"A modified cheapest insertion heuristic for the multi-objective pickup and delivery open VRP with time windows for a homogeneous fleet with heterogeneous freights: A case study"

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Avebe

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"A modified cheapest insertion heuristic for the multi-objective pickup and delivery open VRP with time windows for a homogeneous fleet with heterogeneous freights: A case study"

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Preface

This report is the result of my master's graduation thesis in the field of Industrial Engineering and Management, at the University of Twente. I conducted this research for Avebe in the period from February 2021 till July 2021. I developed the Avebe Planning Tool in which I simultaneously simulate and plan a pool of hired bulk trucks to reduce the transportation costs without significantly increasing the factory downtime because of transportation issues. The magic of the Avebe Planning Tool is in the modified cheapest insertion heuristic which I developed. The modified cheapest insertion heuristic consisting of a selection method followed by a priority rule.

I would like to thank the employees at the Sales and Operations Planning department of Avebe for their hospitality and the fantastic time that I had while conducting this research. I would especially like to thank Colin Steenge who was my daily supervisor from Avebe, for his time and energy invested to make this research possible.

Besides, I would like to thank Gréanne Maan Leeftink and Martijn Koot from the University of Twente for their critical and good feedback which strongly enhanced the quality of my report. I am thankful for their online supervision during the COVID-19 pandemic.

Lastly, I would like to thank my family and especially my father, mother, brother, and girlfriend for their mental support, interest, and feedback.

Ruben Zwiers, 2-7-2021, Enschede

Management summary

To process three million tons of potatoes per year, the transport planning between factories, silos, and customers is of key importance. To make sure that the transport is arranged in a good way, Avebe pays a transportation company to arrange the transport. However, due to price changes in the transportation sector, which make it infeasible for the transportation company to maintain the current contract, a new contract will be active from January 2021 onwards.

According to this new contract, Avebe should decide how many trucks it wants to have in its hired pool of bulk trucks, and how many of these bulk trucks should be assigned to normal and special transport orders. Normal transport orders are orders that must be done by the pool of hired bulk trucks according to the contract and special transport orders are orders that might be done by the hired pool of bulk trucks. The decision on the number of trucks to be hired for normal and special transport is currently made during a weekly expert meeting. However, experts within Avebe describe this planning approach to be time-consuming, and rather arbitrary. Besides, the experts have no idea how good or bad the resulting truck planning is. The uncertainty about the quality of the current bulk truck planning and the time-consuming approach to obtain the bulk truck planning are the motivation for this research, aiming to:

"Develop a model/dashboard that provides insight in the number of bulk trucks to be assigned to normal and special transport, during the intercampaign TAK, in order to reduce the total transportation cost without significantly increasing the factory-downtime because of transportation issues."

This research focuses on the intercampaign TAK period of the year which normally starts around the third week of February and ends around the second week of May. The reason for focusing on this period is that the complexity of the transportation flows is the highest during this period of the year therefore extending the focus to the whole year will be easier when we already researched the intercampaign TAK. The intercampaign TAK is characterized by the fact that the AMF ('Aardappel Meel Fabriek') in Gasselternijveen is still processing potatoes, while the AMF in Ter Apelkanaal is shut down. Therefore, the production facilities are partly supplied from the AMF in Gasselternijveen and partly supplied from the silos in this period.

Method/problem-solving approach

To achieve the defined research objective, we first studied the features of the transportation process and the approach of the experts to come up with a truck schedule. Besides, we combined expert interviews with a literature study to identify performance indicators that we use to assess the transport planning quality. Based on the features of the transportation process, we classified the transportation problem to be a multi-objective Static Open Vehicle Routing Problem with pickup and delivery, where load splitting is not allowed, and vehicles can perform multiple trips. Furthermore, we have a fixed number of non-compartmentalized homogeneous vehicles with heterogeneous freights where transportation orders have hard time windows, and both waiting times and cleaning are considered. Contrary to the current standard in the literature on VRP, we do not consider a vehicle's route to start and end at a depot, but vehicles can start and end at a variety of locations. To the best of the authors' knowledge, this implies that we are studying a new variant of VRP in this research.

To solve this new variant of the Vehicle Routing Problem with Pickup and Delivery, and Time Windows (VRPPDTW), we developed the *'Avebe Planning Tool'* in which we simultaneously assign orders to trucks and generate new transport orders. The orders are assigned to the trucks by applying a modified cheapest insertion heuristic that we designed in this research. In this heuristic, the cheapest insertion is determined using a selection method followed by a priority rule. The selection method and priority

rule consider the deadline of the order, the travel time, waiting time at the (un)loading docks, and cleaning time of the trucks.

Results

To get insight into the number of trucks that Avebe should hire during the intercampaign TAK and how these trucks should be assigned to normal and special transport in order to reduce transportation costs without increasing the factory downtime we experimented with:

1. The number of trucks in the hired pool of bulk trucks
2. The weights given to the 'Earliest Due Date' and the 'Travel, waiting and cleaning time', which are important input parameters in the priority rule that we use to assign orders to trucks.

