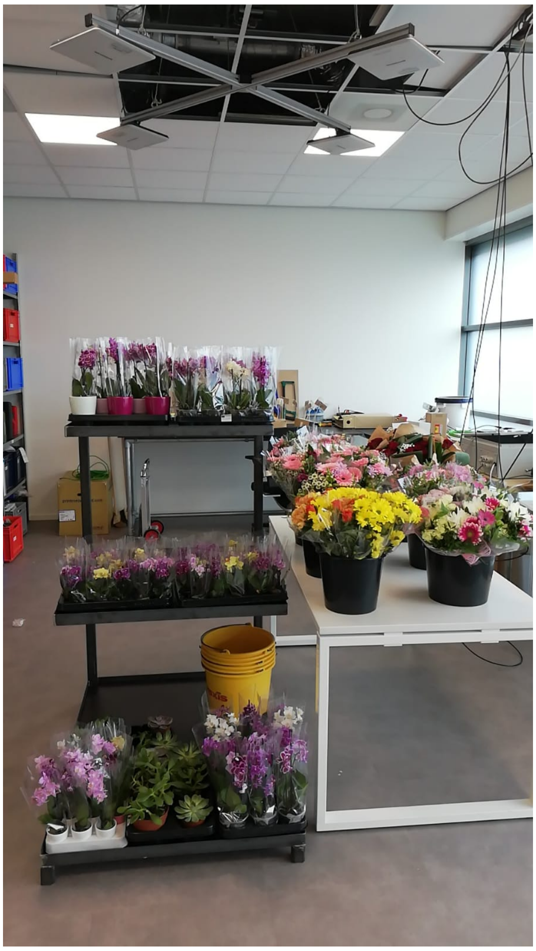


Figure 6.11: Final testing set-up, with real flowers to measure actual performance in most realistic environment.

Furthermore, as in the earlier testing became clear, one tag was performing close to desired. For this experiment the edge of the plant frame was put directly under the center of the reader. This would simulate a situation with a realistic margin to the tags furthest away. For this testing we put the Brand B tags on the packaging, so either foil or paper, divided them over al plants and bouquets and did the 20 minutes testing. This gave the results from table 6.7. The desired 98% is reached after 1 hour of measuring. This time could be defined further, but due to time constraints the choice was made to stick with this accuracy.

Time (min)	20	40	60
Read (%)	92	96	98

Table 6.7: Results of performance testing RFID system

6.6 General outcome of the design testing

As long as the buckets do not completely shield the tags and the tags are on horizontal level not further then 1.5 meter from the center this system has the opportunity to function. It can perform close to a desired 98% read rate with the accuracy of 1 hour. As the stores usually do not sell that much at the later hours of the day, this hour margin should be feasible for realistic real time inventory insight for each day. If DRF stays within these physical boundaries and accepts the time threshold, the inventory solution can perform as desired using the correct tags. Also in the real environment, with customers walking around, picking flowers (and therefore tags) up, reflecting RF waves with their presence, the performance should be better. The design is therefore also accepted, with further iterations possible if for example a location perfectly centered under the reader could be guaranteed.

Chapter 7

Design II: Replenishment strategy

This second design chapter explains about the replenishment strategies are discussed to answer the subquestion: *Which strategies exist for replenishment and inventory control?* First, the boundary condionts and assumptions about the strategies are made. Then the different methods will be given in mathematical form, how the decision making is ordering is executed, and how the KPI will be calculated. Thereafter the strategies will be verified and comments will be made on the senistivity of the modelling, and how they might be validated.

7.1 The working principles and requirements of the model

This section explains how the model mimics the real world, what assumptions are made and what the working principles of the model will be.

- Inventory- The system that the controller works around is inventory. Everything revolves around this: the sales and disposals are taking away from it, replenishment adds to it, and the performance is determined from it.
- First In, First Out (FIFO)- The sales are assumed to be happening in a FIFO order. This means that the flowers with the shortest shelf life left are sold the soonest. Given that there are only two replenishment moments and the assumption that they all had the same harvest moment before the auction there will most likely only be two different expiration dates be present. This way there will not be a mix up in all type of shelf life, and if the flowers are properly restocked from the back this FIFO assumption should be legitimate.
- KPI- The different strategies will be compared in what happens with the KPI. If the system becomes empty at a day, this will be counted. If the sales over the lifetime of the roses are fewer than the amount of that was present at the beginning of the lifetime, the difference will be disposed. This amount will also be counted and compared.
- Lead Time- Currently the lead time is about three days between decision of replenishment in the store. This means it takes 72 hours before the flowers arrived after the order is placed. The replenishment strategy should account for the window in between.
- Shelf life- The assumption is made that shelf life of each bouquet is constant and set. All bouquet have the same time before they are not deemed suited for sale anymore.
- Delivery moments- The restocking is done by the delivery guy. He is also responsible for disposals of products. The model should anticipate different frequencies of arrival. Currently DRF has two replenish moments each week. They usually a Tuesday and Friday delivery, which are ordered on respectively Monday and Wednesday morning.

7.2 Replenishment designs

The goal of this research is to make the flower industry more efficient. This can be done by both reducing uncertainty with the hardware solution, as well as better forecasting. Therefore both the current replenishment method (Direct Stock Replenishment) and a OC based strategy will be designed. After this the situations can be compared, for the improvements based on hardware and on software. Than the results can be evaluated to what extent efficiency is increased.

- Demand Stock Replenishment (DSR)- The foundation of this replenishment strategy is a standard inventory that works as a buffer for sales. The system works that under normal circumstances the products will not be sold out until the next replenishment moment. However, since the product is perishable and the space is limited there is a limit to this. Every product that is expired or sold a certain day is ordered and will arrive in the store after the lead time.
- Expiration anticipation- This strategy acts similar to DSR strategy, except for one key difference. It does not only replenish what is sold or disposed, but also looks ahead of how many products are on the verge of expiring. It anticipates already on the possibility of partly disposal of these products by ordering a percentage of the remaining ones already.
- Predictive Inventory Replenishment Model (PIRM)- This strategy is based on optimal control that tries to predict what will be demanded. Here a prediction is made concern predicted demand, takes into account incoming orders, lead time and expiration for how the inventory will change over time. From this information an optimal order is made The parameters to emphasize either preventing OoS or disposals can be tweaked to switch between how the trade-off can will end up.

The next subsections will go into how these strategies will be designed. The mathematical models of each strategy is presented, what each variable represents as well as how they influence each other given the relevant equations.

7.2.1 DSR

Table 7.1 shows the mathematical model for the DSR strategy. This system works by refilling what is sold and/ or disposed. Main variable in efficiency is lead time, as this is the window that lacks opportunities to act immediately upon change.

Variable	Description
Inventory	Main system, inventory at the store
Disposal	Disturbance, expired products are removed from the inventory
Sold	Disturbance, sold products are removed from the inventory
Order	The products that are send to store
t	Time steps in delivery moments
lead time	Lead time due to transportation
expiration time	Life time of flowers at the store
Availability	Amount of times there is product
Out of stock	Amount of times there is no product available

Table 7.1: Variables of the mathematical model of DSR

The inventory is based on the inventory of the day before, the orders of that day are added, and the sales and disposals subtracted. Equation 7.1 shows how this looks in the mathematical model. Orders are explained next (eq.7.2), the sales are just exact numbers, based on what is purchased by the customers. The

$$Inventory[t] = Inventory[t-1] + Order[t] - Sold[t] - Disposal[t] \tag{7.1}$$

The new orders are based on what is sold or thrown at a day. These orders will arrive the lead time later. This is shown in equation 7.2

$$Order[t + leadtime] = Sold[t] + Disposal[t] \tag{7.2}$$

Since the system is assumed first in first out, the disposals can be determined without any probability involved. They can be measured by taking the inventory from the day that is the expiration time ago, and subtracting all the sales and disposals in the period in between. Everything arrived before should already be gone after this period (sold or thrown out at least the day before). Anything that arrives later will still have the possibility to be sold, otherwise it will be thrown away later. (Equation 7.3

$$Disposal[t] = Inventory[t - expirationtime] - \Sigma Sold[t - expirationtime : t] - \Sigma Disposal[t - expirationtime : t - 1] \tag{7.3}$$

The amounts of times the display is out of roses is counted, as well as the times there actually is product available. This should always add up to the amount of days simulated. They are also not allowed to be negative so about these KPI the following constraint should be said (Eq.7.4)

$$\begin{aligned} t = OutOfStock + Available \\ OutOfStock >= 0 \\ Available >= 0 \end{aligned} \tag{7.4}$$

Furthermore, the system also has a physical limitation how many bouquets could fit on the display and how many can be transported in one delivery. Although in some situations the buckets on the display may be used more modular depending on sales is the constraint for the maximum inventory is shown in equation 7.5, which also shows the maximum constraint for order size.

$$\begin{aligned} Inventory <= 50 \\ Order <= 50 \end{aligned} \tag{7.5}$$

Figure 7.1 shows how the ordering is done using a DSR strategy. It explains how the decision making is executed, based on previous sales and disposals, and in what order.

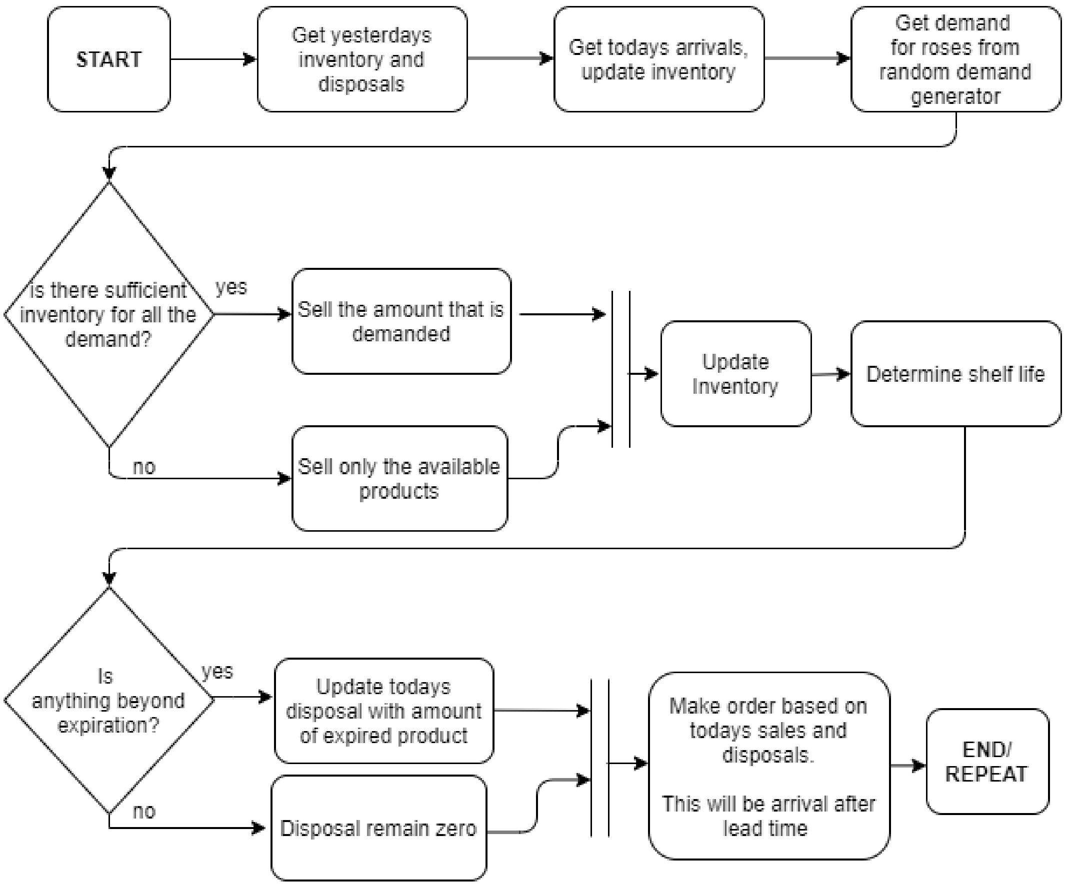


Figure 7.1: Flow diagram of direct stock replenishment

7.2.2 Anticipating expiration

Anticipation of expiration follows the same mathematical model as DSR, however two more variables are added. These are shown in table 7.2.

Variable	Description
Products at Risk(PaR)	Products that expire after the next delivery moment
κ	Factor how many of the products are anticipated for

Table 7.2: additions to the mathematical model of DSR

The additional equations to the mathematical problem are shown in equations 7.6 and 7.7. Products at risk are products that are defined by meeting their expiration time at the next delivery moment. If they are not sold they will be disposed. By ordering products that are at risk before, OoS scenario's due to large disposals at once is already anticipated for and in theory reduced or prevented.

$$PaR[t] = \kappa(Inventory[t-expirationtime+1]-\Sigma Sold[t-expirationtime+1:t]-\Sigma Disposal[t-expirationtime+1:t]) \tag{7.6}$$

$$Order[t+leadtime] = Sold[t] + Disposal[t] + PaR[t] - PaR[t-1] \tag{7.7}$$

Figure 7.2 shows the additions in the flow chart of decision making with the expiration anticipation.

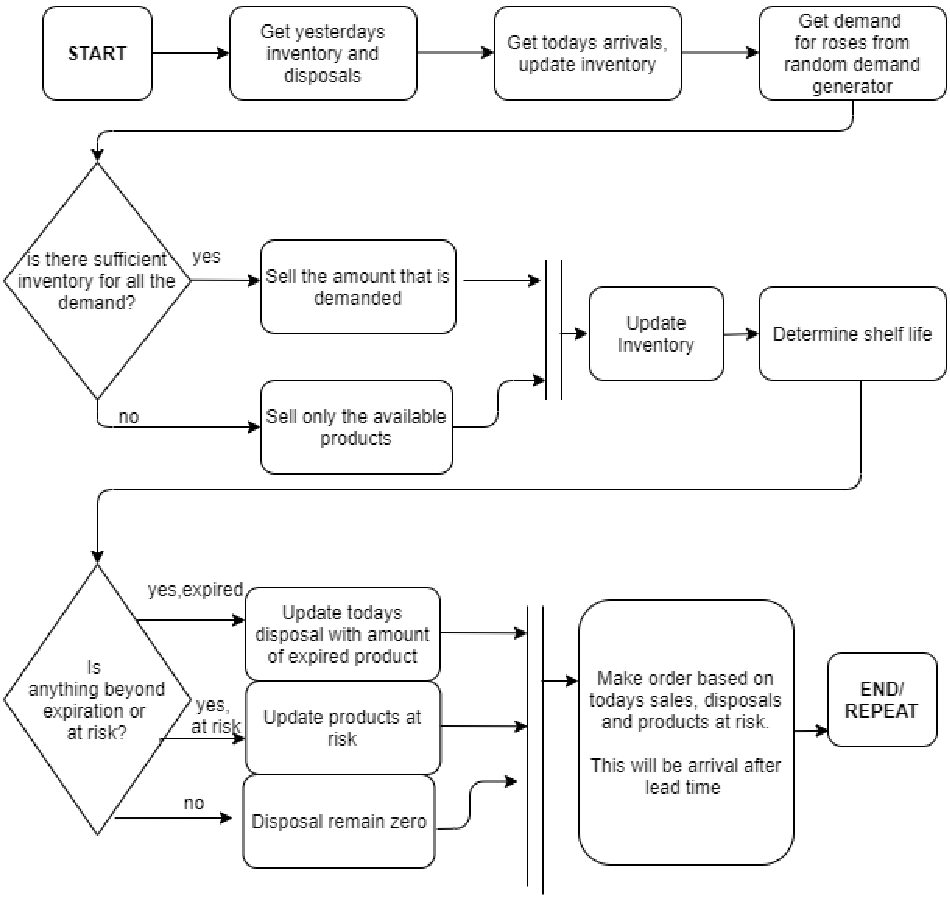


Figure 7.2: Additional steps in the expiration anticipation

The idea is that the disposals are more spread out over time. The amount may increase, but if the OoS scenario's are reduced in a relatively larger part, the efficiency can improve by having a lower base order.

7.2.3 PIRM

The OC based strategy is using an objective function that helps working towards a (locally) optimal replenishment strategy. It has the same components as the DSR modelling, however there is a objective function added to not just follow demand, but to anticipate fluctuations better.

Variable	Description
Inventory	Main system, inventory at the store
Disposal	Disturbance, expired products are removed from the inventory
Sold	Disturbance, sold products are removed from the inventory
Order	The products that are send to store
t	Time steps in delivery moments
lead time	Lead time due to transportation
expiration time	Life time of flowers at the store
Availability	Amount of times there is product
Out of stock	Amount of times there is no product available
Expected Inventory	Inventory expected at arrival moment
Expected Demand	Expected demand from Moving Horizon Estimator
Products at Risk(PaR)	Products that expire after the next delivery moment
Referential stock reserve (RSR)	Reserve Amount above the desired meeting of demand

Table 7.3: Variables of the mathematical model of PIRM

The time derivative of the inventory state has not changed for this system, this remain equation 7.1. The ordering however is not based on replenishing back to a certain predetermined level, but is aiming to use the expected demand for the time until the arrival of products and the existing inventory and shelf life to calculate towards an expected inventory at arrival. Than the order decision is made based on expected sales, the referential stock reserve, and the expected inventory.

$$ExpectedInventory[t] = Inv[t-1] - ExpectedDemand[t] - max(0, (PaR[t-1] - ExpectedDemand[t])) \tag{7.8}$$

$$Order[t+LeadTime] = ExpectedInventory[t] - 0.5(ExpectedDemand[t-1] - ExpectedDemand[t)] + RSR \tag{7.9}$$

This ordering process is only done for as many steps as many steps as the lead time requires. The disposals and products at risk are calculated as before in equation 7.3 and 7.6. The reason the expected demand is average over the last two estimations is the reduction of losses due to over- or underestimations. The Moving Horizon Estimator can best predict the new value of the coming sales based on earlier measurements. However, it can occur that the demand seems to follow a specific trend, despite the stochastic nature of this process. An estimation can easily be a too high or low value. If this is extrapolated for another time step, so not only for estimating expected inventory but also to determine the demand in the next case, the same error is used twice and the KPI are affected negatively. Large seasonal trends like more summer sales can still be followed, due to increasing nature of each estimation, and the buffers takes care of extra sales above the order. Also decreasing will not go as fast as possible, however some expiration might happen, and at the next order the inventory is already at a low level so this will not keep repeating during a lower season. To summerize: although it is slower in following large seasonal trends, the overall loses will be lower due to the reduction accumulation of errors in estimations during a season with the sales distribution with constant mean.

