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Developing a planning and control policy for inventory cycle counting by UAVs

Master thesis Industrial Engineering and Management

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DEVELOPING A PLANNING AND CONTROL POLICY FOR INVENTORY CYCLE COUNTING BY UAVS

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Management summary

Cycle counting is an approach to inventory counting where a small amount of items is continuously counted during a certain period. It is used to find inaccuracies in inventory records. A record is considered inaccurate if there is an error in one of its fields, for example, a wrong number of items. Cycle counting is becoming more favored to count inventory in contrast to a full stock count. Currently, cycle counting is often performed manually. However, Unmanned Aerial Vehicles (UAVs) have become more easily accessible for commercial use. Since using UAVs for inventory cycle counting is relatively new, limited information is available about the performance and handling of this process. This thesis aims to design a planning and control policy for inventory cycle counting by drones. This policy should indicate when and how often to perform inventory cycle counting, which items to count and how to allocate the pallet locations to the available drones. The research question for this thesis is the following:

'How can the inventory cycle counting in a warehouse by semi-autonomous unmanned aerial vehicles (UAV) be planned and controlled in terms of what items to count, when to count, and the allocation of the items to drones?'

For this thesis, we use the case data of Bolk, which is a transport company that offers transportation of goods for third parties. Bolk is interested in adopting cycle counting by drones in their warehouse in Hengelo, The Netherlands. Products from Nouryon, a split-off from Akzo-Nobel, are stored in this warehouse. Nouryon mainly produces consumer salts, like table salt and salt licks for animals. While Nouryon produces and sells the products, Bolk is responsible for the logistic operations. Storage in the warehouse is done on the pallet level. There are two different storage methods in the warehouse: bulk storage, where pallets are stacked on the ground, and pallet racks.

Literature review

A literature review is conducted, from which we learned that drones used for cycle counting should have a tilt-wing or rotary-wing design, they need a combination of cameras, sensors, an Inertial Measurement Unit, and/or an unmanned ground vehicle for navigation, and a barcode scanner to scan barcodes on the pallets. We found multiple key performance indicators for cycle counting and defined inventory record accuracy, as well as potential causes for inaccuracies. Also, multiple types of cycle counting were found. After presenting a taxonomy for task allocation, we found that optimization-based approaches are most appropriate for the allocation problem in this thesis.

Approach

A model is developed to evaluate the performance of various policies. This model uses inventory data, as well as data about inventory record inaccuracies as input. It allows the user to select a type of cycle counting for each storage method, the number of drones, and on which day cycle counting is performed. Based on this information, the pallet locations to be counted are selected. With the use of an allocation heuristic, these pallet locations are assigned to a drone. The output of the model is the average accuracy and the travel time of each drone. The model is implemented in Delphi, an integrated development environment for applications.

Although the model requires data about inventory record inaccuracies as input, the data from Bolk does not contain any inaccuracies. A Monte Carlo simulation is developed to simulate these inaccuracies. For this simulation, we assumed that an inaccuracy always occurs during the transaction of a pallet. With a transaction, we mean that a pallet is moved inside the warehouse, for example from the inbound area to its assigned location in the warehouse. With every transaction, there is a small chance that an inaccuracy occurs.

To estimate the travel time of a drone, it is essential to know the route it flies. However, we do not know the routing, and finding the optimal routing is outside the scope of this thesis. Therefore, assumptions are made about the routing of the drone. We divided the warehouse into 6 zones and estimated the travel times between these zones and inside the zones.

We also developed a mathematical model. The purpose of this model is not to find a cycle counting policy, but rather to serve as a benchmark for other cycle counting policies. Its objective is to maximize the number of accuracies found, while also estimating the travel time.

For the planning and control policy, five types of cycle counting are evaluated: ABC cycle counting, random cycle counting, opportunity-based cycle counting, location-based cycle counting, and location- and opportunity-based cycle counting. These types of cycle counting address the question of what items to count. The two storage methods in the warehouse have different characteristics, like the number of pallets at one pallet location and the time that a pallet stays at the same location. Therefore, it is reasonable to use different types of cycle counting for the two storage methods.

To determine when to perform cycle counting, the term counting periodicity is introduced. Three counting periodicities are considered: counting every day of the week, counting on Monday, Wednesday, and Friday, and counting only on Monday.

Also, a constructive heuristic is developed to allocate the pallet locations to count to the available drones. This heuristic allocates to each drone a group of pallet locations that are as close together as possible.

Multiple decisions were made in this research, like which cycle counting types to use, on which days to count, and the number of drones to use. To get adequate results without having an unreasonable big number of experiments, these subjects are handled sequentially. First, suitable parameter values are found for each type of cycle counting, based on the resulting accuracy and travel time. Note that the parameter values for the bulk storage and pallet racks may differ, as the two storage methods have different characteristics, such as the maximum number of pallets at a pallet location and the average time a pallet stays in the same location. Next, we determine the combination of cycle counting types for the bulk storage and the pallet racks. As this decision involves a trade-off between accuracy and travel time, we select three combinations, based on three approaches: highest accuracy, lowest travel time, and good performance on both accuracy and travel time. Then, the number of drones, as well as the counting periodicity are chosen. This is done based on the accuracy, travel time, and costs of the drones. Finally, we select the best policy.

Results

The method as discussed is applied to the case of the Bolk warehouse in Hengelo. Suitable parameter values for each type of cycle counting are selected after the model was run with various parameter values. Next, the three combinations of cycle counting types were selected, based on the three approaches mentioned in the previous paragraph. These three combinations are denoted with the letters A, B, and C, as the description can become wordy. For the highest accuracy approach, we select the combination of opportunity-based cycle counting and location- and opportunity-based cycle counting and denote this combination A. Location-based and ABCD cycle counting is selected for the lowest travel time approach and called combination B. Finally, we select opportunity-based cycle counting for both the bulk storage and pallet racks for having both high accuracy and low travel time and we call this combination C.

The following step, determining the counting periodicity and number of drones for the three selected combinations, is done by evaluating the costs, accuracy, and average travel time for each combination. For combination A, counting every day with 4 drones was the best solution. We selected counting three times a week with 3 drones for combination B, and for combination C, we choose to count three times a week with 2 drones. Finally, the best policy is selected, which is counting three times with 2 drones and selecting the pallet locations to count with opportunity-based cycle counting in both the bulk storage and pallet racks.

Verification and validation

The developed model was verified by debugging and by running it line-by-line. To ensure the validity of the model, the data from Bolk was split into a training set and a testing set. Furthermore, the results were interpreted since reasonable results are an indication that the model is valid.

Recommendations

Several recommendations for both practice and further research are given. Since the data available for this thesis is from 3 years ago, the first recommendation for practice is to collect more recent data, to ensure an accurate cycle counting policy. The second recommendation is to assess the time available for cycle counting and the goal for inventory record accuracy. This makes that the policy aligns with the goals of the company and that the policy works in practice. Regarding the recommendations for further research, we advise collecting data about the inaccuracies in inventory. This way, better estimations of future inaccuracies can be made. Lastly, it is interesting to differentiate between SKUs, based on their value or criticality since an inaccuracy in the records of one SKU may be worse than an inaccuracy in the records of another SKU.

Limitations

There are a couple of limitations to this thesis. First, we made a lot of assumptions about the routing of drones. There is no guarantee that the travel time estimations are accurate, but they should indicate which policy results in longer travel time than others. Second, we determined the combinations of cycle counting types and their parameter values before the number of drones were known. In practice, the number of drones may be determined first, which makes it possible to adjust the types of cycle counting and the parameter values to the number of drones. Lastly, we did not consider all practical limitations. These include, but are not limited to, the maximum flying time of a drone on a fully charged battery and specific safety measures, like whether humans can be present in the warehouse when a drone is counting inventory.

Preface

This Master's thesis marks the end of my studies at the University of Twente. I could not have written this thesis without the help of a couple of people, who I would like to thank.

First, I want to thank Rob Bemthuis and Engin Topan. Your feedback was very helpful and essential to improving the quality of my thesis. Rob always helped me find points in my argumentation that could be improved. Engin often made me look at parts of the thesis from a different perspective, which gave helpful insights.

Also, I want to thank Peter Schuur, for providing feedback during the final stages of my thesis.

Finally, I want to thank Niek Tijink from Bolk for providing me with data, showing me the warehouse, and answering all the questions I had.

Annemiek Fladderak

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Glossary

- AGV: Automated Guided Vehicle
- AR: Augmented Reality
- CTT: Combi Terminal Twente
- CT: Constrained Tasks
- DA: Dynamic Allocation environment
- EV: External Allocation view
- IA: Instantaneous Assignment
- IT: independent Tasks
- IU: Interrelated Utilities
- IV: Internal Allocation view
- KPI: Key Performance Indicator
- KZV: Klaarzetvak, the Dutch word for set-up outbound area
- MAD: Mean Absolute Deviation
- MSER: Marginal Standard Error Rule
- MR: Multi-Robot
- MRTA: Multi-Robot Task Allocation
- MT: Multi-Task
- RFID: Radio Frequency Identification
- SA: Static Allocation environment
- SKU: Stock Keeping Unit
- SR: Single-robot
- ST: Single-Task
- TA: Time-extended Assignment
- TSP: Traveling Salesman Problem
- UAV: Unmanned Aerial Vehicle
- UGV: Unmanned Ground Vehicle
- UU: Unrelated Utilities
- VRP: Vehicle Routing Problem
- WMS: Warehouse Management System

1 Introduction

This report contains my Master's thesis, in the context of completing the Masters Industrial Engineering and Management at the University of Twente. This chapter introduces the thesis. First, the motivation for the research is explained in section 1.1. Section 1.2 describes the research goal. Section 1.3 contains the research design, which includes the research questions and the scope. We introduce the case study in section 1.4. Lastly, we give an outline of this report in section 1.5.

1.1 Motivation for research

Due to human and system errors in warehouse operations, inaccuracies exist in the inventory records of warehouses (Qiu & Sangwan, 2005). To find these inaccuracies, inventory needs to be counted. There are two approaches for a count of the inventory: a complete stock count and cycle counting (Wild, 2004). When doing a complete stock count, all items in the warehouse are counted. In contrast to this, when performing cycle counting, only a small amount of items is continuously counted during a certain period. Although a complete stock count is most commonly used, cycle counting is becoming more favored, since the warehouse needs to be closed during a complete stock count, but not during cycle counting (Mahtamtama, Ridwan, & Santosa, 2018).

Currently, inventory in warehouses is often counted manually. However, this is time-consuming and costly. It is also not 100% accurate, due to human errors, and it can lead to unsafe situations. A potentially better approach is to count the inventory with (semi-)autonomous unmanned aerial vehicles (UAVs), also known as drones. An advantage of using drones is that they can be used in situations where manual inventory counting is not safe or desirable. Also, drones are mobile, so they can count inventory in multiple warehouses sequentially. Lastly, drones can easily reach narrow storage areas, due to their size.

There are other alternatives to manual inventory cycle counts, such as automated guided vehicles (AGVs) or vision cameras. However, this research will focus on inventory cycle counting using drones since the client sees the most potential in drones.

1.2 Research goal

Limited information is available about the handling and performance of drones used for inventory cycle counting, as this is a relatively new application of drones. So, research is needed. This research aims to design a planning and control policy for inventory cycle counting by drones and to assess the performance of this policy. This planning and control policy will arrange the inventory cycle counting by drones, by determining when and how often the inventory in each part of a warehouse is counted, and which pallet locations are counted. Also, it determines which drone is allocated to count which pallet locations. These are both planning problems on the tactical level. Finally, we will evaluate the performance of the planning and control policy.

1.3 Research design

This section elaborates on the research design. Section 1.3.1 gives the main research question, while section 1.3.2 elaborates on the other research questions. Section 1.3.3 discusses the scope of this thesis.

1.3.1 Main research question

The research question for this research is:

'How can the inventory cycle counting in a warehouse by semi-autonomous unmanned aerial vehicles (UAV) be planned and controlled in terms of what items to count, when to count, and the allocation of the items to drones?'

1.3.2 Research questions

Literature review

Before designing the planning and control policy, we perform a literature review to gain more knowledge on relevant topics. First, UAVs suitable for inventory cycle counting are studied, as well as their specifications. Specifications like the design, navigation, and automation level are considered. Technical details like camera quality, scanning angle, etc. are outside of the scope and when necessary, assumptions are made.

1) What are the characteristics of UAVs suitable for inventory cycle counting that directly influence operational planning?

The second research question concerns how inventory cycle counting is currently organized. We should become familiar with the term inventory record accuracy. Also, we need to find important KPIs for inventory cycle counting as well since we will evaluate the performance of the planning and control policy. Finally, different methods of inventory cycle counting are analyzed.

2) How is the inventory cycle counting in warehouses currently organized?
   a) How can inventory record accuracy be defined?
   b) What are important KPIs for inventory cycle counting in warehouses?
   c) What methods of inventory cycle counting exist?

Lastly, we consider the problem as a capacity allocation problem. Therefore, we research how to allocate tasks to drones. A task is defined as counting the pallets at a specific pallet location. After it is clear which pallet locations to count, these will be allocated to drones. This research question helps to find methods for this allocation. It should be noted that pallet locations must be counted on a certain day, but the sequence in which pallet locations are counted is not relevant.

3) What is currently known in the literature about approaches for allocating tasks to UAVs?

System design

After the literature review, we develop the planning and control policy. Both a mathematical model and a model in Delphi are developed for this purpose. Delphi is an integrated development environment for applications. By solving these models, it can be determined when cycle counting should be performed, how many and which pallet locations are counted each time, and which pallet locations are assigned to which drone.

4) How can be determined when cycle counting should be performed, and which pallet locations should be counted?

5) How can be determined which drone should count which part of the pallet locations in the warehouse?

Performance evaluation

After developing the mathematical model, we evaluate the performance of different planning and control policies. To define performance, a selection is used of the KPIs found in research question 2)a). Different methods of cycle counting and different numbers of drones will be used to find the best policy.

6) How can the performance of the developed planning and control policy be evaluated?

Validation and verification

We need to validate and verify the developed system. The case study from Bolk will be used for validation and verification. Bolk has shared data that can be used for this validation and verification.

7) How can the developed system be verified and validated?
   a) How can the developed system be verified?
   b) How can the developed system be validated?

1.3.3 Scope

Limited time is available for this thesis, so a clear demarcation of the scope is needed. Therefore, we limit the scope in the following ways:

- *Routing is considered a black box*: This thesis focuses on the tactical level, not on the operational level. Therefore, the routing of drones in the warehouse is not part of the scope of this thesis. The routing will be treated as a 'black box'.
- *Technical details of drones are outside the scope*: Specific technical details of the drones that do not directly influence operational planning are outside of the scope, such as positioning and stabilization.
- *Layout and inventory policy are fixed*: The layout and inventory policy of the warehouse and the locations of the stocks are fixed. Optimizing these is outside of the scope.

1.4 Case study Bolk

This section discusses the case study of Bolk. First, an introduction to Bolk is given in section 1.4.1. Then, section 1.4.2 gives more details on the warehouse of the case study.

1.4.1 Introduction Bolk

Bolk is a transport company that offers transportation of goods for third parties in Europe. It is a highly innovative company with diverse activities, collaborations, and clients. Bolk focuses on diverse aspects of logistics, in which they provide clear added value. This includes, for example, taking over the transport and planning, rental of logistics space, direct contact with customers, and the combination of conventional and container transport.

Bolk was founded as Looms & Bolk in 1934 in Almelo, The Netherlands. It was a family business and it mostly provided transport for the drink and coal trades. At the beginning of the 1950s, business partner Looms died and Jan Bolk continued the business independently. After Jan Bolk passed away in 1962, Henk Bolk took over the company. The company gradually expanded, focusing on financial independence and diversification of activities. In 1985, Bolk started to transfer sea containers onto trucks, which were transported by train to Almelo. At the end of the 1990s, sea containers were no longer transported by train. Therefore, Combi Terminal Twente (CTT) was founded to facilitate the inland shipping of sea containers to Rotterdam. At the beginning of the 21 century, Bolk started specializing in exceptional transportation, like long-distance transportation, and projects like large silo transportation. Also, Bolk started with the transportation of windmill parts, exploring the limits of size and weight. Meanwhile, Bolk has expanded to Germany, Austria, Romania, and France, and has a warehouse in Hengelo.

1.4.2 Bolk warehouse

The focus of this thesis is on the public warehouse of Bolk, located next to the terminal in Hengelo. This location provides access to additional services, like ventilation, gas measurement, and intermediate storage of loaded containers. It also ensures a fast and reliable connection to the hinterland.

In the warehouse, products from Nouryon are stored. Nouryon is a split-off from AkzoNobel. They are a producer of chemical products and in Hengelo, they mainly produce consumer salts. Examples of such consumer salts are salt licks for animals and table salt. The plant in Hengelo is within a 2-kilometer distance from the Bolk warehouse. Bolk is responsible for the logistic operations of Nouryon, which means that Nouryon only sells and produces the products. Bolk transports the products from the production site to the warehouse, stores the products, and transports the products from the warehouse into trucks and containers. When products are transported over water to customers, this is managed by CTT. Third parties contracted by Nouryon perform the transport by truck.

Just over 300 different SKUs (Stock Keeping Units) are stored in the warehouse, which is about 2700 square meters in size. Storage is done at the pallet level. Pallets can be stored in *bulk storage* (shown in Figure 1.1), or in *pallet racks* (shown in Figure 1.2). These storage methods have different characteristics, like the number of pallets per location and the amount of time a pallet stays at the same location. Most of the pallets are stored in bulk storage, where block stacking is used. There are 272 bulk storage locations, which can all store multiple pallets. The exact number of pallets that can be stored differs per bulk storage location, depending on stacking height, depth of the storage location, and pallet size. About 10% of the pallets are stored in pallet racks. These pallets are slow movers, that typically stay in the warehouse for more than 30 days. There are 12 pallet racks, each with 480 storage locations. Each of these storage locations can store only one pallet.

Pallets are moved inside the warehouse by forklifts. One forklift can move two pallets at the same time, by spreading the fork of the forklift. The space between the pallet racks is too narrow for a regular forklift, so pallets are placed in front of the designated pallet rack. A small corridor truck picks up these pallets and places them in the right place in the pallet rack.

The warehouse is operational 24 hours per day, 7 days per week. Products can leave the warehouse from Monday to Friday, but they arrive every day of the week. On average, Nouryon produces 1000 pallets per day that are transported to the Bolk warehouse. The transport from the production facility to the Bolk warehouse is done with a shuttle truck. The shuttle truck fits 26 pallets, but it is not always full. So, in practice, the shuttle truck makes approximately 48 trips per day.

Figure 1.1 Bulk storage in the warehouse

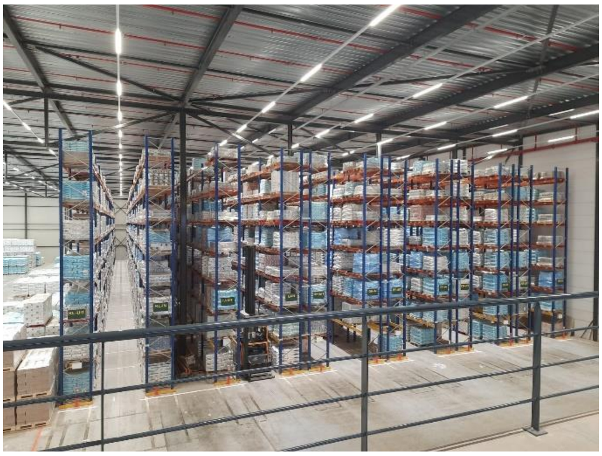

Figure 1.2 Pallet racks in the warehouse

Currently, the complete inventory in the warehouse is counted once every two years. This job is done by 2 people and takes 3 days. The target is that inventory is counted once every month and once a week for new pallets. Since inventory counting does not directly add value, Bolk prefers not to use any manpower for this. So, Bolk is interested in autonomous drones for inventory counting.

1.5 Outline of the report

This section gives an outline of the rest of the report. Chapter 2 discusses the literature review. The model is designed in chapter 3 and the performance evaluation of the planning and control policy is discussed in chapter 4. Chapter 5 concerns validation and verification. Finally, we discuss the conclusions and recommendations in chapter 6. Figure 1.3 also shows this outline.

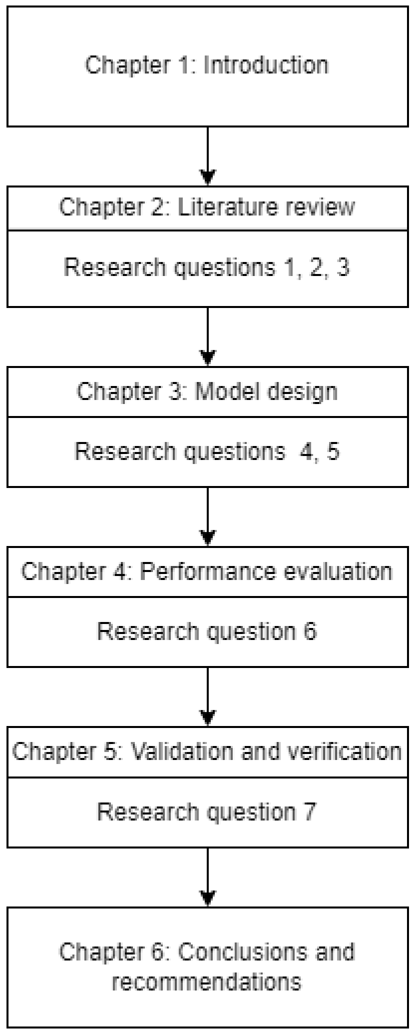

Figure 1.3 Outline of the report

2 Literature review

This chapter contains the literature review for this thesis. First, various drone characteristics are discussed in section 2.1. Section 2.2 elaborates on inventory cycle counting. Section 2.3 discusses task allocation. Finally, section 2.4 concludes this chapter.

2.1 Drone characteristics

This section answers the research question *'What are the characteristics of UAVs suitable for inventory cycle counting that directly influence operational planning?'*. A UAV is defined as '*an aerial vehicle that does not carry a human operator, uses aerodynamic forces to provide vehicle lift, can fly autonomously or be piloted remotely, can be expandable or recoverable, and can carry a lethal or nonlethal payload. It is controlled either autonomously by on-board computers or by remote control of a pilot on the ground.*' (Skorput, Mandzuka, & Vojvodic, 2016). UAVs first appeared in the military, but have also become available for commercial applications due to globalization and modern trends (Škrinjar, Škorput, & Furdić, 2018). The use of UAVs can be divided into three categories: safety control, scientific research, and commercial applications (Mohammed, Idries, Mohamed, Al-Jaroodi, & Jawhar, 2014). In business, companies are finding numerous use cases for UAV technology, which could have advantages for society and the environment. Commercial UAVs are deployed in the fields of agriculture, construction, transportation, traffic management, inspection, public safety, and other civil-government applications (Škrinjar et al., 2018).

This section discusses some characteristics of UAVs. First, the design is discussed in section 2.1.1. Then, section 2.1.2 discusses the navigation of drones, and section 2.1.3 discusses barcode scanning. Lastly, different levels of automation are explained in section 2.1.4.

2.1.1 Design

We can identify four different design configurations for drones that are widely used: fixed-wing, rotary-wing, tilt-wing, and flapping-wing. A fixed-wing drone looks similar to a small plane (Otto, Agatz, Campbell, Golden, & Pesch, 2018). These drones need constant air movement during the flight, so they cannot hover (Macrina, Pugliese, Guerriero, & Laporte, 2020). This makes them less suitable for inventory cycle counting since ideally, a drone can hover during the scanning of a barcode. Rotary-wing drones look like a helicopter, but they often have multiple rotors (Otto et al., 2018). They can take off and land vertically, and they can hover, according to Otto et al. A tilt-wing drone combines features of fixed-wing and rotorcraft drones, by using wings that can be rotated (Otto et al., 2018). The flapping-wing drone mimics the flying of birds (Macrina et al., 2020). These drones have limited flight time endurance, because of the great power needed for the flapping technology, which is explained by Macrina et al. The same article, however, says that they have unique maneuverability advantages. Flapping wing drones are less suited for inventory cycle counting because of their limited flight time endurance. Also, unique maneuverability advantages are not essential for inventory cycle counting inside a warehouse since a warehouse is usually spacious enough due to the forklifts that are used inside.

2.1.2 Navigation

In outdoor applications, drones can use GPS data for navigation. However, drones cannot use GPS data indoors, since this is not generally available inside buildings (Deja, Siemiątkowski, Vosniakos, & Maltezos, 2020). Solving the navigation problem is not in the scope of this thesis. Also, the travel time of the drone is already based on assumptions, as indicated in section 3.1.2. Therefore, we do not see an added value in assuming the method of navigation that is used for drones. Still, we give some examples from other works that proposed solutions to this problem. Multiple solutions are available that use a combination of cameras, sensors, an Inertial Measurement Unit (IMU), and/or an unmanned ground vehicle, each solution with its advantages and disadvantages (Anand, Agrawal, Agrawal, Chandra, & Deshmukh, 2019; Fei, Jin-Qiang, Ben-Mei, & Tong, 2013; Harik, Guérin, Guinand, Brethé, & Pelvillain, 2016; Kwon et al., 2019; Y. Li et al., 2018; López et al., 2017).

Anand et al. (2019) propose a system that uses grid lines in the warehouse for localization. Drones are equipped with a downward-facing camera to detect the grid and a front-facing camera for QR code detection. Algorithms then combine the information to determine the location of the UAV.

A drone that has an IMU for linear accelerations, angular rates, and Euler angles, a barometer for height estimation, a laser range finder for measuring the distance to surrounding objects, and a vision sensor is presented by Fei et al. (2013). Information from these sensors is fused to estimate the UAV's state estimation.

Kwon et al. (2019) introduce a drone with a 2D laser scanner, a 1D range sensor, an IMU, and three cameras: a forward, upward, and downward camera. Also, a simple map is used, that has information about tags attached in the warehouse. The forward camera of the drone is used for tag recognition and this way, the position and orientation of the drone are determined. Furthermore, three robust data fusion methods are proposed by Kwon et al. (2019).

Harik et al. (2016) propose a system in which a UAV and an Unmanned Ground Vehicle (UGV) work together to count inventory. Figure 2.2 shows the global architecture of this system. The UGV is used as a ground reference for the UAV and the UAV is equipped with a down-facing camera for vision-based target tracking. The UAV also has a barcode scanner, for scanning the items in the racks. Racks have Augmented Reality (AR) codes, such that the UGV knows at which rack it is. An example of an AR marker is shown in Figure 2.1. Once the UGV arrives at the first rack, the UAV takes off and flies vertically up to scan the barcodes of items on each level of the rack. If the UAV reaches the top of the first rack, the UGV navigates to the AR marker of the second rack and stops there. Meanwhile, the UAV uses its camera to stay on top of the UGV. At the top of the second rack, the UAV flies vertically down, while scanning the barcodes on items in the second rack. Once it reaches the last barcode, the UGV navigates to the next rack. This is continued for a complete row of racks. If the row of racks is finished, the UAV lands on the UGV to recharge, and the UGV navigates to the next row.