Furthermore, we performed a sensitivity analysis on the production speeds and the number of trucks because these are the input parameters involving the highest uncertainty and for which deviations in the parameter value are expected to have a large impact on the bulk truck planning. Table 1 provides an overview of the performance of the bulk truck planning approach and the performance of the Avebe Planning Tool that we developed, on the performance indicators defined in this research. The performance of the Avebe Planning Tool in Table 1, is based upon the average performance over 10 different input data sets using 8 bulk trucks. These 10 input data sets are obtained by generating production speeds which are uniformly distributed between +10% and -10% of the expected production speeds to account for possible production speed deviations.

Performance indicator	**Performance current planning approach**	**Average performance of developed 'Avebe Planning Tool'**	**Difference**
1. Costs/ton transported	€8.53	€6.14	-€2.39
2. Waiting time in minutes per ton transported	2.85	0.126	-95.58%
3. Factory downtime because of transportation issues	0 min.	46 min.	+46 min.
4. Number of trailers cleaned	Not available	585	Not Available
5. Number of trucks used	10 pool and 2 flex trucks	8 pool and 0 flex trucks	-2 pool and -2 flex trucks

Table 1: Comparison of performance of the current planning approach with the 'Avebe Planning Tool'

From Table 1 we should notice that using the Avebe Planning Tool a potential cost saving of €221,445 during the intercampaign TAK (= 92655 ton * €2.39) can be obtained. This corresponds to a reduction in total transportation costs of 27.52% during the intercampaign TAK (the costs for cleaning, fuel, and trailer rent are not considered in this study for both the current situation and the proposed solution). Discussing this improvement potential with the expert of Avebe, the expert confirmed that a similar cost reduction can be obtained during the other weeks of the year. This implies that the expected yearly potential cost reduction equals €1,151,566. Furthermore, we observe a reduction of 95.58% in waiting time of the bulk trucks and a reduction of 2 pool and 2 flex trucks. All these advantages come at the cost of 46 minutes of factory downtime because of transportation issues over all factories together during the whole intercampaign TAK. This pain of the increase in factory downtime is neglectable when we consider the improvement in terms of cost and waiting time. In the truck schedule generated by the Avebe Planning Tool related to the performance shown in Table 1, 7.43 trucks were needed to perform the normal transport orders and 0.57 trucks to perform the special transport orders.

Concluding, our method to solve the VRPPDTW without a central depot performs well for Avebe. However, the exact quality of the method is hard to measure since we only compared the performance of our planning tool with the performance of the current transport planning approach of Avebe. We furthermore conclude that our developed modified cheapest insertion can be used for all transport processes in which buffers (e.g., silos) are present and there is a demand (e.g., factory or customer) that should be fulfilled by non-compartmentalized homogeneous vehicles. Especially for large transportation processes in which multiple trucks are used, we expect that implementing the logic behind the Avebe Planning Tool will provide good results.

Recommendations and future research

To be able to perform the bulk truck planning with the proposed 8 trucks and to employ the potential cost savings of €221,445 during the intercampaign TAK we advise Avebe to combine the logic behind the Avebe Planning Tool, with the already existing application called the 'ISF app'. Both the truck drivers and the operators at the factory should have access to this combined application, which makes it possible to automatically generate real-time bulk truck planning. However, before Avebe can operationally use this combined application, Avebe should first invest time and money to develop the application, maintain the application, and train its employees on how to use the application.

Furthermore, we advise Avebe to analyze the cost of increasing the storage capacity of the TAK VMF (1000) silo. Our research shows that this silo location is the bottleneck silo. We expect that by increasing the capacity of this silo the number of trucks needed will decrease because the time windows of the orders related to this silo will become larger and therefore the truck planning becomes more flexible. Future research could focus on the implementation of Simulated Annealing improvement meta-heuristics, and alternative order selection methods and priority rules. This will further enhance the optimality of the truck planning generated by the Avebe Planning Tool. Furthermore, the impact of considering the opening hours of the silo locations, deviations in the (un)loading times of the trucks, the possible advantage of using flex trucks, and considering the maintenance stops of the factories could be directions for future research, because assumptions are made related to these process characteristics.

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Reader's guide

This reader's guide provides a concise overview of the information that can be found in the different chapters of this research.

Chapter 1: Introduction

In this chapter, we provide the context description, research motivation, problem statement, problem-solving approach, research objective, research questions, and the research scope.

Chapter 2: The current bulk transport process

In this chapter, we provide insight into the different transportation flows, and the related flow sizes and travel times of the transportation process. Besides, we pay attention to the loading and unloading times, the capacity of the silos, and the current bulk truck planning approach.

Chapter 3: Performance of the current bulk truck planning

In this chapter, we conduct expert interviews and literature research to determine the performance indicators that we use to measure the performance of bulk truck planning. Based on the defined performance indicators, we assess the performance of the bulk truck planning during the intercampaign TAK 2020.

Chapter 4: Literature

In this chapter, we first hierarchically place our planning problem, after which classify the research problem. Based on the classification of the research problem, we conduct literature research to determine our problem-solving approach.

Chapter 5: Model design and validation

In this chapter, we discuss the input data that we use and the assumptions that we make to build the Avebe Planning Tool. Besides, we provide a detailed description of the planning logic consisting of our modified cheapest insertion heuristic. Furthermore, we discuss the steps taken to ensure the validity of the model and to verify whether the model does what we think that it should do. Lastly, we explain how the tool can be used in practice and we show what the tool looks like.

Chapter 6: Experiment design and results

In this chapter, we explain what experiment we do, why we decide to do these experiments, and how we assess the experiment results. Besides, we provide the experiment results on which we do a sensitivity analysis.