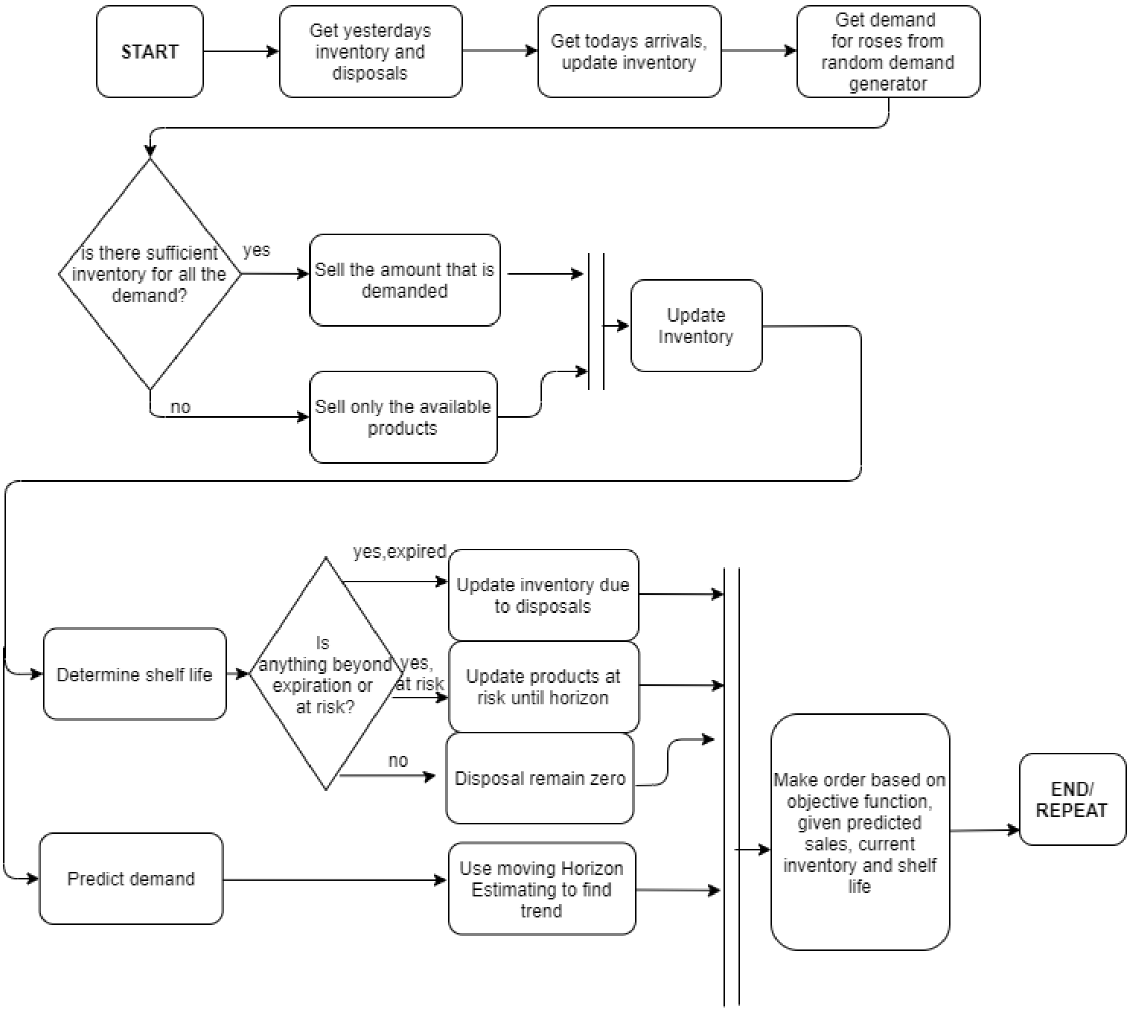


Figure 7.3: Working principle of the MPC

7.3 Verification and validation

This section is about verification, which means it answers the question: *Is the model right?* It tests if the system reacts as expected to certain situations. What happens if extreme values are put into the system, does it still behave as designed for. This way it is determined if the simulation model is programmed right, so the experiments for the gain of the problem is at least done mathematically correct. The final subsection is about validation, which answers the question: *Is it the right model?* It may not give a 100% guarantee that the model is a perfect replication of the real world, but tested hypotheses that are generated from a validated model may be relevant for the real problem.

7.3.1 Verification of DSR

To test the correctness of the model, a few experiments are executed. First a situation is executed with a sales of zero for the first forty days, with the next forty only one rose sold per day, ending with twenty days more of zero sales. The basic inventory of 20 units, that is stocked over the first few days of opening, until the first products can go expired.

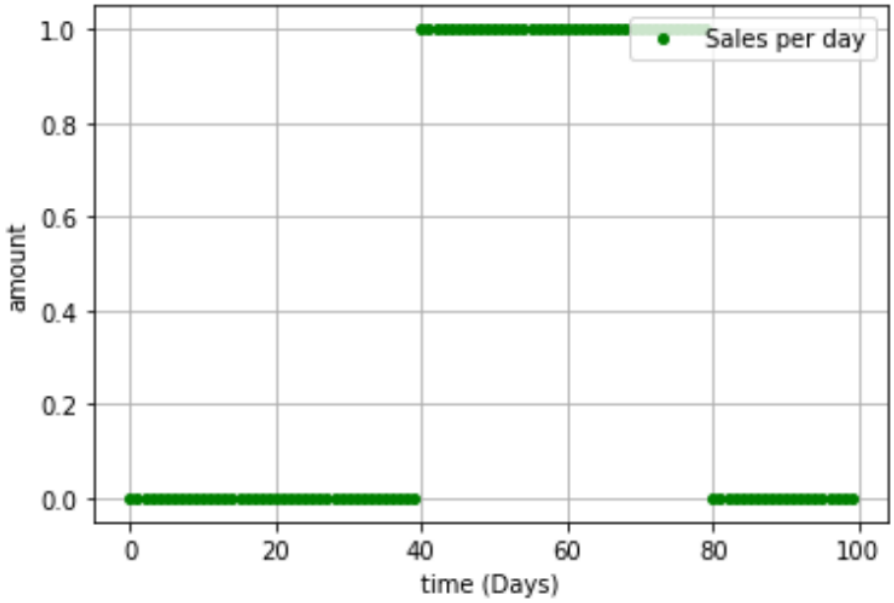


Figure 7.4: sales for the first one hundred days

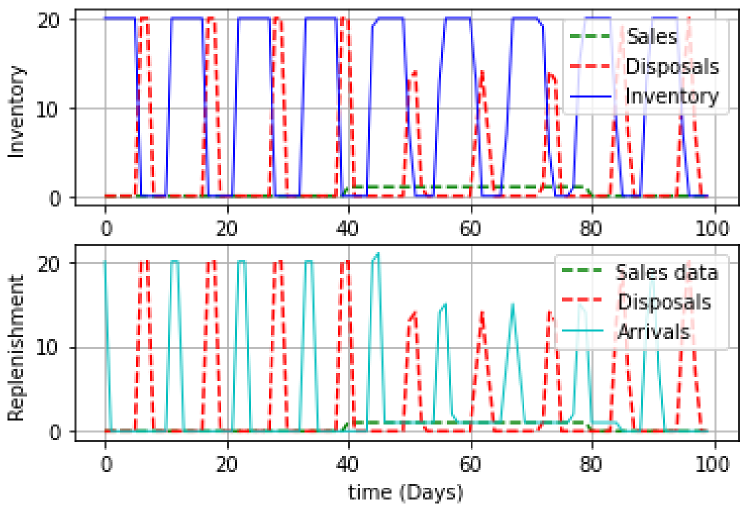


Figure 7.5: Consequences for the DSR model

Figure 7.5 shows the effect of this very limited sales on the products. If no products are sold, all the inventory is disposed and after the lead time the same amount of products are restocked. Once there is some sales, there is more constant arrival, and the peaks are lower. The replenishment is more divided.
However, since there are more variables present, more tests should be executed to verify the whole model. Table 7.4 shows which tests were executed, what the desired outcome would be, and what the results were to (dis)prove this.

Test	**Expection**	**Result**
To change the expiration time	Fewer disposals with longer time, more with shorter time	Disposals increase with shorter time
To change the lead time	The peaks distance between sale and new arrival will change a longer or shorter time inbetween, also OoS occurance change	The arrival follows the sales curve with longer delay, OoS-occurances increase
To have the total of sales in the expiration, window be larger than the basic inventory	No disposals	No disposals, inventory constant
To change the initial order	If smaller, more out of stock,if larger, more disposals	if the begin order starts to small

Table 7.4: Experiments used for verifying the DSR model strategy, in which

Figure 7.6, 7.7, 7.8 show an example of the first experiments where the expiration time of the flowers is shortened. The expectation would be that with the same sales, more products would expire, with the risks of more products being out of stock.

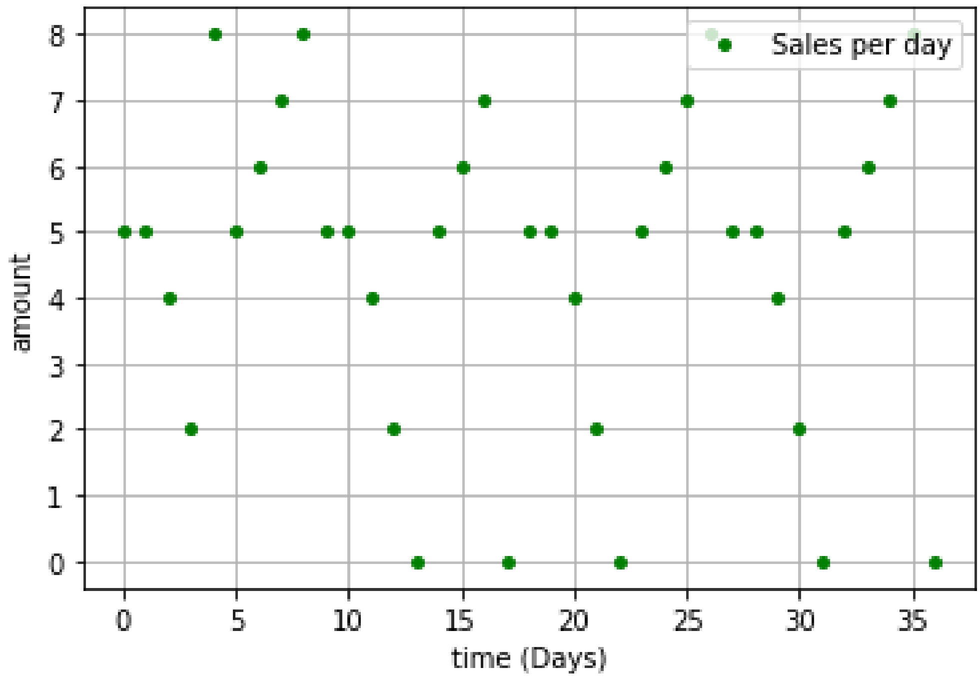


Figure 7.6: The sales with which the verification was done

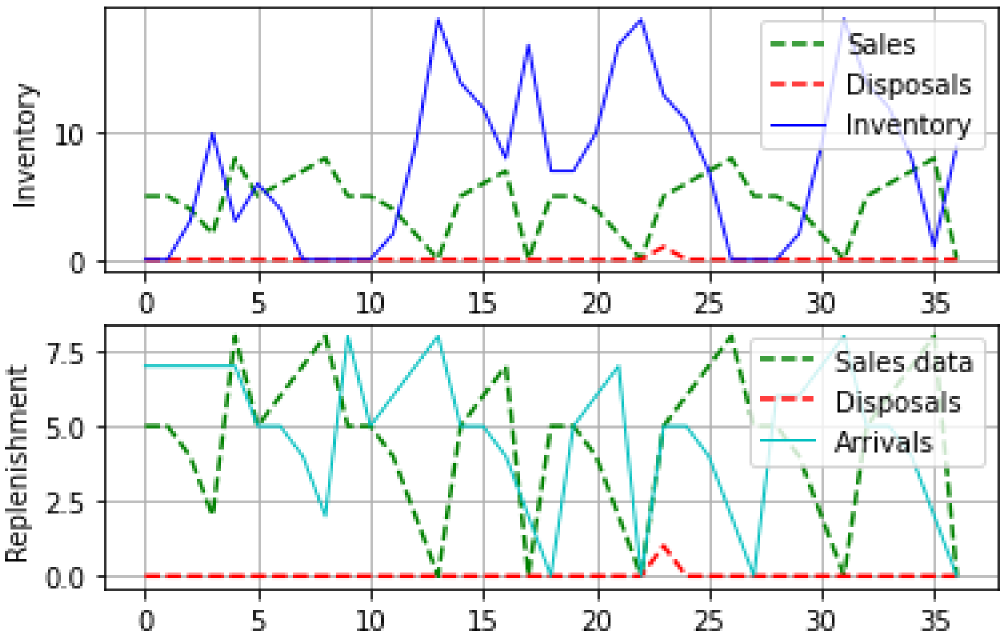


Figure 7.7: Current situation

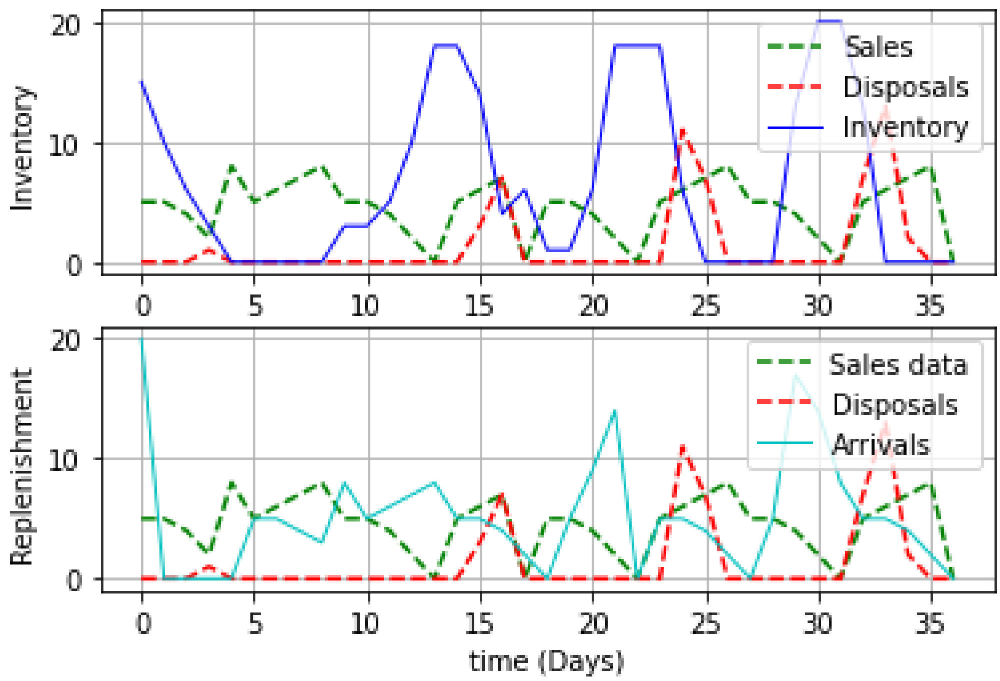


Figure 7.8: Current situation but the flowers have a shorter lifetime

This example shows that indeed more products expire, the red peaks are higher and occur more frequently. The remaining results are presented in Appendix C.

Variables test A1	Results	Variables A2	Results
Expiration time =6 Lead time = 5 Datasetsales4 Basic inventory = 20	------------------------------ total Demand =168.00 ------------------------------ Out of stock occurances =5.00 ------------------------------ Average Inventory at store =10.03 Availability in Store =32.00 ------------------------------ Average disposal at store =0.00 disposals =0.00 ------------------------------	Expiration time =3 Lead time = 5 Datasetsales4 Basic inventory = 20	------------------------------ total Demand =168.00 ------------------------------ Out of stock occurances =13.00 ------------------------------ Average Inventory at store =6.73 Availability in Store =24.00 ------------------------------ Average disposal at store =1.38 disposals =51.00 ------------------------------

7.3.2 Expiration anticipation

The verification of this strategy uses only proof of the expiration being anticipated for. The principle of ordering, selling and disposing has already been proven after all. The way this can be proven is having again a very little demand to the system. The expectancy is that the after the expiration time, the peaks will be half but twice as wide if for 50% of all products at risk is anticipated. The ordering peaks will also appear earlier, since the system anticipates the expiration, and therefore fewer out of stock situations should theoretically appear.