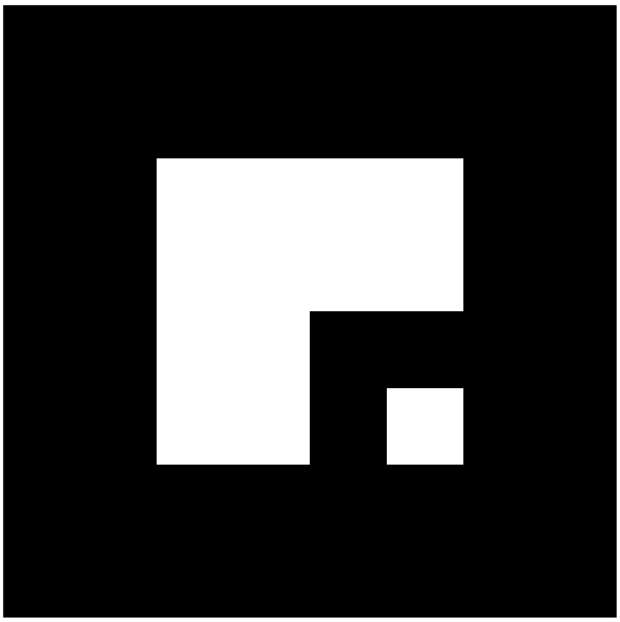

Figure 2.1 Example of an AR marker (Harik et al., 2016)

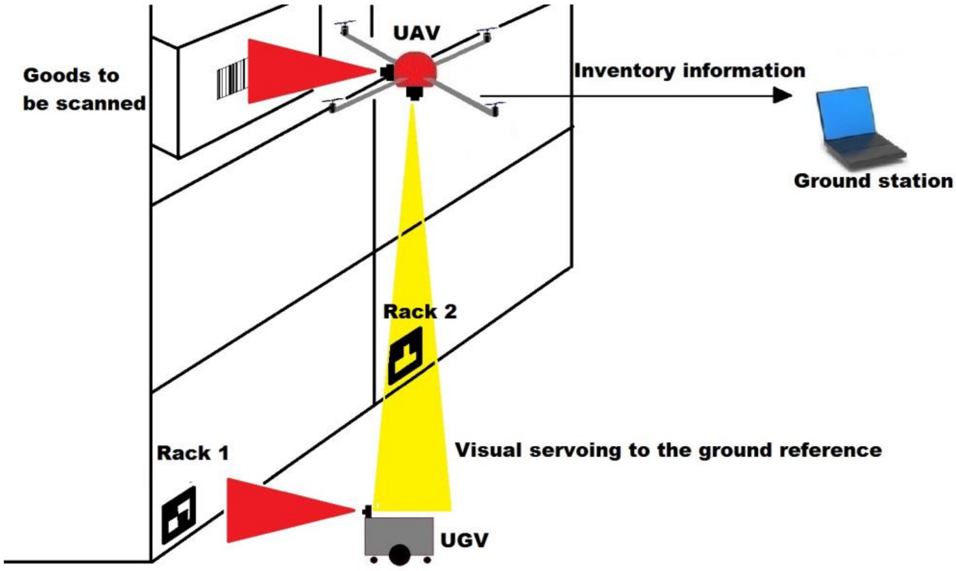

Figure 2.2 Global architecture of the collaboration between UAV and UGV (Harik et al., 2016)

2.1.3 Barcode scanning

There are multiple technologies for labeling products, like barcodes, RFID, and NFC. This thesis focuses on the use of barcodes since these are used often in the industry.

There exist two types of barcodes: 1D and 2D barcodes. 1D barcodes store information only in the horizontal direction. 2D barcodes store information in both horizontal and vertical directions, with the use of organized bars and blanks (Thanapal, Prabhu, & Jakhar, 2017). Therefore, some defects that may exist in 1D barcodes, like low information density, low information capability, and poor stability, can be solved by using 2D barcodes. For this reason, 2D barcodes are used more often than 1D barcodes (J. Li, Yi-Wen, Chen, & Wang, 2013).

Barcodes have a limitation, namely that the barcode must be in the line of sight when the product is being scanned. This means that the scanner must be aimed at the barcode and that the barcode must not be blocked by an obstacle, otherwise, the barcode cannot be scanned. Also, the barcode scanner should be within a range of 3-5 cm of the barcode (Thanapal et al., 2017).

2.1.4 Automation levels

There are a lot of approaches to the levels of automation (Vagia, Transeth, & Fjerdingen, 2016). We use the four automation levels for UAVs by Bloise et al. (2019), since it is not too complex and relatively easy to understand. These four automation levels are as follows:

- No automation: a human remotely controls the UAV. The UAV relies on humans for the detection and avoidance of obstacles.
- Automatic aircraft with pilot-in-the-loop: The UAV can perform a predefined flight mission, but has no decision-making capabilities. Unexpected obstacles can be avoided with a so-called Detect and Avoid system, but the UAV has no knowledge of other vehicles.
- Semi-autonomous aircraft with supervisor-in-the-loop: The UAV can perform autonomous flight operations, and has decision-making capabilities. It can avoid unexpected vehicles, due to sensors. Also, it has knowledge of other vehicles. Support of a ground segment is still needed for coordination and corporation between vehicles and a human supervisor is required.

- Fully autonomous aircraft: UAVs can perform autonomous flight and provide decision-making capabilities. A ground segment is required for cooperation between autonomous UAVs. The UAV can perform complex tasks and the level of safety is maximal.

For the thesis, the semi-autonomous level applies.

2.2 Cycle counting

This section answers the research question *'How is the inventory cycle counting in warehouses currently organized?'*. First, section 2.2.1 discusses inventory record accuracy, including causes of inaccuracies and ways to measure inventory record accuracy. Next, KPIs for cycle counting are discussed in section 2.2.2. Finally, various types of cycle counting are explained in section 2.2.3.

2.2.1 Inventory record accuracy

Inventory records should at least consist of the fields stock number, location, quantity on hand, and condition code. If there is an error in one of these fields, a record is considered inaccurate, according to Rossetti, Collins, and Kurgund (2001). However, there may be cases in which the exact location of an item is not in the Warehouse Management System (WMS). It does not make sense to consider all inventory records inaccurate in these cases. Therefore, we do not consider a record inaccurate if the inaccuracy is caused by a record field that the company structurally does not track.

Inaccurate inventory records will lead to ineffective replenishment decisions, which can lead to higher inventory holding costs and poor service levels (Kök & Shang, 2014). Cycle counting can decrease these inaccurate inventory records, but it is also an additional cost itself. Therefore, cycle counting should be used effectively, to prevent the costs of cycle counting to exceed the benefits that are gained (Gumrukcu, Rossetti, & Buyurgan, 2008).

Inventory record inaccuracies can occur due to various causes. According to Sarac, Absi, and Dauzère-Pérès (2010), errors can be classified into four groups:

- Transaction errors: These errors are for example shipment errors, delivery errors, scanning errors, and incorrect identification of items.
- Shrinkage errors: These errors include every type of error that causes the loss of products ready for sale, for example, employee theft, shoplifting, administration and paperwork errors, vendor fraud, and unavailable products for sale.
- Inaccessible inventory: This is defined as products that are not at the right location and that are not available to customers. If the product is found, the error may be corrected.
- Supply errors: These are errors caused by product quality or yield efficiency.

Measuring accuracy involves a degree of precision: items may have a tolerance on the variance from the inventory record. This means that there is a range for which the inventory record is deemed correct. For example, if the inventory record shows there is a quantity of 100 of an item and the tolerance is ±5%, the inventory record is still accurate if the actual quantity is 96 items. If the actual quantity would be too high or too low, so for example 90 or 120, then the record of this item would be inaccurate. To calculate the accuracy of the total inventory record, formula 2.1 is used (Brooks & Wilson, 2007).

$$Inventory\ record\ accuracy = \frac{total\ accurate\ records}{total\ records\ checked} * 100\% = percentage\ of\ accuracy \tag{2.1}$$

DeHoratius and Raman (2008) have a different approach to inventory inaccuracy. They want to focus on the likelihood of inaccuracies, so they are concerned about the discrepancy between the inventory record and the actual inventory. They define inaccuracy as the absolute difference between the inventory record and the actual inventory. Also, they use mean absolute deviation (MAD), which is the mean of the set of all inaccuracies.

2.2.2 KPIs for cycle counting

The primary goal of cycle counting is to find the causes of errors, correct the conditions causing the errors, keep the level of inventory record accuracy high, and give a correct statement of assets (Rossetti et al., 2001). So, inventory record accuracy can be considered an important KPI for cycle counting. Gumrukcu et al. (2008) mention multiple performance indicators, that fall into three categories: performance, system, and cost. These indicators are shown in Table 2.1.

Table 2.1 KPIs of inventory cycle counting

Performance	**System**	**Cost**
Accuracy	Fill rate	Holding cost
Discrepancy (negative, positive, absolute)	Probability of lost sales	Asset cost
	Probability of backorders	Lost sales cost
	Probability of lost sales due to errors	Transportation cost
	Inventory	Cycle counting cost
		Total cost

2.2.3 Types of cycle counting

As emphasized in the previous section, inventory cycle counting should be used effectively. To achieve this, a suitable type of cycle counting must be used. In this section, the following types of cycle counting are explained: ABC cycle counting, random cycle counting, control group cycle counting, process control cycle counting, opportunity-based cycle counting, location-based cycle counting, and cycle counting using historical inventory data.

ABC cycle counting

ABC cycle counting assumes that a small number of items contributes to a majority of the inventory value, which is also known as the Pareto principle (Brooks & Wilson, 2007). The basic principle is as follows: a small number of items with the highest annual value is the A class. In the C class are items with the lowest annual values and the rest is in the B class. In ABC cycle counting, the A items are counted more frequently than the B items, and the B items are counted more frequently than the C items. Typical frequencies for ABC cycle counting are to count items in class A 4 times a year, items in class B 2 times a year, and items in class C once a year (Rossetti et al., 2001). Based on the counting frequencies, the number of SKUs in each class, and the number of items that can be counted every day, the number of cycle counters can be determined.

A disadvantage of ABC cycle counting is that the counting workload is dependent on the number of items in inventory. Another disadvantage is that it only focuses on the financial perspective. The materials perspective is not considered. For example, an item in the C class can be just as important as an item in the A class with respect to delaying production or shipments. So when classifying the SKUs, it is important to also consider other criteria than the value of the SKU and to upgrade an item to the

A class if that seems necessary. These criteria could be, for example, criticality, lead time, or usage (Rossetti et al., 2001). This is, for example, applied in Fathoni, Ridwan, and Santosa (2019), where an ABC-VED analysis is used, where items are not only classified as A-, B- or C- items, but also as Vital, Essential, or Desirable item.

Random cycle counting

In random sample cycle counting, a sample from the population is generated at random and the items in this sample are counted (Rossetti et al., 2001). Since the generation is at random, each item has an equal opportunity of being picked. Random cycle counting is generally considered the best method for measuring inventory accuracy, if the sample is sufficiently large and if it has stability.

There are two techniques for random sample cycle counting: the constant population counting technique and the diminishing population counting technique. In the first technique, a generated sample stays in the population from which the sample is picked, while in the latter technique, a generated sample is excluded from the population from which the sample is picked (Brooks & Wilson, 2007). This means that with constant population cycle counting, the population from which the sample is picked stays the same. Thus, some items can be counted more often than other items. In theory, it is even possible that certain items are included in (almost) every sample, while certain other items are (almost) never included in a sample. With the diminishing population counting technique, samples are excluded from the population until no items are left and then sampling is done from the original population again. This way, each item is counted the same number of times. However, the last item counted in the last sample of the population can be the first item counted in the next sample. This can be avoided by using the diminishing population counting technique with timing. With this technique, the generated samples are used again in the next cycle (Brooks & Wilson, 2007).

Control group cycle counting

In control group cycle counting, a sample of items in the same location is counted multiple times within a short period. The control group consists of the items that are counted. This method is the only one that is not used to measure inventory record accuracy. Its purpose is to find errors in the process. It is primarily used if there is a new design of the inventory process and should be done before other cycle counting types (Brooks & Wilson, 2007). By reducing the time between counts, the time in which an error can occur is reduced and there are fewer possible causes of the errors. This makes it easier to analyze and correct errors.

Process control cycle counting

Process control cycle counting is called "controversial in theory but effective in practice" by Brooks and Wilson (2007). It can only be used if two prerequisites are met. The first prerequisite is that inventory records have piece count by multiple location capability, which means that it must be possible to store information about the number of items stored at each location. The second prerequisite says that a record of all items with all the quantities and locations is available to the counter. There are three criteria used for process control cycle counting, namely location, ease of counting, and obvious errors. First, each counter is assigned to a specific area. Then the counter verifies the location of each item. However, only the easy-to-count items are counted. These are typically items that are either low in quantity or are packaged in a manner that allows quick and easy counting. If there is a large quantity of a certain item, an *eyeball assessment* is made: the large quantity is verified with the inventory record for the location and order of magnitude of the item. This is not considered as a *count* but as a *skip*. When an item is misidentified or mislocated, or if the order of magnitude does not match the inventory record, this item is counted and included in the sample. To determine the accuracy, all skips are ignored and formula 2.1 is used (Brooks & Wilson, 2007).

Process control cycle counting seems to be a very efficient method for cycle counting: 10 to 20 times more items can be counted with process control cycle counting than with random cycle counting or with ABC cycle counting (Brooks & Wilson, 2007). Still, there are some concerns with process control cycle counting. The first one is that the cycle counter has the freedom to determine whether an item is easy to count or not. This causes fear that the result is skewed such that it misrepresents the total population of items. The second concern is that it is not clear when difficult-to-count items are counted. This can easily be solved by keeping track of which items are counted and scheduling a count for items that were not counted (Brooks & Wilson, 2007).

Opportunity-based cycle counting

When performing opportunity-based cycle counting, items are counted when particular key events occur. These key events are for example when an item is reordered, when an item is stored, when an item is issued, or when the inventory drops below a certain threshold. A specific form of opportunity-based cycle counting is transaction-based cycle counting, in which an item is counted after a certain number of transactions. So, an item could for example be counted after every 5 transactions. For both types of cycle counting, deciding which items to count and how often they are counted are important decision parameters (Rossetti et al., 2001).

Opportunity-based cycle counting only counts the item that causes an opportunity, but we can take inspiration from an approach that is used in maintenance management. With opportunity maintenance, a system shutdown or intervention provides an opportunity for doing maintenance on items that did not cause the opportunity (Rausand & Hoyland, 2003). For cycle counting, this would mean that if an opportunity occurs for a certain item, a set of other items is counted together with this item. This method would be useful if there is a certain setup time or setup cost for cycle counting. Consider the example of cycle counting with drones, if the drones are stationed far away from the items that need to be counted, there is a setup time. Counting multiple items would then save time, compared to counting items individually.

Location-based cycle counting

In location-based cycle counting, the sample is formed by the items in a certain area. All the items in this area are counted. This method is similar to process control group cycle counting, but the counter is not allowed to skip items that are hard to count and he does not have a record count (Rossetti et al., 2001).

A disadvantage of location-based cycle counting is that the generation of the sample is not based on the characteristics of the items, but solely on their locations. For certain cases, the location of items may be irrelevant to generating a sample.

Cycle counting using historical inventory data

In Wijffels, Giannikas, Woodall, McFarlane, and Lu (2016), an approach is developed to find items that are most likely to be inaccurate based on both current and historical inventory data. Data mining is used to classify items as either accurate or inaccurate. A classification model based on logistic regression as well as one based on a neural network was used. By data mining, the properties of items that were previously inaccurate are revealed. It must be noted that these are correlations and that nothing is inferred about the cause of the inaccuracies.

This type of cycle counting does not necessarily outperform other cycle counting types (Wijffels et al., 2016). However, it does provide some benefits above other cycle counting types. First, it offers insight into the root causes of inventory inaccuracies. Second, the model is easily applicable and does not require warehouse expertise. Lastly, the model can be frequently retrained, such that it can be easily adapted to changes in the causes of inventory inaccuracies.

The types of cycle counting discussed in this section are used throughout the rest of this research. However, not every type of cycle counting is applicable to this research. Section 3.3.1 discusses which types of cycle counting are used and which ones are not.

2.3 Task allocation

This section answers the research question *'What is currently known in the literature about approaches for allocating tasks to UAVs?'*. The task allocation problem is defined as '*the problem of determining a suitable mapping between robots and tasks*' (Tang & Parker, 2007). A task is a subgoal, necessary for achieving the overall goal of the system and which is achieved independently of other subgoals (Gerkey & Matarić, 2004). This section first discusses a taxonomy for task allocation in section 2.3.1 and then the solution approaches in section 2.3.2.

2.3.1 Taxonomy

Gerkey and Matarić (2004) propose a taxonomy for Multi-Robot Task Allocation (MRTA) problems, which uses the following three axes:

- Single-task robots (ST) versus Multi-task robots (MT): With ST, each robot can only execute one task at a time, while with MT, some robots are capable of executing multiple tasks simultaneously.
- Single-robot tasks (SR) versus Multi-robot tasks (MR): SR means that every task requires precisely one robot, while MR means that some tasks can require multiple robots.
- Instantaneous assignment (IA) versus time-extended assignment (TA): With IA, the available information about the robots, tasks, and the environment allows only an instantaneous allocation of tasks to the robots, without planning for future allocations. TA means that there is more information available, like the set of tasks that will need to be assigned, or a model of how tasks will arrive over time.

This taxonomy covers many problems, but there are several problems excluded. According to (Gerkey & Matarić, 2004), these problems have interrelated tasks (for example when the cost of task A depends on whether it is executed by the same robot as task B) and tasks with constraints between them (for example sequential or parallel execution). Landén, Heintz, and Doherty (2010) propose an extension of the taxonomy with four dimensions. To cover the two problems mentioned before, the taxonomy is extended with the dimensions of unrelated utilities (UU) versus interrelated utilities (IU) and independent tasks (IT) versus constrained tasks (CT). The third dimension is about who makes the task allocation: it can be an external process, or it is done by the robots themselves. This new dimension is called the external allocation view (EV) versus the internal allocation view (IV). The last dimension concerns the task allocation environment. A task allocation can unexpectedly change, for example, if future tasks need to be taken into account, or if robots are added or removed. This last dimension is called the static allocation environment (SA) versus the dynamic allocation environment (DA) dimension.

Within the allocation problem for this thesis, a task can be defined as counting the pallets at a specific pallet location. The allocation problem can be positioned on the single-task robot, single-robot tasks, and time-extended assignment axes since each drone can only count one pallet location at a time, a pallet location is counted by exactly one drone, and all pallet locations to be counted on each day are known before they are allocated to drones. The tasks have unrelated utilities and their tasks are independent. Since drones do not make the task allocation themselves, there is an external allocation environment. Finally, there is a static allocation environment. The task allocation problem in this thesis can be summarized as ST-SR-TA-UU-IT-EV-SA.

2.3.2 Solution approaches

This section discussed two approaches for solving MRTA problems: market-based approaches and optimization-based approaches. Both are discussed in this section.

Market-based approaches

Market-based approaches are decentral approaches, which means that decisions are made by multiple agents, instead of one centralized agent (Khamis, Hussein, & Elmogy, 2015). In market-based approaches, robots, or drones in our research, are considered agents. Agents act as self-interested entities that operate in a virtual economy by bidding on tasks (Korsah, Kannan, Browning, Stentz, & Dias, 2012).

This process, where a set of goods or services are assigned to bidders, is called an auction (Khamis et al., 2015). Auctions require explicit communication between robots about the required tasks. The negotiation process is based on the market theory, in which the team of robots aims to optimize an objective function based on robot utilities for performing particular tasks (Khamis et al., 2015). Gerkey and Matarić (2004) explain that utility is a concept based on the notion that each individual can internally estimate the value of executing an action. In multi-robot systems, this estimation includes the expected quality of task execution, as well as the expected resource cost. The utility of a robot executing a certain task can then be determined by subtracting the resource costs from the quality of task execution (Gerkey & Matarić, 2004).

Market-based approaches are mainly suitable for multi-robot task allocation in a dynamic environment (Yao, Qi, Wan, & Liu, 2019). These approaches do not provide an optimality guarantee (Korsah et al., 2012). Still, they have significant advantages, such as robustness, flexibility, and fast operational speed (Yao et al., 2019). Also, new tasks can easily be introduced and market-based approaches seem to be able to arrive at an efficient solution with limited resources (Khamis et al., 2015).

Optimization-based approaches

Optimization is the branch of applied mathematics that focuses on solving a certain problem to find the optimum solution out of a set of available solutions. The set of available solutions is restricted by a set of constraints and the optimum solution is chosen based on an objective function that quantitatively describes the goal of the system (Badreldin, Hussein, & Khamis, 2013). Optimization-based approaches work in a central manner, where one single computer coordinates all drones (De Ryck, Pissoort, Holvoet, & Demeester, 2021).

There exist deterministic and stochastic techniques. Deterministic techniques follow a strict and repeatable procedure, which is explained in Khamis et al. (2015). When beginning at the same starting point, these techniques will follow the same path whether the program is run today or tomorrow. Deterministic techniques include numerical and classical methods, such as graphical methods and quadratic programming (Khamis et al., 2015).

Stochastic techniques always involve some randomness and can be classified into trajectory-based and population-based algorithms (Khamis et al., 2015). Trajectory-based metaheuristics are algorithms that use one single solution that moves through the search space to find the optimal solution, such as simulated annealing (Badreldin et al., 2013). A better solution is always accepted, while a not-so-good move can be accepted with a certain probability (Khamis et al., 2015). This way, it is possible to reach the global optimum. Population-based algorithms iteratively transform a population of solutions throughout the algorithm to generate a new population of solutions to find the optimal solution (Badreldin et al., 2013). Khamis et al. (2015) mention genetic algorithms and particle swarm optimization as examples of population-based algorithms.

An advantage of stochastic techniques is that they have greater potential to explore new research areas in search space, because there are random algorithm variables, as explained by Shelkamy, Elias, Mahfouz, and Shehata (2020). They also say that a good solution is found relatively fast with stochastic techniques. A study by Badreldin et al. (2013) shows that optimization-based approaches outperform the market-based approach in multiple aspects, like the total time taken to reach the best solution, as well as the optimality of the found solution. However, this study used only two algorithms (one trajectory-based and one population-based), while there are a wide variety of optimization algorithms. Therefore, this study cannot guarantee that all stochastic techniques outperform market-based approaches.

This thesis focuses on semi-autonomous UAVs, so a centralized approach to task allocation fits best. Therefore, an optimization-based approach is used for this research. Both static and dynamic techniques can be applied.

2.4 Conclusion

Multiple research questions are answered in this literature review. First, we identified the characteristics of UAVs suitable for inventory counting. Tilt-wing or rotary-wing drones have a suitable design, because of their ability to hover. The drones need a combination of cameras, sensors, an IMU, and/or a UGV for navigation since GPS does not work inside a warehouse. 2D barcodes are used on the pallets, such that the drone can identify these pallets. For this thesis, the semi-autonomous level applies to drones, which means that the drone can perform autonomous flight operations, but still needs a human supervisor. Next, we learn how inventory cycle counting in warehouses is currently organized. Different KPIs for cycle counting are identified, which fall into one of the following three categories: performance, system, and cost. Inventory record accuracy is defined and possible causes for inaccuracies are discussed. These causes for inaccuracies can be categorized as transaction errors, shrinkage errors, inaccessible inventory, or supply errors. A formula for inventory record accuracy is given. Also, we discussed multiple types of cycle counting. Finally, the allocation of tasks to drones is discussed. A taxonomy for task allocation is presented and the location inside this taxonomy of the allocation problem for this thesis is identified. Also, we discussed market-based solution approaches and optimization-based approaches. We indicated that optimization-based approaches are more appropriate for the allocation problem in this thesis.

3 Model design

This chapter discusses the design of the model. First, section 3.1 explains the assumptions. Then, section 3.2 discusses the mathematical model that is developed. The heuristics are discussed in section 3.3. Finally, section 3.4 concludes this chapter.

3.1 Assumptions

This section goes into the assumptions that are made. To start, assumptions about the inventory data are discussed in section 3.1.1. Then, section 3.1.2 explains the assumptions about the travel time approximation.

3.1.1 Inventory data

Bolk provided us with data from 2019 about the inventory in their warehouse and the transactions that were made. However, no data is available about which inaccuracies occurred in their warehouse and when these occurred. It is only possible to make an educated guess about how often an inaccuracy occurs. Therefore, we make some assumptions about these inaccuracies. This way, data including inaccuracies can be simulated.

Causes of inaccuracies at Bolk

Recall from section Inventory record accuracy2.2.1 that there are several possible causes of inaccuracies. Bolk indicates that inaccuracies mostly occur due to transaction errors. These inaccuracies are discussed in the next paragraph. Another cause for inaccuracies is shrinkage errors, like theft, administration errors, and vendor fraud. Theft is not likely, since pallets are not easily transported and the warehouse is operating 24/7. Since all pallets are registered in the WMS, administration errors are also not expected to occur. Vendor fraud is not relevant, because pallets in the warehouse are both produced and sold by Nouryon. Another potential type of error is caused by inaccessible inventory, which are products that are at the wrong pallet location. If these products are found, the error can be corrected. Although these errors are not categorized as transaction errors, they occur when a transaction of the pallet from one location to another is made. The last possible type of error is supply errors, which are errors caused by product quality or yield efficiency. Again, Nouryon produces and sells the products, and Bolk is responsible for warehousing. Therefore, supply errors are not relevant to the case of Bolk. To conclude, this thesis will focus on transaction errors.

Transactions

We define a transaction as the movement of a pallet from one pallet location to the next. Before a pallet is moved, the barcode on the pallet is scanned by the driver of the forklift that moves the pallet. However, the driver may occasionally forget to scan this barcode. This creates an inaccuracy. So, with every transaction of a pallet, there is a small probability that an inaccuracy occurs. To gain more insight into these types of inaccuracies, we now briefly discuss the movements of a pallet inside the warehouse.

Figure 3.1 shows the movements of a pallet inside the warehouse. Each square represents a pallet location and each arrow represents a movement from one pallet location to another. All pallets are transported to the warehouse with a shuttle truck. If they arrive at the warehouse, they are unloaded onto a conveyor belt. They remain on the conveyor belt until a forklift is ready to move them. For bulk storage, the pallet is moved directly to the pallet location that is indicated in the WMS. For storage in the pallet racks, the pallet is moved to the 'in-box' of the pallet rack where it should be stored according to the WMS. A normal forklift cannot place a pallet in the pallet rack, so a small corridor truck is used to perform this action.

When pallets need to be set up for transport to a customer, they are retrieved and placed in a so-called KZV. A KZV is an abbreviation for the Dutch word 'klaarzetvak', which is a set-up outbound area. Pallets in bulk storage are moved directly from their pallet location in bulk storage to the dedicated KZV. Pallets in a pallet rack are first moved to the 'out-box' by the small corridor truck. A forklift then moves the pallet to the dedicated KZV.

From this process can be concluded that pallets stored in pallet racks are moved twice as often as pallets in bulk storage. Therefore, their barcodes also need to be scanned twice as often. This indicates that probably more inaccuracies occur when storing pallets in pallet racks than in bulk storage. This can be confirmed by the fact that Bolk indicates that more inaccuracies are found in pallet racks than in bulk storage.