Chapter 7: Conclusion and recommendations

In this chapter, we provide the theoretical and practical conclusions of this research. Besides, we formulate recommendations for Avebe based on the insights that we obtained. Furthermore, we discuss the limitations of our research which we translate into possible directions for future research.

Definition of key concepts, variables, and abbreviations

Native Potato Factories (NPF) = Factories located in Gasselternijveen and Ter Apelkanaal (called 'AMF GNV' and 'AMF TAK', AMF stands for 'Aardappel Meel Fabriek') where potatoes are processed into potato starch.

Derivative lines = The non- NPF of Avebe in which native starch is modified to different end products of Avebe.

Campaign = The period in which farmers deliver their potatoes to Avebe's NPF in Gasselternijveen and Ter Apelkanaal (called 'AMF GNV' and 'AMF TAK').

Intercampaign TAK = The period in which the AMF in Gasselternijveen is operational and the AMF in Ter Apelkanaal is not operational.

Intercampaign = The period in which no potatoes are delivered by farmers. Both AMF in Gasselternijveen and Ter Apelkanaal are out of use in this period.

Wet starch = Is starch extracted from potatoes. Wet starch is the output of the NPF.

Native/dried starch = Once the wet starch, which is the output product of the NPF, is dried in one of the dryers of Avebe wet starch becomes native/dried starch.

Matured/aged potato starch = Native/dried potato that is stored for more than six weeks in a sealed silo becomes matured/aged potato starch.

Bulk truck = A truck used by Avebe to transport bulk products between NPF, silos, and customers. The trucks are owned by a transportation company and hired by Avebe. Different trailers are needed to transport native respectively wet starch.

Normal transport = Transport between silos, factories, and customers that should be executed by the hired pool of bulk trucks according to the contract that Avebe has with the transportation company.

Special transport = Transport that is normally performed by trucks outside the hired pool of bulk trucks but can be done by trucks from the pool in case capacity permits.

GNV food = The highest quality starch is called 'GNV food'. GNV food starch is used for human food and there are certain restrictions to the way the starch is treated (e.g., concerning hygiene) to classify the starch as GNV food starch.

TAK food = TAK food starch is the second highest quality of starch. TAK food is of less quality than GNV food starch and is mainly used in food derivatives. The difference between GNV food and TAK food is that for GNV food peracetic acid ('perazijnzuur' in Dutch) is used to clean the starch while for TAK food chlorine bleach ('chloorbleekloog' in Dutch) is used.

TAK food oude droger = The lowest quality of starch is 'TAK food oude droger' starch. TAK food oude droger starch has non-food applications. The starch is cleaned using chlorine bleach but dried using an old dryer that has a conveyor belt which does not fulfill the requirements concerning hygiene to qualify the starch as TAK food starch.

Avebe Planning Tool = The tool that we develop to schedule the pool of bulk trucks during the intercampaign TAK.

Silo/factory down time = The duration that a factory is not operational because of transport issues. When the silo is classified as a push silo, factory downtime occurs in case the output silo preceding the factory is filled. In case the silo is classified as a pull silo, factory downtime occurs when the input silo of the factory is empty.

Earliest Due Date (EDD) = The order's end time window minus the time that the selected truck is available.

Travel, Waiting, and Cleaning time (TWC) = Is the time needed for traveling, waiting, and cleaning. The TWC time depends on the location of the truck selected, the material in the truck, and the transport order to be performed.

1. Introduction

In this chapter, we provide an introduction to the research motivation and the resulting research objective. Section 1.1 provides a brief description of the research context. Section 1.2 discusses the research motivation. Section 1.3 provides the problem context from which we extract the core problem. Section 1.4 gives insight into our problem-solving approach. Section 1.5 formulates the research objective. Section 1.6 states the research questions. Section 1.7 discusses the research scope.

1.1 Context description

The organization that this research focuses on, is Avebe. Avebe is a corporation of approximately 2500 potato farmers and has its headquarters in Veendam, The Netherlands. The core business of Avebe is extracting starch and protein from potatoes. This starch and protein have many applications in, amongst others, the paper, animal feeding, and human food industry. The extraction of starch and protein takes place in the production plants of Avebe which are located in Germany, Sweden, and The Netherlands. These factories process about three million tons of potatoes each year, after which the extracted starch and protein are distributed all over the world. All this is done by approximately 1350 employees of Avebe.

The main challenge that will be tackled in this research is to reduce the cost of bulk transport trucks that are used to transport bulk products between the production facilities, storage locations (silos), and customers of Avebe, without significantly increasing the factory downtime due to supply issues.

1.2 Research motivation

To process the three million tons of potatoes per year and to distribute the extracted starch and protein, Avebe has about 230-kiloton storage capacity divided over different silos in amongst others Ter Apelkanaal, Gasselternijveen, and Foxhol. Processing, transporting, and storing such large volumes yields a complex supply chain.

Roughly speaking, a year can be split into three periods where the start and end date of the period are dependent on the size of the potato harvest, and therefore on the weather. From the first week of September till the third week of February (called 'the campaign') farmers deliver their potatoes to Avebe's Native Potato Factories (NPF) in Gasselternijveen and Ter Apelkanaal (called 'AMF GNV' and 'AMF TAK', where 'AMF' stands for Aardappel Meel Fabriek). Here the potatoes are processed into potato starch. Since the daily capacity of the NPF is larger than the total consumption of the production lines (derivatives), being all factories where potato starch is treated to obtain a specific product, the starch surplus needs to be stored in silos. These silos are located in the northeastern part of the Netherlands.