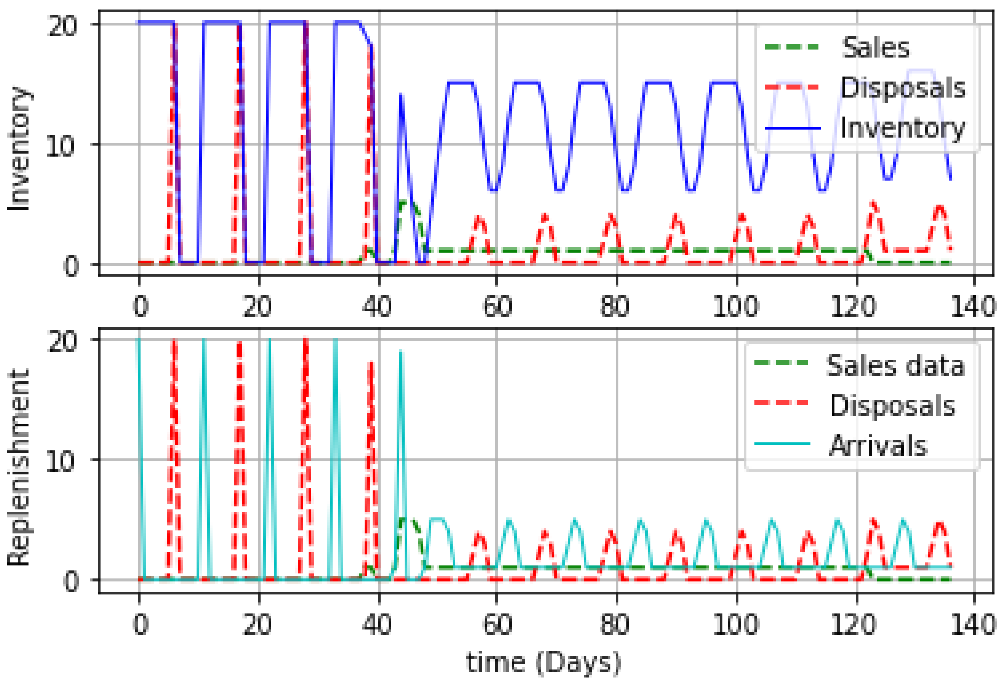


Figure 7.9: The original situation with low demand, similar to figure 7.5, but with a few tweaks to better visualise the changes and confirm the verification

Figure 7.9 shows how the current situation develops over time, with low demand. The replenishment is done in high peaks, and only after the flowers have been disposed. This leads to several periods of no products. Also once there starts being sales, the inventory drops to zero and requires time before it gets to available products. Figure 7.10 shows the new situation, where the first peaks are shortened yet broader. This meets the expectation of how this addition to regular DSR should work. The model seems right. The remaining results of this verification are displayed in Appendix D.

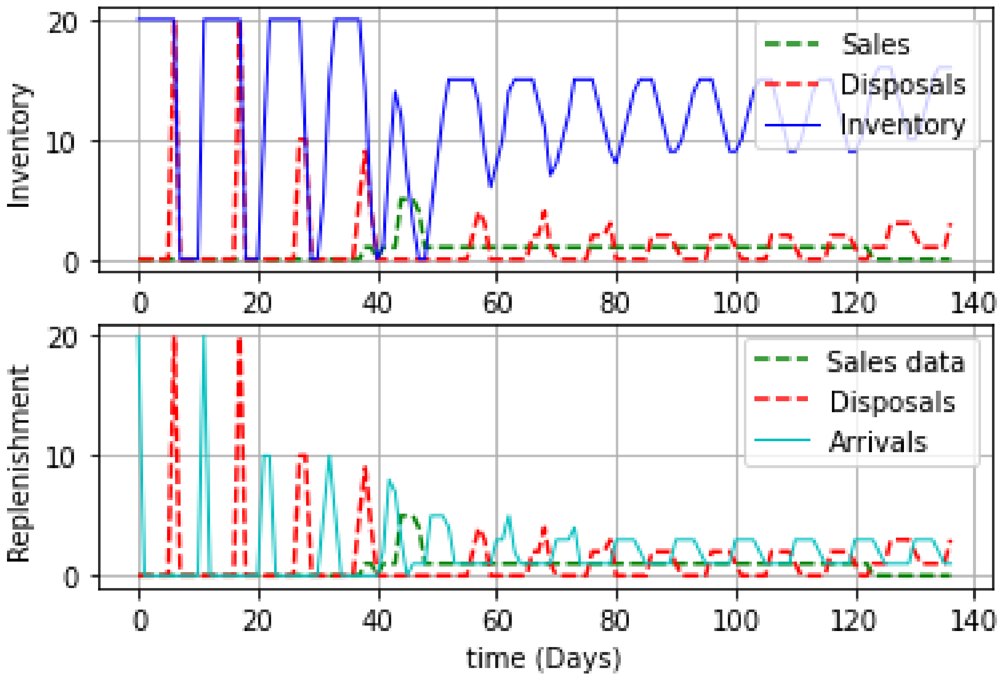


Figure 7.10: The new situation which anticipates expiration

7.3.3 PIRM

The inventory state is still calculated the same, so the verification of the PIRM model is mostly based on whether or not the predicting works as desired. Four scenario's are used to see the desired effect, constant demand, sinusoidal wise fluctuation of the demand, linear increasing demand and linear decreasing demand. The expectation is that each pattern is recognised, and that this estimated demand is anticipated for. For the verification is instant delivery used to see the direct effect of prediction without overestimation due to using multiple predictions. The principle of accumulating errors is more of use at the actual experiments.

Constant demand	**Results**
Expiration time =2 Lead time = 1 Demand=15 RSR=2 Basic inventory =30	----------------------------- Total Sales = 585.00 ----------------------------- Total missed_sales = 4.00 OoS occassions = 1.00 ----------------------------- disposals = 0.00 ----------------------------- Order at t=29 /30 = 15/ 15

Table 7.5: Tabel with the exact results after running a simulation for 40 days with constant demand using PIRM

The results are as expected. From table 7.5 and figure 7.11 can be determined that the optimal control can estimate the next amount that is desired. The demand trend is recognised and the inventory and ordering becomes constant. The only out of stock occasion occurs when the initial inventory is sold and the ordering is not yet up to full replenishment.

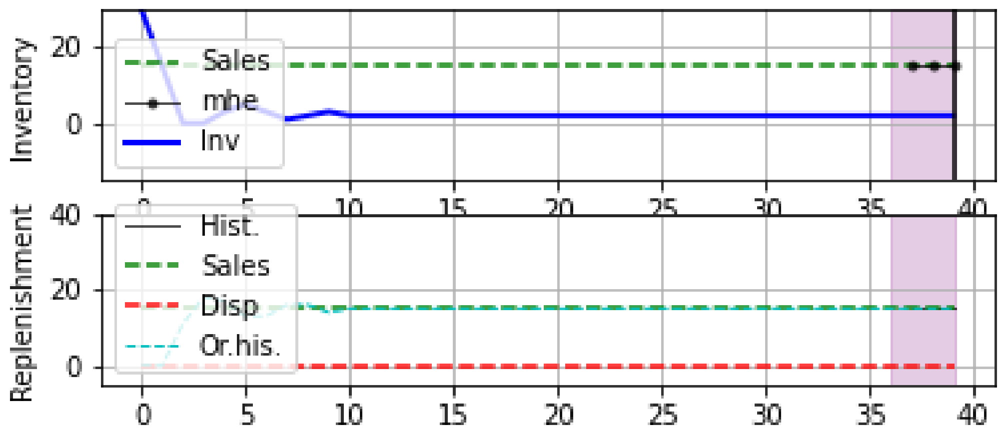


Figure 7.11: The effect of constant demand on the ordering and inventory using PIRM

Sinusoidal demand	**Results**
Expiration time =2 Lead time = 1 Demand=10*5sin(t/2) RSR=2 Basic inventory =30 MHE history=5	--------------------------------- Total Sales = 741.00 --------------------------------- Total missed_sales = 3.00 OoS occassions = 2.00 --------------------------------- disposals = 27.00 --------------------------------- Order at t=29 /30 = 30/ 31

Table 7.6: Tabel with the exact results after running a simulation for 40 days with sinusodal demand using PIRM

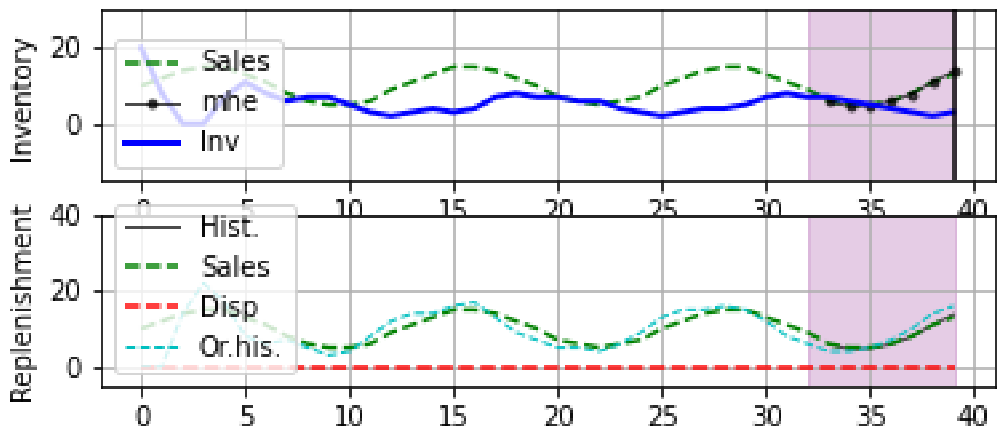


Figure 7.12: The effect of increasing and decreasing demand on the ordering, inventory and disposals using PIRM

The states of the model react in this situation again as expected. The ordering follows the demand curve, as presented in figure 7.12.
The other tests are executed similarly and their figures and tables to prove verification hypotheses will be given in Appendix E.

7.3.4 Sensitivity analysis

[H] Before the scenario's for the real world are tested, the effect of several parameters on the KPI is tested. The variables: expiration time, distribution of demand, and ratio for demand between high and low season. The strategies are checked in a generic test set-up, to just get an general idea of the sensitivity of reactive replenishment compared with predictive replenishment. In this sensitivity analysis, only DSR and PIRM are compared as anticipation of expiration follows DSR in the basic principles.

Expiration time

To check whether or not the strategies also make a different impact if the shelf life of the products is enlarged, a sensitivity analysis is executed for different shelf life duration. Table 7.7 shows the KPI of the system with different values for shelf life. The remaining parameters were set constant.

		expiration time (days)				
		1	2	3	4	5
DSR	disposals #	25.32	2.76	0.04	0	0
	OoS %	38.5	38.4	37.4	37.8	38.8
PIRM	disposals #	62.56	7.04	0.32	0.08	0
	OoS %	39.7	37.6	37.6	37.9	38.9

Table 7.7: Sensitivity analysis of strategies for expiration time

Both react similar to longer shelf life, fewer disposals, but since the demand can rise above the initial value of inventory, OoS are not reduced.

Distribution

Due to the limited amount of data available, there remains uncertainty in what distribution the demand has yearly. The uncertainty is expressed in the standard deviation in which the data is expected. To check how much impact the width of the normal distribution has on performance the standard deviation is altered in the range from 1 to 5. Both systems have a margin of 2 above the average demand and start with that buffer as well. Table 7.8 shows the result of this sensitivity test.

		Standard deviation distribution				
		1	2	3	4	5
DSR	disposals #	0	0	0	0.84	4.56
	OoS %	6.6	22.2	30.0	34.7	38.5
PIRM	disposals #	0	0	0.16	2.12	7.04
	OoS %	17.7	30.0	34.9	36.5	37.8

Table 7.8: Results of sensitivity analysis to see the influence of standard deviation of the demand distribution on the KPI

The DSR is less sensitive to larger deviation, as is to be expected. The PIRM has as a risk that a few random demand data points in specific order can easily cause a large under or overestimation of what is the upcoming demand. Therefore the disposals increase faster, and also the OoS moments occur more frequent with the PIRM.

Ratio of demand between seasons

As not only the deviation is unknown, but also the difference in demand for high and low season the influence of the ration between a high demand and the lower demand is calculated. The higher demand is set constant at 20, and the lower demand starts half way the tested time period and decreases for each test(20, 10, 6.6, 5). See figure 7.9 for the results of the sensitivity experiments.

		ratio between seasons			
		1	2	3	4
DSR	disposals #	0	2.28	77.12	148.76
	OoS %	4.4	1.92	1.72	1.92
PIRM	disposals #	0	0.04	7.4	16.84
	OoS %	10.12	8.48	8.72	9.04

Table 7.9: Sensitivity analysis of strategies for ratio between high and low seasonal demand

The DSR is more sensitive to large differences between high and low season. This is to be expected, since replenishing the same amount to serve in the high season in the low season will lead to more exponentially more disposals. The OoS moments will reduce a bit because there is less demand to miss. The PIRM is able to adapt changes in demand and will not overproduce. The PIRM has also an almost constant OoS, this is due to the buffer that allows only little overstocking, but is therefore relatively sensitive to understocking, even if the demand drops.

7.3.5 Validation

The principle of model validation is checking whether or not the model correctly mimics the real world situation as intended. [50] In other words, the process of model validation is determining if it is the right model to simulate the actual process. Most commonly it involves confirming that the model is accurate given the boundary conditions of the intention of its use. The validation could be accomplished by using historical data to compare it with the expected results if this historical data is used. That could be done for this project. However, such process would only prove that the model is valid to an extend that it is more of an indication of what qualitative effect better information or other strategies might have. It cannot be stated that the model is fully valid.

To completely validate the model there should be pilot stores that work with the RFID systems for validating the improvement with their current DSR method, and others that use the anticipation of expiration or the PIRM strategy. All strategies should be implemented and operated with to see how similar the model is to the actual operation. To fully test these over longer periods of time is out of reach for this research. Next to the time constraint, it is also risking resources to experiment with different processes to measure possible gain.

Furthermore, the DSR situation is only useable to show how reactive replenishment performs. Currently the human ordering can also have some predicting elements. Also if during a low season a lot of disposals occur, the human ordering will probably be to a lower level. Therefore this research is more valid to compare regular reactive ordering to predictive ordering.

This is why the model is build in the first place, to be a quick and cost efficient mean of comparing possible improvements. If DRF is willing to change strategy over time, it will become clear how valid the model is. Nevertheless is it still an useful tool to better make decisions concerning for example more delivery moments or also opening stores further away and hence longer lead time. This model can give an indication to what extend it could deliver benefits.

However, expert validation can be used to have an idea whether or not the experiments mirror the real world. An interview with Annemarie van Mil (owner of grower company Sunsister from glasshouse hotspot Westland that sells to auction, wholesalers, and direct to customers) was conducted to get better insight of the flower economics. The model could be verified to the extent that an experiment with high and low season is indeed a situation that could realistically happen. She provided personal data that followed the mayor trend also visible in overall auction data [51]. The modelling of the strategies was considered legitimate to the extent that with unknown FIFO picking makes it harder to predict. Moreover, the numbers of disposals due to other picking sequence, could be similar for each strategy and therefore not give unrealistic indication of improvements.

It is hard to determine whether it is *The right model* since no original/ real world data for the DRF situation can used for comparison. If eventually such data set arrives the model can be tested and tweaked until it better represents the actual process. From this validation can be concluded that the model can only offer insight into the consequences of better information and strategies to a limited extend. The limit is caused by the underlying assumptions and the lack of large sets of accurate historic data. However the model is still useful to (partly) fill the research gap and giving an answer to the research (sub-)questions. No exact quantification of improvements can be determined with this model only an indication.

Chapter 8

Experiments: comparing different information situations and strategies

This chapter compares different improvements on how the flower industry can be made more efficient. First, the testing criteria are stated, to have an idea of how the situations will be compared and when an improvement is actually feasible from a costs- benefits approach. Next, the hypotheses are given on what is the expected outcome for different situations and scenarios. The experiments plan will be explained, and which scenarios all improvements are simulated for. Thereafter, the results of the experiments will be presented to quantify the improvements in efficiency. Then these can be compared and these comparisons will be used in the analysis at the end of this chapter. All these steps result in the answers of the question **What is the effect of predictive replenishment with real-time information on the inventory management of flowers?**

8.1 Testing criteria

As stated before the goal of the research is to make the industry more efficient by using both a hardware solution for better inventory information and a software solution to better predict correct replenishment. This will be measured by the KPI's overproduction (disposals) and no-sells (out-of-stock situations). Since the efficiency improvement is only worth it if it saves enough money that the investment saves more than just biological resources. The financial side also has to be considered before efficiency improvements are feasible.

8.1.1 Minimizing overproduction vs. "Never" out-of-stock

Since DRF does not have exact data on how many times they are sold out or allow an out-of-stock situation to happen, multiple situations with initial inventory are investigated. With better information on what is in stock and with better prediction methods there is less need for higher inventories as risk covering since the replenishment should anticipate faster and better. To compare the situations, experiments for all situations (better information or predicting) are done and compared on similar out-of-stock occurrences. That way the reduction of disposals given a similar (or even improved) availability for demand is measured as gain.

8.1.2 Return on investment

A solution or improvement is only feasible if it actually breaks even in the financial area. The main goal of DRF remains having good financial results and higher efficiency is only in the service of higher profits. Therefore the investment should be returned by having fewer flowers to throw away, lower inventory purchase investments with the same sales number leads to higher profits.
The inventory solution is not offered by M&A as a one-time investment, but with a monthly payment for hardware and software as a service. Therefore there is no turnaround time but with the monthly savings of unsold flowers, it is possible to determine what level of monthly savings will make the investment worth it.
The monthly fee for each reader system lowers as more are ordered. The first 40 cost 160 euro per month, system 41-100 cost 140 and more will be 120 a month. Furthermore, the tags are sold separately for 45 euro per thousand (depending on

order size). With about 600 products sold per month per store this would lead to an additional 27 euro extra cost for this time period. Therefore the monthly savings should be in the range of 187 euro to break even for the first 40 stores.
For break-even calculation is only looked at the benefits from fewer disposals of flowers. The benefits from a deeper differentiation of products and better information about individual status of plants are ignored.
Rose bouquets are not the only product sold by DRF. When looking at historic sales data they consist only of about 20% of all flower sales and only 13% of the total sales. The gain from rose bouquet savings is only truly applicable for other flowers and not plants due to the difference in shelf life. Therefore, the monthly savings of roses should be a fifth of the 187 euro, equalling about 38 euro. Hereby the assumption is made that the savings behave similarly for all flower types.
As the profit margin of flower are already determined in section 5.6.2 to be about 15%, and the rose bouquets have a price of 6,99 euro, the costs per bouquet are assumed to be about 6 euros. For the first 40 stores to break even, slightly over 6.33 roses each month per store should be saved.