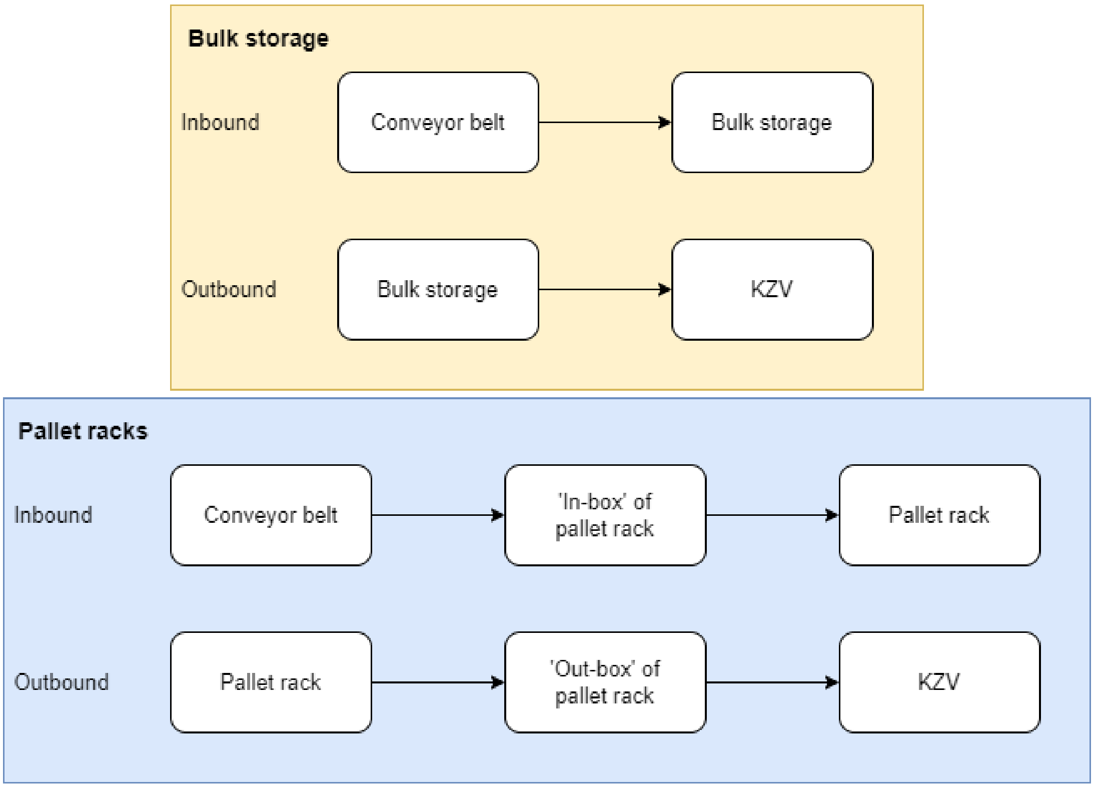

Figure 3.1 Transactions of pallets in the warehouse

Simulation of inaccuracies

Recall that with every transaction there is a small probability that an inaccuracy occurs. Also, Bolk has an idea about the number of inaccuracies in the warehouse when a full stock count is done. Since we know the number of transactions done per year from the Bolk data, we determine the probability that an inaccuracy occurs at a transaction. Then we use a Monte Carlo simulation to simulate inventory records with inaccuracies. This simulation is performed using Excel VBA, as it is easy to use.

3.1.2 Travel time approximation

As indicated in Section 1.3.3, the routing of drones in the warehouse is outside the scope of this thesis, so it is treated as a black box. However, to estimate the cost of counting a certain set of pallet locations by a drone, we need to approximate the travel time. Since the travel time depends on the routing of the drone and we do not want to solve the routing problem, we make some assumptions about the route of a drone. These assumptions are reasonable since at the end of the day we do not need detailed travel times, rough estimations are sufficient. Our assumptions will give us these rough estimations. Still, it should be noted that the method used is just one of many approaches.

To estimate the travel time, the warehouse is divided into zones. For the case study of Bolk, there are six zones, which can be seen in Figure 3.2. Zone 5 uses pallet rack storage and the other zones use bulk storage. The estimation of the travel time of a drone is split into two parts: its travel time between the zones and the charging point, and the travel time inside each zone it visits. These factors are discussed separately in sections 3.1.2.1 and 3.1.2.2.

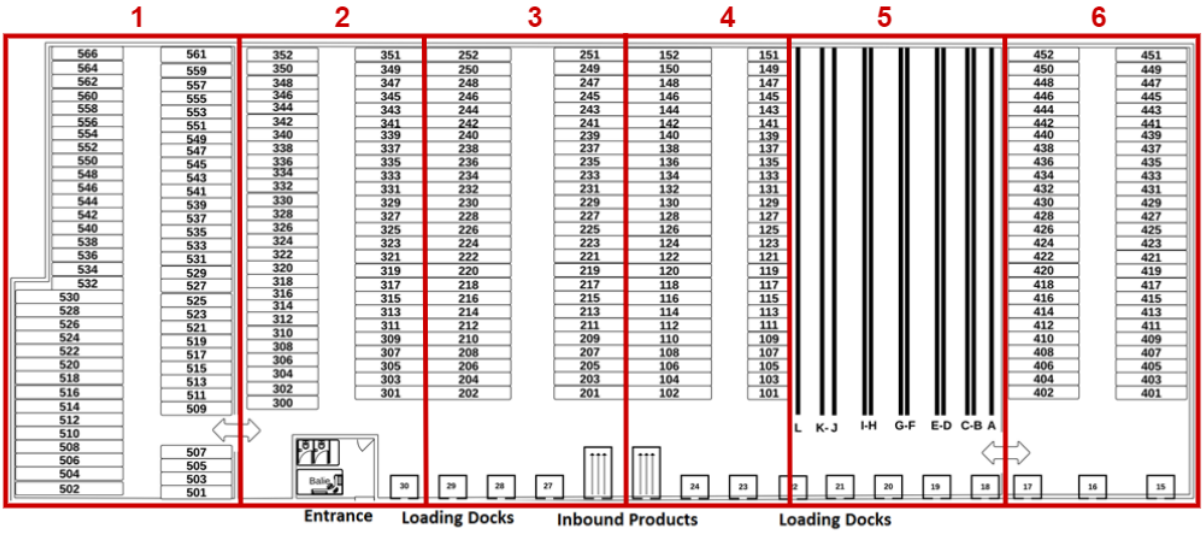

Figure 3.2 Division of the warehouse into zones

3.1.2.1 Travel time approximation between zones

Each day, every drone flies according to a specific path, which is a sequence of the zones that it has to visit. Appendix A: Paths specifies all zones. Bolk has indicated that locations 502, 504, and 506 are suitable locations for charging drones. These locations are on the left side of zone 1. So, we assume that a drone always starts counting from there. Furthermore, we assume that zones are always visited in the order from left to right. This means the zone that is most to the left and contains pallet locations to be counted, is visited first. Then the zone that is second-most to the left with pallet locations to be counted is visited, et cetera. Finally, the drone flies from the last zone to be visited back to the charging point. If a zone does not have pallet locations that need to be counted, that zone is not visited. Now let us give an example. If a drone needs to count pallet locations in zones 2 and 4, then it starts in zone 2, and then goes to zone 4. This example is shown in Figure 3.3. In this figure, the route inside the zones is represented by a dashed line, as this section only focuses on the travel time between zones. The approach discussed in this section is chosen since it is an efficient order of visiting the zones. As an alternative approach, a drone can also visit zones from right to left, which would result in the same travel time.

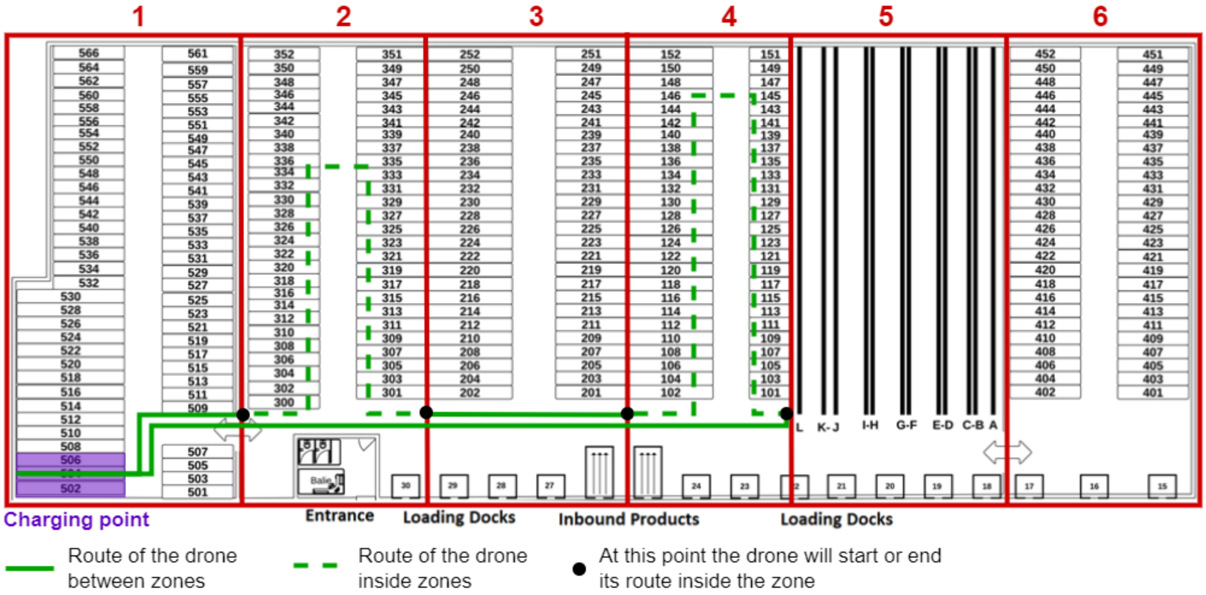

Figure 3.3 Route of a drone between zones 2 and 4

For the travel time estimations between zones, multiple distances are summed: the distance from the charging point to the left side of the first zone to be visited, then for each next zone to be visited (if any) the distance from the right side of the previous zone to the left side of the next zone, and the distance from the right side of the last zone back to the charging point. With these distances, the drone has to travel both in the width and length of the warehouse. We use Manhattan distances, so the distances in the length and the width are summed. The distance from the left side of a zone to be visited to the right side of the same zone is not taken into account, as that is part of the travel time inside the zone. This is also shown in Figure 3.3 since the dashed line between the left and right sides of the visited zones belongs to the route inside the zone. Finally, the distances are converted into travel time. It is assumed that the drone flies at an average speed of 5 km/h, which is about the same as the walking speed of a human. In general, drones can fly faster but due to safety concerns, we assume that a drone does not fly much faster than a walking human. Also, a drone needs to accelerate and decelerate, which limits the average speed of the drone.

3.1.2.2 Travel time approximation inside zones

A zone can contain either bulk storage or pallet racks. A difference between these two that influences the estimation of the travel time in these zones is the number of aisles. A zone with bulk storage has only one aisle with pallet locations on both sides, while a zone with pallet racks has multiple aisles. For a zone with pallet racks, we assume that the aisles are visited from left to right. An aisle is only visited if at least one pallet location has to be counted in that aisle.

Again, we use Manhattan distances for estimating the travel times inside the zone. We assume that inside each aisle with pallet locations to be counted, a drone starts by counting the closest pallet location at the left. Then it counts all other pallet locations on the left, in order from closest pallet location to furthest pallet location. Next, it counts the pallet locations on the right, from the furthest to the closest pallet location. Finally, when the closest pallet location at the right is counted, the drone leaves the zone to go to the next destination on its path. Figure 3.4 shows an example were three pallet locations are counted in a zone. Just like with the travel time between zones, we assume that a drone flies at a speed of 5 km/h.

These assumptions provide a good setting for estimating the travel time since the travel time inside zones is based on four elements: the travel times in the width and length, the travel time in the height, and the positioning time of a drone at each pallet location. The travel time inside a zone is equal to the summation of these four elements. With the assumptions discussed before, these elements can easily be determined. Below, we will explain these elements in more detail.

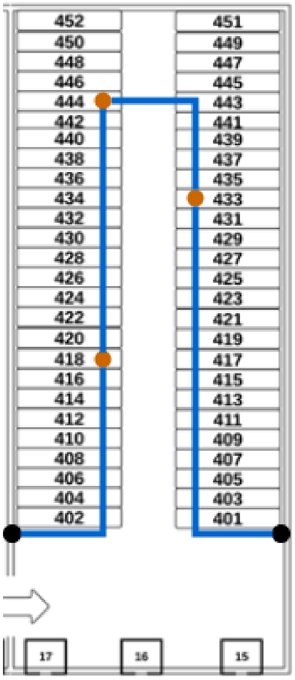

Figure 3.4 Example of the route of a drone inside a zone

The travel time in the width is always the time to travel from the left side of the zone to the right side of the zone since a drone first counts pallet locations on the left side and then on the right side of the zone.

The travel time in the length is based on the furthest pallet location that needs to be counted. If a zone contains pallet racks, there are different aisles in a zone. For the travel time in the length of these zones, the travel times to the furthest pallet location in each aisle need to be summed. In the case of the Bolk warehouse, this is done in zone 5.

For *the travel time in the height*, we assume that a drone flies at half the height of the pallet rack. It goes up or down to count a pallet location and then returns to the original height. So, the travel time in the height is based on the difference between the height of the pallet location and half the height of the pallet rack. In reality, it is more likely that the drone does not go back to the original height after counting a pallet location, but that it goes to the height of the next pallet location to count. However, this approach is not used for this thesis, because it would make the model far more complex.

The positioning time at each pallet location is an estimation of the time that the drone needs to position in front of the pallet location and to find the barcode that it needs to scan. We assume that the positioning time is the same at each pallet location.

3.2 Mathematical model

In this section, we discuss a mathematical model for our cycle counting problem. The solution to this model can be used as a benchmark for various cycle counting policies. We made multiple attempts to solve this model in AIMMS, which is software that allows the user to develop optimization-based applications. However, we were not able to find the optimal solution to this model. We still discuss this model as it presents the cycle counting problem concisely.

First, we will discuss the requirements of the model in section 3.2.1. Next, section 3.2.2 discusses alternative models. Finally, section 3.2.3 presents our mathematical model.

3.2.1 Model requirements

A logical objective function for the model is to maximize the inventory record accuracy. Recall from formula 2.1 that inventory record accuracy is the number of accurate records divided by the number of records counted. However, if the objective is to maximize the inventory record accuracy, we expect the model to only count pallet locations that are accurate. Since this is not the intention of the model, we will use a different objective function, which aims to maximize the number of inaccuracies found. This is reasonable because finding more inaccuracies leads to a higher inventory record accuracy. This objective function will use a correction ratio, which is the number of pallets too few or too many, divided by the number of pallet locations in the warehouse.

The inventory in reality and according to the WMS are considered to be parameters in the model and not variables. The reason for this is that it is not possible to let this information magically appear in the model after the decision is made to count a certain pallet location. However, in practice, the inventory, in reality, is only known after counting. Therefore, this model is not used to find the best policy for inventory cycle counting, but rather as a benchmark for the different types of cycle counting.

Finally, the model should be able to estimate the travel times for counting the pallet locations that are selected each day. This should be done based on the assumptions of the travel time in section 3.1.2.

3.2.2 Alternative models

Before diving into the mathematical model, we explore if any existing models can be used directly or after adaptation. Potential candidates are the Traveling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP). In the TSP, a traveling salesman needs to visit each city from a list of m cities exactly once and then return to the home city, where the cost of traveling from city i to city j is c_{ij}. The aim is to find the least costly route (Hoffman, Padberg, & Rinaldi, 2013). This problem focuses on the routing of the traveling salesman, while our thesis focuses on the pallet locations to count and when to count them. However, if the inaccuracies are known beforehand and the assumption is made that a pallet location is counted as soon as the inaccuracy occurs, this problem can help us give an estimation of the travel time. A limitation of this model is that there is only one salesman, but it should be possible to use multiple drones for cycle counting.

The VRP consists of several customers, each requiring a number of goods to be delivered. Vehicles must deliver the goods from a depot, and each vehicle can carry a limited number of goods and the total distance it can travel may be restricted. Each customer can only be visited by one vehicle. The aim is to find delivery routes that minimize the total costs while satisfying the before-mentioned requirements (Baker & Ayechew, 2003). The VRP has the same limitations as the TSP, with the exception that the VRP allows for multiple vehicles. Since we want to apply our assumptions for the travel time estimations from section 3.1.2, we prefer to build our own mathematical model.

3.2.3 Model description

First, the sets, parameters, and decision variables are introduced. Then, the objective function and constraints are discussed.

Indices

i	Pallet locations (1, …, I)
k	Drones (1, …, K)
t	Time periods (1, …, T)
r	Zone (1, …, R)
g	Path (1, …, G)
o	Aisle in the pallet rack zone (1, …, O)

It is assumed that the fleet of drones *k* is homogeneous, so they all have the same properties. During all periods, the same amount of drones is available. The different zones *r* are described in section 3.1.2 and the paths *g* are specified in Appendix A: Paths. Zone 5 holds all the pallet racks. Between these pallet racks are aisles, which are specified by the index *o* for the sake of calculating the distance traveled in the length by a drone counting inventory.

Parameters

n	Total number of pallet locations in the warehouse
d_{it}	Number of pallets at pallet location i according to the WMS at the end of day t
e_{it}	Number of pallets at pallet location i in reality at the end of day t
l_{ir}	$\begin{cases} 1 \text{ if pallet location i is located in zone r} \\ 0 \text{ otherwise} \end{cases}$
q_{io}	$\begin{cases} 1 \text{ if pallet location i is located in aisle o} \\ 0 \text{ otherwise} \end{cases}$
a_{rg}	$\begin{cases} 1 \text{ if zone r is included in path g} \\ 0 \text{ otherwise} \end{cases}$
c_g	Travel time of path g
w_r	Travel time from the left side to the right side of zone r
b_i	Travel time in the length from the beginning of the zone to location i
h_i	Travel time from half the pallet rack height to the height of pallet location i
s	Time needed at each counted location for the drone to position and find the barcode

The travel time of a path c_g includes the travel time from the charging station to the first zone, between zones, and from the last zone to the charging station, as described in section 3.1.2.

Decision variables

X_{ikt}	$\begin{cases} 1 \text{ if pallet location i is counted by drone k on day t} \\ 0 \text{ otherwise} \end{cases}$
Xa_{it}	$\begin{cases} 1 \text{ if pallet location i is counted on day t and the inventory according to the WMS is bigger than in reality} \\ 0 \text{ otherwise} \end{cases}$
Xb_{it}	$\begin{cases} 1 \text{ if pallet location i is counted on day t and the inventory, in reality, is bigger than according to the WMS} \\ 0 \text{ otherwise} \end{cases}$
Ya_{it}	Number of pallets that are counted more in reality than according to the WMS at pallet location i at day t
Yb_{it}	Number of pallets that are counted less in reality than according to the WMS at pallet location i at day t
Γ_t	Correction ratio on day t
f_{kt}	Total travel time of drone k on day t

v_{rkt}	$\begin{cases} 1 \text{ if zone r is visited by drone k on day t} \\ 0 \text{ otherwise} \end{cases}$
p_{gkt}	$\begin{cases} 1 \text{ if drone k takes path g on day t} \\ 0 \text{ otherwise} \end{cases}$
m_{rkt}	Maximum travel time in the length by drone k in **zone r** on day t
mm_{okt}	Maximum travel time in the length by drone k in **aisle o** on day t

The decision variable X_{ikt} indicates whether pallet location *i* is counted by drone *k* on day *t*. However, when a pallet location is counted, the inventory, in reality, can be bigger than according to the WMS, but also the other way around. To find these absolute differences, the decision variables Xa_{it} and Xb_{it} are used. Xa_{it} indicates that pallet location *i* is counted on day *t* and that the inventory in reality, is bigger than according to the WMS. For Xb_{it} this is the same, but the inventory according to the WMS is bigger than in reality. The decision variables Ya_{it} and Yb_{it} are the numbers of pallets that should be respectively removed from or added to the WMS to match the inventory in reality after counting. Recall that the inventory according to the WMS is a parameter and can thus not be changed. The variables Ya_{it} and Yb_{it} serve as a correction for the inventory according to the WMS for the rest of the year.

The maximum travel time in the length in a zone, m_{rkt}, indicates the travel time in the length to the pallet location that has to be counted furthest from the beginning of the zone. The decision variable mm_{okt} is similar to m_{rkt}, but it indicates the travel time in the length to the pallet location that has to be counted furthest from the beginning of the aisle.

Objective function

$$\max \sum_{t=1}^{T} \Gamma_t \tag{3.1}$$

The objective is to maximize the correction ratio, as shown in formula 3.1.

Constraints

General constraints

$$\Gamma_t = \frac{\sum_{i=1}^{I} Xa_{it} * (d_{it} - e_{it}) + Ya_{i(t-1)} + Xb_{it} * (e_{it} - d_{it}) + Yb_{i(t-1)}}{n} \qquad \forall \text{ t} \tag{3.2}$$

$$Ya_{it} = Xa_{it} * (e_{it} - d_{it}) + Ya_{i(t-1)} \qquad \forall \text{ i, t} \tag{3.3}$$

$$Yb_{it} = Xb_{it} * (d_{it} - e_{it}) + Yb_{i(t-1)} \qquad \forall \text{ i, t} \tag{3.4}$$

$$Xa_{it} + Xb_{it} = \sum_{k=1}^{K} X_{ikt} \qquad \forall \text{ i, t} \tag{3.5}$$

$$\sum_{k=1}^{K} X_{ikt} \leq 1 \qquad \forall \text{ i, t} \tag{3.6}$$

Constraint 3.2 determines the correction ratio at each day *t*. This constraint is based on formula 2.1 in the literature review, but it divides the inaccuracies found by the number of pallet locations. The numbers of pallets that are counted more and less in reality than according to the WMS at pallet location *i* at day *t* are determined by constraints 3.3 and 3.4. Constraint 3.5 indicates that if pallet location *i* is counted on day *t* with either the inventory, in reality, being bigger than according to the

WMS or the other way around, then this pallet location *i* must be counted on day *t* by a drone *k*. Also, if a pallet location *i* is counted on a day *t*, it is counted by only one drone *k*, which is ensured by constraint 3.6.

Travel time constraints between zones

$$v_{rkt} = \sum_{i=1}^{I} X_{ikt} l_{ir} \qquad \forall \text{ r, k, t} \tag{3.7}$$

$$\sum_{g=1}^{G} p_{gkt} = 1 \qquad \forall \text{ k, t} \tag{3.8}$$

$$v_{rkt} = \sum_{g=1}^{G} a_{rg} * p_{gkt} \qquad \forall \text{ r, k, t} \tag{3.9}$$

The following constraints are regarding the estimation of the travel time between zones, as explained in section 3.1.2.1. Constraint 3.7 states that a certain drone *k* only visits zone *r* on day *t* if it has to count at least 1 pallet location *i* in that zone on that day. A drone *k* can only use only one path *g* on day *t*, which is guaranteed by constraint 3.8. Constraint 3.9 states that each zone *r* that is visited by drone *k* on day *t* must be in the path *g* of that drone.

Travel time constraints inside zones

$$m_{rkt} \geq 2 * l_{ir} * X_{ikt} * b_i \qquad \forall \text{ i, r} \neq \text{5, k, t} \tag{3.10}$$

$$mm_{okt} \geq 2 * q_{io} * X * b_i \qquad \forall \text{ i, o, k, t} \tag{3.11}$$

$$m_{5kt} = \sum_{o=1}^{O} mm_{okt} \qquad \forall \text{ k, t} \tag{3.12}$$

The travel time constraints inside zones are based on the assumptions made in section 3.1.2.2. The constraints above focus on determining the travel time in the length since the other elements of the travel time inside the zones are more straightforward and are included in constraint 3.13. Each time an aisle is visited, the maximum travel time in the length must be found, which is the travel time in the length to the furthest pallet location to be counted. Constraint 3.10 does exactly this for all zones with bulk storage. In the case study, these are zones 1 to 4 and zone 6. Constraint 3.11 finds the maximum travel time in the length for each aisle in a zone with pallet racks. This is zone 5 in the case study. These travel times are then summed in constraint 3.12 to find the total maximum travel time in the length of each zone with pallet racks.

Total travel time constraints

$$f_{kt} = \sum_{g=1}^{G} p_{gkt} * c_g + \sum_{r=1}^{R} (m_{rkt} + v_{rkt} * w_r) + \sum_{r=1}^{R} \sum_{i=1}^{I} l_{ir} * X_{ikt} * (s + 2 * h_i) \qquad \forall \text{ k, t} \tag{3.13}$$

Information from the constraints about the travel time between zones and inside zones is combined in constraint 3.13 to calculate the total travel time for drone *k* on day *t*. The first part of the summation represents the travel time between the zones. The second part calculates the total travel time in the width and the length inside the zones and the last part calculates the total travel time in the height and the total positioning time inside the zones.

Sign constraints

$$X_{ikt}, Xa_{it}, Xb_{it}, v_{rkt}, p_{gkt} \in \{0,1\} \tag{3.14}$$

$$Ya_{it}, Yb_{it} \geq 0 \; and \; \in \mathbb{Z} \tag{3.15}$$

$$\Gamma t, f_{kt}, m_{rkt}, mm_{okt} \geq 0 \; and \; \in \mathbb{R} \tag{3.16}$$

Finally, constraints 3.14, 3.16, and 3.15 state the sign constraints.

3.3 Heuristics

For this thesis, different types of heuristics are used. First, section 3.3.1 discusses the cycle counting methods and how they can be implemented. Then, section 3.3.2 discusses the heuristic that is used to allocate these pallet locations to the available drones.

3.3.1 Types of cycle counting

As explained in section 1.4, *bulk storage* and *pallet racks* have different characteristics. Therefore, it only makes sense that different types of cycle counting are used for the different storage methods. So, the types of cycle counting discussed below can be used for both storage methods, but the type of cycle counting used for bulk storage can be different from the type used for the pallet racks. Also note that because of the different characteristics of the two storage methods, we expect that the best parameter values for each type of cycle counting differ per storage method.

From the cycle counting methods discussed in section 2.2.3, we select 5 cycle counting methods, while 3 cycle counting methods are not selected. First, we do not select process control cycle counting because it is complex to determine the ease of counting. Second, historical data about inaccuracies in the Bolk warehouse are not available so, cycle counting with historical data is also not selected. Third, we do not select control group cycle counting since its purpose is to find errors in the process and not to measure the inventory record accuracy. For the cycle counting methods that are selected, we discuss their implementation below. For each type of cycle counting, we need to find suitable parameter values. This is done in section 4.3.

In this thesis, the terms items, pallet locations, and SKUs are used. We now give a concise explanation of these terms, to prevent any confusion. Previous sections use the term *item*. For example, section 2.2.3 discusses how each type of cycle counting determines which item to count. The term item is used when the concept of cycle counting and types of cycle counting in general are discussed. For this thesis, *pallet locations* are counted. So, a pallet location is a specific type of item, relevant to this application. A pallet location can contain zero, one, or multiple pallets that need to be counted. The warehouse contains multiple *SKUs*. However, one SKU can be located at multiple pallet locations. For simplicity, pallet locations are counted and not SKUs.

Random cycle counting

Random cycle counting is pretty straightforward: the pallet locations to be counted are picked at random. There is one parameter, namely sample size, which is the number of pallet locations to count. For simplicity, the same sample size is used each day that cycle counting is performed. The requirement for the sample size is that it should be big enough that every pallet location is counted at least once a year. For the case of Bolk, this means that the sample size should be at least 2 for the bulk storage and at least 16 for the pallet racks.

ABCD cycle counting

In ABC cycle counting, the counting frequency of the pallet locations is based on the ABC classification, which classifies the pallet locations according to demand value. Traditionally, SKUs are classified according to the ABC classification, as is discussed in section 2.2.3. However, in this thesis pallet locations are counted, and not SKUs, so a classification is made for the pallet locations instead of the SKUs. There can be multiple SKUs at the same location throughout the year, so the annual value at a pallet location is an aggregation of the number of pallets of each SKU at that location.