The second period, called the 'intercampaign TAK', starts directly after the campaign and ends around the second week of May. During this period, some potatoes are harvested but the size of the harvest decreases implying that only the AMF in Gasselternijveen is still operational. To make sure that all production lines have a sufficient supply of starch in this period, part of the production lines should be supplied from silos instead of from the AMF in Ter Apelkanaal.

The third and last period we define is called the 'intercampaign'. Normally, the intercampaign starts directly after the intercampaign TAK and ends when the new potatoes are harvested, around the first week of September. During this period both the AMF in Gasselternijveen and the AMF in Ter Apelkanaal are out of use. This implies that all production lines must be supplied from silos. The campaign differs from the intercampaign in the sense that during the intercampaign, the focus is to transport starch from the silos to the derivative lines, while during the campaign starch should also be distributed among the different silos.

Currently, a dedicated pool of identical bulk trucks is hired twenty-four hours a day and 365 days per year from a transport company to arrange the transport of the starch from the native potato factories to the production lines and the silos. During the campaign, nine of these bulk trucks are used to transport dry starch and three are used to transport wet starch (for wet starch transport another trailer is needed than for dry starch). In the intercampaign TAK and the intercampaign, the starch is transported back from the silos to the production lines by the same pool of hired bulk trucks. During the intercampaign, typically fewer trucks are needed than during the campaign. The reason that fewer trucks are needed during the intercampaign is that no wet starch has to be transported to the production lines. Besides the AMF's are not operational in the intercampaign which implies that there is no transport demand related to the disposal of the AMF's.

Avebe has made the agreement with the external transportation company, that Avebe hires a fixed number of bulk trucks for the whole campaign, intercampaign TAK, and intercampaign to transport bulk products between the factories, silos, some customers. The operational planning of this transport is made by the transportation company. The agreement also involves that when the transportation company encounters overcapacity in terms of trucks for this 'normal' transportation process, the transportation company should use the bulk trucks for 'special' transport of Avebe. Therefore, we define special transport to be transport that is normally performed by bulk trucks outside the dedicated pool of bulk trucks but can be done by trucks from the pool in case capacity permits. While normal transport is the transport the must be done by the hired pool of bulk trucks.

Due to price changes in the transportation sector which make it infeasible for the transportation company to maintain the current contract, a new contract will be active from January 2021 onwards. According to this new contract, Avebe should inform the transportation company on a weekly basis how many of the hired bulk trucks should be used for the normal transportation process, and what special transport should be performed in case of over-capacity. To prevent factory stockouts at the beginning of 2021 from happening, Avebe started in December 2020 with planning as if the new contract is already active. This implies that the decision on the number of trucks used for normal and special transport is made based on a weekly expert meeting. Experts within Avebe describe this planning approach to be time-consuming, and rather arbitrary. The experts do not know how good or bad the resulting planning is.

This uncertainty about the quality of the planning made by expert meetings and the time-consuming character of the current approach, make it interesting to research how this truck assignment to normal and special transport, could be done optimally within reasonable time. Planning this optimally will likely reduce the number of trucks that Avebe has to rent and therefore decrease the cost of bulk transport. Another effect of planning these trucks more optimally could be that bulk trucks in the pool are used more often for customer deliveries, which saves customer delivery costs for Avebe since Avebe has to pay less customer delivery trips which are more expensive than trucks from the pool.

Therefore, Avebe asked to investigate:

"How the pool of hired bulk truck should be planned in order to reduce the transportation costs during the intercampaign TAK"

Important is, that the cost reduction does not come with an increase in the factory downtime. Besides, the optimal planning should be presented such that it supports the decision-making of the planners. Furthermore, the reason for focusing on this period is that the complexity of the transportation flows is the highest during this period of the year therefore extending the focus to the whole year will be easier when we already researched the intercampaign TAK. The research is performed at Avebe within the department of Sales and Operations Planning.

1.3 Problem context and core problem

To tackle the perceived problem of high transportation costs for the hired pool of bulk trucks a clear understanding of the causes for the high transportation costs is needed. Figure 1 shows the problem cluster, derived after meetings with Avebe's Sales and Operations Planning department, providing insights into the causes for the high transportation costs. Below Figure 1, the problem cluster is explained.