8.2 Hypothesis

Given the principle of the strategies, these are the hypotheses for the experimental outcome.

- In general, is expected that with limited information, a lot of safety stock is required to get avoid OoS. Consequence of this is that significantly more disposals will occur than with up-to-date information. Independent of strategy, better information will lead to better results due to the reduction of uncertainty
- Due to the lead time is practically being halved, expected is that the return on investment is around breaking even. Especially for the first 40 stores, the other stores are expected to be profitable with only the disposal savings already.
- Anticipation expiration will lead to fewer out-of-stock scenarios as a result of disposals. However, in general, more disposals might occur. It is expected that if the amount anticipated for is small enough, only the large amount of disposals are anticipated for, while not overproducing more.
- Fewer out-of-stock scenarios occur when there is optimal control using predicted sales and clear seasonal trends occur. As the prediction can better anticipate trends, less risk needs to be taken.

8.3 Experimental plan

To determine the quantified gain in efficiency different scenarios are simulated for the three different possible improvements. These are compared with the modelled situation of the current situation without good information and using conventional DSR.
First, an experiment is executed which shows the performance of the current situation. This is to have a zero measurement for determining the exact improvements with other improvements. Then the situation using DSR and by RFID technology enabled better information. This is to measure the direct influence of real-time information. Then different strategies with this better information are simulated as well. First an experiment with expiration anticipation added to the DSR strategy is executed, to measure if taking shelf life into account can avoid out-of-stock situations due to disposals better without overproducing more. Finally the PIRM strategy is simulated, to measure the effect of forecasting for replenishment.

8.3.1 Scenario 1: Normal distribution with constant mean and deviation

This scenario is used for the situation where the demand does not follow seasonal trends, and has large deviations. This scenario is based on the available historical data. Currently almost all the products they supply are sold out, very few disposals, but also a lot of OoS, missed sales. Also the full demand is not measured this way. If the historical data is studied a single normal distribution with a mean of 9.6 and a standard deviation of 7.3 can be determined. Figure 8.1 shows this random sales pattern, with no relation between points.

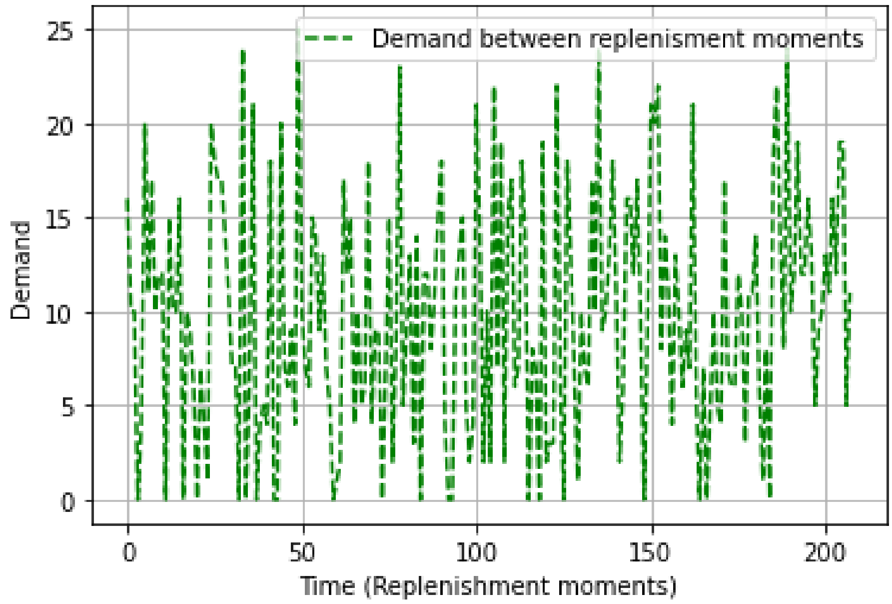


Figure 8.1: Example of the demand pattern for scenario 1

8.3.2 Scenario 2: Altering demand over time

This scenario is based on the situation that follows market numbers, the sales of flowers varies over time. In the spring and summer, popularity of flowers is high compared with autumn and winter. For the roses a similar trend is also possible, although it is not yet confirmed by historical data from DRF sales, but it is by the expert validation. This scenario will therefore consist out of an increasing trend and decreasing trend over the year, peaking around June and having the lowest demand in the winter months, a trend that follows the auction sales trend of Flora Holland [51] and is confirmed by the experts from validation, which show that the difference between high and low season of specific flowers can realistically be of a factor four to five. The means of the distribution for each season is based on the range of sales of the historical data of DRF, and the deviations are based on the yearly sales overall of the auction. Figure 8.2 shows such a demand curve for two years time. The two seasonal peaks in the spring are clearly visible.

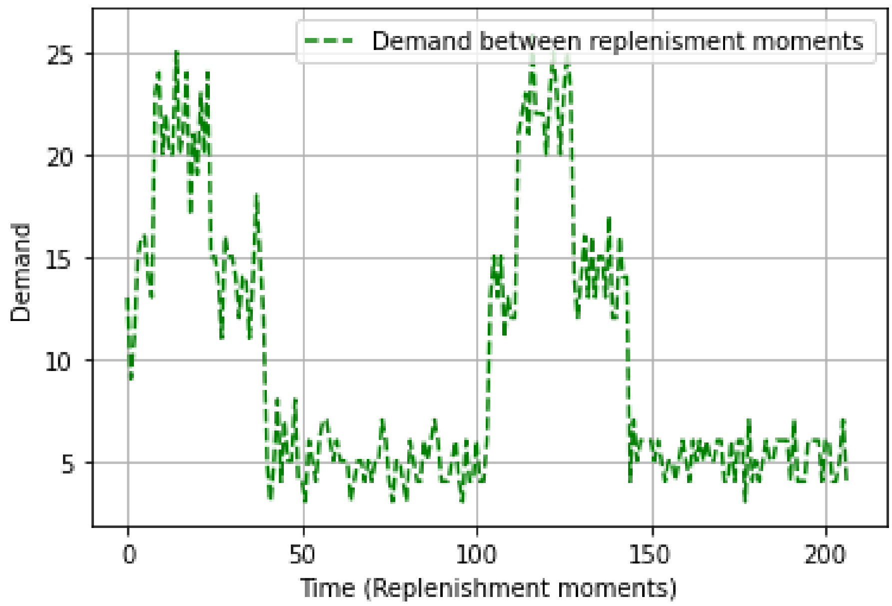


Figure 8.2: Example of the demand pattern for scenario 2

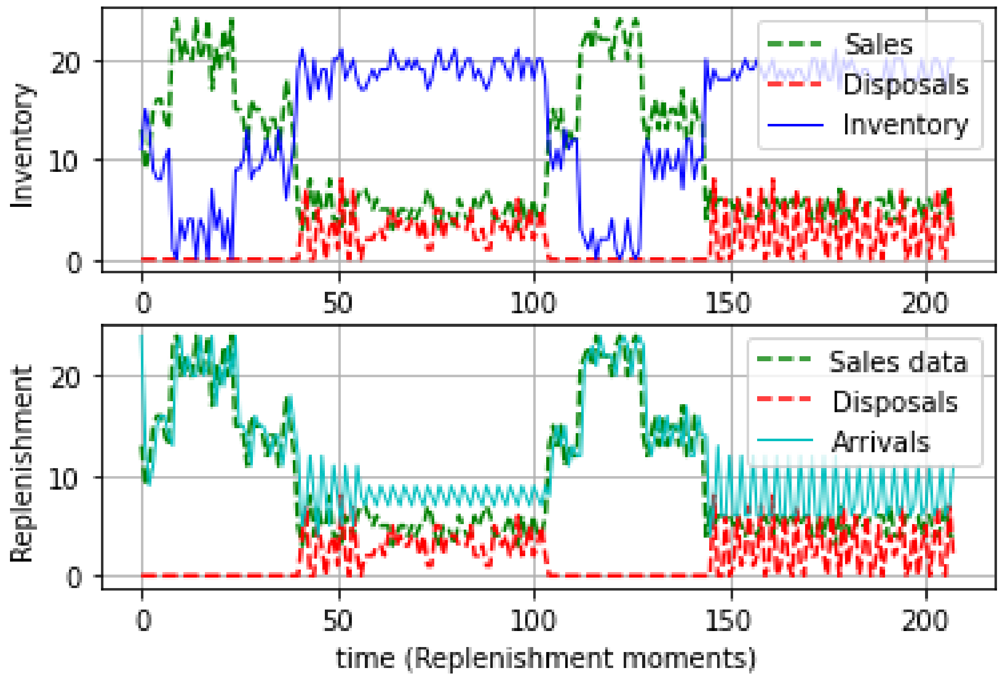


Figure 8.3: Example of how the DSR would order in a reactive manner, based on sales over a time of two years

The working principle for both scenarios is that the demand is subtracted at every time step, and the ordering is done as well. Figure 8.3 shows an example of DSR, for which the out of stock moments and disposals are counted.

8.4 Confidence interval

To ensure trustworthy results is executed to confirm the improvements are not just present in a specific set of sales and delivery. Stochastic sales patterns based on historic sales are used to test how robust the improvements are. These historic sales are from several weeks of sales of roses bouquets, which form a normal distribution. Using the mean, the standard deviation a student t-test is executed. This way it is statistically proven how trustworthy the results are. This way robustness of the system is tested and bias from an incidentally beneficial or detrimental sales pattern is reduced. The results will therefore also be presented with confidence interval, to show how legit certain claims of improvements are.

8.4.1 Number of runs

To determine how many runs the stochastic simulation has to run to get a mean within acceptable range. Using the formula for confidence interval the following formula for the correct number of runs can be determined.

$$n = (\sigma * z/w)^2 \tag{8.1}$$

In this equation, n is the number of runs, σ is the standard deviation, z is the statistical value that correlates to the desired confidence interval (f.e. 80, 90, 95 or 98%) and w is the desired width of the interval [52]. Z for the desired interval of 95% is 1.96, the width is 10% of the total disposals and the sigma is to be determined from earlier simulations. From this is calculated that $n = 25$ leads to a situation that gives the desired interval.

8.5 Results of Scenario 1

The results of the scenario with constant demand are shown in this section. First, the addition of good information is compared with the zero measurement. Next up the effect of expiration anticipation on this new situation is tested. Finally, the results of the PIRM are presented, to see if predictive replenishment works when the demand is relatively unpredictable due to the wide range.

8.5.1 Influence of good information

The differences in the effect of different basic inventory for the DSR strategy with or without good information are shown in figure 8.4

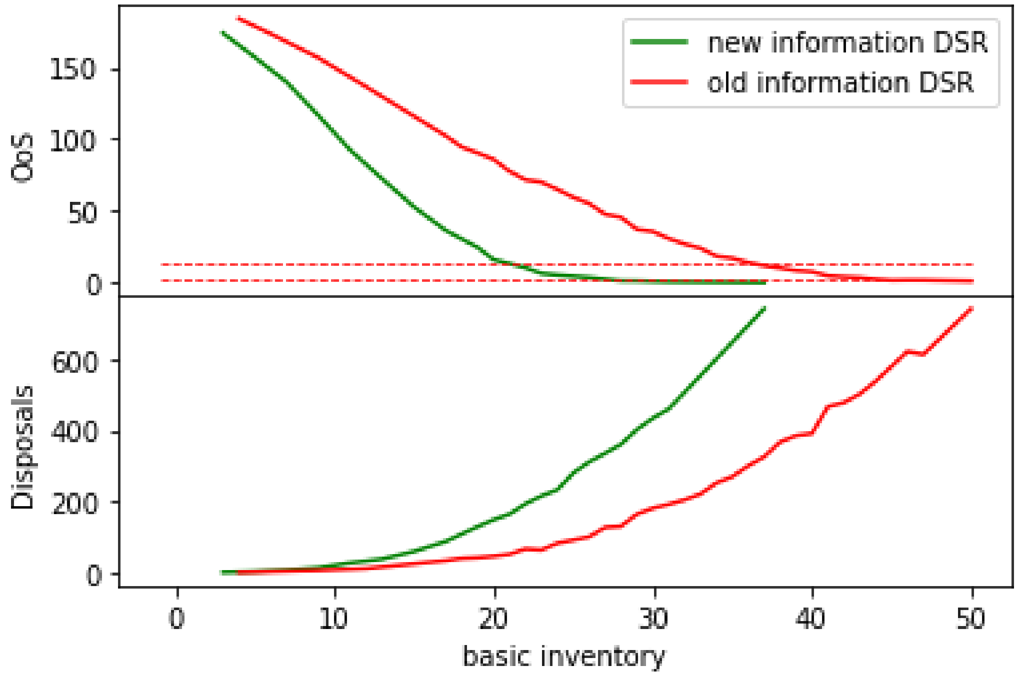


Figure 8.4: The basic inventory vs the KPI for the DSR strategies

To compare the strategies in performance difference is to keep one of the KPI constant. The selected range is maximally 16 occasions of out-of-stock allowed, and a situation with only 4 OoS out of 208 occasions is already sufficient. The next tables show the results with this range, which is also pointed out in figure 8.4 by the red dotted line.

base order	OoS	Missed Sales	Disposals (95%)
41	4	13,16	466,64+-21,4
40	6,16	18,68	390,96+-22
39	7,48	26,76	384,96+-20,3
38	8,28	27,04	367,04+-23,6
37	10,08	33,72	325,56+-25,4
36	11,68	42,68	300,12+-22,6
35	13,88	45,96	269,8+-18,5
34	16,92	58,76	252,44+-18,8

Table 8.1: Results for current situation for DSR strategy with 2 years of operation

The results of the zero measurement are presented in table 8.1. To ensure correct availability of a maximum of 4 OoS, the old situation requires a beginning order of at least 40 bouquets. Consequentially, there are 390 rose bouquets thrown

away in this period. If the beginning order is lowered, disposals decrease. However, more out-of-stock situations occur as well in this period of constant demand.
Table 8.2 shows the range of base orders that deliver similar availability levels as the current situation given the improved information. About 35-40% fewer inventory is required to get similar OoS occurances.

base order	OoS	Missed Sales	Disposals (95%)
26	3,48	6,72	310,96+-14,9
25	4,32	9,72	279,72+-13
24	5,16	12,48	232,96+-18,9
23	6,28	16,6	215,48+-17,1
22	10,28	26,6	193,6+-12,7
21	13,2	36,48	164,32+-9,4
20	15,96	46,52	148,56+-12,9

Table 8.2: Results for DSR strategy with good information for 2 years of operation

Figure 8.5 shows how the disposals decrease with similar out-of-stock levels, if the ordering is done with better information. The savings are in the range of 160-110 savings per two years of operation. Depending on the desired availability the monthly savings would range between 6.7 and 4.6 rose bouquets.

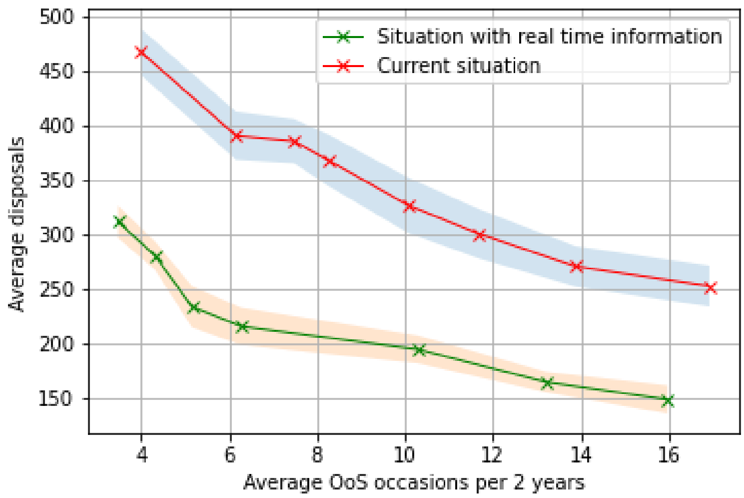


Figure 8.5: The improvements in Disposals over out-of-stock scenarios

8.5.2 Adding expiration anticipation

As the comparison is solely made on the disposals with the same OoS's allowed, the input with base inventory is not shown here, but solely the relevant parts of comparison. Different anticipation factors are experimented with to measure if partial anticipation of potential expiration improves the availability compared with regular real-time DSR. The results are shown in table 8.3, 8.4 and 8.5. Figure 8.6 shows how all these factors impact the balance between out-of-stock and disposal. From these tables and the figure can be seen that the impact of such a system does not give a significant improvement.

base order	OoS	Missed Sales	Disposal (95%)
24	2,84	5,96	292,04+-18,8
23	4,2	8,44	271,76+-19,8
22	7	19,36	221,12+-15,2
21	8,84	23,8	192,64+-15,9
20	12,88	32,72	168,08+-11,1

Table 8.3: Results with anticipation factor of 0.5

base order	OoS	Missed Sales	Disposal (95%)
24	3,48	7,48	277,96+-16
23	6,2	16	223,16+-15,7
22	7,44	18,12	219,72+-14,1
21	11,32	29,2	181,44+-19,4
20	13,56	34,96	150,88+-13,8

Table 8.4: Results with anticipation factor of 0.25

base order	OoS	Missed Sales	Disposal (95%)
24	3,76	8,8	261,36+-14,2
23	5,36	12,28	242,24+-15,7
22	9,6	25,16	184,64+-17,8
21	12,6	31,76	178,96+-17,8
20	14,6	44,56	152,24+-11,1

Table 8.5: Results with anticipation factor of 0.2

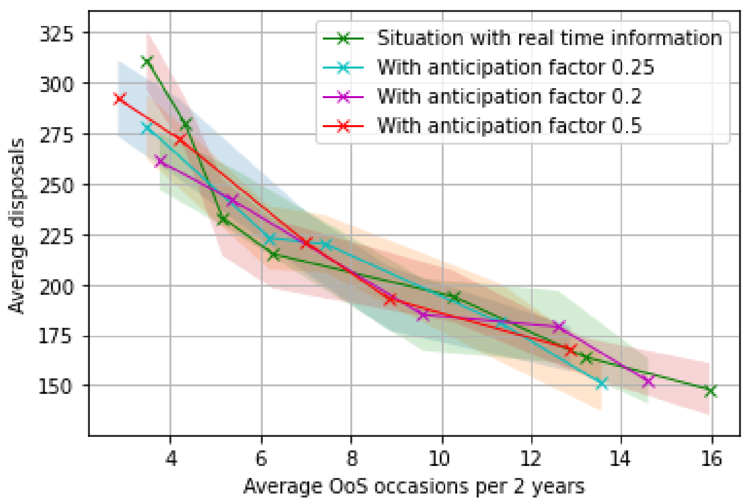


Figure 8.6: The influence of different anticipation factors on the amount of disposals for different OoS occurances

8.5.3 PIRM

As the PIRM simulation works with predicting instead of reacting as ordering principle, there is no basic inventory to compare the systems on. However, the KPI can be measured for multiple amounts of buffer inventory.