We do not know the exact value of each SKU at the Bolk warehouse, but it is known to which of the 6 price categories each SKU belongs. So, these price categories are changed into the numbers 1 to 6, with 6 being the most expensive and 1 the least expensive. Then, we determine the annual value at each pallet location by multiplying the price category with the number of pallets for each SKU and summing these values.

We will use ABCD cycle counting in this thesis, where 4 classes are used, as opposed to the 3 classes that are common in ABC cycle counting. The reason for this is that a significant part of the pallet locations, namely 48%, is empty at the beginning of the year and also stays empty for the rest of the year. So, these account for 0% of the value in the warehouse. All these pallet locations are in the D-class.

We do not make separate classifications for pallet locations in the bulk storage and the pallet racks, but one classification for both. This way, a pallet location in the bulk storage would be in the same class as it would have been if it was in the pallet racks. Also, classifying pallet locations in the bulk storage and the pallet racks separately would complicate things unnecessarily. On top of that, the pallet locations are all counted by the same set of drones. As a result, the bulk storage will mostly hold A- and B-class pallet locations, while the pallet racks mostly hold C- and D- class pallet locations. This is reasonable since the bulk storage mostly holds fast movers and each pallet location can hold multiple pallets, so the demand value at a pallet location in the bulk storage is generally high. The pallet racks mostly hold slow movers and can only hold one pallet per pallet location, so there the demand value is generally low.

Typically, the first 5-10% of the pallet locations make up the A-class, although this can be up to 20% of the pallet locations. They account for around 50% or more of the total annual value (Silver, Pyke, & Thomas, 2016). The B-class contains a lot of pallet locations, usually 50% of the pallet locations or more, and also accounts for a large portion of the remaining annual value. The C-class pallet locations make up a small portion of the annual value but are relatively numerous.

For determining the different classes, the graph in Figure 3.5 is used. Note that there is a sharp change in annual value after the first about 5% of the pallet locations. This is caused by the high annual value of most of the bulk storage pallet locations. Since there is such a big difference in annual value, it is logical to let this first 5% make up the A-class pallet locations. Then the next about 17% of the pallet locations make up the B-class. This class contains some pallet locations in the bulk storage that are not used that often, as well as some pallet locations in the pallet racks. Next, the C-class contains the rest of the pallet locations in the pallet racks. Finally, the pallet locations that are empty during the whole year and account for 0% of the annual value make up the D-class.

Additionally, Table 3.1 shows the percentages of the annual value that each class accounts for and the number and percentage of all pallet locations.

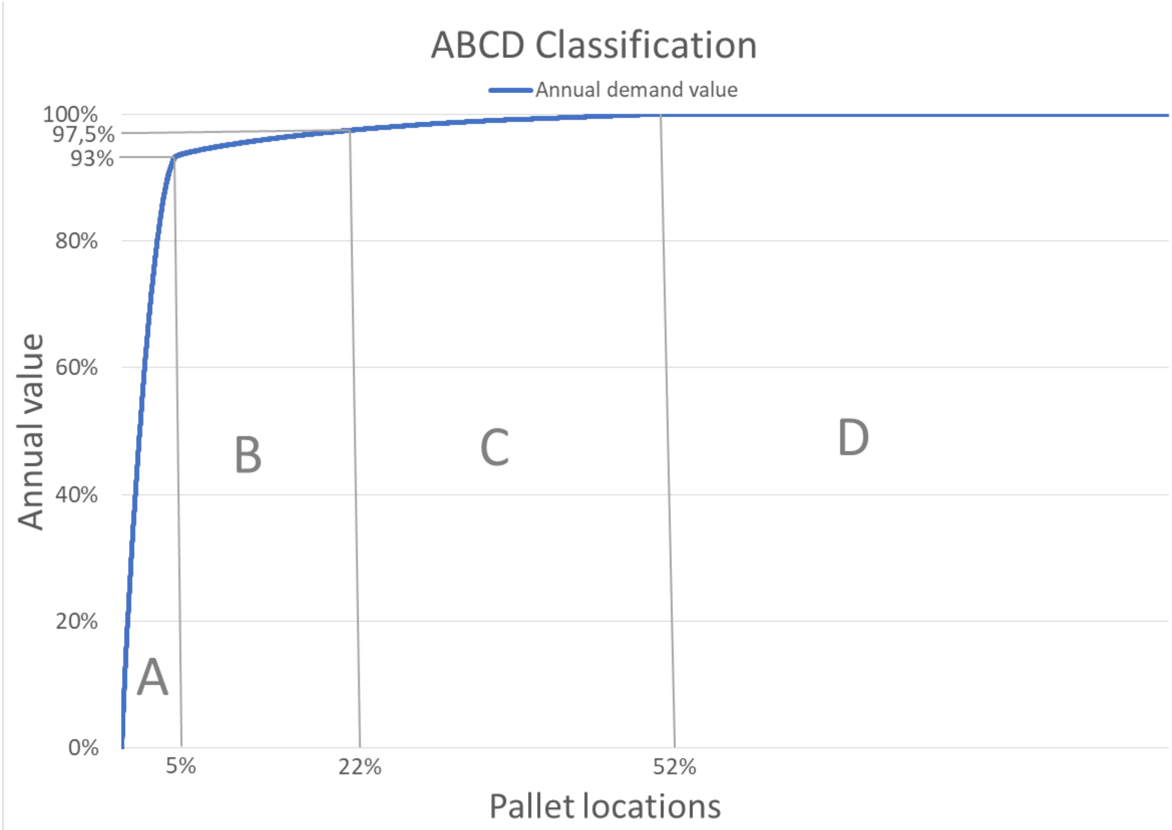

Figure 3.5 ABCD Classification

Table 3.1 ABCD Classification specification

Class	Annual value	Number of pallet locations	Percentage of pallet locations
A	Until 93%	303	5%
B	Until 97,5%	1028	17%
C	Until 100%	1806	30%
D	Rest	2950	48%

The parameters for ABCD cycle counting are the counting frequencies of the pallet locations in each class. Then based on the counting periodicity and the total number of pallet locations, the number of pallet locations to count each day is determined. The pallet locations in the same class are always counted in the same order. So, for example, pallet locations 1 to 10 in class A are counted on day 1, and pallet locations 11 to 20 in class A are counted on day 2.

Location-based cycle counting

For location-based cycle counting, the pallet locations are divided into areas and every day, all the pallet locations in one of these areas are counted. For determining the areas, two things are taken into account. First, it is ensured that all pallet locations in the same area are as close to each other as possible. In practice, this meant that the pallet locations in the same area were also in the same zone for the bulk storage and in the same aisle for the pallet racks. Also, there were no pallet locations from another area in between pallet locations from the same area. Second, there had to be a reasonable number of areas. For example, it does not seem reasonable to have a lot of areas, e.g. 500, since then many pallet locations are not counted in one year. Also, there should not be too few areas, e.g. 2, because then the number of pallet locations to count on one day becomes way too big. For this thesis, there are 5 to 80 areas per area division for the bulk storage and 12 to 360 areas per area division for the pallet racks.

Opportunity-based cycle counting

With opportunity-based cycle counting, a pallet location is counted after a certain opportunity occurs. For this thesis, a specific form of opportunity-based cycle counting is used: transaction-based cycle counting, where we count a pallet location after a minimum number of transactions occurred at that location. There is one parameter important for this type of cycle counting, which is the number of transactions after which a pallet location is counted. The number of transactions after which to count a pallet location may differ for the bulk storage and the pallet racks since they have different characteristics. However, it is the same for all pallet locations in the same storage method. This number should not be too high to ensure that the pallet locations are counted often enough. On the other side, it should not be too low to prevent too much unnecessary counting.

Location- and opportunity-based cycle counting

Recall from section 2.2.3 that we took an idea for a new type of cycle counting from opportunity maintenance. We call this type of cycle counting location- and opportunity-based cycle counting. Just like with opportunity-based cycle counting, a pallet location is counted after a key event. Again, this key event is a certain number of transactions that are performed at the pallet location. However, not only that pallet location is counted, but also the rest of the pallet locations in the same area. The same area divisions are used as for location-based cycle counting. But, it may be that a different area division performs best for location- and opportunity-based cycle counting than for location-based cycle counting.

3.3.2 Drone allocation

When using one drone for inventory cycle counting, this drone counts all the pallet locations. However, if 2 or more drones are used, a task allocation of which drone counts which pallet location needs to be made. Recall from section 2.3.2 that there are market-based and optimization-based approaches for task allocation, of which optimization-based is suited for this research. We use a deterministic technique rather than a stochastic technique in this thesis. This will make it easier to compare the travel times for various policies since the pallet locations are always divided amongst the drones in the same way.

To allocate tasks among drones, we use a constructive heuristic. The main idea of this heuristic is that each drone counts pallet locations that are as close to each other as possible. The heuristic consists of two steps: first, sorting the pallet locations to be counted, and then allocating these pallet locations to drones. We will illustrate the allocation heuristic with an example. Figure 3.6 shows a set of pallet locations to count that need to be allocated amongst two drones. Both steps from the allocation heuristics will be applied to this example.

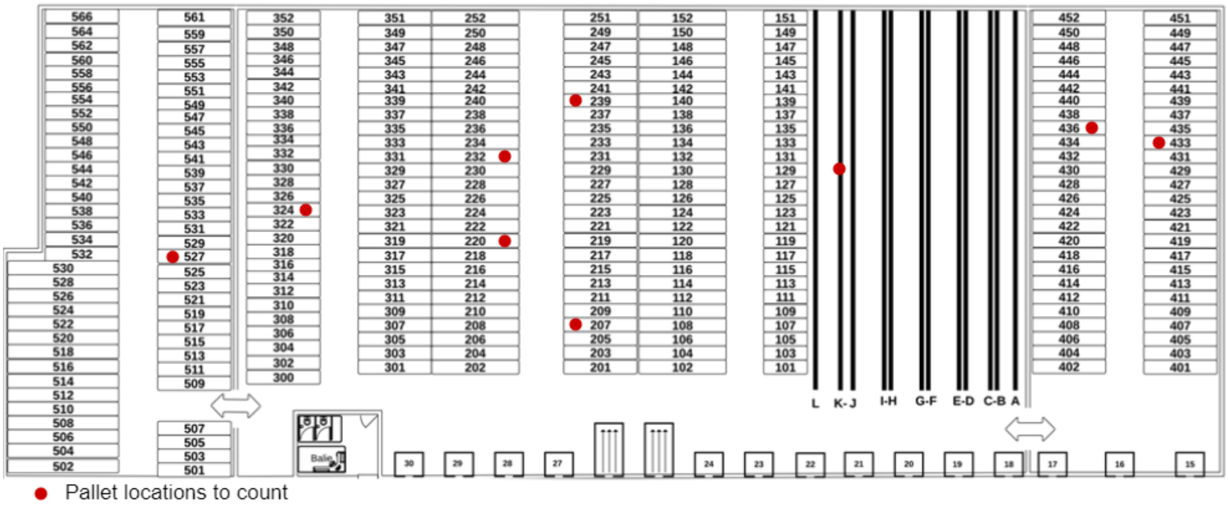

Figure 3.6 Example: pallets location to count

For sorting, we use the idea of the plane-sweep algorithm. This algorithm sweeps the plane from left to right, where a 'front' advances from one point to the next (Nievergelt & Preparata, 1982). For this thesis, the plane is the warehouse and the points are the pallet locations to be counted. To indicate how far to the left or right a pallet location is, each pallet location has been given a position value. Pallet locations on the left side of the most left aisle get the value 1, pallet locations on the right side of the left aisle get the value 2, and so on.

When running the heuristic, all pallet locations to be counted are sorted based on their position values. It will happen that multiple pallet locations with the same position value have to be counted. In that case, they will be sorted based on the number of their locations. The sorting of the pallet locations from our example is shown in Table 3.2.

Table 3.2 Example: sorted pallet locations

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Pallet location	527	324	218	232	229	207	21300104	436	433
Position value	2	3	5	5	6	6	10	21	22

After sorting the pallet locations to be counted, they are allocated to the drones. We divide the pallet locations equally among the drones, such that every drone counts about the same number of pallet locations. Some drones will count 1 more pallet location than others since the number of pallet locations to be counted divided by the number of drones does not always result in an integer. Suppose there are n drones available. Then from the sorted list of pallet locations, the first about $1/n$ pallet locations are assigned to the first drone, then the next $1/n$ pallet locations are assigned to the second drone, and so on. Table 3.3 and Figure 3.7 show the final allocation of the pallet locations from our example.

Since this way of allocating the pallet locations to the drones is a heuristic, there is no guarantee whatsoever that this results in an optimal solution. However, intuitively, this heuristic gives a good solution. This is because the drones count pallet locations close to each other and they do not have to travel from the far left to the far right of the warehouse. Furthermore, this heuristic is easy to understand and implement.

Table 3.3 Example: pallet locations allocated to drones

	Pallet locations				
Drone 1	527	324	218	232	229
Drone 2	207	21300104	436	433	

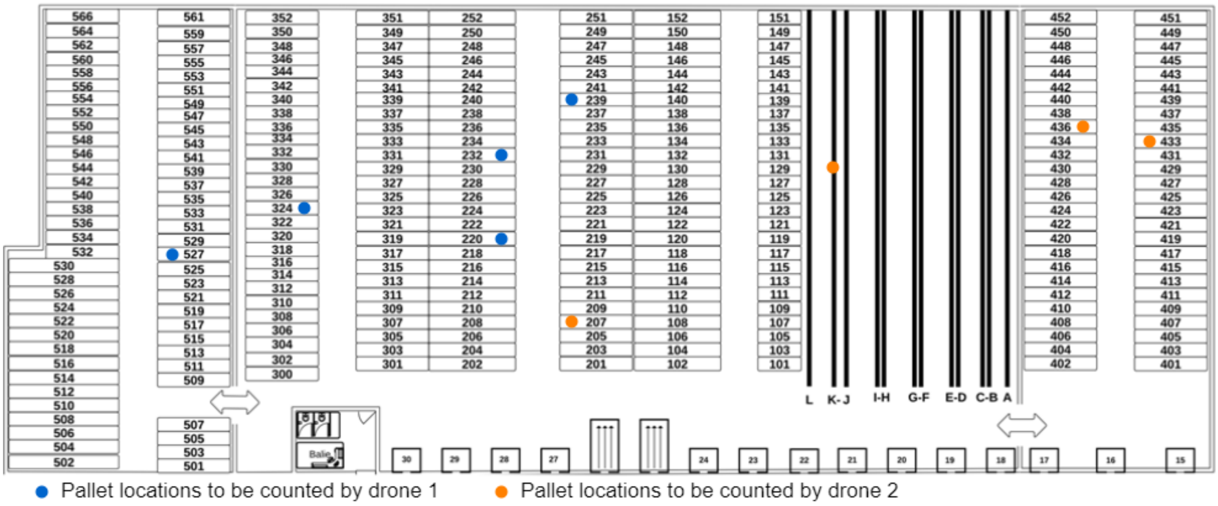

Figure 3.7 Example: locations of allocated pallet locations

3.4 Conclusion

We made multiple assumptions in this chapter. First, an assumption is made about the causes of inaccuracies. Based on these causes and further exploration of the transactions of a pallet in a warehouse, we performed a Monte Carlo simulation to create inventory data with inaccuracies. With every transaction, there was a small chance that an inaccuracy occurred. Also, we made assumptions about the routing of the drones, to be able to estimate travel times. We divided the warehouse into zones, and the travel time estimations were based on the travel time between zones inside each zone. The travel time between the zones is based on the assumption that zones are always visited from left to right. The travel times in the width, length, and height, and the positioning time of a drone at each pallet location determine the travel time inside the zones. Furthermore, a mathematical model is presented. The purpose of this model is not to find an optimal cycle counting policy, but to provide us with a benchmark for other policies. Unfortunately, we were not able to find the optimal solution to this model. Five types of cycle counting will be implemented: ABCD cycle counting, random cycle counting, location-based cycle counting, opportunity-based cycle counting, and location- and opportunity-based cycle counting. This chapter discussed how these types of cycle counting can be implemented, for example, the ABCD division is made for ABCD-cycle counting, and bounds for the size of the areas for location-based cycle counting are determined. Finally, we developed a task allocation heuristic that allocates pallet locations that are close together to the same drone.

4 Performance evaluation

This chapter first discusses the general setup of the experiments in section 4.1. Then, in section 4.2 the warm-up period is determined. Next, suitable parameters are determined in section 4.3. In section 0 the best combination of cycle counting types is found. The best counting periodicity and number of drones for each combination are discussed in section 4.5 and a final policy is selected in section 4.6. Section 4.7 concludes this chapter.

4.1 Experiment design

To evaluate the performance of different policies, simulation is used. Simple paper calculations or calculations on a spreadsheet cannot be used since too much data is used. Also, doing experiments in the Bolk warehouse itself is not preferred: trying out only one policy, in reality, takes weeks or even months to get reliable results. On top of that, it negatively affects the inventory record accuracy and the travel time, if a poorly performing policy is tested. With simulation, multiple policies can be evaluated in a short amount of time and it does not directly affect the inventory record accuracy or the travel time. So, simulation is a good approach for evaluating the performance of policies.

We perform the simulation using a model in Delphi. Appendix C: Delphi dashboard shows a screenshot of the dashboard in Delhi. The model is made in such a way, that the counting periodicity, number of drones, types of cycle counting, and their parameter values are easily changed. The results that are shown after the simulation are the accuracy of the whole warehouse, as well as each storage method individually, and the travel time for each drone on each day.

Before any simulation experiments are done, the warm-up period should be determined. At the beginning of the year, there are no inaccuracies yet. As the year progresses, inaccuracies occur and are also corrected. So, the days at the beginning of the year are not representative of the rest of the year. It is, therefore, necessary to determine a warm-up period, which indicates the dates that are not used for evaluation. Determining the warm-up period will be done with the MSER, which is further explained in section 4.2.

After determining the warm-up period, there are multiple elements to optimize. The best heuristics need to be found, as well as their parameters. Also, the number of drones to use needs to be determined. Furthermore, how often and on which days inventory cycle counting is performed needs to be determined. When all these things are optimized simultaneously, the number of runs will become unmanageable. Therefore, the number of runs is limited in two ways.

First, for the question of when and how often to perform inventory cycle counting the number of options is limited to 3 *counting periodicities*. Inventory cycle counting is either performed every day of the week, three times a week (on Monday, Wednesday, and Friday), or once a week (on Monday). These options are chosen since it gives multiple counting frequencies, ranging from 1 to 7 times a week. Also, the cycle counting days are spread throughout the week.

The second way of limiting the number of runs is to do the optimization of the different elements sequentially. The first step after determining the warm-up period is tuning the parameters for each type of cycle counting. We need to find suitable parameters for both storage methods, but also for each counting periodicity. To this end, runs are performed with different types of cycle counting, counting periodicities, and parameters. From these runs, suitable parameter values are determined, which will be used for the rest of the thesis.

Next, the best types of cycle counting are found. This is done by running every combination of types of cycle counting with the parameters found before. To prevent an impractical big number of runs, the runs are only done for the case in which inventory cycle counting is done every day. We assume that the performances of the types of cycle counting do not change a lot per counting periodicity, as long as the appropriate parameters are used. The 3 best performing combinations of cycle counting types are selected based on their accuracy and travel times.

The best combination of counting periodicity and the number of drones then needs to be found. Since a decision about the number of drones is also influenced by the costs of a drone, these costs will be discussed. Again, the accuracy and travel time are also considered when selecting the counting periodicity and number of drones.

Finally, the best policy is selected, which consists of the combination of types of cycle counting, counting periodicity, and the number of drones.

To perform the runs mentioned in the last paragraphs, data from the Bolk warehouse in Hengelo is used. This data set will be split into a training and a testing data set, as described in Stone (1974). The training data set will be used to estimate suitable parameter values for each heuristic, while the testing data set is used to assess the performance of various policies. The reason to do this is to prevent overfitting (Joseph & Vakayil, 2022). Overfitting means that the model does not improve its ability to solve the problem anymore, but rather starts to learn the random regularities in the training set (Jabbar & Khan, 2015). On the other hand, underfitting is also possible. Jabbar and Khan (2015) describe this as the model being unable to capture the variability of the data. There are complete studies to find a balance between overfitting and underfitting, for example, Zhang, Zhang, and Jiang (2019), and Gu et al. (2016). To avoid too much complexity, we choose to split the data equally in a training and testing set.

So, the first part of the data set from Bolk will be the warm-up period, with the length as discussed in section 4.2. Then the first half of the remaining data will be used for training in section 4.3 and the second half of the remaining data will be used for testing in section 0.

When performing the optimizations above, there is a trade-off between accuracy and travel time. On one hand, the aim is to have an accuracy as close to 100% as possible, but on the other hand, this may not be worth it if a big amount of time needs to be spent on inventory cycle counting every day. To manage this trade-off, the focus on either accuracy or travel time will shift throughout the optimizations. The focus when selecting the best heuristics will mostly be on accuracy since the selected heuristic has more impact on the accuracy than the number of drones and the counting periodicity. However, when the number of drones and the counting periodicity are determined, the focus will be more on travel time. More details on how the optimizations are performed are in sections 4.3, 0, 4.5, and 4.6.

A flowchart of the experimental setup is shown in Figure 4.1.

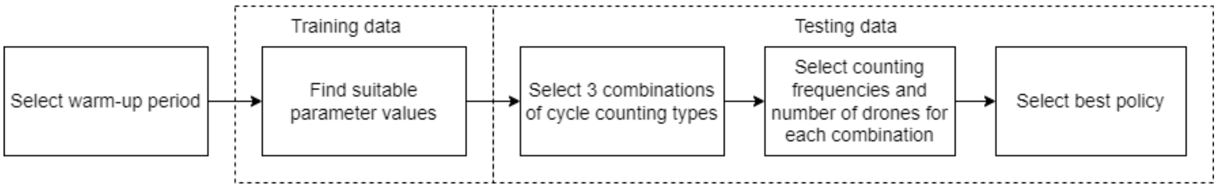

Figure 4.1 Experiment set-up

4.2 Warm-up period

To determine the warm-up period, we use the Marginal Standard Error Rule (MSER). The MSER aims to minimize the width of the confidence interval about the sample mean (Robinson, 2014). This is done by deleting the initial transient data. Intuitively, minimizing the confidence interval is a good way to find the warm-up period, since the smaller the confidence interval, the more accurate the estimate of the mean. So, by increasing the proposed warm-up period, the estimate becomes more accurate since the bias of the initial transient data is eliminated. However, when the sample of data becomes too small, the precision decreases for the observations that are left (Oh & Park, 2015). How to determine the MSER for each proposed warm-up period is shown in Formula 4.1, as described in Robinson (2014). Here *d* is the proposed warm-up period, *m* is the number of observations in the time-series of output data, and $\bar{Y}(m,d)$ is the mean of the observations from Y_{d+1} to Y_m.

$$MSER(d) = \frac{1}{(m-d)^2} \sum_{i=d+1}^{m} (Y_i - \bar{Y}(m,d))^2 \tag{4.1}$$

Also, Welch's method was considered for determining the warm-up period. This is a graphical method to find the warm-up period *l*. A graph with moving averages based on different time windows is constructed and the warm-up period *l* is chosen such that the graph seems to have converged around a certain value *v* after the warm-up period (Law & Kelton, 2007). However, the graph did not flatten out around a certain value: it dropped at the beginning of the year and after that, there was an increasing trend. This is shown in Figure 4.2 Result from Welch's methodFigure 4.2. It is not expected that the graph will keep increasing since new inaccuracies will occur, which will decrease the moving averages. It may be that there is some cycling behavior in the graph but this cannot be shown since no more data is available. Generating more data is possible but after discussing with multiple stakeholders the decision was made to not do this since this is not the focus of this thesis. Although Welch's method does not give a definite answer as to how long the warm-up period must be, it is clear that the graph stays within a small range (0.9998-0.99995) after a while. To get a more reliable answer, the MSER will be used to determine the warm-up period.

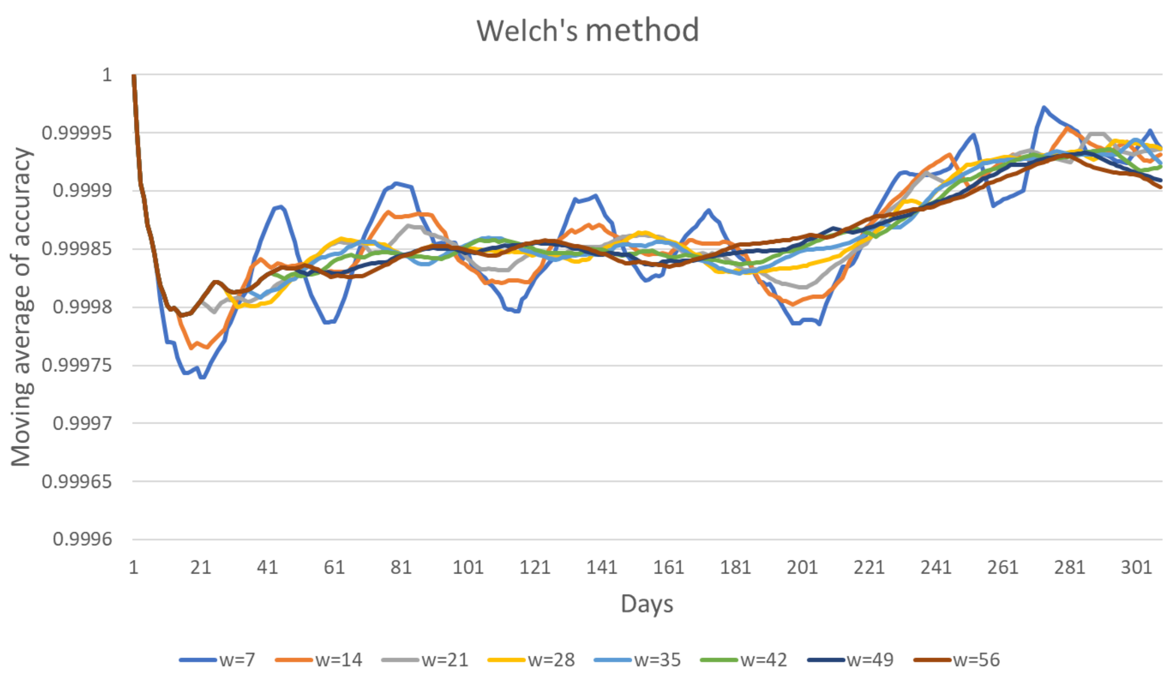

Figure 4.2 Result from Welch's method

For the implementation of the MSER, 30 replications are used: the model in Delphi is run for 2 sets of output data, where every type of cycle counting is run for every counting periodicity. The parameters for each type of cycle counting were based on some assumptions. For example, the sample size for random cycle counting was chosen such that on average each pallet location in the bulk storage is counted 15 times a year and in the pallet racks 5 times a year. The parameters for each type of cycle counting and each counting periodicity can be found in Appendix B: Parameters warm-up period. The resulting graph is shown in Figure 4.3. Table 4.1 shows a part of the MSER values that are calculated. The lowest value is found on day 29. Since different cycle counting types, counting periodicities, and input data sets are used for each run, it is worth overestimating the warm-up period (Robinson, 2014). To round the warm-up period up to one month, it is set at 31 days. This is also reasonable when looking at the resulting graph from Welch's method. Although it was not possible to find a warm-up period from this graph since it does not converge around a certain value, the warm-up period can be compared with the graph. At 31 days, the graph has had its initial drop and has started with a slow but steady increase, so this warm-up period seems reasonable.