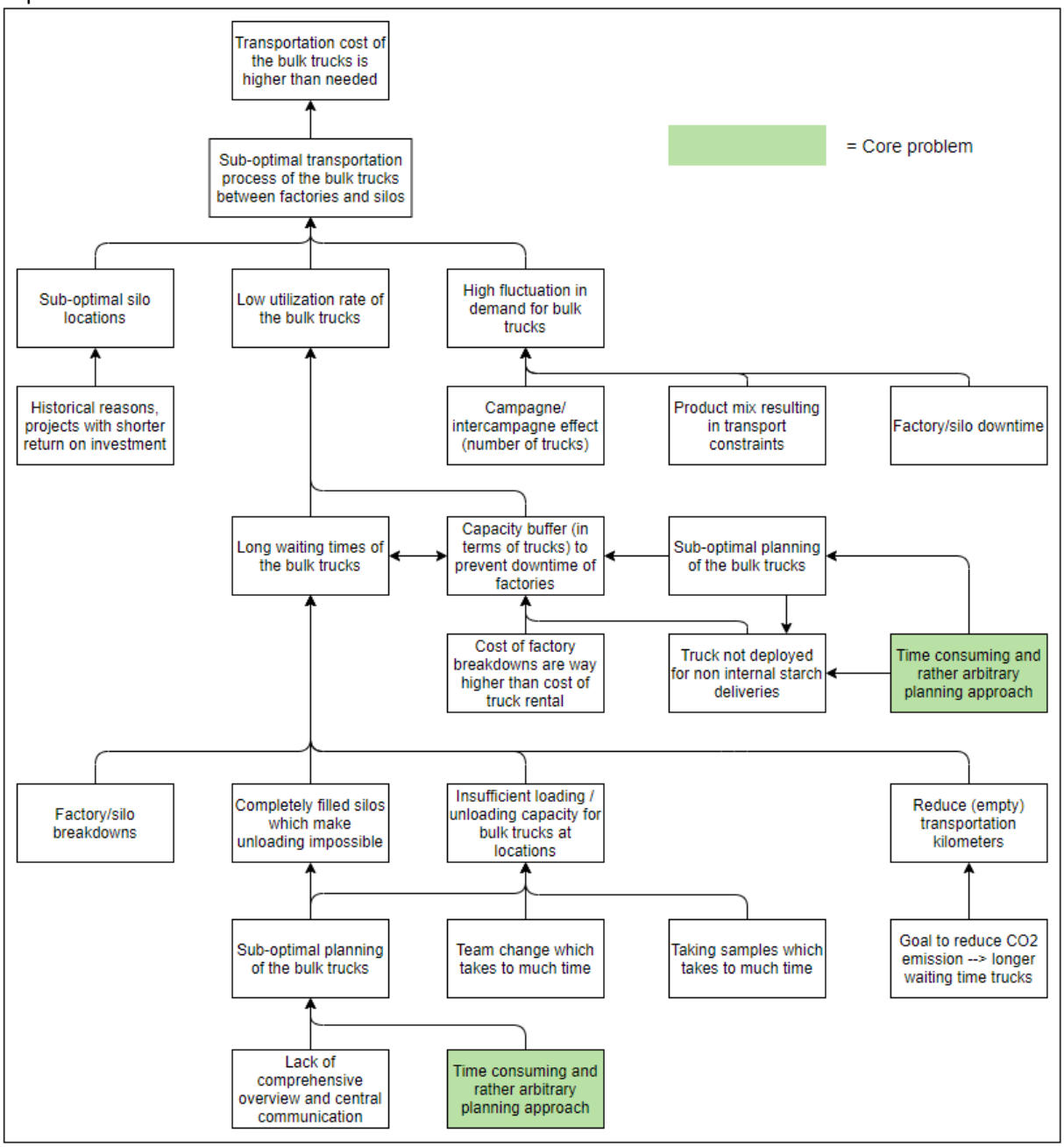

Figure 1: Problem cluster

The reasoning behind the problem cluster is as follows. Within Avebe the feeling prevails that the transportation cost of the dedicated pool of hired bulk trucks is higher than needed. This feeling is based upon the recognition that the transportation process of bulk trucks between factories and silos is sub-optimal. During expert meetings, three causes for this sub-optimality in the transportation process are identified. First of all, the geographical silo locations are sub-optimal for historical reasons. Avebe already investigated that relocating the storage silos is economically attractive. However, currently, there are projects within Avebe that have a shorter payback time and a higher return on investment. These projects are prioritized by Avebe.

Secondly, the high fluctuation in demand for bulk transport contributes to the sub-optimality of the transportations process in the following manner. High fluctuations in demand for bulk trucks make it hard to plan the required number of trucks for each trajectory between factory and silo. Imagine that the demand for transport on each trajectory is 365 days per year the same. Then it is easy to know how many trucks are needed tomorrow given that it is known how many trucks were needed today, namely the same amount. When this is the case, it is easy to make an optimal schedule for the number of trucks on each trajectory. However, within our transportation process, there is a fluctuating demand for bulk trucks making it harder to come up with an optimal planning for the trucks.

This demand fluctuation has three main causes. First of all, the number of trucks needed is different during the campaign, intercampaign TAK, and intercampaign period. This difference implies that we cannot simply organize the transportation process for the whole year in the same manner. The approach in three periods should differ since there is a different demand for trucks in the respective periods. Secondly, the product mix treated at Avebe accounts partly for the fluctuations in the demand for bulk trucks. Roughly speaking Avebe has three different qualities of starch, three different categories of proteins, two different categories of dry flours, and several waxies and customer-specific products. With about 85% of the total volume, starch is the main product of Avebe. To imagine the complexity of only this starch flow, one should know that it is of key importance that starch of lower quality should not be mixed with starch of higher quality since this implies that the higher quality starch is downgraded to the quality of the lower quality starch. To prevent this from happening, factories and silos are dedicated to a specific quality of starch. The resulting capacity separation together with the different processing times for the different qualities of starch cause fluctuations for the bulk transport demand. The third reason for bulk truck demand fluctuation is factory/silo downtimes. Once a factory/silo is down, less starch has to be transported from the factory to the silos. Two types of factory/silo downtimes can be identified as being planned and unplanned factory/silo downtimes. Planned factory/silo downtimes are caused by maintenance and holiday breaks while unplanned factory/silo break downtime is caused by a malfunctioning of the factory/silo.