As could be expected based on the sensitivity analysis of the distribution, a large standard deviation affects the KPI negatively. The results are displayed in table 8.6 and visually compared with the other main strategies in figure 8.7

RSR	OoS	Missed Sales	Disposals (95%)
13	12.56	56.48	435.04+-22.86
15	6.52	24.04	530.16+-29.59
18	3.08	9.88	722.32+-43.13

Table 8.6: Results with PIRM

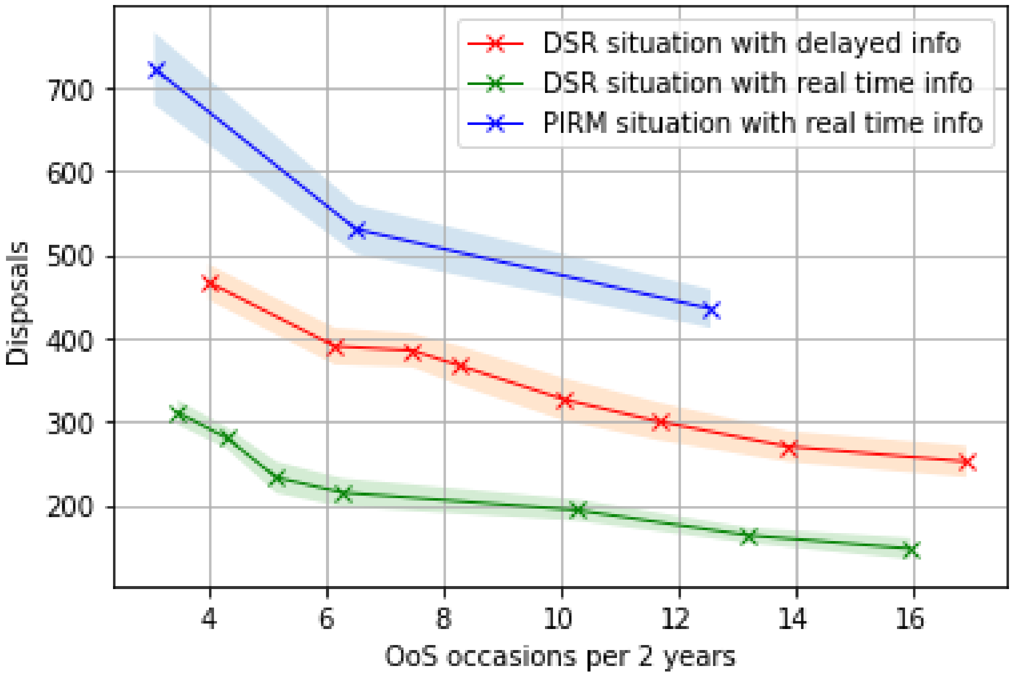


Figure 8.7: The results of PIRM in scenario 1 compared with DSR with good and bad information

The results show a large increase in disposals for the same availability. This is probably due to the unpredictable nature of the demand. The PIRM can understock and overstock constantly because of the lack of trend that can be estimated. The randomness makes it unpredictable, especially with the large deviations.

8.6 Results of Scenario 2

In this section the results of scenario 2 with DSR with bad and good information are shown. Next, the results for expiration anticipation are shown and compared with the normal DSR situation. Finally, the DSR situations with good and bad information are compared with the PIRM situation. However, in this situation a different window is researched, only allowing 4 to 10 OoS occurances.

8.6.1 The influence of good information

In tables 8.7 and 8.8 the KPI of the DSR strategy with respectively delayed and up-to-date information.

basic inventory	OoS	Missed Sales	Disposals (95%)
45	10.76	14.24	801.16+-4.62
46	7.56	7.84	836.96+-4.49
47	5.52	5.2	866.12+-3
48	2.88	2.16	903.68+-5.97

Table 8.7: Results for DSR strategy with delayed information for scenario 2

basic inventory	OoS	Missed Sales	Disposals (95%)
23	12.88	13,24	338.44+-4.65
24	6,68	6,56	382.4+-4.65
25	3,92	3,24	427.76+-4.93
26	3,92	3,24	469.16+-3,18

Table 8.8: Results for DSR strategy with good information for scenario 2

In figure 8.8 the difference between are compared in a graph. For the same availability, there is a saving possible in the range of 450 disposals.

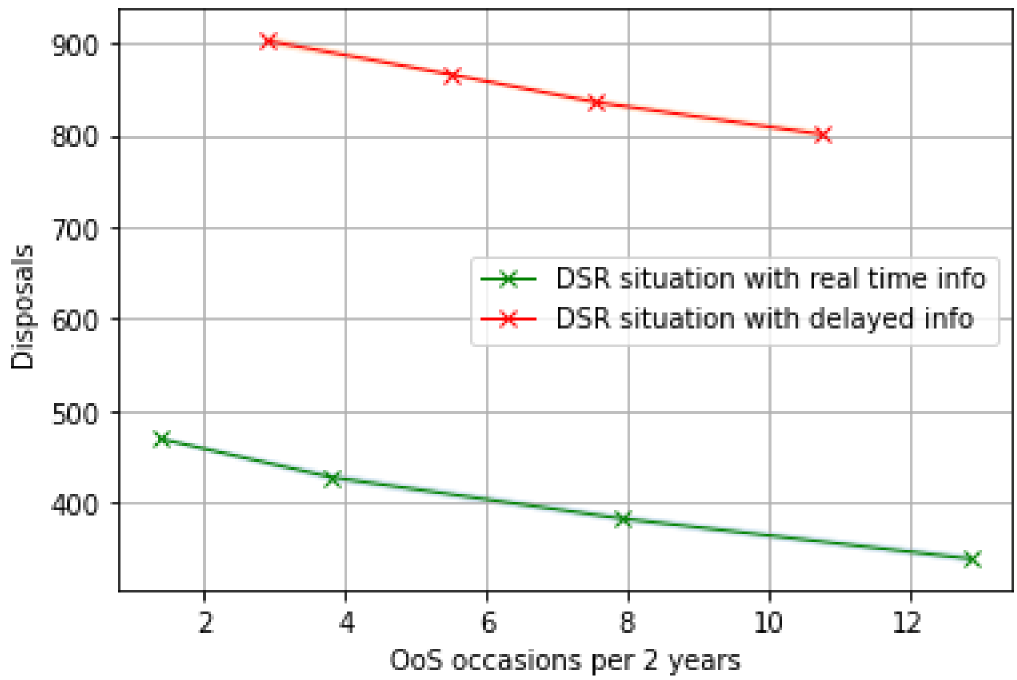


Figure 8.8: The results for scenario 2, comparing DSR with good and bad information

8.6.2 anticipation of expiration

Tables 8.9 8.10 and 8.11 show the results for the anticipation of expiration strategies with a κ of respectively 0.5, 0,25 and 0.2. The visual representation and comparison of each with the DSR strategy is given in Figure 8.9

basic inventory	OoS	Missed Sales	Disposals (95%)
53	10.08	17.6	580.76+-53.3
54	6.32	9	688.88+-77.07
55	3.36	3.24	731.04+-53.3

Table 8.9: Results for anticipation of expiration with a factor 0.5 for scenario 2

basic inventory	OoS	Missed Sales	Disposals (95%)
51	15	30	418.84+-43.02
52	9.44	14.12	493.8+-51.55
53	8.2	12.72	500.28+-45.48
54	3	2.68	571.4+-36.57

Table 8.10: Results for anticipation of expiration with a factor 0.25 for scenario 2

basic inventory	OoS	Missed Sales	Disposals (95%)
52	11.64	21.72	455.72+-52.62
53	8.4	10.2	487.92+-39.49
54	4.56	5.12	582.32+-52.62
55	3.48	2.6	565.84+-39.49

Table 8.11: Results for anticipation of expiration with a factor 0.2 for scenario 2

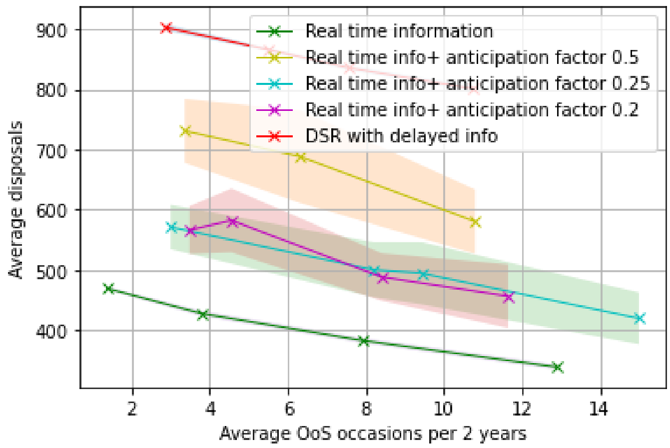


Figure 8.9: comparing the anticipation strategies with DSR with good information

If the anticipation of expiration is added to the DSR, the simulations show that in this situation any anticipation has no positive effect on the KPI compared with the regular DSR situation. The trend seems to be that any extra anticipation has an inclining effect on disposals for the same availability. The main reason for this might be the reduced demand in the low season, that a lot of products are constantly on the verge of expiration, so everything is constantly unnecessarily overstocked.

8.6.3 PIRM

In table 8.12 the results of the PIRM strategy are shown. These are compared with the DSR strategies in figure **??**.

RSR	OoS	Missed Sales	Disposals (95%)
7	12.08	30.36	35,36+-3.82
8	9.48	26.28	54.44+-4.03
9	7.2	15.76	77.6+-5.2
10	6.2	15.76	118.96+-6.04
11	4.56	12.44	209.12+-11.7

Table 8.12: Results for PIRM for scenario 2

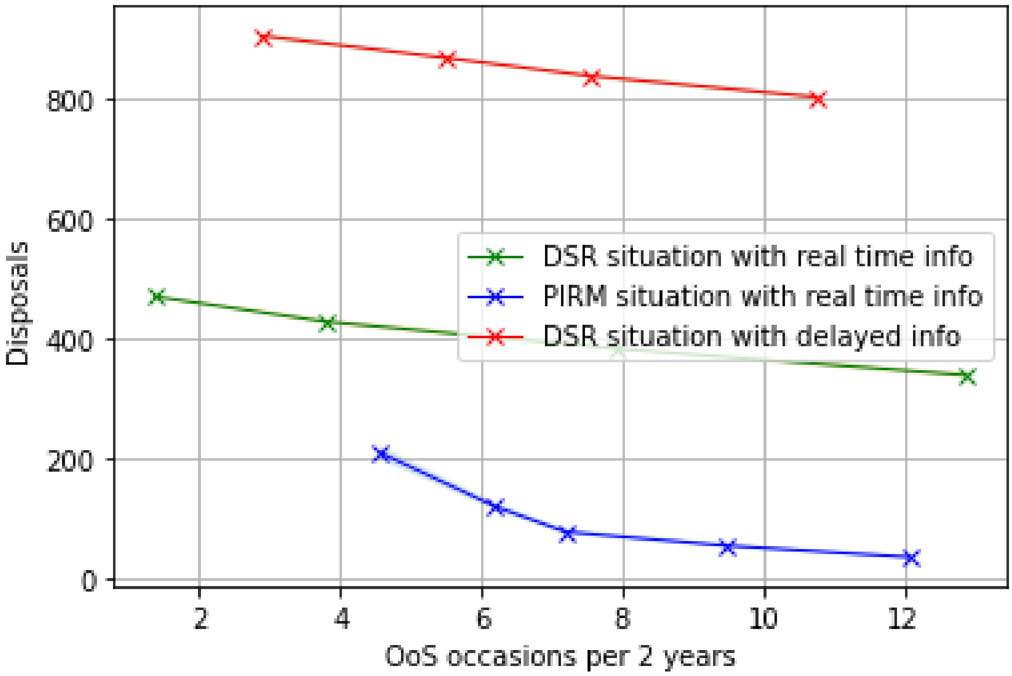


Figure 8.10: The results for scenario 2, comparing PIRM with up-to-date information DSR

As the PIRM strategy is able to adapt to demand, it can reduce the disposals by even more than only the good information. By predicting the demand, even fewer products are required as buffer zone for preventing empty shelves. So next to the DSR strategy with good information, the PIRM strategy can reduce the disposals with an additional 200-250 bouquets, depending on the required availability.

8.7 Analysis of the results

In this section, the results from both experiments are analysed, what can be said over the results, what is the most efficient strategy in which situation. It is also determined if the new inventory system is efficient enough for a return on investment for each of the scenarios.

8.7.1 Improvements compared with current system: scenario 1

The first scenario showed that having real-time information results in a situation that is in a reasonable range of return on investment due to disposal savings. If the inventory is truly random, DSR with good information seems the best strategy, as this has the best opportunity to cover demand, while not overstocking seems minimised, this is shown by the smallest amount of disposals. If the goal is reduction of OoS's, anticipation of expiration can have a beneficial effect if the amount of flowers send at once is limited. More disposal will occur, and in similar ratio as regular DSR with good information. Optimal control has no benefits in this trendless situation, since the demand can deviate so largely, any prediction has the risk to be far out of range and will likely lead to overstocking, if not understocking.

The best strategy in a scenario with large deviations in demand is therefore DSR with good information. This has a reduction of 110-160 disposed bouquets or a relative reduction of around 30 to 40%

8.7.2 Improvements compared with current system: scenario 2

Also in the second scenario, the DSR situation improves significantly with the addition of better information. There is already a reduction of around 450, or relative around 50%. The demand is met in full every time in the high season with the base inventory. Due to the low season being around half of the high season and the expiration taking long enough that the base inventory is sold almost every time right before it expires. Therefore adding anticipation of expiration has only a negative effect compared with the regular DSR situation. It causes unnecessary replenishment as everything is sold just in time. PIRM is in scenario 2 even a better performer, as the improvement are in the range of 600-750, or 90% compared with the current situation. This is probably because the prediction are easier in a close range of the eventual value, and the buffer zone is sufficient to absorb any over-estimations, but not to big that underestimations lead to an increase in disposals. Also the disadvantage of re actively holding on to base level is shown with this outcome, as was confirmed in the sensitivity analysis.

8.7.3 Checking hypothesis

Better information is indeed significantly beneficial for the performance of the inventory management. The savings are in both scenarios close to breaking even, and this is only the return on investment from savings in disposals. Only if there is a limit on the maximum amount to replenish, the anticipation of expiration is a way to reduce the OoS scenarios if that is of higher importance than minimizing disposals. Finally, optimal control performs indeed better at meeting demand which follows seasonal trends without large deviations.

Chapter 9

Conclusion and recommendations

This chapter concludes the research. What can be said about the found results and what is the answer to the main research question: *How can the supply chain of flowers be made more efficient?* .

9.1 Conclusion

Beginning by reflecting on the main question: it is possible to improve efficiency using RFID technology and optimal control. This answer is determined after dividing the lack of efficiency into two key elements. The lack of information in some nodes in the supply chain, and the reactive nature of ordering. By tackling these two parts the efficiency in inventory management can be significantly improved.
It is possible to retrieve up-to-date information in the flower industry for better inventory information. The environment and physical requirements are not limiting the automated inventory system as long as they are present long enough, in range of the antennas and not moved too fast.
Better information results in better performance of inventory management for both scenarios to somewhere in the range of return on investment. Not precisely for all situations, nevertheless, this is only in the disposal savings. Other benefits such as the solved problem with product differentiation and other business management decisions that can be made easier are not taken into account with this break-even calculation. This break-even point is also more likely to be achieved if more stores acquire this solution so average overall costs decline.
Furthermore, if the demand turns out to be not too random, but follows some sort of seasonal trend, then using PIRM as replenishment strategy is the best option. Especially if the difference between high and low season is more than a factor 2 as a larger difference will impact the KPI significantly negatively. This can be concluded from the sensitivity analysis. In that case and if the deviation for each season is not too random, the PIRM strategy will have significantly better results.
There can be concluded that inventory can be automated with a 98% performance and predictive replenishment with better information can theoretically reduce disposals by 90%
The results from the case study can be used for further implementation in other parts of the industry. The RFID system can be used for warehousing with an overstay ¿1 hour for example. The optimal control issue can also be used for growers that sell a small part of their products directly to customers, as this research is focused on direct replenishment.

9.2 Recommendations

The recommendations part is split up into two parts, one for DRF specific, how to act upon the results of this research, and one academic part for what could be of value to research next.

9.2.1 DRF

To validate this research would be of value to DRF. If the reader systems are all active, it is possible to get insight around several assumptions. Due to the possibility to follow a product at item level, the picking behaviour of customers can be better approached (FIFO/LIFO). Furthermore to have larger amounts replenished, to have a better insight of demand over time instead of replenishing so little that almost weekly an out of stock scenario occurs.

9.2.2 Follow-up research

These are the topics that I would recommend follow-up research for.