Table 4.1 MSER values

d	**MSER**
0	1,4E-11
1	1,39E-11
…	…
27	1,32E-11
28	1,3E-11
29	1,28E-11
30	1,29E-11
31	1,29E-11
…	…
358	6,24E-11
359	5,71E-11

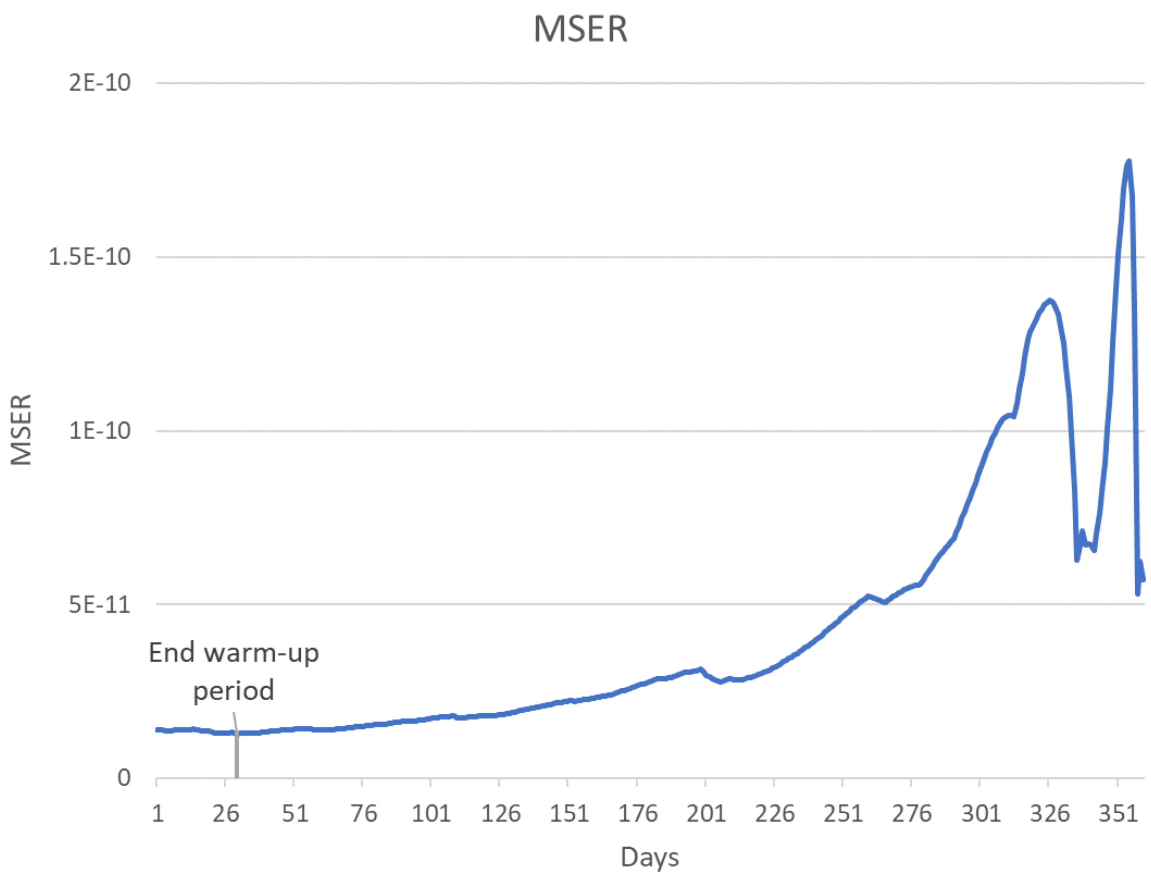

Figure 4.3 Result from MSER

4.3 Parameter values

Recall from section 3.3.1 that each type of cycle counting has different parameters. The performance of the cycle counting types depends on the values that are chosen for these parameters. So, it is important to find suitable parameter values. The approach to do this is discussed in section 4.3.1. Next, sections 4.3.2, 4.3.3, 4.3.4, 4.3.5, and 4.3.6 explain how the parameter values for each type of cycle counting are found.

4.3.1 Approach

We are not necessarily trying to find the optimal parameter values. The reason for this is that finding optimal parameter values is not in the scope of this thesis. Although using optimal parameter values may give better results for each type of cycle counting, it is time-consuming: one could make a whole study on its own. Therefore, we are just looking for parameter values that are suitable for the corresponding types of cycle counting.

We find an appropriate parameter value for each type of cycle counting by performing experiments with different parameter values. The number of drones in the experiments is set to 2. As long as we keep the number of drones the same for the parameters of the same type of cycle counting, it does not matter too much what number of drones is used since the travel times of the various parameters can still be compared. As explained in section 4.1, the training data set is used for these experiments. The training data set contains days 32 to 167, as the first 31 days are part of the warm-up period.

As discussed in section 3.3.1, the two storage methods in the Bolk warehouse (bulk storage and pallet racks) have different characteristics, and therefore, which parameter values are suitable differs per type of cycle counting. Consequently, appropriate parameter values are determined for each storage method individually. There is one exception, namely ABC cycle counting. For this type of cycle counting, the parameter value is based on the class of the pallet location and not on the storage method, which was previously explained in section 3.3.1.

The accuracy of one storage method only depends on its own heuristic and corresponding parameter. However, the travel time is also dependent on the heuristic and corresponding parameter value of the other storage method since a drone can count both pallet locations in the bulk storage and the pallet racks on the same day. So, for one parameter value, multiple experiments are performed where the parameter values for the other storage method differ. We then calculate the average travel time, so the average travel times for the different parameter values can be compared. For simplicity, the heuristics of the storage methods are the same when determining the parameter values, just the parameter values differ.

To find suitable parameter values, we use two input data sets. These are created by running the Monte Carlo simulation from section 3.1.1 two times. All runs are performed once with the first data set and once with the second data set. The averages of the resulting accuracy and travel time are used as KPIs for determining the suitability of a parameter value. During the rest of this chapter, with average accuracy and travel time, we mean the averages of these two data sets. The reason for using two data sets is that using only one data set may not give reliable results. The accuracy may be higher or lower, just because the data set is coincidentally suited or not for a certain parameter value of a heuristic. For example, with location-based cycle counting, a pallet location where an inaccuracy occurs may be located in an area that is counted the next day. However, it may also be that this pallet location with an inaccuracy is in an area that is not counted until one month later. This has to do with the data set and not necessarily with how well the parameter value performs. Using two data sets may not completely prevent this, but it will lower the effect.

For some heuristics, it is not necessary to make experiments for all counting periodicities since the counting periodicity does not influence how often a year a pallet location is counted. This is the case for ABC cycle counting, opportunity-based cycle counting, and location- and opportunity-based cycle counting. For example, the parameter for ABC cycle counting is how often a year a pallet location in each class is counted. Changing the counting periodicity does not change the total number of times a year each pallet location is counted. The accuracy may be a little bit lower or higher with a different counting periodicity because it can take a little longer or a little shorter before an inaccuracy is found. For example, if we perform cycle counting every day and an inaccuracy occurs on Saturday, then with cycle counting once a week, the inaccuracy is not found until Monday next week. However, we do not expect that this will cause one parameter value to outperform another with one counting periodicity if it does not outperform that other parameter value with another counting periodicity. For the heuristics where experiments are done for just one counting periodicity, we base the parameter values on counting inventory every day.

As indicated earlier in this section, we are not necessarily looking for parameter values that dominate others in both accuracy and travel time. Instead, there is a trade-off between accuracy and travel time. The accuracy is most important for selecting parameter values since, for this study, the travel time can still be changed by using a different number of drones or choosing a different heuristic or parameter value for the other storage method. However, in case of a substantial increase in travel time and just a small increase in accuracy, we choose the parameter value with the lower accuracy.

An alternative approach is to select parameter values based on a minimum accuracy: the parameter value resulting in the smallest travel time with an accuracy above the minimum accuracy is then chosen. It is also possible to have a similar approach with a maximum travel time instead of a minimum accuracy, but one should realize that the travel time is based on the heuristics and parameter values of both storage methods. If a parameter value for one storage method is chosen and the parameter value for the other storage method changes, then the travel time will also change. This makes it more difficult to stick to a maximum travel time. Both alternative approaches are not used for this thesis since it is interesting to explore the differences in heuristics. One heuristic may give a high accuracy and high travel time, while another gives a lower accuracy, but also a lower travel time. Just selecting the parameter values based on a minimum accuracy or maximum travel time omits these differences.

4.3.2 ABC cycle counting

For ABC cycle counting, the parameters are the number of times a year a pallet location in each class is counted. As explained in section 4.3.1, the parameter values for bulk storage and the pallet racks will always be the same since the number of times a pallet location is counted depends on the class, not on the storage method.

Table 4.2 shows the parameter values considered in the experiments. We always the pallet locations in class D once a year since these pallet locations are empty for the whole year. A pallet may arrive at one of these locations without being registered in the WMS, so it is reasonable to count them once a year. However, counting them more often takes more time and is thus expensive, so this option is not considered. Furthermore, pallet locations in class A are counted more often than pallet locations in class B, which are counted more often than pallet locations in class C.

Table 4.2 Parameter values considered in the experiments for ABC cycle counting

Class	**Number of counts per year for each pallet location**							
A	5	10	15	20	25	30	35	40
B	3	5	8	10	13	15	18	20
C	2	3	4	5	7	8	9	10
D	1	1	1	1	1	1	1	1

Figure 4.4 shows the results of the experiments. Both the average accuracy and travel time increase as the number of times pallet locations in a class are counted increases, which is reasonable. There is an exception, namely at parameter values {35,18,9,1}, which has a lower accuracy than parameter values {30,15,8,1}. An explanation for this is that a pallet location may be counted earlier if it is counted more often. So, an inaccuracy may occur just after a pallet location is counted. This causes the inaccuracy to exist longer than when the pallet location was counted at a later moment. For example, if we count a pallet location in the A class 35 times a year, we count it about every 10 days. If it is counted 30 times a year, we count it about every 12 days. If an inaccuracy occurs at a pallet location on day 11 and that location is counted 30 times a year, we find the inaccuracy the next day. If it is counted 35 times a year, it takes longer to find the inaccuracy. This impacts the accuracy negatively.

From Figure 4.4 can be seen that the parameter values {30,15,8,1} and {40,20,10,1} have the highest average accuracy. However, the latter has a considerably higher travel time. So, the parameter values chosen are {30,15,8,1}.

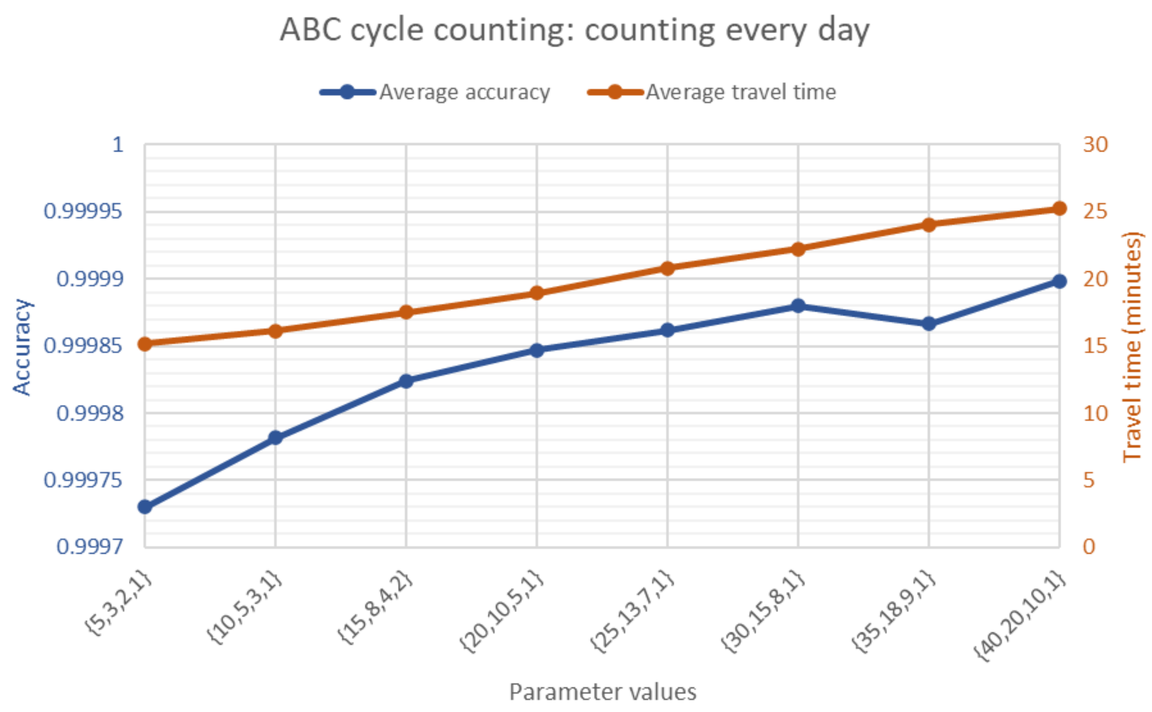

Figure 4.4 Performance of parameter values for ABC cycle counting in the bulk storage

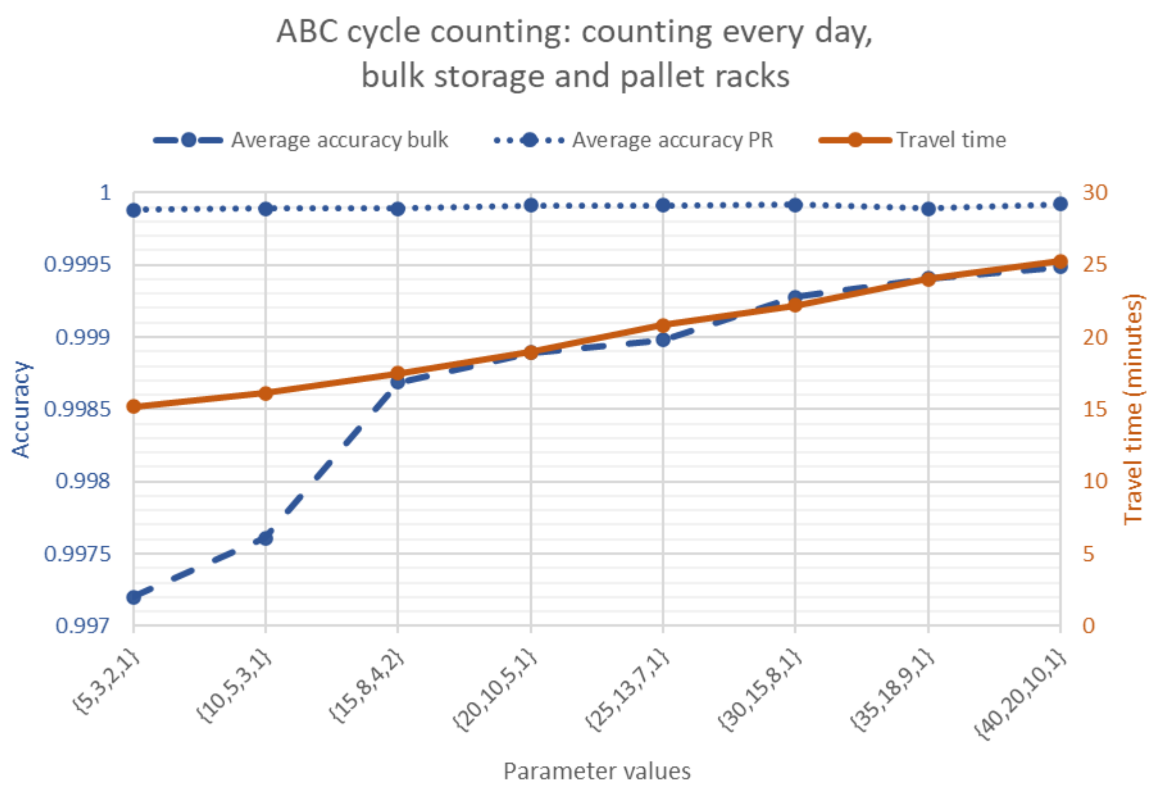

Figure 4.5 Performance of parameter values for ABC cycle counting in the pallet racks

ABC cycle counting is not necessarily used for both bulk storage and pallet racks, but it may also be used for just one storage method, while another heuristic is used for the other storage method. So, it is useful to also pay attention to the accuracy of the bulk storage and pallet racks individually. These are shown in Figure 4.5. It is clear from this figure that the parameter values {30,15,8,1} perform well for both storage methods. Although the parameter values {40,20,10,1} result in a slightly better average accuracy for the bulk storage, the travel time is substantially higher. The average accuracy for the pallet racks shows little difference between the parameter values. This is reasonable since the average accuracy is already close to one, making it hard to improve. So, the parameter values {30,15,8,1} are still the best option for ABC cycle counting.

4.3.3 Random cycle counting

We select the pallet locations to count randomly with random cycle counting, so the resulting accuracy and travel time are stochastic. Therefore, multiple replications are needed to determine the average accuracy. Section 4.3.3.1 discusses what number of replications is sufficient. Next, the parameter values for each counting periodicity are discussed. The parameter for random cycle counting is the sample size. First, we discuss the sample size for counting every day in section 4.3.3.2. For the other two counting periodicities, the assumption is made that if the sample size for counting every day is known, the sample size of the other counting periodicities can be derived from that. This is possible since the sample size is just the number of pallet locations counted each day and the pallet locations are selected randomly. Section 4.3.3.3 discusses the selection of parameter values for the other counting periodicities.

4.3.3.1 Number of replications

Multiple experiments are necessary to determine the travel time, therefore, a certain number of replications are done already. To check if this number of replications is sufficient, we use the confidence interval method as discussed in Robinson (2014). With a confidence interval, a range can be estimated in which the true estimated average is expected to lie. This estimate is deemed to be more precise if the interval is narrower, and the interval becomes narrower if more sample data is included. So, for simulation output, this means that we perform more replications until the confidence interval is sufficiently narrow. Formula 4.2 shows how to calculate a confidence interval.

$$Confidence\ interval = \bar{X} \pm t_{n-1,\propto/2} \frac{S}{\sqrt{n}} \tag{4.2}$$

In formula 4.24.2, $\bar{X}$ is the mean of the output data from the replications, S is the standard deviation of the output data, n is the number of replications, and $t_{n-1,\alpha/2}$ the value from the student t-distribution with n-1 degree of freedom and significance level α/2. The significance level is divided by 2 since there is an upper and a lower bound to the confidence interval.

To find out if the confidence interval is sufficiently narrow, we determine the deviation of the cumulative mean from the confidence interval for each replication. If this deviation is below a certain value, called γ, then enough replications are performed. Once the deviation is smaller than γ, it has to stay smaller than γ since the deviation may be sufficiently small by chance.

We only apply the confidence interval method to counting every day with one sample size for the bulk storage and one sample size for the pallet racks. There are three reasons for this. First, Robinson (2014) mentions that the results from the confidence interval method can be extended to other instances. It is worth it to overestimate the results when that is done. Second, the only purpose is to check if the number of replications used is sufficient. Lastly, it is time-consuming to apply this method to all sample sizes and all counting periodicities.

Table 4.3 shows the confidence intervals and deviations for random cycle counting every day with a sample size of 50 in the bulk storage. Data from the warm-up period is not included. Since the results are extended to other counting periodicities, as well as other sample sizes, the significance level is more strict, namely 0,01. For that same reason, we use a γ of 0,01. From the third replication, the deviation from the confidence interval is small enough. The confidence intervals and deviations for random cycle counting every day with a sample size of 5 for the pallet racks are shown in Table 4.4. Again, data from the warm-up period is not included and the same significance level and γ are used. Here the deviation is small enough from the second replication.

As explained earlier in this section, we extend the results for the confidence interval method to other sample sizes and counting periodicities, so it is worth overestimating the number of replications needed. For both the bulk storage and the pallet racks, 12 replications are used anyway since there are 2 input data sets and 6 different sample sizes for each storage method. The number of replications used is far more than the number of replications resulting from the confidence interval method. So, the number of replications used is sufficient.

Table 4.3 Confidence interval method for random cycle counting every day in the bulk storage with a sample size of 50

Replication	Average accuracy	t-value	Sample mean	Sample variance	Lower bound	Upper bound	% deviation	
1	0.992554							
2	0.993260	63.6567	0.992907	2.49135E-07	0.9704	1.0154	0.022628	FALSE
3	0.993119	9.9248	0.992978	1.39516E-07	0.9908	0.9951	0.002155	TRUE
4	0.996372	5.8409	0.993826	2.97302E-06	0.9888	0.9989	0.005067	TRUE
5	0.994059	4.6041	0.993873	2.24056E-06	0.9908	0.9970	0.003101	TRUE
6	0.998074	4.0321	0.994573	4.73327E-06	0.9910	0.9982	0.003601	TRUE
7	0.991280	3.7074	0.994103	5.49341E-06	0.9908	0.9974	0.003304	TRUE
8	0.995280	3.4995	0.994250	4.88196E-06	0.9915	0.9970	0.002750	TRUE
9	0.993929	3.3554	0.994214	4.28312E-06	0.9919	0.9965	0.002328	TRUE
10	0.997465	3.2498	0.994539	4.86427E-06	0.9923	0.9968	0.002279	TRUE
11	0.990248	3.1693	0.994149	6.05214E-06	0.9918	0.9965	0.002365	TRUE
12	0.996726	3.1058	0.994364	6.05516E-06	0.9922	0.9966	0.002219	TRUE

Table 4.4 Confidence interval method for random cycle counting every day in the pallet racks with a sample size of 5

Replication	Average accuracy	t-value	Sample mean	Sample variance	Lower bound	Upper bound	% deviation	
1	0.999795							
2	0.999826	63.6567	0.999811	4.99838E-10	0.9988	1.0008	0.001006529	TRUE
3	0.999776	9.9248	0.999799	6.39598E-10	0.9997	0.9999	0.000144945	TRUE
4	0.999788	5.8409	0.999797	4.5681E-10	0.9997	0.9999	6.24319E-05	TRUE
5	0.999815	4.6041	0.999800	4.08845E-10	0.9998	0.9998	4.16414E-05	TRUE
6	0.999845	4.0321	0.999808	6.60179E-10	0.9998	0.9998	4.23033E-05	TRUE
7	0.999776	3.7074	0.999803	6.88566E-10	0.9998	0.9998	3.67775E-05	TRUE
8	0.999826	3.4995	0.999806	6.58173E-10	0.9998	0.9998	3.17478E-05	TRUE
9	0.999953	3.3554	0.999822	2.97282E-09	0.9998	0.9999	6.09934E-05	TRUE
10	0.999798	3.2498	0.999820	2.70298E-09	0.9998	0.9999	5.34393E-05	TRUE
11	0.999951	3.1693	0.999832	4.00576E-09	0.9998	0.9999	6.04893E-05	TRUE
12	0.999825	3.1058	0.999831	3.64555E-09	0.9998	0.9999	5.41425E-05	TRUE

4.3.3.2 Counting every day

Figure 4.6 shows the results for the bulk storage for random cycle counting every day. The accuracy is highest for sample sizes 20, 25, and 30. Since the average travel time for sample size 30 is considerably higher than for the other sample sizes, the other sample sizes are more suitable. The average accuracy for sample size 25 is higher than for sample size 20, so we choose sample size 25 as the sample size for random cycle counting every day at the pallet racks.

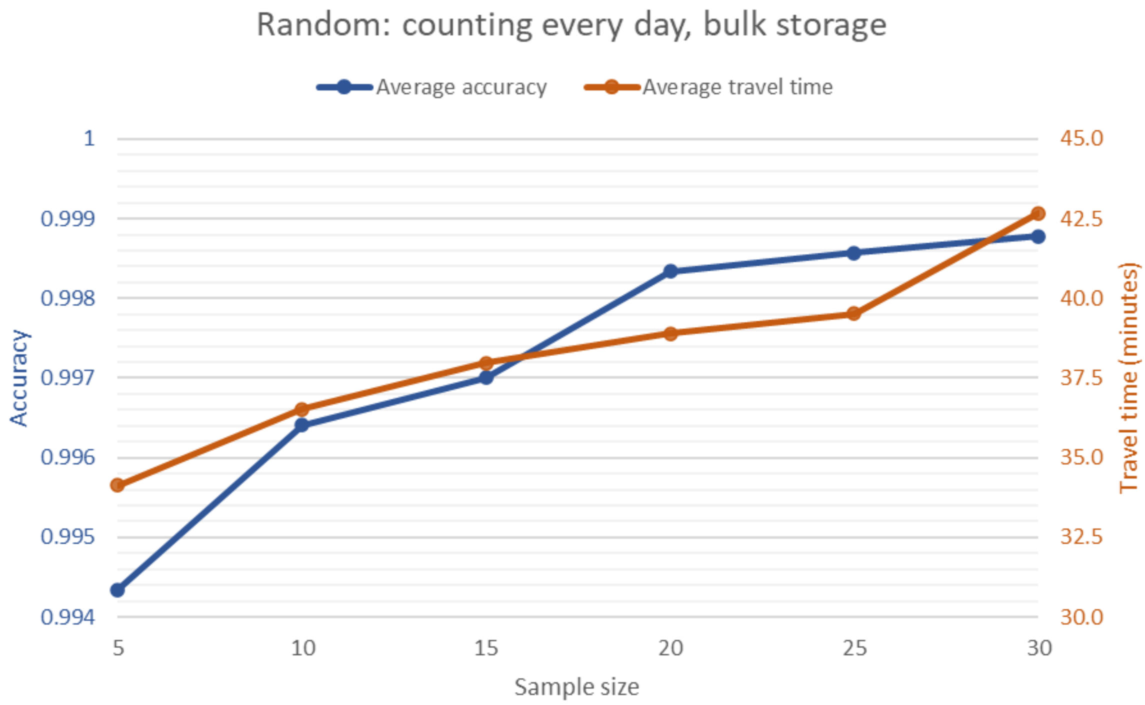

Figure 4.6 Performance of parameter values for random cycle counting every day in the bulk storage

Figure 4.7 shows the results for the pallet racks with random cycle counting with counting every day. The highest average accuracy is at a sample size of 250. The average travel time is about as high as the sample size with the second-highest average accuracy. All other sample sizes have a notably lower average accuracy. Therefore, 250 is an appropriate sample size for random cycle counting every day.