The third, and for this research most interesting, cause of the sub-optimal transportation process is the low utilization rate of the bulk trucks. A recent study identified that the utilization rate of the bulk trucks is only 65% during the intercampaign (Kuperus, 2020, p. 22). Experts expect this utilization rate to be only a bit higher during the campaign and intercampaign TAK. Clearly, such a low utilization of the main resources results in a sub-optimal process.

Two reasons for this low truck utilization rate are identified. First of all, experts mentioned that there is a buffer of trucks present in the transportation process. The reason for this buffer is threefold. First of all, the planning of the process is focused on minimizing the factory downtime because of transportation issues since factory downtime is much more expensive than the rental costs for the trucks. Secondly, the trucks are hired from and planned by an external transportation company. Avebe has agreed with this transportation company that the transportation company can use the trucks, that Avebe in principle rents for the whole campaign, intercampaign TAK, and intercampaign, for special transport in case that Avebe's trucks are not needed in the normal transportation process. Avebe will then financially benefit from the reassignment of the otherwise unutilized trucks. However, according

to experts this reassignment of the trucks to special transport is not fully deployed, resulting in higher capacity buffers. The reason that the reassignment is not fully deployed is that the trucks initially are not optimally planned, which is caused by the fact that the trucks are planned based on expert experience. Currently, there are no quantitative models on which the experts base their decision. This results in a rather time-consuming and arbitrary planning approach according to these experts themselves. Thirdly, the sub-optimal planning and assignment of the bulk trucks itself also directly increases the capacity buffer present in the process.

Analyzing the output of a system that is used by the truck drivers to keep up the status of their transportation order, yielded the insight that during the intercampaign, trucks are about 32% of the total order fulfillment time waiting (Kuperus, 2020, p. 24). When a truck is waiting, the truck is not fulfilling its core function and therefore not utilized. In this way, the long truck waiting times contribute to the low truck utilization.

During expert meetings, four causes for the long truck waiting times are identified. First of all, factory/silo breakdowns can result in waiting trucks. As mentioned before, two types of factory/silo downtimes can be identified as being planned and unplanned factory/silo downtimes. Planned factory/silo downtimes are caused by maintenance and holiday breaks while unplanned factory/silo break downtime is caused by a malfunctioning of the factory/silo. Unplanned silo breakdowns do not happen often and therefore the impact of this cause on the waiting time will be marginal. A second cause for long truck waiting times is related to Avebe's goal to reduce (empty) transportation kilometers to reduce the company's CO_2-emission footprint. In this way, the company tries to contribute to the worldwide challenge to stop climate change. However, reducing the (empty) transportation kilometers by letting trucks wait until a transport order arrives that is sufficiently close to the current location of the truck will increase the truck waiting time of that specific truck. A third cause for the long truck waiting times is that trucks regularly have to wait for unloading at the silos because the silo is fully loaded. The fact that the silo is fully loaded when a truck driver wants to unload can be explained by a sub-optimal planning of the trucks which is fed by a lack of comprehensive overview and central communication in the current situation. During the trial period (of the new contract) in which experts of Avebe have weekly meetings with the transportation company, the planning is described by experts as being time-consuming and rather arbitrary. Based on this description, the time-consuming and rather arbitrary planning approach seems to be a cause for the sub-optimal planning as well. The fourth and final cause of the long truck waiting times is insufficient loading/unloading capacity at the silos. This capacity can be thought of as the number of loading/unloading docks and/or people. The capacity shortage is caused by the need to take samples of the starch to ensure the product quality (and that mixing of different qualities of starch takes place), team/shift changes, and again a sub-optimal planning of the bulk truck arrivals at the silos. The people at the silos work in three teams which change every eight hours and the truck drivers in shifts of twelve hours. When the teams change, a small impact on the continuity of the process is observed.

Based on the problem cluster in Figure 1 and the explanation of this problem cluster, we formulate the core problem of this research:

"The bulk trucks are planned/assigned in a time consuming and arbitrary way resulting in higher transportation costs than needed."

The reason for choosing this to be the core problem is that we, together with the experts of Avebe, concluded that tackling the time consuming and rather arbitrary planning approach of the bulk trucks, for which we have to create a quantitatively supported model, has the highest reduction of the transportation costs potential while maintaining an acceptable factory downtime. The lack of comprehensive overview and central communication should be solved by someone who knows all the different processes in the company. It will be hard, for me as an external researcher to obtain sufficient

overview of all different processes within half a year in which this research should be conducted. Besides, the impact of doing research on the team changes and taking samples before unloading will be relatively small and is therefore not the core problem of this research. Furthermore, we conclude that the impact of climate change and the resulting goal to reduce the CO_2 emission within Avebe will have less impact on the cost of transportation than the time-consuming and arbitrary planning approach.