- To test RFID in warehousing, in the case of daily delivery and more nodes in the supply chain. Possibly to design a system that is able measure the moving of passive tags, and has active tags on the carts in which they are moved that measure temperature/ moist etc. to better use quality in combination with supply chain management.
- To try and build a model predictive controller for demand with large deviations to make one with a probabilistic constraint. If there is no idea of what range the distribution will behave, such a controller will find a better optimum than just trial and error with buffer amounts.
- To find the gain of more frequent delivery, on an industry wide scale this may give insight in how often should be replenished. For more nodes in the supply chain it may be useful to involve MPC, to have better communication between the nodes.

To check the validity of the modelling these assumptions could be experimented with.

- To check the system without 100% FIFO picking by customers. This can be done by using a queue-based system or a stochastic picking and expiration addition.
- Also the behaviour of customers might be looked into more, what is the effect of fuller displayed, more sales, or is scarcity a pull factor for more demand. Also the behaviour with more products, if there are expensive flowers at risk to expire, maybe it is more beneficial to supply fewer cheap products to throw fewer away. There might be an optimum in this part of decision making as well.

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Appendices

Appendix A

Research paper:Implementation of tracking system in short shelf life products for more efficient inventory management

starts on the next page

Increasing the efficiency of flower inventory management using RFID technology and optimal control

R.C. van Adrichem, A. Pesler MSc, W. Romijn MSc, Dr. Ir. Y. Pang, Prof. Dr. R.R. Negenborn

***Abstract*—Due to the short shelf-life of flowers (± 7 days) good inventory management is required to minimize disposals. The trade-off between supplying enough to meet demand yet not too much to prevent expiration is a delicate matter. However, in the current situation uncertainty about inventory levels due to inadequate information and conventional replenishment strategies lead to a situation that does not perform efficiently. This paper demonstrates how an RFID overhead system can be designed that has 98% reading performance for inventory. Furthermore is showed how this access to better information can already lead to a reduction between 30-50%, depending on the type of distribution the demand follows. If there are obvious seasonal trends, then the better information in combination with optimal control can have a reduction of 90% in disposed products with the same availability of products. These reductions are significantly sufficient to conclude that the benefits comfortably break-even with the investments from the inventory system.**

I. INTRODUCTION + BACKGROUND

When the Covid-19 pandemic started, all not necessary events were cancelled [1]. With weddings postponed, festivals cancelled and funerals in modest sizes, the demand for flowers dropped. Some luxury markets like fashion or perfumes, can keep in store and relocate resources more easily because these products do not expire within months. It is also possible to improve on webshops and therefore online sales for seasonal products. On the other side was the flower market, which took large hits due to the short life cycle. New York Times reported that 140 million Dutch tulips were disposed of in the spring of 2020 [2]. The EU cut flower market lost €1bn in just the first six weeks of the lockdown. This affected the global supply chain of the flowers. Kenya lost 85% of its flower exports and two million households were affected financially [3]. There is of course to be taken into account that a pandemic impacts everyone, and it is near impossible to provide a robust supply chain system that prepares for situations like this. However, the losses in this market are exemplary for how fragile the product is, how the demand can be erratic and how careful this market should be approached for making large changes.

The main research question is: **How can the inventory management of flowers be made more efficient?** This research will provide a framework for a more efficient inventory management especially for products with short shelf-life. It first covers the literature of the flower industry and its gaps concerning inventory information and replenishment strategies. Then a case study is introduced to determine the boundary conditions for both inventory system and replenishment strategies, Then the design of the inventory solution, including physical lay-out, digital structure and decision logic, is presented with the results from performance testing. Then the different strategies are given in mathematical form, verified, analysed for sensitivity and validated. Then two different scenarios are experimented with to measure the influence of good information and different strategies. The outcome of this research should therefore be a solution for inventory tracking with quantified performance, as well as a new replenishment strategy with measured improvement. The conclusion will be the answer to what extent the inventory management of flowers is made more efficient.

II. LITERATURE REVIEW

A. Flower industry

The flower industry is one of the oldest industries in the Netherlands. First the tulip mania in the golden age, then the centralization during the industrial revolution and currently with a few of the largest flower auctions worldwide. The beauty, as well as the delicate and perishable nature of the product makes it both popular and a luxury product. With a shelf-life of only slightly over a week, correct replenishment of flowers is important, even more than for inventory management of regular, nonperishable products. The supply chain of flowers is represented in figure 1, and underneath are the lead times between steps mentioned. The efficiency of this

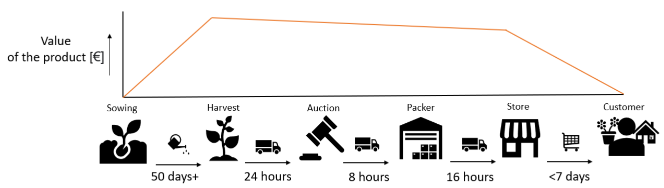

Fig. 1: The supply chain of flowers, from growers to customers in the store

replenishment is determined by two key performance indicators (KPI). These are the losses due to overstocking, measured in disposals, and the losses due to understocking, measured in times the inventory is out-of-stock (OoS). Two reasons for problems in the decision making for correct replenishment and avoiding both under- and overstocking are lacking inventory information and conventional ordering strategies. Both have not extensively researched for the specific case of the flower industry

B. Inventory system

An important factor for efficient replenishment is having good information about inventory levels throughout the supply chain. With more uncertainty about these parameters, more risks need to be taken in order to meet demand correctly. Dutch flower companies cooperate with foreign partners in the supply chain, and are therefore dependent on the information provided by these partners. Due to lack of automation nor up-to-date communication, the inadequate information is resulting in wasteful processes for the flower companies. To prevent this from happening, an automated inventory system at the aforementioned partner will give the Dutch flower companies continuously up-to-date insight in inventory levels. Multiple technologies can be selected for automated inventory systems and each has different pros and cons:

- Bar or QR code. This is a system similar to regular bar codes as in supermarkets. With a light sensor the bar code, with a unique spacing between and width of bars, is scanned and recognised. However, these can only specify down to product type level, and not be identified on an individual item level. It also requires active manual scanning, for registration of arrivals and/ or sales [4].
- Magnetic strip. This technology is used in for example in credit cards. It works similar to bar codes, only now it an unique magnetic strip (and therefore flux difference) and a magnetic coil for registration [5]. Downside of this technology is the close distance range and precision on velocity in which it needs to operate. Similar to bar codes, the actual inventory is not measured, only calculated.
- Optical character recognition. With this identification method, the actual product is identified and not a code that contains information about what item is put onto. This technology is based on cameras being able to recognize flowers based on shape and color [6]. This way each seen flower is registered and if it leaves this departure is instantly measured as well. However state of the art image recognition technology is expensive. It also needs to differentiate between items of the same product type.
- Radio Frequency Identification (RFID). This is a technology that can identify, track, and trace an object, using radio waves. RFID has multiple benefits in logistic tracking, as it can serialize data (this comes in hand with shelf-life tracking), does not require any human intervention. The objects can be tracked using the attachment of tags that consist out of a chip with an integrated circuit for storing a unique serial number and an antenna to receive external power and exchange the data from the chip to a reader system. Tags can be either active, with their own power supply, or passive, which require energy from the transmitted radio signal waves of the reader. Active tags continuously communicate with other tags or readers, and can overcome very large distances to readers. However these tags only last as long as their power source lasts, and are more expensive. Passive tags only send a modulated data stream with the tag's information after being charged by the Radio frequency waves from the reader. Once the reader receives the information, the object is registered and the data is communicated to the host [7]. Figure 2 shows how passive tags are powered and read. In case active tags are used, the reader is only sending information and no charging is required, the rest remains.

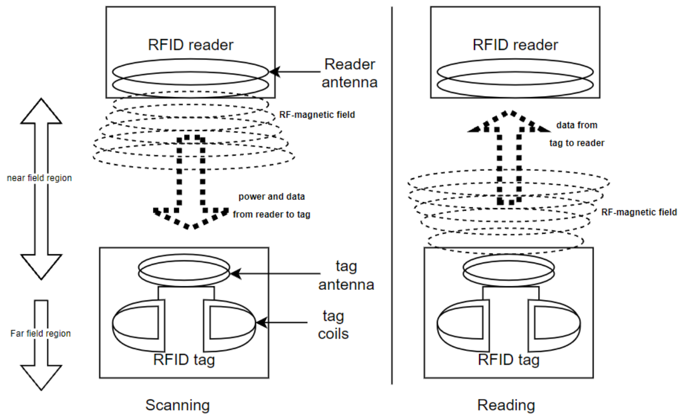

Fig. 2: How passive tags are charged and read by RFID readers

However, since the system cannot require manual registration past for example bar code scanners, and the distances to overcome are therefore in the range of meters, only one technology remains feasible: RFID. This technology will be used for the design of the inventory system

C. Strategy modelling

Currently, the replenishment in the flower industry can be outdated. It is mainly reactive, with one general that is maintained. If this is transformed into proactive or predictive, waste in processes can be reduced. The following optimizations are considered for optimizing.

- Continuous simulation (CS)
- Discrete Event Simulation (DES)
- Linear Programming (LP)
- Machine Learning (ML)
- Optimal control (OC)
- Model Predictive Control (MPC)

CS, DES and LP are not suited due to their initial inability to predict and make decisions, ML is also not feasible due to the amount of data required. OC and MPC are left, and the differences will be explained here¿

1) Optimal control: Optimal control is a closed-loop controller that uses measurements to predict system behaviour and works towards a preliminary determined ideal state. It is only required this one step, to calculate what input it should deliver to reach that state based on the predicted value that is a consequence of a moving horizon estimation (MHE). This MHE uses historical data to recognise patterns and to generate a predicted value for the system in the next discreet or continuous moment.

2) Model predictive control: It works similarly to OC, however MPC calculates for future state was is expected, and anticipates these steps as well. This anticipation will be based on an objective function that measures how well the system performs, giving a penalty if certain undesirable events happen. This way it will work towards a target value that may change over time, depending on what the historic sales indicate. The reason MPC is considered robust is that it requires little data to form a foundation to start forecasting. Every new time step of information is used, and as it only predicts until a prediction horizon. If the information is different from what is predicted the system can adapt to it at the next time step already with little computation time. There will also be boundary conditions, that the inventory can not become negative for example. Figure 3 shows how the system predicts, calculates and decided what to deliver from now until the prediction horizon, and there is demonstrated how this differs from OC.

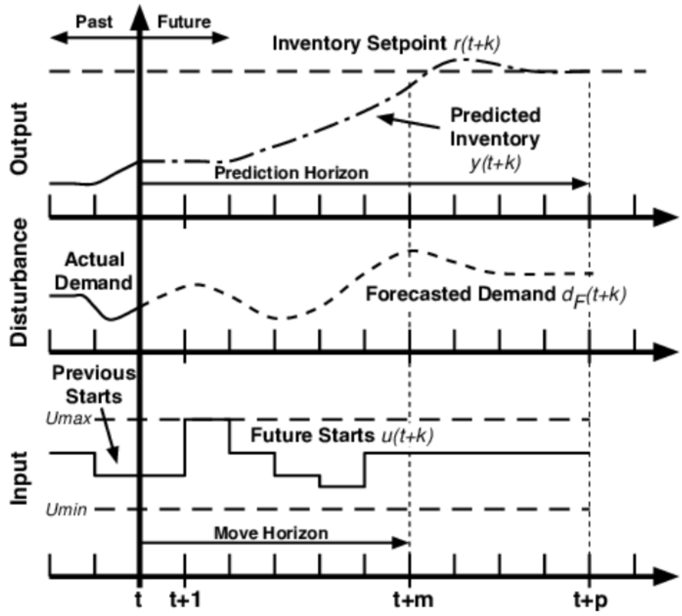

Fig. 3: Example of the decision making in OC and MPC. Both use a forecast for the demand based on historic measured demand. Then is calculated how this will influence the inventory, OC then calculates for that specific moment what the correct input $u(t)$ should be, while the MPC does this for all time steps until the prediction horizon t+m before it generates the input action [8].

Model predictive control is usually more precise as it can anticipate disturbances itself. However, the demand can be quite unpredictable, especially if it is direct replenishment, and no buffer zone with multiple nodes over which the inconsistency of the demand can be spread out. With the limited shelf-life of only a few times steps, looking ahead further than the next time step is not rewarding (figure 4). Model predictive control can therefore do nothing more than optimal control in only recognising major trends. By tweaking an objective function to anticipate possible larger disturbances or turn stochastic demand into probabilistic constraints MPC can create an optimal situation for replenishment [9]. However this requires a lot of calculation time, the tweaking might be harder due to the large deviation compared with physical processes, it is also harder to program correctly and to verify the correctness. Moreover, an ideal reference level with buffer inventory can

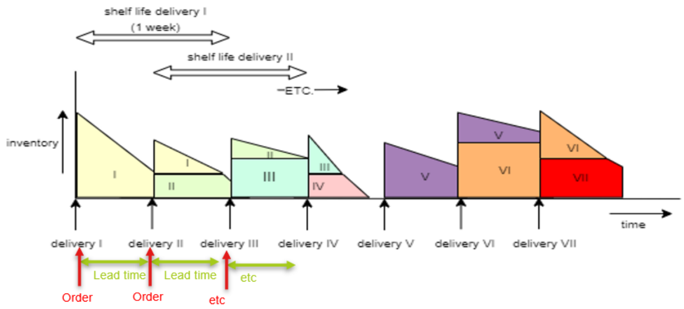

Fig. 4: Example of freshness and level of inventory over time, including lead time, decision moments and delivery moments

be defined in front for optimal control, can lead to a situation that performs equally well. The relative robustness, ability to make decisions and the limited information that is required for a (local) optimum makes this optimal control a suited method to improve the supply chain of flowers [10].

III. Case Study: Direct Retail France

A case study can be used to determine the boundary conditions and to measure the success rate of the improvements. The case used for this is Direct Retail France (DRF). This supply chain director controls the nodes in the supply chain from auction to customer, as shown in figure 5.

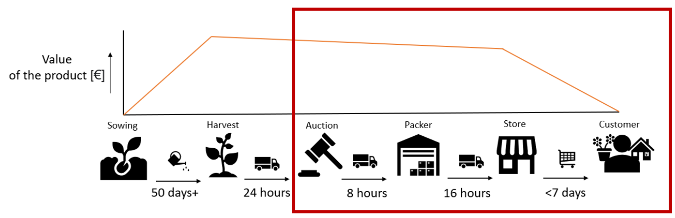

Fig. 5: The focus of DRF in the supply chain of flowers

A. *Physical situation for the flowers*

The flowers are bought in bulk at the auction in Naaldwijk (Holland), divided over the required products per store, and shipped to the relevant stores, total time of travel is around 3 days. These stores are supermarkets in France in which DRF rents space for their display (figure 6). They also pay for the check out service that the supermarkets provides. However, the information about the check out is often delayed, which impacts the inventory management negatively. The display consists up to 200 flowers or plants, covers is 2 m^2 and the area over which it can be placedis 14 m^2. The exact location of the frame in this area is modular. The physical boundaries/ environment for the inventory solutions are based on the situations in these stores. The products should be registered in a store environment, an due to the modular nature of the display, an overarching system is required to reach the entire area.

Fig. 6: Frame filled with flowers at one of their stores in store.

B. *Ordering and finances*

They are currently using manual ordering and ordered are made based on what is sold or disposed. They deliver twice a week and disposals are executed by the delivery person at the time of delivery. Moreover, the specific lead time, expiration time and historical sales data can be used as a foundation for modelling specific situations. Also with the costs per flower and the savings can be approximated, and therefore a break-even point in efficiency can be calculated. As is common in the flower industry [11] DRF has have a mark-up of about a factor three for buy-in from the auction. This should cover other expenses like transport, packing, labour etc. as well. The exact profit margin in this revenue was also classified. In general the gross profit margin of flowers is around 40% [12]. However, due to other cost like taxes and operating cost, the net profit is approximated to be around 15% of the retailer price. This will be used for the calculation on return on investment.

IV. Inventory System Design

The RFID system should be delivered to the supermarkets and implemented in the existing set-up for the flowers. As the location for the frame is modular, the system should be hanging from the ceiling. This section will cover the variables that are presented, and show performance of the overhead system, depicted in figure 7 with flowers present.

A. *Design parameters*

1) Environment: Radio frequency waves are not able to easily surpass environments with a lot of water and moist. As flowers are put in buckets with water for a longer shelf-life, and the flowers still hold water inside their cells, this can shield the tags. The idea is to put the tags inside the pricing labels, and these are put on the packing. Furthermore it is important that the tags are able to energise with the surface they are put on. As the antennas of the tag are charged by how the RF waves pass through, the tags should be able to work when attached to the packings.

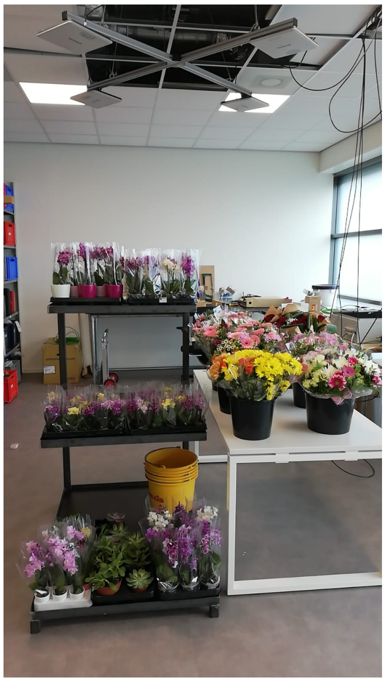

Fig. 7: Final testing set-up, with real flowers to measure actual performance in most realistic environment.

2) Antennas: For these type of applications two type of antenna's can be selected from, either standard, cheaper antenna's, that can only cover left handed circular polarization (LHCP). The other choice is the KRAI antenna, which covers all 4 types of polarization. This option costs more but increases the reading possibilities within the reading field. For both antenna's the radio waves leave at an angle of 30-35 degree circular relative to the normal. This has a consequence that one antenna on a low ceiling of 2.5 meter high can only cover a circular surface with a 1.75 m radius. The KRAI antenna is picked, due to the reflecting nature of the environment.