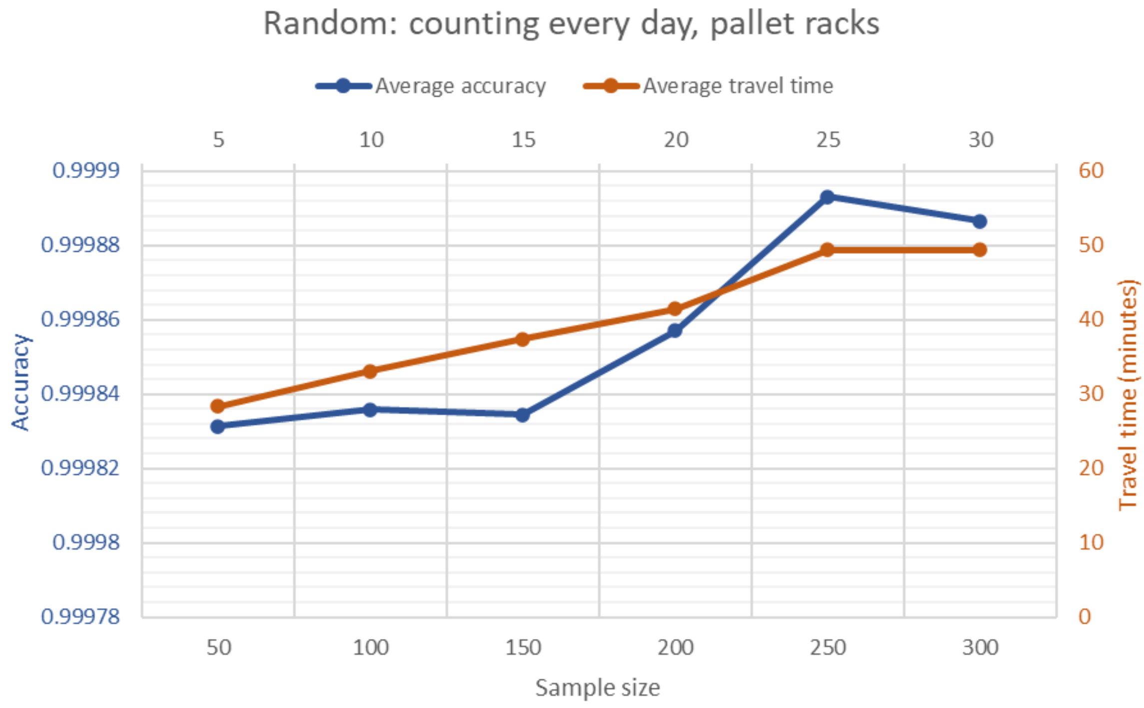

Figure 4.7 Performance of parameter values for random cycle counting every day in the pallet racks

4.3.3.3 Counting three times a week and once a week

To determine the sample sizes for counting three times a week and once a week, we use the total number of counts per year for counting every day. The total number of counts per year is the sample size multiplied by the number of days per year that cycle counting is performed. To keep the average accuracy for all counting periodicities at about the same level, we assume that the total number of counts per year stays the same. The number of days that cycle counting is performed is known for each counting periodicity, and the total number of counts per year can be determined for counting every day. So, with this information we determine the sample sizes for counting three times a week and counting once a week, using Formula 4.3. Table 4.5 and Table 4.6 show the resulting sample sizes.

$$Sample\ size = \frac{Total\ number\ of\ counts\ per\ year}{Number\ of\ days\ cycle\ counting\ is\ performed} \tag{4.3}$$

Table 4.5 Sample sizes bulk storage

Counting periodicity	Number of counting days	Total counts per year	Sample size
Every day	365	9125	25
Three times a week	156	9125	58
Once a week	51	9125	179

Table 4.6 Sample sizes pallet racks

Counting periodicity	Number of counting days	Total counts per year	Sample size
Every day	365	91250	250
Three times a week	156	91250	585
Once a week	51	91250	1789

4.3.4 Opportunity-based cycle counting

For opportunity-based cycle counting, the parameter is the number of transactions at a pallet location after which that pallet location is counted. We expect the accuracy to decrease if this number of transactions increases.

Figure 4.8 shows the results for the bulk storage. As expected, both the average accuracy and the average travel time decrease as the number of transactions after which a pallet location is counted increases. There is one exception: the average accuracy with 30 transactions is lower than with 35 transactions. A possible explanation is that an inaccuracy at one or more pallet locations occurs between transactions 31 and 35. If we count the pallet location after 35 transactions, these inaccuracies are quickly found. However, if the pallet location is counted after every 30 transactions, then 25 to 30 more transactions need to be done before we count the pallet locations again and correct the inaccuracy.

Based on Figure 4.8, the pallet locations at the bulk storage are best counted after every 35 transactions. At this number, the average accuracy is highest, while the difference in travel time with the other parameter values is less than 35 seconds.

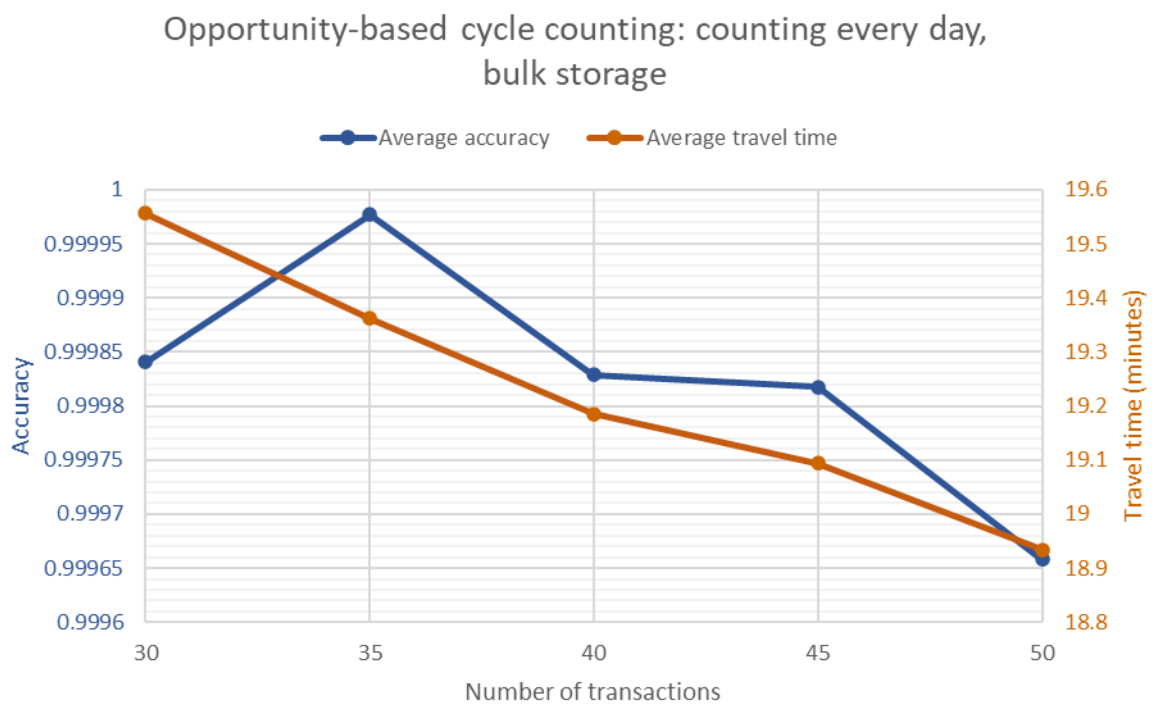

Figure 4.8 Performance of parameter values for opportunity-based cycle counting in the bulk storage

Figure 4.9 shows that both the average accuracy and the average travel time decrease when the number of transactions after which a pallet location is counted increases, as expected. A suitable number of transactions after which to count a pallet location is 3 because the accuracy is highest with that number of transactions.

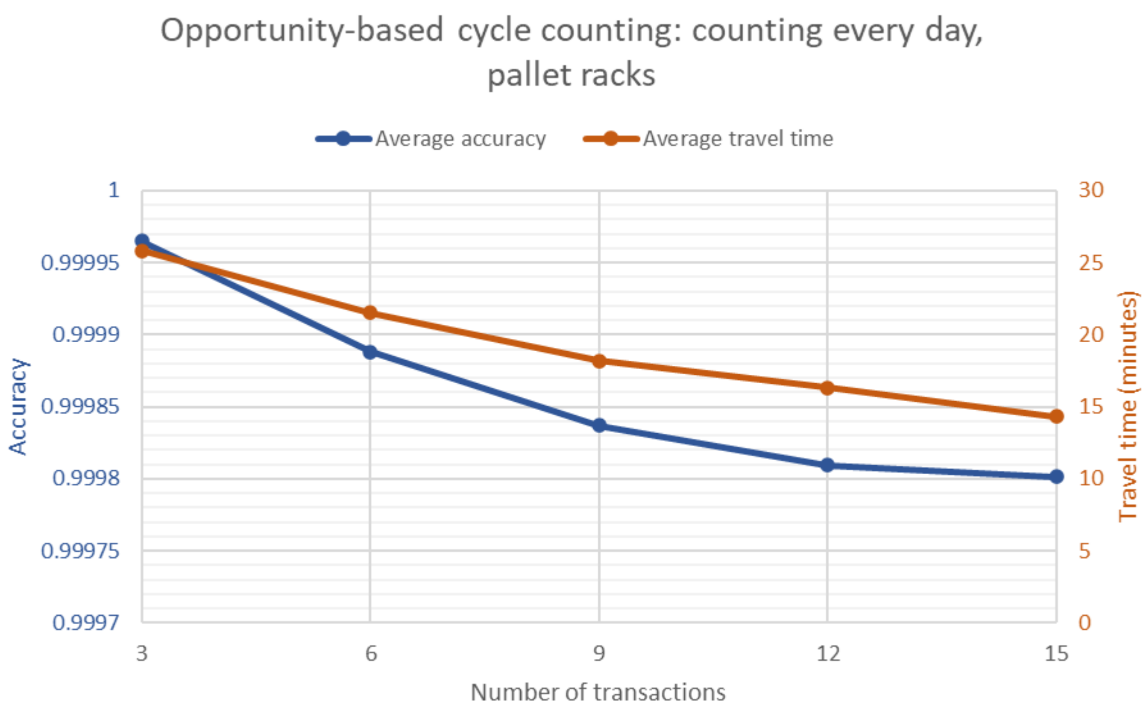

Figure 4.9 Performance of parameter values for opportunity-based cycle counting in the pallet racks

4.3.5 Location-based cycle counting

The parameter for location-based cycle counting is the area division used. We numbered the area division from the smallest areas to the biggest areas. So, the areas in area division 1 contain fewer pallet locations than in area 2. Each day that cycle counting is performed, exactly one of the areas is counted.

For each counting periodicity, experiments are performed to determine the appropriate area division. The reason for this is that if an area division is chosen for one counting periodicity, then the number of times each pallet location is counted will be different for the same area division but with a different counting periodicity. For example, let us say that area division 1 is chosen when cycle counting is done every day. When area division 1 is also chosen for counting three times a week, each pallet location is counted less often since the number of pallet locations counted on a day stays the same but the number of days that cycle counting is performed decreases.

It is expected that if the counting periodicity lowers, the area division increases or at least stays the same. So, if we perform cycle counting less often, then the number of pallet locations that are counted per day should not decrease to prevent the accuracy from becoming too low.

4.3.5.1 Every day

Figure 4.10 shows the average accuracy and average travel time for each area division with counting every day. An appropriate area division for this counting periodicity is 3. Both area divisions 3,4, and 5 result in a high accuracy of more than 0.99 but the difference between these three is small. However, the average travel time for area division 3 is substantially lower than for area divisions 4 and 5. So, we select area division 3 for this counting periodicity.

Figure 4.10 shows that the average travel time does not always increase as the area division increases. As more pallet locations are counted per day when the area division increases, it would be reasonable that the average travel time increases. However, even with small areas, the pallet locations in that area can be far away from the drone charging point. When a small area that lies far away needs to be counted, the travel time is still high for that day. If on the last days of the year areas need to be counted that are far away, that may cause the average travel time to get higher than when an area division with a bigger number is used but with close areas on the last days of the year.

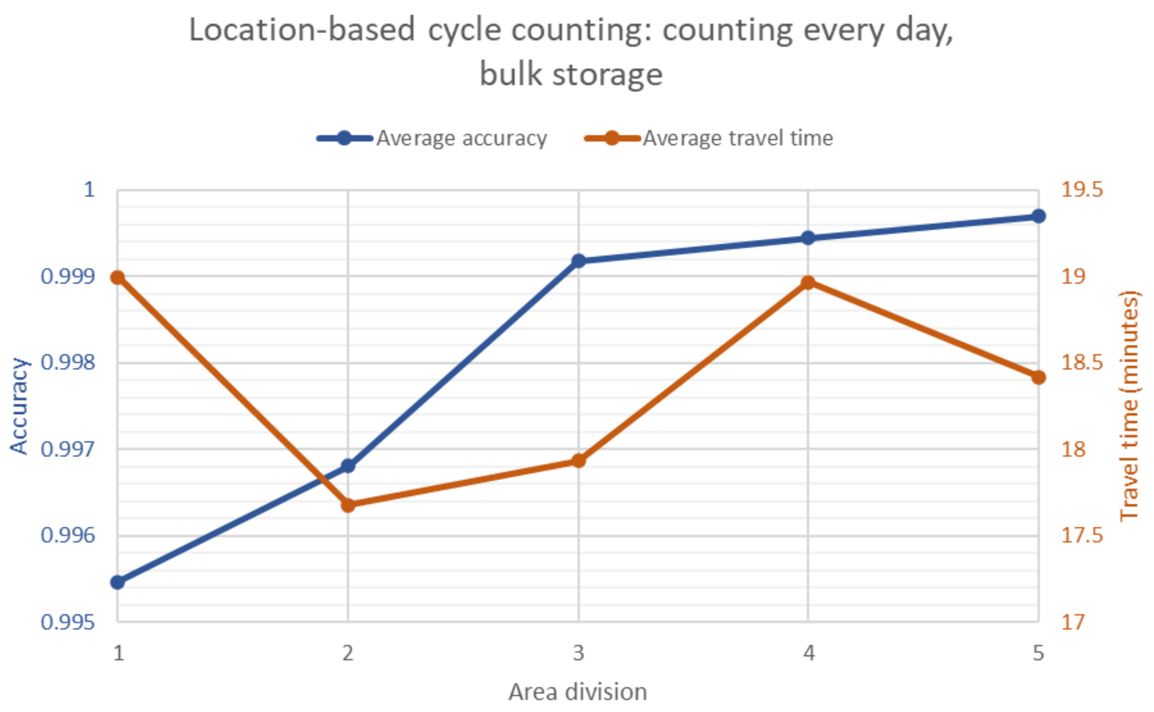

Figure 4.10 Performance of parameter values for location-based cycle counting every day in the bulk storage

The results for counting every day in the pallet racks are shown in Figure 4.11. Area division 4 is suitable for this counting periodicity. The average accuracy is not as high as for area divisions 5 and 6, but the average travel time is notably lower.

The accuracy in Figure 4.11 is not increasing every time the area division increases. It would be reasonable for the average accuracy to increase, as more pallet locations are counted each day that cycle counting is performed. A reason that the average accuracy does not always increase could be the timing when an inaccuracy occurs and when a pallet location is counted. For example, let us say that an inaccuracy at a certain pallet location occurs on day 70. With one area division, that pallet location is counted every 40 days, and with another area division, it is counted every 30 days. With the first area division, the inaccuracy is found after 80 days, and with the second after 90 days. So, even though the pallet location is counted more often with the second area division, it took longer to find the inaccuracy than with the first area division.

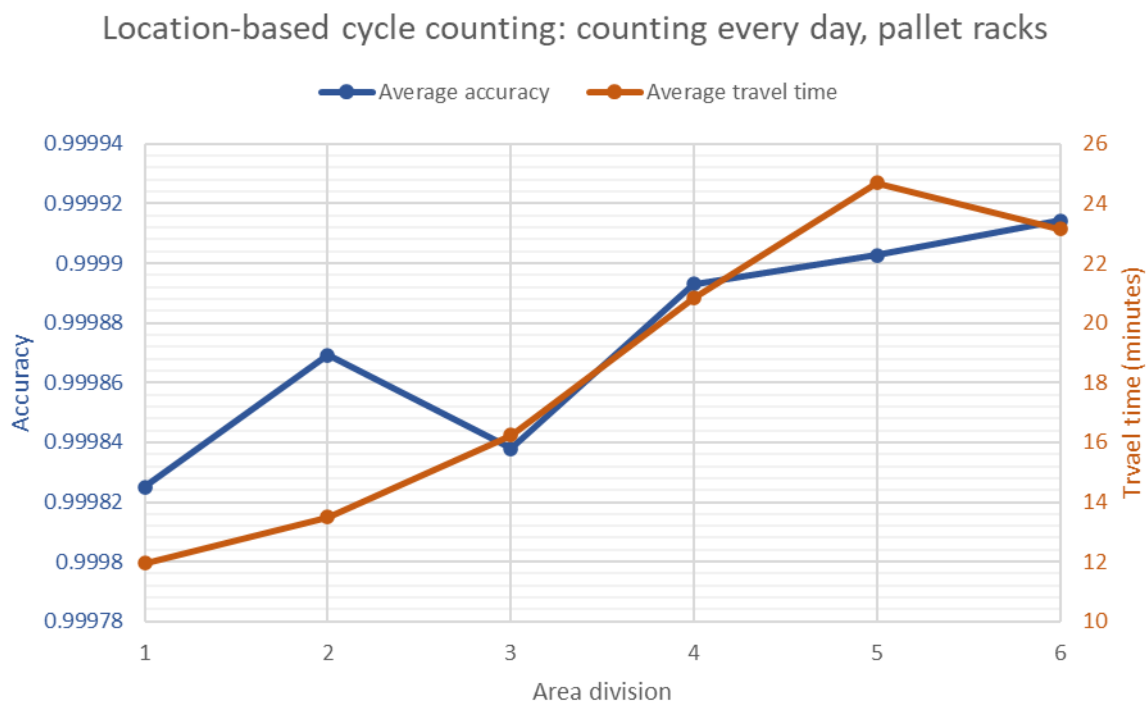

Figure 4.11 Performance of parameter values for location-based cycle counting every day in the pallet racks

4.3.5.2 Three times a week

The results for each area division for counting three times a week are shown in Figure 4.12. Area division 3 is chosen for this counting periodicity. Although the average accuracy for area division 4 and 5 are higher than for area division, the difference is not that big, while the average travel time is substantially higher. Therefore, area division 3 is a suitable parameter value.

The area divisions for counting every day and three times a week are the same. So, since the same number of pallet locations is counted each day, but cycle counting is performed less often, the average accuracy of counting three times a week is lower than when counting every day with the same area division (0.9975 versus 0.9992 respectively). Figure 4.13 shows the average accuracy and travel time for counting three times a week. The highest average accuracy is at area division 4. Since the average travel time is not exceptionally high or low compared with the other area divisions, we choose area division 4 for counting three times a week.

This area division is the same for counting three times a week as for counting every day. This shows in the average accuracy: the average accuracy is 0.99989 for counting every day versus 0.99987 for counting three times a week. As explained earlier in this section, this is reasonable since each pallet location is counted less often.

Figure 4.13 also shows that the average accuracy and travel time do not always increase as the area division increases. Section 4.3.5.1 gives possible explanations for this.

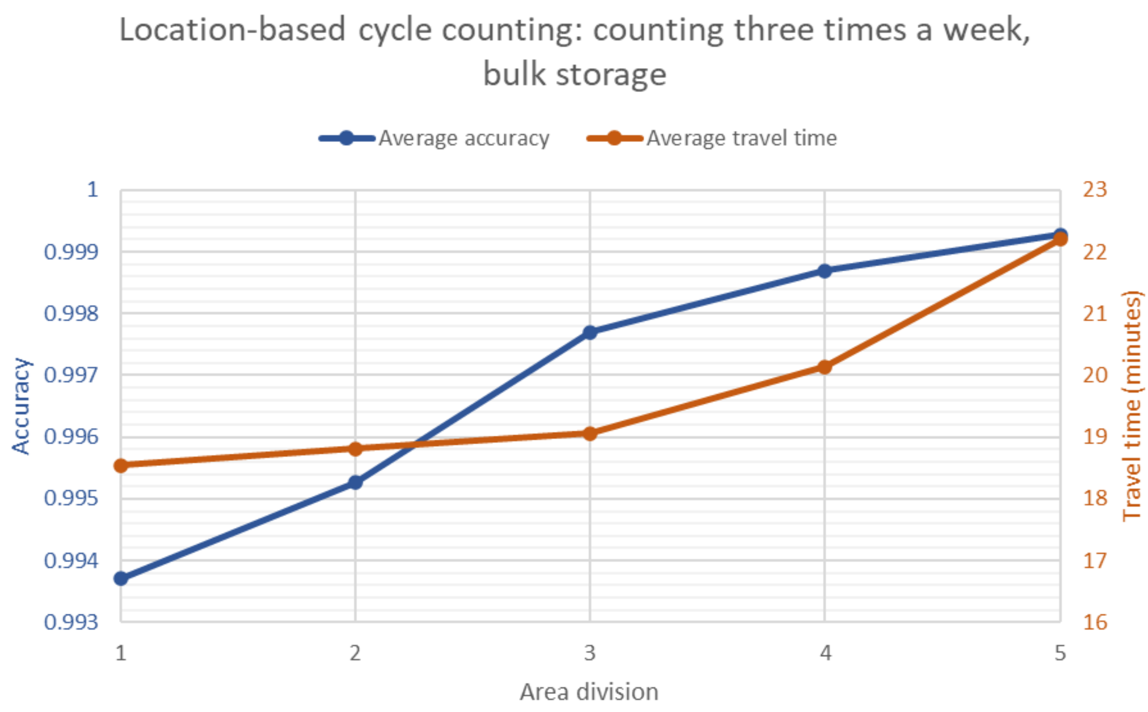

Figure 4.12 Performance of parameter values for location-based cycle counting three times a week in the bulk storage

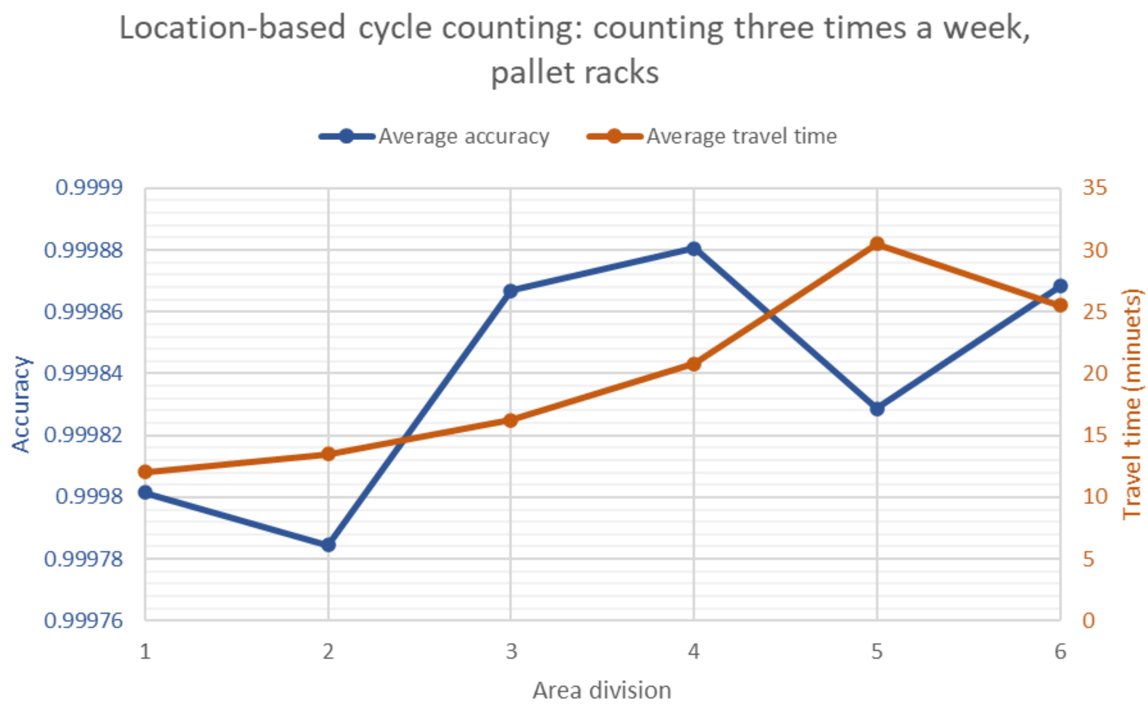

Figure 4.13 Performance of parameter values for location-based cycle counting three times a week in the pallet racks

4.3.5.3 Once a week

Figure 4.14 shows the results for each area division when counting once a week. Area division 5 is appropriate for this counting periodicity. The difference between this area division and the other ones is quite substantial in terms of accuracy, for example, the average accuracy for area division 5 is more than 0.998, while it is about 0.996 for area division 4. In terms of average travel time, the difference is not as big as the average accuracy. Therefore, area division 5 is a suitable parameter value.

Finally, the area division of counting once a week has a higher number than for counting every day and counting three times a week, which is in line with our expectations set at the beginning of section 4.3.5.

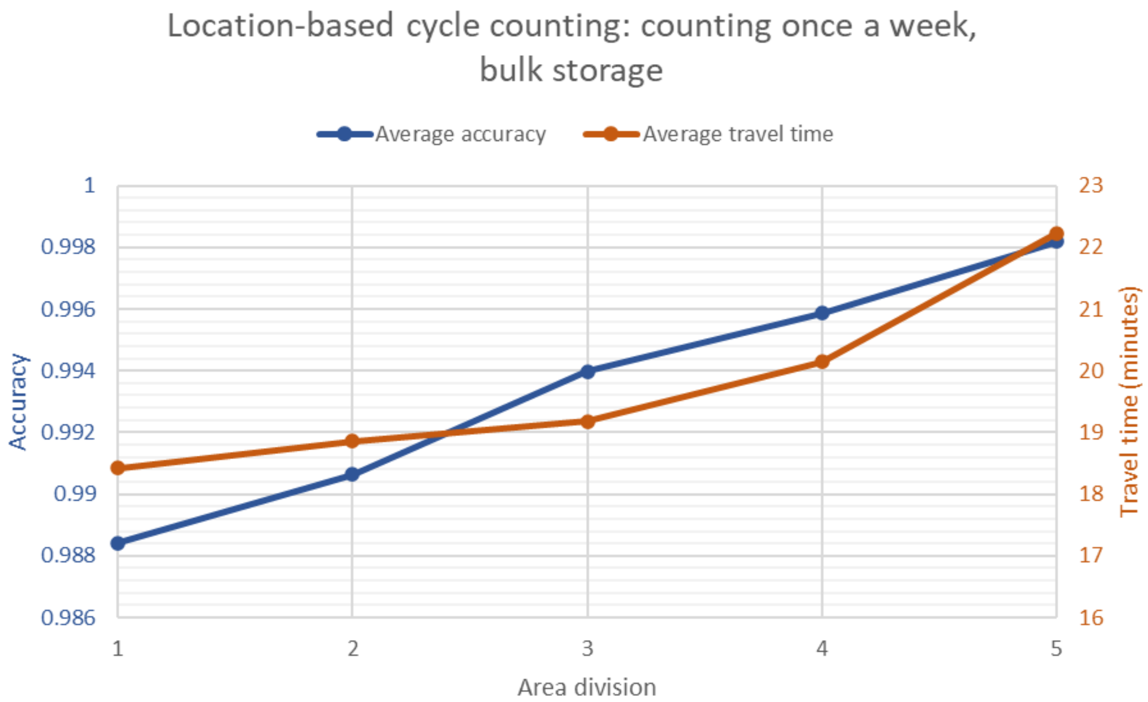

Figure 4.14 Performance of parameter values for location-based cycle counting once a week in the bulk storage

The average accuracy and average travel time for counting once a week in the pallet racks are shown in Figure 4.15. At area division 5, the average accuracy is highest. Although the average travel time is also highest at that area division, the difference in average accuracy is convincing enough to justify choosing area division 5 for this counting periodicity. The number of this area division is also higher than the ones appropriate for counting three times a week and once a week, which was anticipated.

The average accuracy and travel time do not always increase as the area division increases, as shown in Figure 4.15. The reasons for this are given in section 4.3.5.1.