1.4 The problem approach

To solve the formulated core problem, several steps should be taken. First of all, we study the current transport planning process and the reasoning behind this. Part of studying the current situation will be visiting the transportation company to also take their perspective into consideration. Based on the current transportation process and planning approach, we will identify causes for the sub-optimality in the current planning of the trucks. These sub-optimalities will be input for a literature study focusing on how similar problems are tackled by others. Besides, we conduct expert interviews at Avebe to gain extra insights and possible solution approaches when needed. Based on the information and insights gathered we develop a model to tackle the identified core problem. The results of this model will then be the input for our recommendation to Avebe and the plan towards implementing the recommendations into practice.

1.5 The research objective

Based on the core problem we derive the following research question:

"How many trucks should Avebe have in the hired pool of bulk trucks, for normal and special transport, during the intercampaign TAK, in order to reduce the total transportation cost without significantly increasing the factory downtime because of transportation issues."

This leads to the following research objective:

"Develop a model/dashboard that provides insight in the number of bulk trucks to be assigned to normal and special transport, during the intercampaign TAK, in order to reduce the total transportation cost without significantly increasing the factory-downtime because of transportation issues."

1.6 The research questions

To achieve our research objective, we divide the research problem into the following research questions. Below each research question, we mention the chapter in which the research question is answered.

1. What is the current bulk transport planning process?
    a. What transportation flows exist?
        - We identify the different transport flows between the silos, production locations, and customers that are facilitated by the bulk trucks. Based on this we will make a separate visual overview for the starch flows during the campaign, intercampaign TAK, and the intercampaign. Furthermore, visualizations of the transportation flows related to proteins, derivatives, dry flours, and customer deliveries will be given. The data needed to make these visualizations will be gathered through expert interviews and the data available within the company concerning all transportation orders that took place in 2020 and the available forecasts for 2021.

b. What are the volumes of the different transportation flows?
   - The transportation volumes for the different flows can be extracted from the data available within the company concerning all transportation orders that took place in 2020. Besides, the sales forecasts for 2021 are considered.
c. What are the transportation times between the different locations?
   - To determine the transportation times between the silos, production locations, and customers we will make use of the addresses of the silos, customers, and the production locations, after which we will determine transport times using Google maps.
d. What are the loading and unloading times at the different locations?
   - To properly assign the bulk trucks, we need to know how long the trucks will be utilized when they are assigned to a certain job. Therefore, the traveling times which as well as the time needed for loading/unloading are important. We will provide the loading and unloading times, which are material dependent, partly based on historical data and partly based on expert interviews.
e. How are the bulk trucks currently planned?
   - To get an insight into how the planning of bulk trucks currently is done, we will have expert interviews with both experts from Avebe and the transportation company.

2. What is the performance of the current bulk truck planning?
   a. How can we measure the performance of the bulk truck planning?
      - The performance indicators to assess the bulk truck planning are determined through expert interviews and by consulting recent literature.
   b. What is the performance of the current bulk truck planning?
      - The performance of the current bulk truck planning will be assessed based on the performance indicators obtained by answering question 2a.

3. What modeling approach present in the literature can best be applied to plan the pool of hired bulk trucks?
   a. How can our research problem be hierarchically placed?
      - According to the framework of Hans et al. (2012), a research problem can be defined as a strategical, tactical, offline operational, or online operational problem which we refer to as hierarchical levels. We will hierarchically place our research problem by adapting the framework of Hans et al. (2012) to the transport planning context.
   b. To which class of problems does our research problem belong?
      - We will first determine the problem class to which our research problem belongs (e.g Transport Problems, Machine Scheduling problems, or Vehicle routing problems). Once we determined the problem class, we will define the research problem in more detail using the taxonomy of Lahyani et al. (2015). This detailed classification will help us to determine what modeling approaches might be successful to fulfill our research goal.
   c. Which models, present in the literature, can be applied to our problem?
      - We identify the type of model that suits our research best by analyzing the different flavors of the model we concluded by answering question 3b. The literature research will be performed by employing the 'Scopus' database.
   d. What optimization model or heuristic can best be applied/adjusted to our research?
      - We will answer this question based on the insights obtained by answering question 3c.

4. What is the logic behind the Avebe Planning Tool that we build?
   a. What input data do we use to build the Avebe Planning Tool?
      - We explain what input data we use to build the Avebe Planning Tool and how we obtain the input data. The Avebe Planning Tool is the model that we build to schedule the bulk trucks during the intercampaign TAK in order to answer the main research question of this research being: *"How many trucks should Avebe have in the hired pool of bulk trucks, for normal and special transport, during the intercampaign TAK, in order to reduce the total transportation cost without significantly increasing the factory downtime because of transportation issues."*
   b. What assumptions do we make to build the Avebe Planning Tool?
      - We explain the assumptions that we made to build the Avebe Planning Tool.
   c. What decisions are made in the Avebe Planning Tool?
      - We explain step by step how the Avebe Planning Tool generates a bulk truck planning. We devote special attention to our experiments with different order selection methods and to our priority rule.
   d. How is the Avebe Planning Tool verified and validated?
      - We explain the steps that we took to verify and validate the Avebe Planning Tool.
   e. What does the resulting Avebe Planning Tool look like?
      - We provide insight into how the Avebe Planning Tool should be used and how the dashboard of the tool should be interpreted.