B. *Performance*

After extensive testing with real flowers, it seems possible that within 1 hour, 98% of all tags could be registered in a passive environment that mimicks a store. Table I shows the results of this time threshold test. This performance can be realised anywhere within a square 14 m^2 area. Therefore can be concluded that it is possible to have an automated inventory system using RFID in the flower industry.

Time (min)	20	40	60
Read (%)	92	96	98

TABLE I: Results of performance testing RFID system

V. Strategy Design

This section explains how the model mimics the real world, what assumptions are made and what the working principles of the model will be given their mathematical form.

A. Basic principles of modelling

- Inventory- The system that the controller works around is inventory. The disturbances will be sales and disposals are taking away from it, orders are added, and the performance is determined from it wrt OoS.
- First In, First Out (FIFO)- The sales are assumed to be happening in a FIFO order. This means that the flowers with the shortest shelf-life left are sold the soonest.
- Lead Time- Currently the lead time is about three days between decision of replenishment in the store. This means it takes 72 hours before the flowers arrived after the order is placed.
- shelf-life- The assumption is made that shelf-life of each bouquet is constant and set. All bouquet have the same time before they are not deemed suited for sale anymore.
- Delivery moments- The restocking is done by the delivery guy. He is also responsible for disposals of products. The model should anticipate different frequencies of arrival. Currently DRF has two replenish moments each week. They usually a Tuesday and Friday delivery, which are ordered on respectively Monday and Wednesday morning.

B. Strategies

Three strategies have been designed.

1) DSR: Table II shows the mathematical model for the DSR strategy. This system works by refilling what is sold and/ or disposed. The main principle of this strategy is reacting to what is sold from a predetermined buffer level.

Variable	Description
Inv	Inventory at the store, main system,
Disposal	Disturbance, get removed from the inventory
Sold	Disturbance, get removed from the inventory
Order	The products that are send to store
t	Time steps in delivery moments
lead time	Lead time due to transportation
exp. time	Life time of flowers at the store
Availability	Amount of times there is product
out-of-stock	Amount of times there is no product available

TABLE II: Variables of the mathematical model of DSR

The inventory is based on the inventory of the day before, the orders of that day are added, and the sales and disposals subtracted. Equation 1 shows how this looks in the mathematical model. Orders are explained next (eq.2), the sales are just exact numbers, based on what is purchased by the customers. The

$$Inv[t] = Inv[t-1] + Order[t] - Sold[t] - Disposal[t] \quad (1)$$

The new orders are based on what is sold or thrown at a day. These orders will arrive the lead time later. This is shown in equation 2

$$Order[t + leadtime] = Sold[t] + Disposal[t] \quad (2)$$

Since the system is assumed first in first out, the disposals can be determined without any probability involved. They can be measured by taking the inventory from the day that is the expiration time ago, and subtracting all the sales and disposals in the period in between. Everything arrived before should already be gone after this period (sold or thrown out at least the day before). Anything that arrives later will still have the possibility to be sold, otherwise it will be thrown away later. (Equation 3

$$Disposal[t] = Inv[t - exp.time] - \Sigma Sold[t - exp.time : t] - \Sigma Disposal[t - exp.time : t-1] \quad (3)$$

2) Anticipating expiration: Anticipation of expiration follows the same mathematical model as DSR, however two more variables are added. These are shown in table III.

Variable	Description
Products at Risk(PaR)	Products that expire at the next delivery moment
κ	Factor how many of the products are anticipated for

TABLE III: additions to the mathematical model of DSR

The additional equations to the mathematical problem are shown in equations 4 and 5. Products at risk are products that are defined by meeting their expiration time at the next delivery moment. If they are not sold they will be disposed. By ordering products that are at risk before, OoS scenarios due to large disposals at once is already anticipated for and in theory reduced or prevented. The idea is that the disposals are more spread out over time. The amount may increase, but if the OoS scenarios are reduced in a relatively larger part, the efficiency can improve by having a lower base order.

$$PaR[t] = \kappa(Inv[t - exp.time + 1] - \Sigma Sold[t - exp.time + 1 : t] - \Sigma Disposal[t - exp.time + 1 : t]) \quad (4)$$

$$Order[t + leadtime] = Sold[t] + Disposal[t] + PaR[t] - PaR[t-1] \quad (5)$$

3) Predictive Inventory Replenishment Model (PIRM): This OC based strategy is using an objective function that helps working towards a (locally) optimal replenishment strategy. It has the same components as the DSR modelling, however there is a objective function added to not just follow demand, but to anticipate fluctuations better.

Variable	Description
Inv	Main system, inventory at the store
Disposal	Disturbance, are removed from the inventory
Sold	Disturbance, are removed from the inventory
Order	The products that are send to store
t	Time steps in delivery moments
lead time	Lead time due to transportation
exp. time	Life time of flowers at the store
Availability	Amount of times there is product
out-of-stock	Amount of times there is no product available
Expected Inventory	Inventory expected at arrival moment
Expected Demand	forecast from Moving Horizon Estimator
Products at Risk(PaR)	Products that expire at the next moment
(RSR)	Buffer amount for guaranteed inventory

TABLE IV: Variables of the mathematical model of PIRM

The time derivative of the inventory state has not changed for this system, this remain equation 1. The ordering however is not based on replenishing back to a certain predetermined level, but is aiming to use the expected demand for the time until the arrival of products and the existing inventory and shelf-life to calculate towards a reference inventory level based on the referential stock reserve.

$$ExpectedInventory[t] = Inv[t-1] - ExpectedDemand[t] - max(0, (PaR[t-1] - ExpectedDemand[t])) \tag{6}$$

$$Order[t + LeadTime] = ExpectedInventory[t] - 0.5(ExpectedDemand[t-1] - ExpectedDemand[t)] + RSR \tag{7}$$

This ordering process is only done for as many steps as many steps as the lead time requires. The disposals and products at risk are calculated as before in equation 3 and 4

VI. Experiments

The experiments to measure the performance of the strategies and the influence of the better information. To compare the situations, experiments for all situations (better information or predicting) are done and compared on similar out-of-stock occurrences. That way the reduction of disposals given a similar (or even improved) availability for demand is measured as gain. Furthermore, a solution or improvement is truly efficient if it actually breaks even in the financial area. For the break-even calculation is only looked at the benefits from fewer disposals of flowers. As the profit margin of flower is determined to be about 15%, slightly over 6.33 roses each month per store should be saved to break-even with the monthly fee for the inventory system.

A. Hypothesis

Given the principle of the strategies, these are the hypotheses for the experimental outcome.

- In general is expected that with limited information, a lot of buffer is required to get avoid OoS. Consequence of this is that significantly more disposals will occur than with up-to-date information. Independent of strategy, better information will lead to better results due to the reduction of uncertainty
- Due to the lead time is practically being halved, expected is that the return on investment is around breaking even. Especially for the first 40 stores, the other stores are expected to be profitable with only the disposal savings already.
- Anticipation expiration will lead to fewer out-of-stock scenarios as a result of disposals. However, in general, more disposals might occur. It is expected that if the amount anticipated for is small enough, only the large amount of disposals are anticipated for, while not overproducing more.
- Fewer out-of-stock scenarios occur when there is optimal control using predicted sales and clear seasonal trends occur. As the prediction can better anticipate trends, less risk needs to be taken.

B. Scenarios

Two scenarios will be tested due to the unknown demand for flowers. Scenario 1 will be simulations with demand curve that follows one normal distribution based on all the available sales data of roses. It has large deviations, and follows no overall trend, only has one mean and a standard deviation. An example of this demand over a time period of two years is shown in figure 8. Scenario 2 will simulate a situation with obvious seasonal trends, as shown in the example of figure 9. The curve is based on historical data, as well as flower sales from the Dutch auction [13]. It follows different normal distribution, with high and low season. Both scenarios simulate a period of two years, to reduce the effect of starting up bias in the first year.

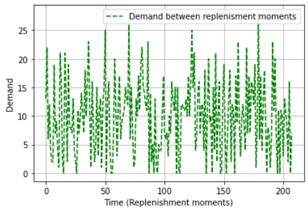

Fig. 8: Example of the demand pattern of scenario 1.

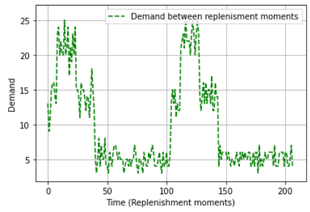

Fig. 9: Example of the demand pattern of scenario 2.

C. Results

To compare the strategies in performance difference is to keep one of the KPI's constant. The selected range is maximally 16 occasions of out-of-stock allowed, and a situation with only 4 OoS out of 208 occasions is already sufficient. Figure 10 shows an example how the values for the KPI are measured. The other graphs are the comparison for the range that is indicated with the red dotted line

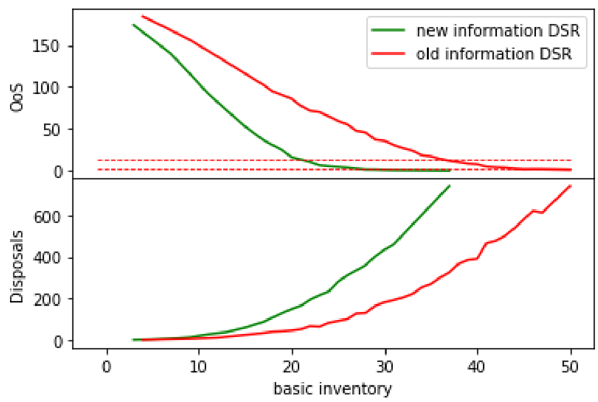

Fig. 10: The basic inventory vs the KPI for the DSR strategies with and without good information for scenario 1

1) Scenario 1: Figure 11 shows the influence of good information on the DSR situation for scenario 1. For the same availability, there is a reduction of 110- 160 disposals, or around 30%

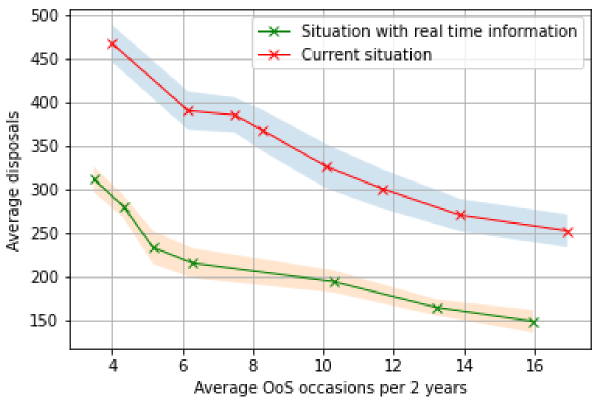

Fig. 11: The result of good information for DSR in scenario 1

Adding expiration anticipation with good information does not improve anything significantly compared with regular DSR with good information. Figure 12 shows that for the same availability levels similar out of stock situations occur.

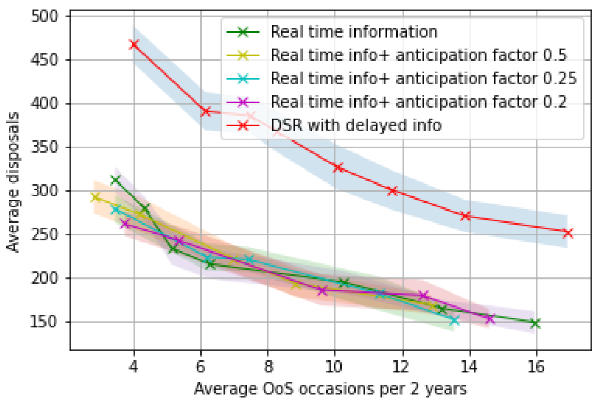

Fig. 12: The effect of different expiration anticipation factors for scenario 1

PIRM is not a reliable way of improving the inventory if the demand has large deviations. Figure 13 shows how it will lead to more disposals than the current system with DSR and delayed information.

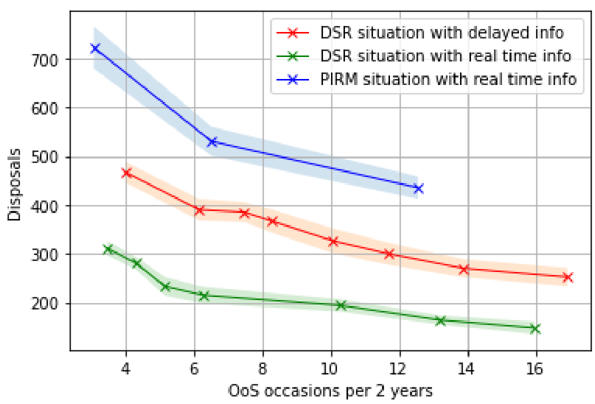

Fig. 13: The results of PIRM compared with DSR for scenario 1

2) Scenario 2: Figure 11 shows the influence of good information on the DSR situation for scenario 2. For the same availability, there is a reduction of 400 disposals, or around 50%

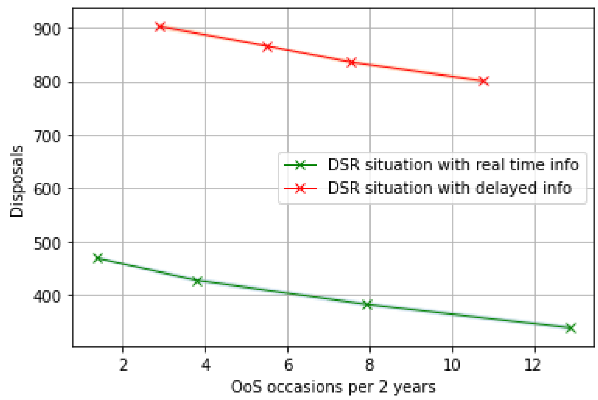

Fig. 14: The result of good information for DSR in scenario 1

If the anticipation of expiration is added to the DSR, the results (figure 15 show that in this situation any anticipation has no positive effect on the KPI compared with the DSR situation. The trend seems to be that any extra anticipation has an inclining effect on disposals for the same availability. The main reason for this might be the reduced demand in the low season, that a lot of products are constantly on the verge of expiration, so everything is constantly unnecessarily overstocked.

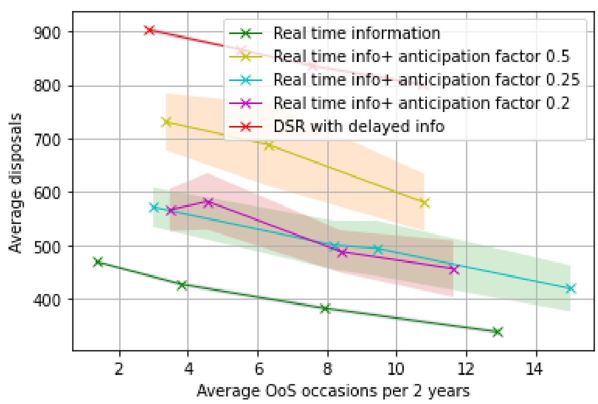

Fig. 15: The effect of different expiration anticipation factors for scenario 1

As the PIRM strategy is able to adapt to demand, it can reduce the disposals by even more than only the good information. By predicting the demand, even fewer products are required as buffer zone for preventing empty shelves. So next to the DSR strategy with good information, the PIRM strategy can reduce the disposals with an additional 200-250 bouquets, depending on the required availability or 90% from the reactive situation without good information.

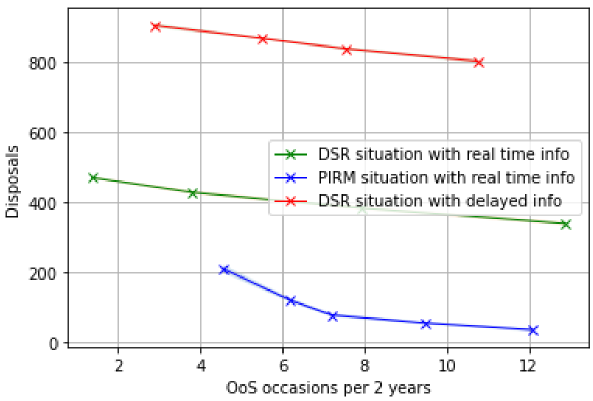

Fig. 16: The results of PIRM compared with DSR for scenario 2

D. *Checking hypothesis*

Better information is indeed significantly beneficial for the performance of the inventory management. The savings are in both scenarios close to breaking even, and this is only the return on investment from savings in disposals. Only if there is a limit on the maximum amount to replenish, the anticipation of expiration is a way to reduce the OoS scenarios if that is of higher importance than minimizing disposals. Finally, optimal control performs indeed better at meeting demand which follows seasonal trends without large deviations.

VII. Conclusion

The efficiency of inventory management of flowers can be made more efficient by better information and predictive replenishment. If the passive state of flowers at the location, such as a store, is around one hour, 98 % of the inventory can be registered automatically. This better information for the current replenishment strategy can save up to 30% for scenarios with highly differentiating demand, or 50% in the case of smaller deviations following a seasonal sales pattern with smaller deviation. Using optimal control and good information the second scenario can be improved even further, a reduction of 90% in disposals with respect to the current situation.