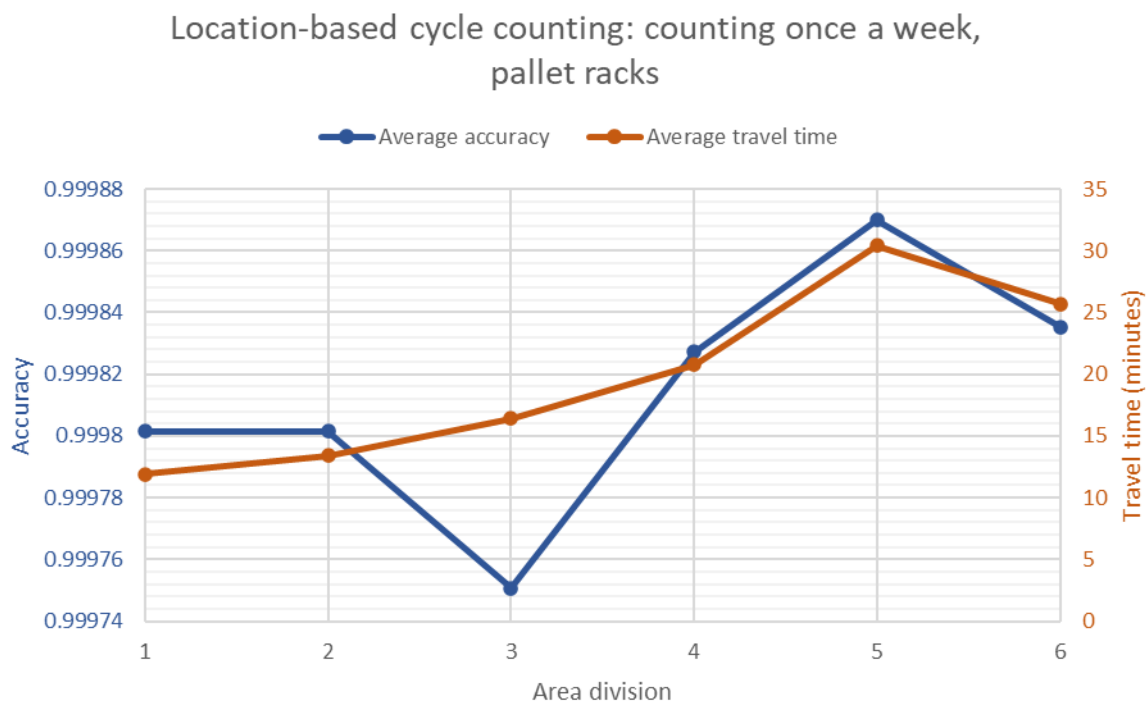

Figure 4.15 Performance of parameter values for location-based cycle counting once a week in the pallet racks

4.3.6 Location- and opportunity-based cycle counting

Location- and opportunity-based cycle counting has two parameters: the area division and the number of transactions. We consider just the area divisions 1, 2, and 3 for this type of cycle counting because the areas in these area divisions are the smallest, and on some days, multiple areas may need to be counted. If multiple areas from area divisions 4, 5, or 6 would be counted, the travel time would become unreasonably high.

The results from location- and opportunity-based cycle counting in the bulk storage are shown in Figure 4.16. The parameter value chosen is {2,300}. Compared with the other parameter values, {2,300} has a high average accuracy, but a low average travel time.

Figure 4.17 shows the results from location- and opportunity-based cycle counting in the pallet racks. Note that the differences in travel times between the parameter values are big, especially compared with the travel times in the bulk storage Figure 4.16. This shows that the parameter value for the pallet racks has a big influence on the travel time.

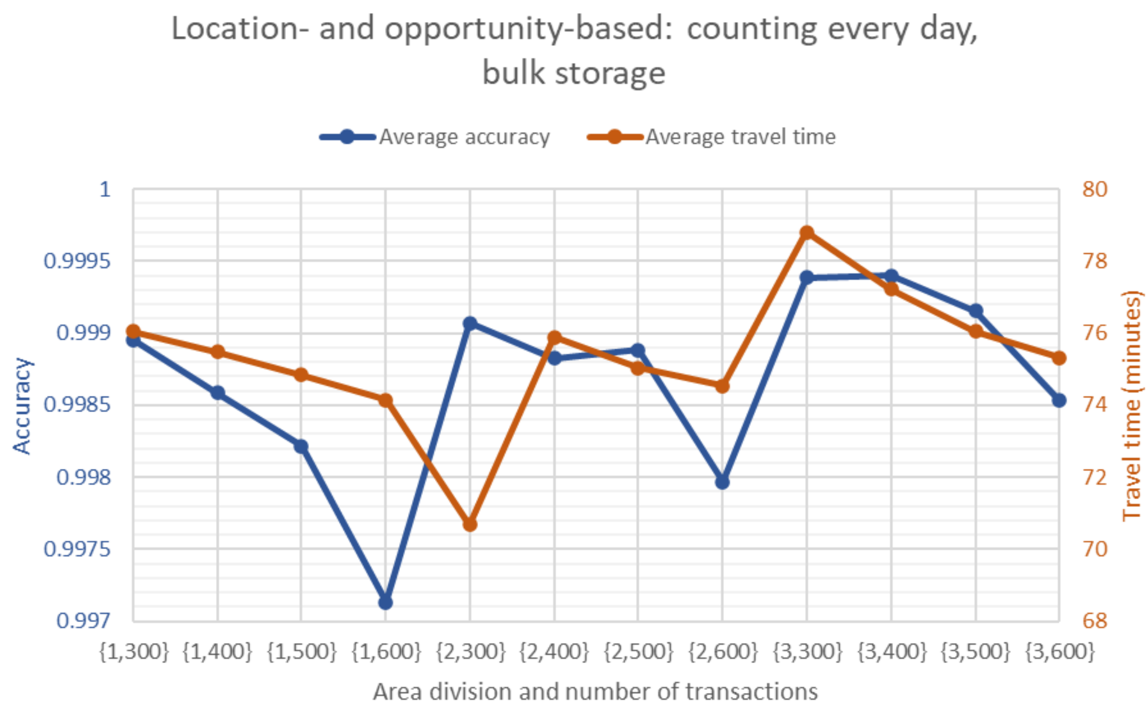

Figure 4.16 Performance of parameter values for location- and opportunity-based cycle counting in the bulk storage

We choose {2,8} as the parameter value. The travel times for the parameter values with the highest accuracy can become unreasonably high. Therefore, a parameter value is chosen that has a reasonable travel time, but still a high accuracy.

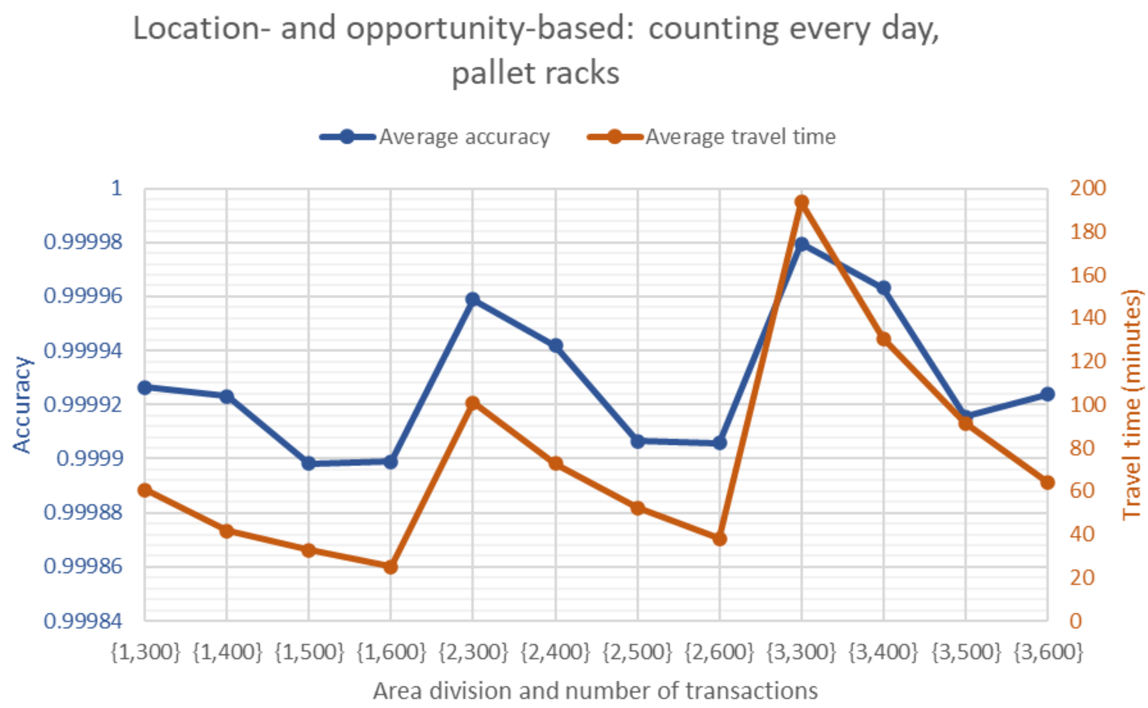

Figure 4.17 Performance of parameter values for location- and opportunity-based cycle counting in the pallet racks

4.3.7 Summary parameter values

The parameter values for all types of cycle counting and each counting periodicity are shown in Table 4.7 for the bulk storage and in Table 4.8 for the pallet racks. As we explained in section 4.3.1, these parameter values are not necessarily optimal, but they are considered suitable for the corresponding types of cycle counting and storage method.

Table 4.7 Parameter values for the bulk storage

Type of cycle counting	Parameter	Every day	Three times a week	Once a week
ABC	Number of counts per class per year	{30,15,8,1}		
Random	Sample size	25	58	179
Opportunity-based	Number of transactions	35		
Location-based	Area division	3	3	5
Location- & opportunity-based	Number of transactions	300		
	Area division	2		

Table 4.8 Parameter values for the pallet racks

Type of cycle counting	Parameter	Every day	Three times a week	Once a week
ABC	Number of counts per class per year	{30,15,8,1}		
Random	Sample size	250	585	1789
Opportunity-based	Number of transactions	3		
Location-based	Area division	4	4	5
Location- & opportunity-based	Number of transactions	8		
	Area division	2		

4.4 Combination of types of cycle counting

Now that we determined the parameter values for all types of cycle counting, the best combination of types of cycle counting for the bulk storage and the pallet racks can be determined. As in section 4.3, the number of drones used is set to 2.

To find the best combination, we perform runs for every combination of cycle counting types. For these runs, the testing data set is used, as discussed in section 4.1. This testing data set contains days 168 to 365 since the warm-up period contains days 1 to 31 and the training data set contains days 32 to 167. To keep the number of runs manageable, runs are only performed with the counting periodicity of counting every day. We assume that if one combination of types of cycle counting outperforms another combination when counting every day, it also outperforms that one when another counting periodicity is used. Again, two input data sets are used, for the same reason as discussed in section 4.3. So, we use the average accuracy and the average travel time from the two data sets to find the best combination of heuristics.

When we select the best combination of types of cycle counting, a trade-off is made between accuracy and travel time. There are multiple approaches to this trade-off. It depends on the business case which approach is most beneficial. For this thesis, we select three combinations of types of cycle counting, each based on a different approach regarding accuracy and travel time. One combination of cycle counting types will be chosen with the aim to maximize accuracy, another one to minimize travel time, and for the last one, accuracy and travel time are equally important. We indicate every combination of types of cycle counting with the letter A, B, or C since the description of each combination can become wordy.

Figure 4.18 shows the results from the runs for every combination of cycle counting types. With the maximizing accuracy approach, the combination of opportunity-based cycle counting at the bulk storage and location- and opportunity-based cycle counting at the pallet racks is chosen. This combination of types of cycle counting will be called combination A.

Next, location-based cycle counting at the bulk storage and ABCD cycle counting at the pallet racks is selected as the combination of cycle counting types when aiming for the lowest travel time. We call this combination of cycle counting types combination B. Although using ABCD cycle counting for both the bulk storage and the pallet racks results in a higher accuracy with just a slightly higher travel time, we stick with location-based and ABCD cycle counting. With 25 different combinations of cycle counting types, it is reasonable that some combinations give similar results. It is easy to make an exception because another combination seems to be better, that way you could just keep making exceptions. Therefore, we stick with the approach of selecting the combination of cycle counting types that has the lowest travel time.

Lastly, opportunity-based cycle counting for both the bulk storage and pallet racks is chosen as the combination of heuristics that has both high accuracy and low travel time. This combination of cycle counting types is called combination C.

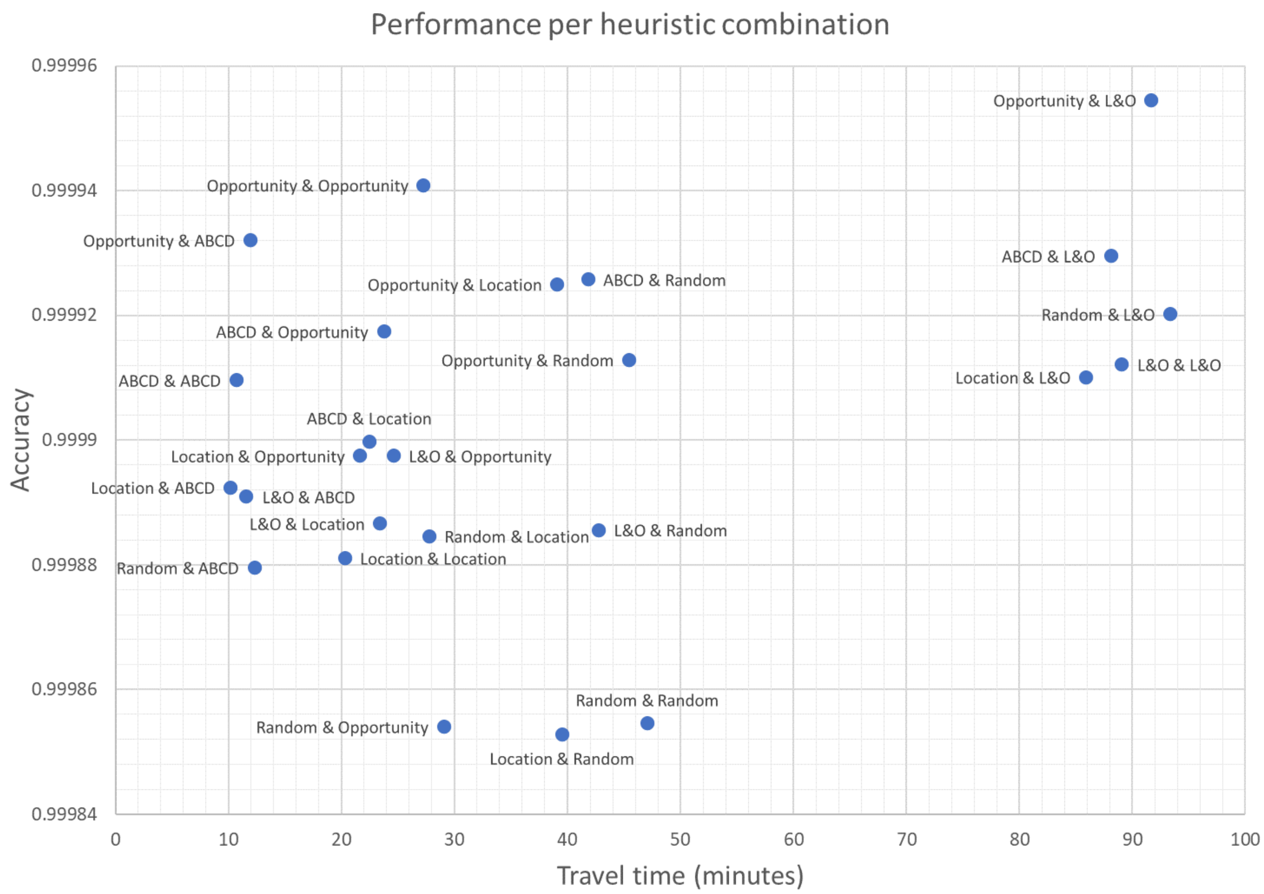

Figure 4.18 Performance per combination of heuristics

4.5 Counting periodicity and number of drones

Recall that we selected three combinations of cycle counting in section 4.4. The next step is to determine the counting periodicity and number of drones to use. To this end, we perform runs for the selected combinations with every counting periodicity and different numbers of drones. Just like in sections 4.3 and 0, two data input sets are used for the runs. Again, we use the average of the accuracy and travel time from these two data sets. Also, we consider the costs of drones when determining the number of drones.

Since multiple aspects are considered in this section, we give a short explanation of which aspects are influenced by the number of drones and which by the counting periodicity.

- The counting periodicity influences the inventory record accuracy. When cycle counting is performed more or less often, an inaccuracy at a pallet location may be found sooner or later, which influences the inventory record accuracy. On the other hand, we assume that the number of drones does not influence the inventory record accuracy. The reason is that we already decided which pallet locations to count by selecting the types of cycle counting and their parameter values. Using more or fewer drones does not change which pallet locations to count. Although in practice, using an additional drone may mean that more pallet locations can be counted, we do not consider this to avoid too much complexity. Section 6.3 also discusses this subject.
- The number of drones influences the costs of drones.

- Both the number of drones and the counting periodicity influence travel time. Using more drones lowers the travel time. Also, performing cycle counting less often decreases the travel time and vice versa.

As we discuss different counting periodicities, it is interesting to look at both the daily and the weekly travel time. The daily travel time indicates the average travel time for counting on each day that cycle counting is performed. On the other hand, the weekly travel time shows the total number of hours cycle counting takes per week. When counting once a week, the daily and weekly travel times are the same, for obvious reasons. So, for counting once a week there is no need to make a distinction between daily and weekly travel time, we just discuss the travel time for counting once a week. Weekly travel time was not used in earlier sections, because we only compared policies with the same counting periodicities. Therefore, considering weekly travel times did not have added value.

This chapter first discusses the costs of a drone in section 4.5.1. Next, sections 4.5.2, 4.5.3, and 4.5.4 select the counting periodicity and number of drones for each combination of types of cycle counting.

4.5.1 Costs of a drone

To assess the counting periodicity and the number of drones to use, it is essential to know the relevant costs. This section discusses the costs of drones.

The costs of buying a drone can vary a lot. So, it is important to indicate which type of drone is suitable for inventory cycle counting in warehouses. As indicated in section 2.1, a rotary-wing or tilt-wing drone with a barcode scanner is suitable for cycle counting. We do not need a fast racing drone or a drone with a high-quality photography camera for this application. However, it needs to be of good quality, such that it does not break too often. An autonomous drone can be bought for about 1700 euros (RC Racing, September 2021). We assume that the drone does not have a barcode scanner yet since barcode scanning is a quite specific application for drones. Let’s say that installing the barcode scanner costs an additional 300 euros, so the purchase costs for the drone are about 2000 euros. The drone will also need maintenance. Furthermore, the training of employees to work with drones will bring costs. Both are estimated at 500 euros. If one or more additional drones are bought, the costs for training employees only need to be paid once, while all other costs are multiplied by the number of drones bought. Table 4.9 summarizes the costs for 1 up to 4 drones.

Table 4.9 Costs of drones

Number of drones	**1**	**2**	**3**	**4**
Purchasing	€ 1,700	€ 3,400	€ 5,100	€ 6,800
Barcode scanner	€ 300	€ 600	€ 900	€ 1,200
Maintenance	€ 500	€ 1,000	€ 1,500	€ 2,000
Training	€ 500	€ 500	€ 500	€ 500
Total	**€ 3,000**	**€ 5,500**	**€ 8,000**	**€ 10,500**

4.5.2 Combination A

Figure 4.19 shows the average accuracy for each counting periodicity for combination A. The differences between accuracies for each counting periodicity are minuscule. So, we do not have a preference for one of the counting periodicities based on the average accuracy.

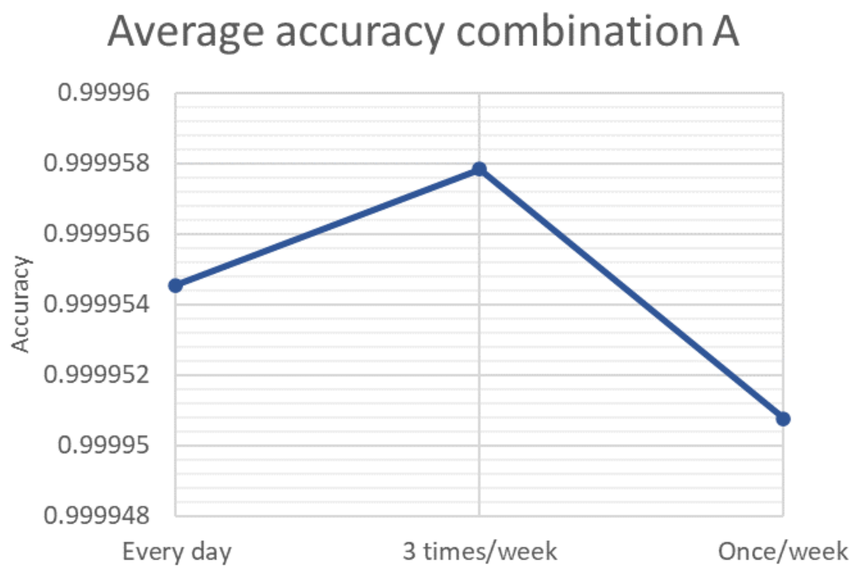

Figure 4.19 Average accuracy for the combination of cycle counting types A

Figure 4.20 shows the average travel times for combination A with different counting periodicities and numbers of drones. The average travel times for combination A are high: for counting three times a week and once a week, the daily travel time is often more than an hour on average. Even when counting every day, the daily travel time is still more than half an hour for 1 to 3 drones. Although using 4 drones is the most expensive option, we think that it is worth the money to limit the travel time to less than half an hour. The weekly travel time when counting every day is higher than for counting three times a week, but we still choose to count every day since it results in half the daily travel time of counting three times a week. Also, this spreads out the cycle counting more evenly over the week. So, cycle counting every day with 4 drones is chosen for combination A.

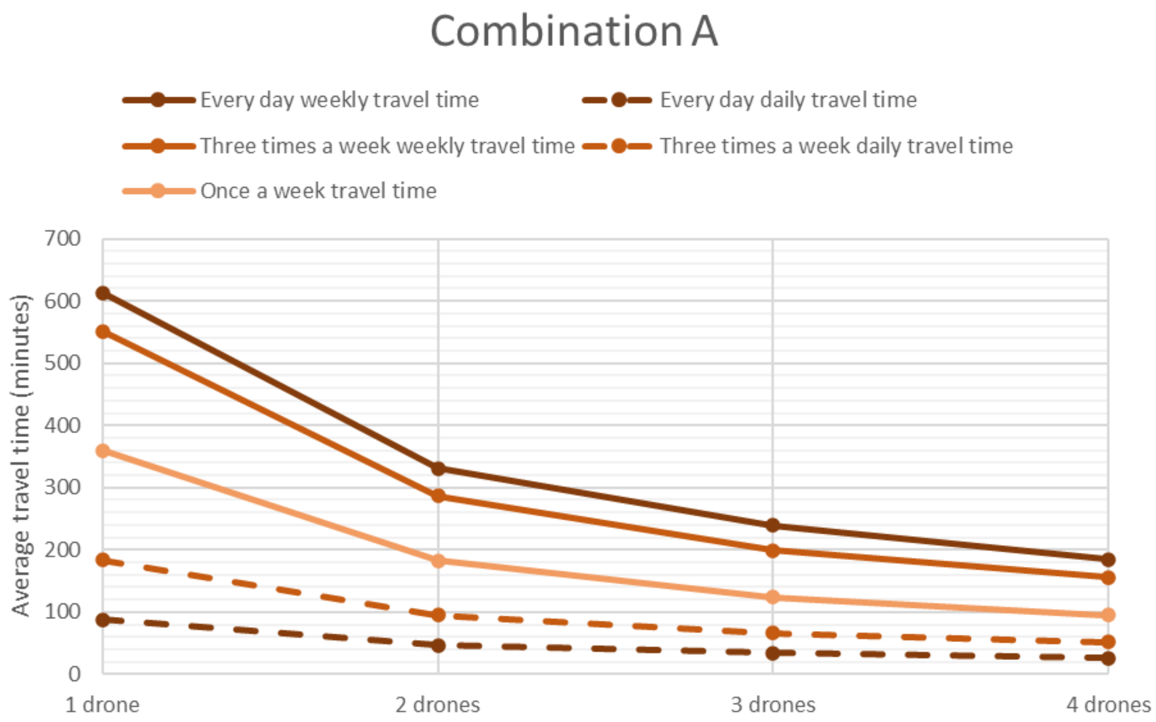

Figure 4.20 Travel times for the combination of cycle counting types A

4.5.3 Combination B

Figure 4.21 shows the average accuracy for each counting periodicity for combination B. It is clear that if cycle counting is performed less often, the average accuracy decreases. The difference between counting every day and three times a week is not so big, but the difference between counting three times a week and once a week is more significant. So, in terms of average accuracy, cycle counting should be performed three times a week or, preferably, every day.

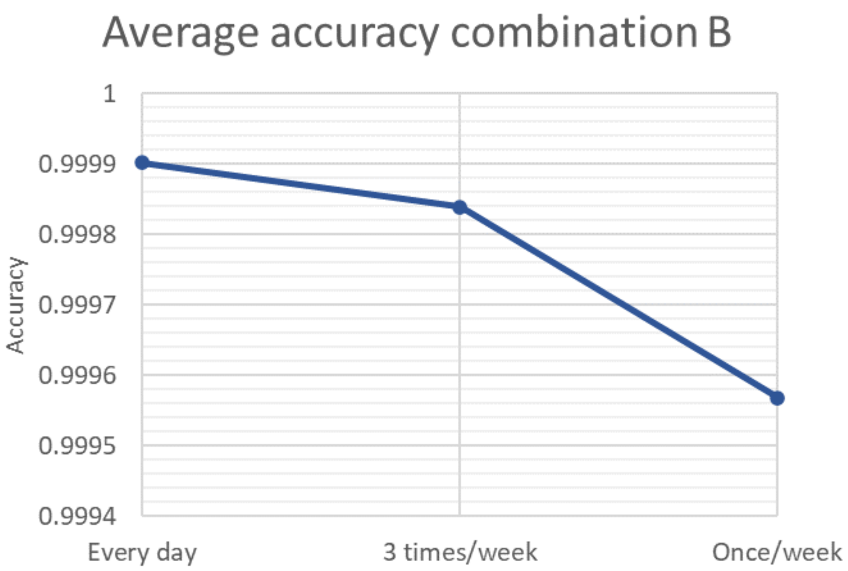

Figure 4.21 Average accuracy for the combination of cycle counting types B

The travel times for each counting periodicity and each number of drones for combination B are shown in Figure 4.22. This figure shows that using 3 or 4 drones causes only a small decrease in both the average travel time and the travel time per week. On the other hand, using 2 drones instead of one shows a significant decrease in daily and weekly travel time for counting every day, as well as counting three times a week. So, two drones are used. Counting once a week is not preferable for combination B since it results in lower accuracy, as indicated earlier in this section. Also, it gives the highest daily travel time and the difference in weekly travel time with counting three times a week is not big. Counting every day is also not the best option. Although it gives the smallest average travel time, the average travel time for counting three times a week is close. Also, counting every day results in a significantly higher weekly travel time than counting three times a week. To conclude, counting three times a week with two drones chosen for combination B.