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Appendix B

DRF digital structure

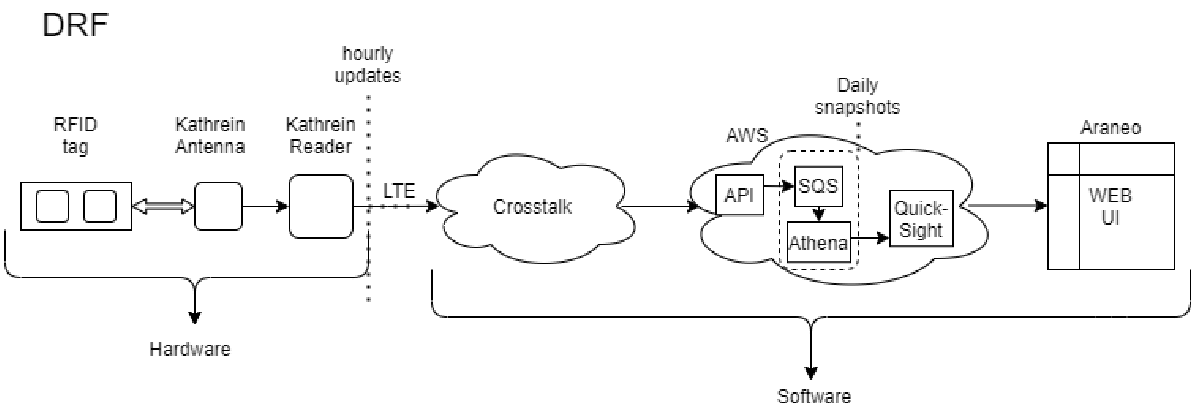

Figure B.1: eventual lay out of the DRF digital structure

Appendix C

Verifying the DSR model

Variables zero measurement	Results	Variables test group	Results
Expiration time =6 Lead time = 5 Datasetsales4 Basic inventory = 20	------------------------------ total Demand =168.00 ------------------------------ Out of stock occurances =5.00 ------------------------------ Average Inventory at store =10.03 Availability in Store =32.00 ------------------------------ Average disposal at store =0.00 disposals =0.00 ------------------------------	A Expiration time =3 Lead time = 5 Datasetsales4 Basic inventory = 20	------------------------------ total Demand =168.00 ------------------------------ Out of stock occurances =13.00 ------------------------------ Average Inventory at store =6.73 Availability in Store =24.00 ------------------------------ Average disposal at store =1.38 disposals =51.00 ------------------------------
Expiration time =6 Lead time = 5 Datasetsales4 Basic inventory = 20	------------------------------ total Demand =168.00 ------------------------------ Out of stock occurances =5.00 ------------------------------ Average Inventory at store =10.03 Availability in Store =32.00 ------------------------------ Average disposal at store =0.00 disposals =0.00 ------------------------------	B Expiration time =6 Lead time = 10 Basic inventory = 20 Datasetsales4	------------------------------ total Demand =168.00 ------------------------------ Out of stock occurances =7.00 ------------------------------ Average Inventory at store =8.05 Availability in Store =30.00 ------------------------------ Average disposal at store =0.00 disposals =0.00 ------------------------------
Expiration time =6 Lead time = 5 Datasetsales4 Basic inventory = 20	------------------------------ total Demand =168.00 ------------------------------ Out of stock occurances =5.00 ------------------------------ Average Inventory at store =10.03 Availability in Store =32.00 ------------------------------ Average disposal at store =0.00 disposals =0.00 ------------------------------	C Expiration time =6 Lead time = 5 Datasetsales5 (3 sales daily) Basic Inventory = 20	------------------------------ total Demand =111.00 ------------------------------ Out of stock occurances =0.00 ------------------------------ Average Inventory at store =5.81 Availability in Store =37.00 ------------------------------ Average disposal at store =0.00 disposals =0.00 ------------------------------
Expiration time =6 Lead time = 5 Datasetsales4 Basic inventory = 20	------------------------------ total Demand =168.00 ------------------------------ Out of stock occurances =5.00 ------------------------------ Average Inventory at store =10.03 Availability in Store =32.00 ------------------------------ Average disposal at store =0.00 disposals =0.00 ------------------------------	D Expiration time = 6 Lead Time = 5 Datasetsales4 Basic inventory 10	------------------------------ total Demand =168.00 ------------------------------ Out of stock occurances =8.00 ------------------------------ Average Inventory at store =9.22 Availability in Store =29.00 ------------------------------ Average disposal at store =0.00 disposals =0.00 ------------------------------

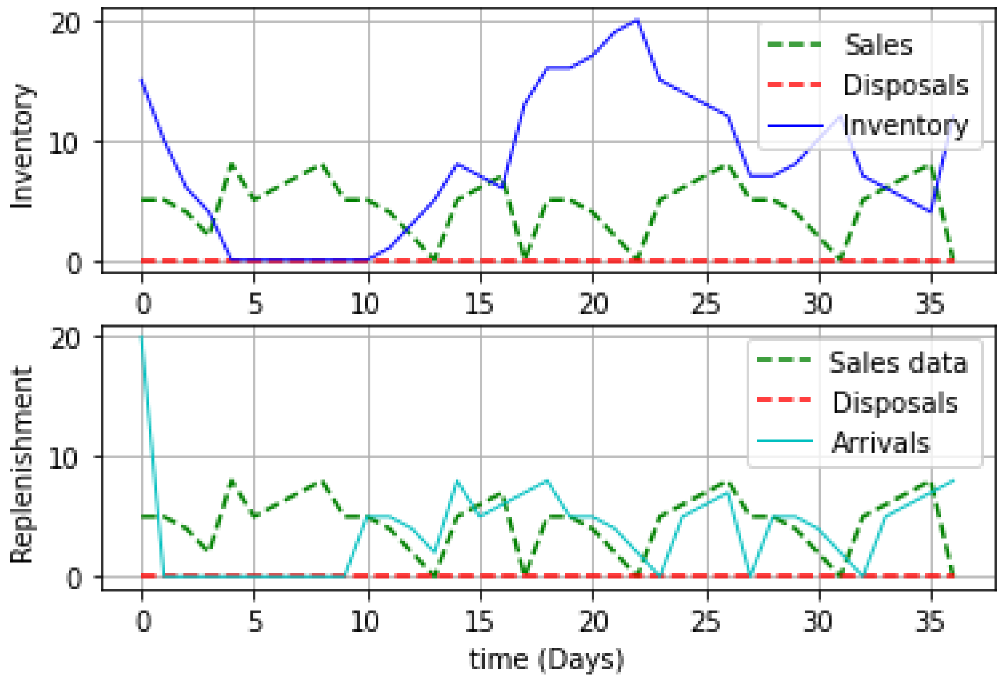

Figure C.1: Graphic results of experiment B

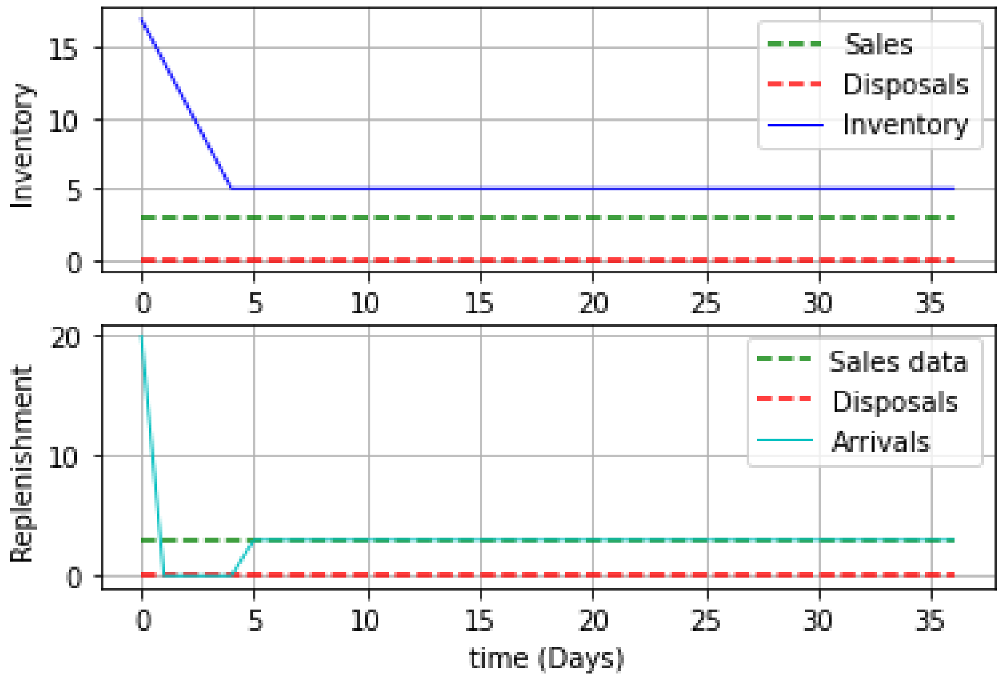

Figure C.2: Graphic results of experiment C

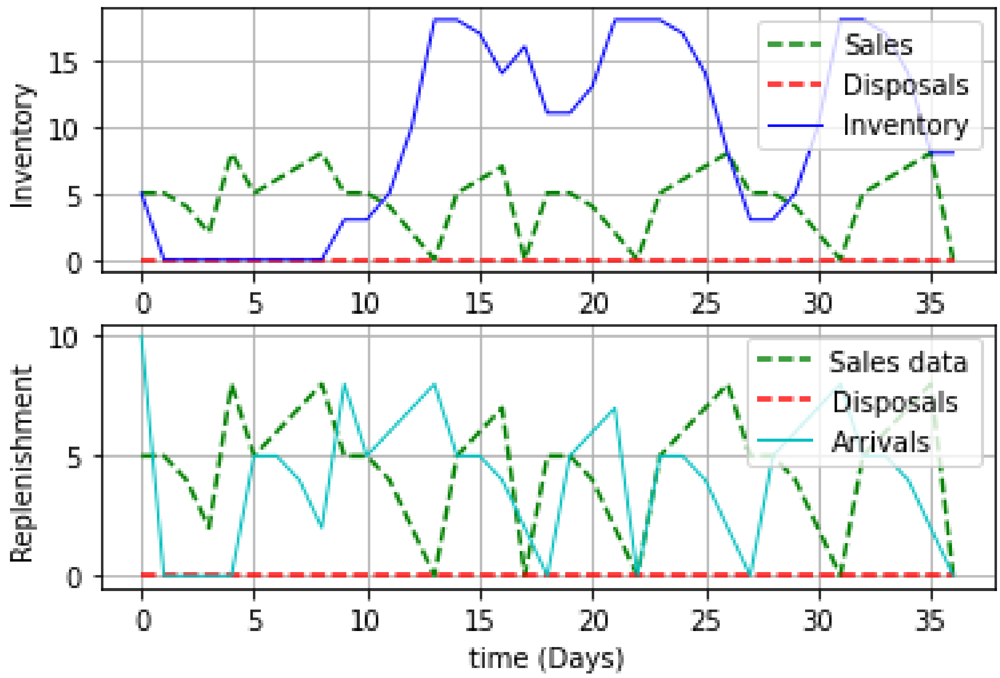

Figure C.3: Graphic results of experiment D

Appendix D

Verifying the expiration anticipation

normal situation	Results	Expiration anticipation	Results
Expiration time =6 Lead time = 5 Low sales pattern Basic inventory =20	------------------------------ total Demand =101.00 ------------------------------ Out of stock occurances =18.00 Missed sales =4.00 ------------------------------ Average Inventory at store =11.88 Availability in Store =119.00 ------------------------------ Average disposal at store =1.20 disposals =164.00 ------------------------------	Same variables anticipation factor=0.5	total Demand =101.00 ------------------------------ Out of stock occurances =12.00 Missed sales =2.00 ------------------------------ Average Inventory at store =12.36 Availability in Store =125.00 ------------------------------ Average disposal at store =1.21 disposals =166.00 ------------------------------

normal situation	Results	Expiration anticipation	Results
Expiration time =6 Lead time = 5 Low sales pattern Basic inventory =20	------------------------------ total Demand =101.00 ------------------------------ Out of stock occurances =18.00 Missed sales =4.00 ------------------------------ Average Inventory at store =11.88 Availability in Store =119.00 ------------------------------ Average disposal at store =1.20 disposals =164.00 ------------------------------	Same variables anticipation factor=0.25	------------------------------ total Demand =101.00 ------------------------------ Out of stock occurances =13.00 Missed sales =3.00 ------------------------------ Average Inventory at store =12.04 Availability in Store =124.00 ------------------------------ Average disposal at store =1.20 disposals =164.00 ------------------------------

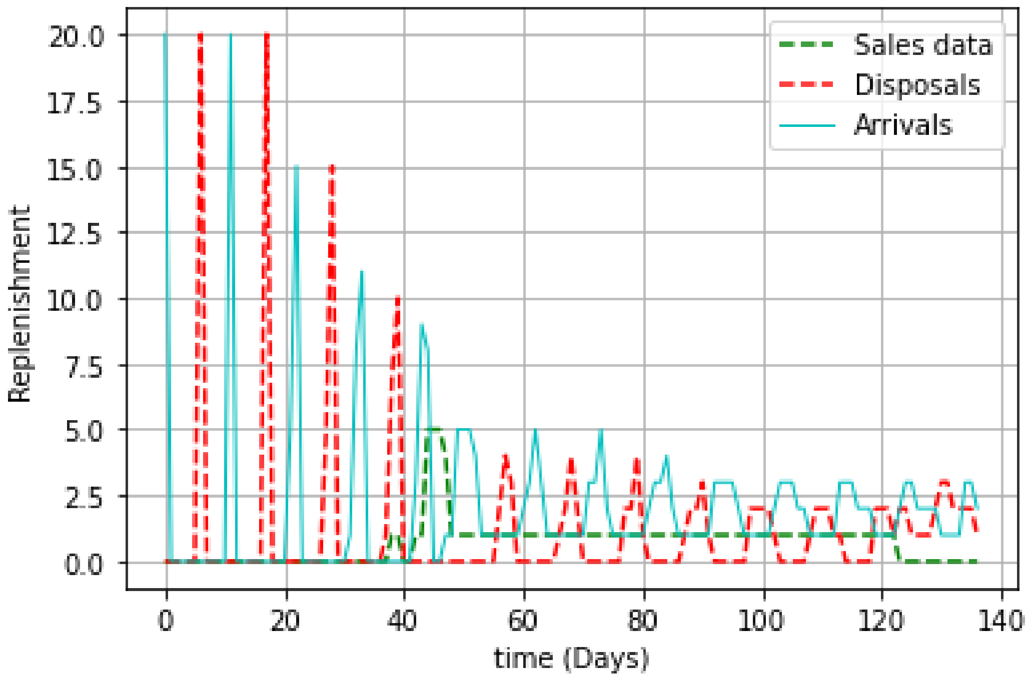

Figure D.1: Graphic results of expiration anticipation verification

Appendix E

Verifying the MPC model

declining demand	Results
Expiration time =2 Lead time = 1 Demand=max(0, 15-t) RSR=2 Basic inventory =20	------------------------------ Total Sales = 120.00 ------------------------------ Total missed_sales = 5.00 OoS occassions = 1.00 ------------------------------ disposals = 16.00 ------------------------------ Order at t=29/ 30 = 1/ 0

Table E.1: Results of declining demand exact

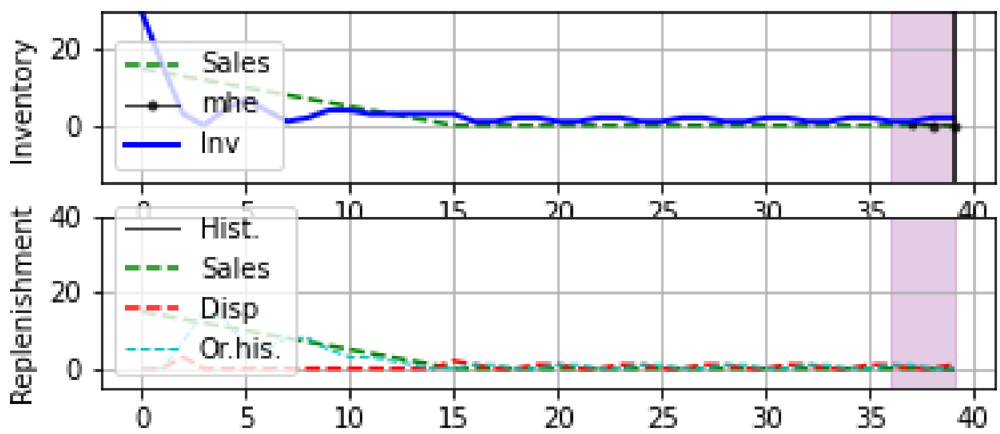

Figure E.1: The effect of declining demand on the ordering and inventory

Incling demand	Results
Expiration time =2 Lead time = 1 Demand=t RSR=2 Basic inventory =30	------------------------------ Total Sales = 741.00 ------------------------------ Total missed_sales = 3.00 OoS occassions = 2.00 ------------------------------ disposals = 27.00 ------------------------------ Order at t=29 /30 = 30/ 31

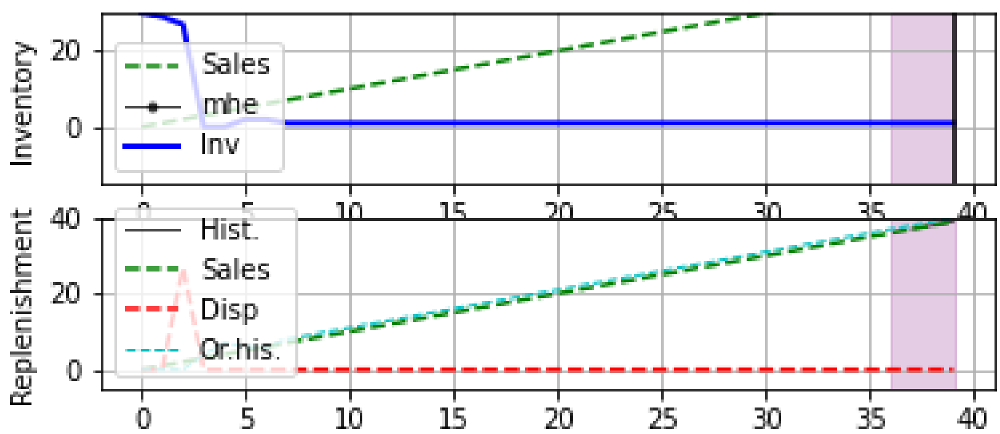

Figure E.2: The effect of increasing demand on the ordering and inventory