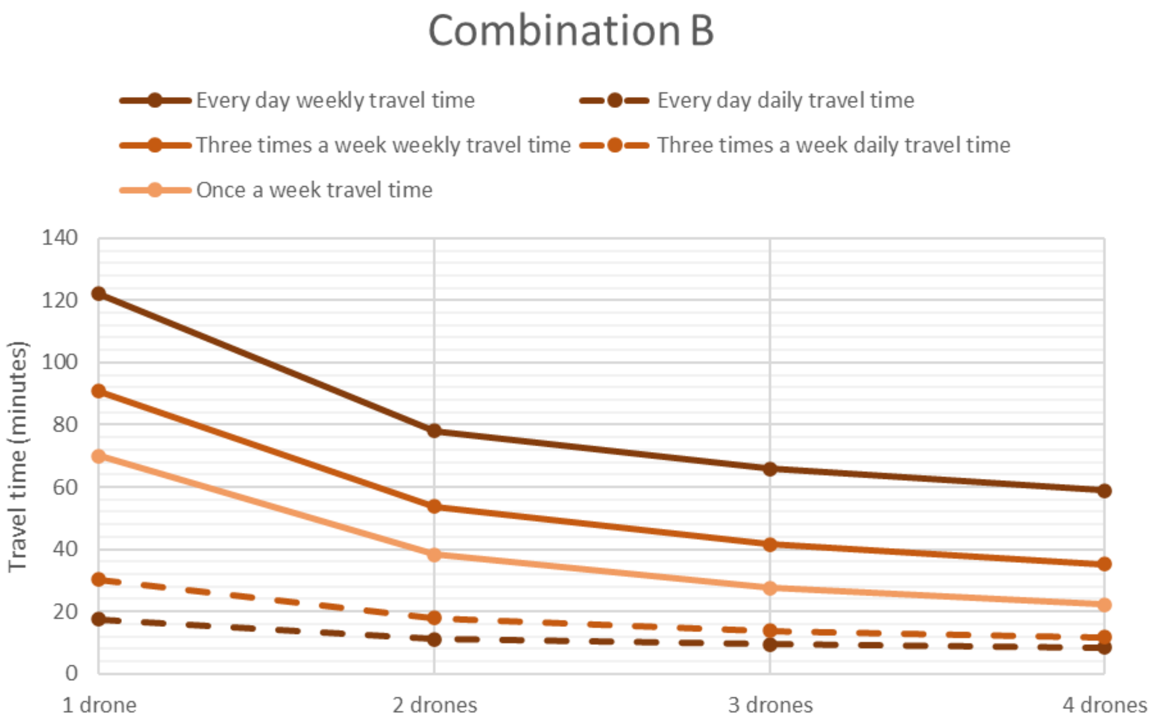

Figure 4.22 Travel times for the combination of cycle counting types B

4.5.4 Combination C

The average accuracy for combination C with different counting periodicities is shown in Figure 4.23. Just like with combination A, the differences in the average accuracies for the counting periodicities are minuscule. So again, there is no preference for one of the three counting periodicities based on the average accuracy.

Figure 4.24 shows the average travel times for each counting periodicity and each number of drones for combination C. Counting every day results in just a little bit smaller daily travel time than counting three times a week, while it gives a much bigger weekly travel time than counting three times a week. So, this is not the best counting periodicity for this combination. Counting once a week does also not seem the best solution since it results in a pretty high travel time compared with the daily travel times from the other counting periodicities. Therefore, counting three times a week is chosen for this combination. Regarding the number of drones, 2 or 3 drones seem to be the best solution since they significantly reduce the travel time compared to using one drone, but 4 drones are not worth the additional costs since they decrease the travel time very little. We choose to use 3 drones, as we think that the investment in the additional drone is worth the decreased travel time.

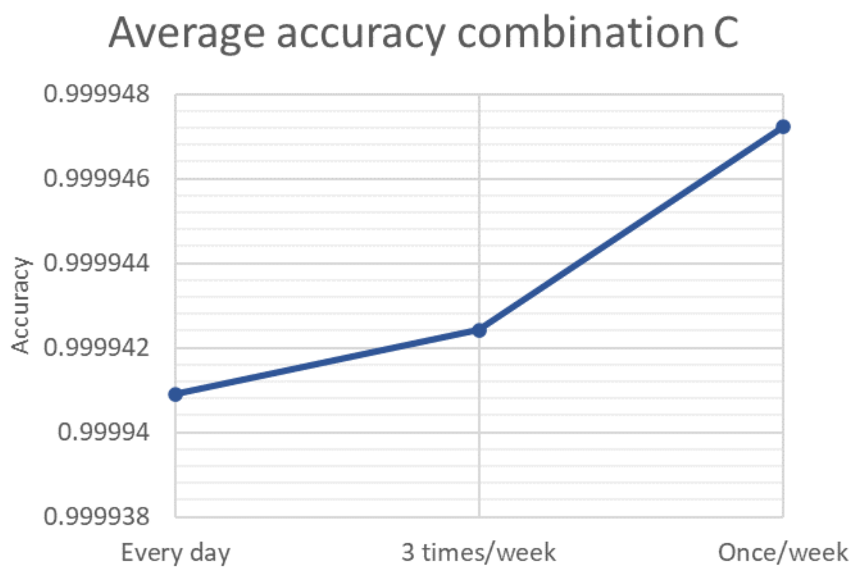

Figure 4.23 Average accuracy for the combination of cycle counting types C

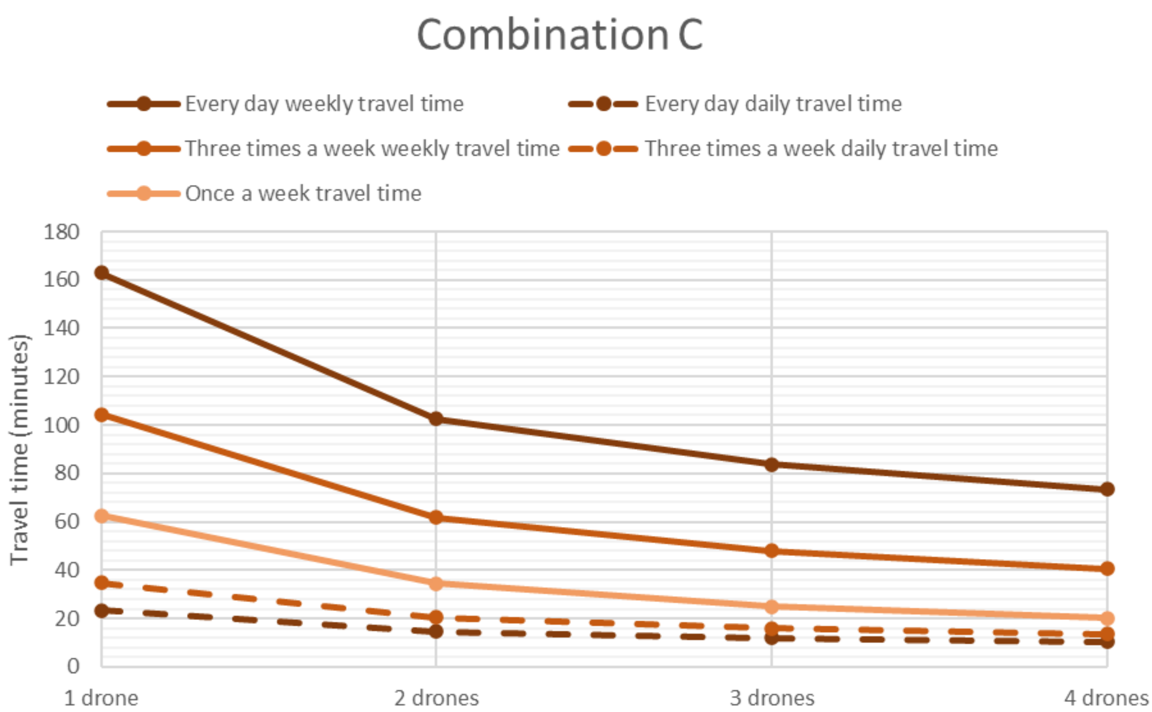

Figure 4.24 Travel times for the combination of cycle counting types C

4.6 Selection of the final policy

Figure 4.25 shows the average travel times, accuracy, and costs for the three combinations with their selected counting periodicities and number of drones. Combination A results in the highest accuracy, but also in the highest costs and travel times. The accuracy with combination C is just a little bit smaller than with combination A, while the costs are €2500 less. The daily travel time is less, but the weekly travel of combination C is only 1/3 of the weekly travel time of combination A. Although combination B results in lower travel times and costs, the accuracy is significantly lower than for the other combinations. Therefore, combination C is selected. This means that we select opportunity-based cycle counting in the bulk storage and the pallet racks with 3 drones three times a week as the final policy.

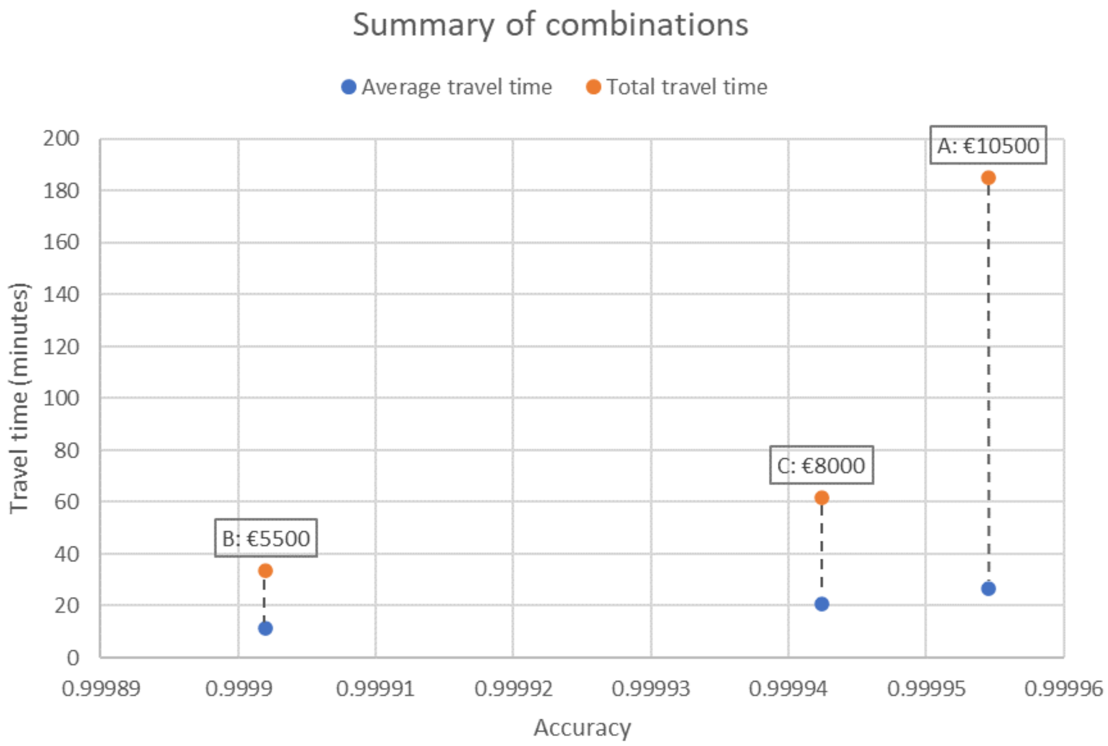

Figure 4.25 Summary of cycle counting type combinations

4.7 Conclusion

The cycle counting policy is developed in several steps. First, a warm-up period of 31 days is found with the MSER. Welch's method is also applied, but this did not give a definitive answer. Therefore, the warm-up period found with the MSER is used. Next, suitable parameter values were found for each type of cycle counting and each storage method. This was done by running the Delphi model with various parameter values and selecting the ones that performed best. Next, three combinations of cycle counting types were selected, based on different approaches. The combination of opportunity-based and location- and opportunity-based cycle counting is chosen for the maximizing accuracy approach. This combination is denoted as combination A. For the minimizing travel time approach, we selected location-based and ABCD cycle counting and called this combination B. Opportunity-based cycle counting for both storage methods is chosen for having both high accuracy and low travel time, and is denoted combination C. Then, for each combination, we choose a counting periodicity and the number of drones, based on the accuracy, travel times, and drone costs. For combination A, counting every day with 4 drones is chosen. We choose to count three times a week with 2 drones for combination B. For combination C, counting three times a week with 3 drones is selected. Lastly, we selected policy C as the final policy.

5 Verification and validation

To be able to place confidence in the results of this thesis, we discuss verification and validation. Verification is the process of ensuring that the model design is transformed into a sufficiently accurate computer model, while validation is the process of ensuring that the model is sufficiently accurate for its purpose (Robinson, 2014). First, section 5.1 discusses verification and then, section 5.2 discusses validation. A conclusion to this chapter is given in section 5.3.

5.1 Verification

We verified the implementation of the model in Delphi by debugging the model and checking that it works the way that it should. Each time a couple of lines were finished, the model was debugged. When a procedure was completed, the model was run line-by-line, to ensure that it was working as intended. Also, we evaluated the resulting values of variables in a procedure, to find out if they were within our expectations. For example, when implementing a heuristic, it was checked that the Delphi model selected the right pallet locations to be counted.

5.2 Validation

Two methods are used to ensure the validity of the model. First, we made a training and testing split for the datasets that were used, which is explained in section 5.2.1. Second, an interpretation of the results is given, which is done in section 5.2.2.

5.2.1 Training and testing split

The first method of validation, the training and testing split of the data, is discussed in section 4.1. With this split, we use different data for determining parameter values and determining the best heuristics. The data is split equally between training and testing. This way, we attempt to prevent overfitting as well as underfitting.

5.2.2 Interpretation of results

The second method of validation is the interpretation of results. If the results are reasonable, this indicates that the Delphi model, and consequently the conceptual blueprint describing the model, is valid. We limited the validation to the interpretation of the results of finding the best heuristics, counting periodicity, and number of drones, and not the selection of the parameters. The reason for this is that the same model is used for selecting parameters as well as the best heuristics, counting periodicity, and the number of drones. Therefore, the amount of value added by interpreting the selection of parameters is limited. Also, the selection of the parameters is not the main focus of this thesis.

Best heuristic

For the best heuristics, the three selected combinations of cycle counting types are interpreted for each approach. Figure 4.18 shows the average accuracy and travel times for each combination of cycle counting types.

For the maximizing accuracy approach, we choose opportunity-based cycle counting and location- and opportunity-based cycle counting. This is a reasonable solution because this means that pallet locations with a high number of transactions are counted more often. Pallet locations with a high number of transactions are also the ones with a high probability of becoming inaccurate. So, counting these pallet locations more often results in high accuracy.

Location-based cycle counting and ABCD cycle counting are selected for the lowest travel time approach. The selection of location-based cycle counting is reasonable, since the pallet locations that are counted on the same day are close together, so the travel time stays low. For ABCD cycle counting, the pallet locations with a lot of transactions and high value are counted more often. Since the probability of inaccuracies is low if the number of transactions is low, the pallets with a low probability of inaccuracies are counted less, which means that there is less unnecessary traveling. So, it is reasonable that the combination of location-based and ABCD cycle counting is chosen.

The combination of cycle counting types that we selected as the one with both high accuracy and low travel time is opportunity-based cycle counting for both the bulk storage and pallet racks. The pallet locations with a lot of transactions are counted more, and these pallet locations have the highest chance of getting inaccurate, so opportunity-based cycle counting results in high accuracy. However, pallet locations with few transactions are barely counted, while an inaccuracy can still occur. This explains that opportunity-based cycle counting may not give the highest accuracy possible. It also does not give the lowest travel time since the pallet locations to be counted on a day may not be close.

Counting periodicity

We expect that if cycle counting is performed fewer times a week, the accuracy decreases. Figure 4.23 shows that this is the case for location-based and ABCD cycle counting. For the other two combinations of cycle counting types, this is not the case, as can be seen in Figure 4.19 and Figure 4.21. For opportunity-based and location-and opportunity-based cycle counting, the accuracy for counting once a week is lowest, but for counting three times a week it is higher than for counting every day. When using opportunity-based cycle counting for both storage methods, the accuracy increases when cycle counting is performed fewer times a week. At first glance, the results for these last two combinations of cycle counting types do not seem reasonable. However, the differences in accuracy are minuscule, they are less than 0,00001. An explanation of why the accuracy may increase a little when cycle counting is performed less often can be given by a small example. Let's say that a pallet location is counted after 300 transactions. On a Tuesday, more than 300 transactions are done, for example, 350. Then on Sunday, 100 additional transactions are done, of which one causes an inaccuracy. If cycle counting is performed 3 times a week, then this pallet location is counted on Wednesday, before the inaccuracy occurs. It is then not counted again 200 additional transactions are done, which may take a couple of days, but also multiple weeks. But, if cycle counting is performed once a week, this pallet location is counted on Monday, the day after the inaccuracy occurred. So, with this counting periodicity, the inaccuracy is found quickly, which has a positive influence on the accuracy.

It is also reasonable that the daily travel time decreases and the weekly travel time increases if cycle counting is performed more often. Figure 4.20, Figure 4.22, and Figure 4.24 show that this is the case for this thesis.

Number of drones

For the number of drones, we expect that the travel time lowers if the number of drones increases. The pallet locations to be counted are divided over more drones, so they finish counting earlier. Our results in Figure 4.20, Figure 4.24, and Figure 4.22 show the same, so they seem to be reasonable.

5.3 Conclusion

By using various techniques, we can conclude that the results from this thesis are valid and verified. By debugging and running the model line-by-line, the model was verified. Validation was done by using a training and testing split for the data and by interpreting the results.

6 Conclusions and recommendations

This chapter finalizes the report. Section 6.1 presents the conclusions of this research. Then, the scientific contribution of this thesis is discussed in section 6.2. Section 6.3 discusses the limitations, and finally, section 6.4 gives recommendations for both practice and further research.

6.1 Conclusions

This research focused on inventory cycle counting by drones. It aims to design a planning and control policy and evaluate the performance of this policy. The research question for this thesis is as follows:

> 'How can the inventory cycle counting in a warehouse by semi-autonomous unmanned aerial vehicles (UAV) be planned and controlled in terms of what items to count, when to count, and the allocation of the items to drones?'

From the literature, we found what characteristics make a drone suitable for inventory cycle counting. A semi-autonomous drone with a tilt- or rotary-wing design, barcode scanners, and a combination of cameras, sensors, an IMU, and/or an additional UGV for navigation is essential. Also, we learned how inventory cycle counting in warehouses is currently organized. There are multiple KPIs for cycle counting, which can be categorized as performance, system, and cost KPIs. We also found a definition for inventory record accuracy. Possible causes for inventory record inaccuracy were identified, which fall into one of the categories transaction errors, shrinkage errors, inaccessible inventory, or supply errors. We learned a formula for inventory record accuracy, and multiple types of cycle counting were explored. Lastly, task allocation among drones is discussed, where a taxonomy, as well as two solution approaches, are discussed. Both market-based solution approaches and optimization-based approaches were presented, where optimization-based approaches seemed most suitable for this thesis, because of the decentral approach.

A model is developed for the evaluation of different policies. We made multiple assumptions in this model. Bolk provided inventory data about their warehouse in Hengelo, but it did not contain data about inventory record accuracy. So, inaccuracies were simulated through a Monte Carlo simulation. With every transaction of a pallet, there is a small chance that an inaccuracy occurs. Also, assumptions about the routing of drones were made, to estimate the travel times of drones. Next, the model was presented concisely with a mathematical model. The purpose of this model is to provide a benchmark with other cycle counting policies, rather than presenting a new cycle counting policy.

We selected five types of cycle counting from the literature review to evaluate in this research: ABCD cycle counting, random cycle counting, opportunity-based cycle counting, location-based cycle counting, and location- and opportunity-based cycle counting. Since the two storage methods (bulk storage and pallet racks) in the Bolk warehouse have different characteristics, it is reasonable that a different type of cycle counting can be used in each storage method. Also, a heuristic is developed for the allocation of pallet locations to drones. This heuristic aims to allocate pallet locations that are relatively close to each other to the same drone.

To evaluate potential policies, the model is implemented in Delphi. A warm-up period of 31 days was determined with the use of the MSER. We performed runs with various parameter values and selected suitable parameter values for each type of cycle counting by evaluating the resulting accuracy and travel time. Next, different combinations of cycle counting types were researched. Again, based on the accuracy and travel time, three combinations were selected. One combination had the highest accuracy, one the lowest travel time and one performed well on both the accuracy and the travel time. For these three combinations, we choose a suitable counting periodicity and number of drones. The accuracy, travel time, as well as costs of drones, were considered in this decision. This resulted in three policies. Finally, we selected one policy based on the same aspects. We can conclude that the results in the Bolk warehouse are best when using opportunity-based cycle counting in both the bulk storage and the pallet racks while counting three times a week with 3 drones.

For verification, the developed model in Delphi was debugged and run line-by-line. To validate it, we made a training and testing split of the data and interpreted the results. We can conclude that the model is valid.

6.2 Scientific contribution

This research has several scientific contributions. First, we introduced a new type of cycle counting: location- and opportunity-based cycle counting. This type of cycle counting was not found in the literature but was inspired by opportunity maintenance. It resulted in a high travel time, but also a high accuracy. So, this is a good option in a business case where much time is available for cycle counting and thus a valuable contribution to scientific literature.

Also, in the literature found for this thesis, only one type of cycle counting is used in a warehouse. In this thesis, it was possible to use different types of cycle counting for the bulk storage and the pallet racks, so two types of cycle counting were combined in one warehouse. This is valuable since different storage methods may require different types of cycle counting.

Finally, we presented a mathematical model to determine what pallet locations to count, when to count them, and with which drone. For this model, the inventory in reality is considered a parameter, which means that information about inaccuracies should already be available when using the model. So, in practice, this model cannot be used to develop a cycle counting policy, but it can be used as a benchmark for other cycle counting policies.

6.3 Limitations

For the routing of the drone, as well as the calculation of its travel time, we made a lot of assumptions. The routing of the drone is based on the decision in which order the drone counts the selected pallet locations. Finding the optimal routing can be a whole study in itself since there are multiple approaches for routing. We made a logical assumption about the routing, but there is no guarantee that it is the best approach. Furthermore, the speed, acceleration, and deceleration depend on the drone that is used, but also on the maximum speed that is allowed for the drone in a warehouse. Although this thesis may not give a perfect estimate of the travel time, we think it indicates which policy has a longer travel time than another policy.

For this research, the type of cycle counting and parameter values are determined before the number of drones is determined. As a result, we assumed that the number of drones did not have an influence on the pallet locations to be counted and consequently, that it had also no influence on the accuracy. However, in practice, the number of drones may be determined first. This way, more drones allow for more pallet locations to be counted in the same amount of time.

Finally, there may be some practical limitations that are not taken into account in this thesis. These include the maximum flying time of a drone on a fully charged battery. Also, safety measures are not considered, apart from a maximum speed for the drone. For example, whether drones can fly in the warehouse when humans are present is not discussed, but this is a very relevant question for practice.

6.4 Recommendations

In the section, we discuss multiple recommendations, which are divided into recommendations for practice and recommendations for further research. Section 6.4.1 discusses the recommendations for practice and section 6.4.2 discusses the recommendations for further research.

6.4.1 Recommendations for practice

The inventory data available for this thesis was for the year 2019. We recommend collecting more data about the pallets entering and leaving the warehouse, as well as their transactions inside the warehouse. The reason for this is that we do not know if the year 2019 is representative of the inventory of the Bolk warehouse. Having data from multiple years will give a better picture of what the inventory typically looks like. Also, the number of pallets entering and leaving the warehouse can change. Especially since the data is from before Covid, there may very well have been some changes in the number of products in the warehouse. Also, the current high levels of inflation might affect the number of products. We expect that adjusting the cycle counting policy to recent data will make the policy perform better.

Another recommendation for practice is to assess the amount of time that is available for cycle counting and the goal for inventory record accuracy. This recommendation does not only apply to the Bolk warehouse in Hengelo but to any other case where cycle counting by AUVs is implemented in a warehouse. The approach for cycle counting should align with the goals of the company but it should also work in practice. Furthermore, every business case is different, so no approach suits every case.

6.4.2 Recommendations for further research

For this thesis, no data about when and where inaccuracies occurred was available. While section 6.4.1 recommends collecting more inventory data, this paragraph discusses the recommendation to collect data about the inaccuracies found by inventory counting. This way, it is clear where there are inaccuracies, and it gives a time frame in which they occurred. This can be helpful in two ways. First, a better estimation of the inaccuracies can be given, such that both the parameter values and cycle counting types chosen will give better results. Also, cycle counting using historical inventory data, as discussed in section 2.2.3, can be used. This will offer insights into the root causes of inaccuracies. It may also perform better than other types of cycle counting, but that is not guaranteed.

Another recommendation for further research is to differentiate between SKUs. For this research, an inaccuracy at one pallet location is just as bad as at any other pallet location. However, in practice, an inaccuracy at one pallet location may be worse than at another pallet location. The reason for this may be that one pallet is more expensive than another, but also criticality may play a part. It may be interesting to take these differences into account. There are multiple ways to do this. First, the classes for ABCD cycle counting can be based on the value or criticality of pallet locations. Also, with opportunity-based cycle counting the number of transactions after which a pallet location is counted can be increased or decreased for more or less important pallet locations.

The last recommendation for further research is to look at decentralized decision-making, instead of centralized decision-making. While this thesis focused on semi-autonomous drones, it may also be interesting to use fully autonomous drones. To implement this, a multi-agent system can be designed. This allows for real-time modifications in the pallet locations to count for multiple drones, based on the results from one drone. For example, if a drone finds multiple inaccuracies at pallet locations with transactions in the same period, then other drones may start counting pallet locations that had transactions in that same period. Alternatively, other drones may start counting more pallet locations handled by the same employee as one that caused an inaccuracy.

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Appendix A: Paths

Path	Zones to visit		
1	None		
2	1		
3	2		
4	3		
5	4		
6	5		
7	6		
8	1	2	
9	1	3	
10	1	4	
11	1	5	
12	1	6	
13	2	3	
14	2	4	
15	2	5	
16	2	6	
17	3	4	
18	3	5	
19	3	6	
20	4	5	
21	4	6	
22	5	6	
23	1	2	3
24	1	2	4
25	1	2	5
26	1	2	6
27	1	3	4
28	1	3	5
29	1	3	6
30	1	4	5
31	1	4	6
32	1	5	6

Path	Zones to visit					
33	2	3	4			
34	2	3	5			
35	2	3	6			
36	2	4	5			
37	2	4	6			
38	2	5	6			
39	3	4	5			
40	3	4	6			
41	3	5	6			
42	4	5	6			
43	1	2	3	4		
44	1	2	3	5		
45	1	2	3	6		
46	1	2	4	5		
47	1	2	4	6		
48	1	2	5	6		
49	1	3	4	5		
50	1	3	4	6		
51	1	3	5	6		
52	1	4	5	6		
53	2	3	4	5		
54	2	3	4	6		
55	2	3	5	6		
56	2	4	5	6		
57	3	4	5	6		
58	1	2	3	4	5	
59	1	2	3	4	6	
60	1	2	3	5	6	
61	1	2	4	5	6	
62	1	3	4	5	6	
63	2	3	4	5	6	
64	1	2	3	4	5	6

Appendix B: Parameters warm-up period

	Random	ABC	Location-based	Opportunity-based	Location- and opportunity-based
Every day	Bulk: 15	A: 20 times a year, B: 10 times a year, C: 5 times a year, D: once a year	Bulk: 3	Bulk: 5 transactions, PR: 2 transactions	Bulk: 8 transactions, area division 1, PR: 3 transactions, area division 2
	PR: 80		PR: 3		
3 times a week	Bulk: 30		Bulk: 4		
	PR: 185		PR: 5		
Once a week	Bulk: 95		Bulk: 5		
	PR: 555		PR: 6		

Appendix C: Delphi dashboard