5. What is the performance of the different parameter settings in the Avebe Planning Tool?
   a. What experiments are interesting to do?
      - We explain what experiments we perform with the Avebe Planning Tool and why we decide to do these experiments.
   b. How are we going to assess the performance of the experiments?
      - We explain how the performance of the experiments will be assessed and how we obtain the assessment method.
   c. What input parameters should we perform a sensitivity analysis on?
      - We explain on which input parameters we will perform a sensitivity analysis and why we decide to perform a sensitivity analysis on this input data.
   d. How can the performance of different parameter settings be explained?
      - We provide interpretation to the observed performances of different parameter settings of the Avebe Planning Tool. Besides, we discuss additional insight that can be obtained for the experiment results.

6. What is our advice to Avebe based on this research?
      - By answering this research question, we translate our results into a conclusion. Based on this conclusion, we write a recommendation for Avebe. This recommendation also provides insight into how Avebe should use the Avebe Planning Tool in the future.

Now that we translated the research objective into research questions, we will define the scope of this research in the next section.

1.7 Scope

In this section, we describe the research performed by Kuperus concerning the bulk transport process. The research of Kuperus will, together with the problem identification, research goal, and research questions that we defined above, be used to define the scope of this research.

Kuperus' research consists of a simulation study investigating the impact of four different factors on the two main output measures, being the number of unloading silo runouts per simulation run (economical KPI) and the average empty driven distance in kilometers per order (sustainability KPI). The first factor of analysis in the research of Kuperus is the number of trucks in the pool of vehicles. The second factor is the impact of different assignment rules for assigning trucks to orders is investigated. Thirdly, two different repositioning policies for the bulk trucks are evaluated. These policies are waiting at the last delivery location and moving back to the last pickup point. The fourth and last factor of analysis in the study of Kuperus is implementing the diversion capability for the bulk trucks. This means that empty trucks can immediately change their destination to serve a new order.

The focus of this research will be on the assignment of the bulk trucks to the normal and special transportation orders during the intercampaign TAK. Our goal is to develop a model/dashboard that provides insight into the number of bulk trucks to be assigned to normal and special transport, during the intercampaign TAK, in order to reduce the total transportation cost without significantly increasing the factory downtime because of transportation issues. To achieve this goal, the current way of planning the bulk trucks and the current state-of-the-art literature on similar planning problems will first be taken as input to develop our planning tool.

2. The current bulk transport process

In this chapter, we analyze the current transportation process and the assignment of pool trucks to the different transport demands in order to answer the first research question defined in Section 1.6. To analyze the various transportation flows present we categorize them based on the material type. Five types of material categories can be distinguished being starch, protein, derivatives, dry flours, and waxy. Next to these five material categories, we define a sixth category which contains the customer deliveries. All transportation flows discussed in this chapter must be executed by the dedicated pool of bulk trucks according to the new contract, unless stated otherwise.

Section 2.1 explains the transportation flows for each of the six categories that we defined. Once we understand the flows that are present, we present the volumes and transportation distances of the flows. The results in Section 2.1 are supported by visualizations. Section 2.2 provides an analysis of the loading and unloading times of the bulk trucks at the silos, factories, and customers. Section 2.3 provides insight into the capacity of the silos that are used in the transportation process.

Based on the information gathered in the sections up until Section 2.3, we analyze the current bulk truck assignment approach of Avebe and the transportation company in Section 2.4. This analysis is based upon interviews with planners at the transportation company and Avebe. Furthermore, observations from the planning-related meetings are incorporated. Lastly, Section 2.5 reflects the differences between the transportation flows and the current bulk truck planning approach.

The insights that we gain in this chapter are input to our investigation of the performance of the current truck planning in Chapter 3, our literature study in Chapter 4, and the model that we develop in Chapter 5.

2.1 The transportation flows, volumes, and distances

In this section, we analyze all transportation flows executed by the pool of bulk trucks that Avebe hires from the transportation company. To structure this analysis, sub-sections 2.1.1 till 2.1.5 below focus on one product flow being:

- Sub-section 2.1.1 analyzes the starch product flow.
- Sub-section 2.1.2 analyzes the protein product flow.
- Sub-section 2.1.3 analyzes the derivatives product flow.
- Sub-section 2.1.4 analyzes the dry flours product flow.
- Sub-section 2.1.5 analyzes the waxy product flow.

However, Sub-section 2.1.6 does not contain just one product type. Instead, Sub-section 2.1.6 discusses the transportation flows related to customer deliveries. At the end of each sub-section, we will refer to the appendices in which the transportation times are given using visual overviews.

2.1.1 Transportation flows, volumes, and distances: Starch

This sub-section first indicates the total transport volume of the starch flows. Secondly, the three different levels of starch quality and three different states of starch are distinguished. Then the impact of nature on the production and transportation process of starch, resulting in three different periods is explained. Lastly, the actual starch transportation flows are explained using visualizations of these flows.

Three levels of starch quality
Yearly the pool of hired bulk trucks transports about 330 kiloton starch (1 kiloton is equivalent to 1 million kilograms). The average weight transported by a single truck is about 26,350 kilograms. This implies that the hired pool of bulk makes about 12,525 trips per year to transport the starch of Avebe, where potato starch entails about 85% of the total volume transported by the pool of bulk trucks.
Within Avebe, three different levels of starch quality are distinguished. The highest quality starch is called *'GNV food'*. The flows of GNV food quality starch are indicated by the black arrows in Figure 2. As the name suggests, GNV food starch is produced at the AMF in Gasselternijveen. GNV food starch is used for human food, such as noodles, and there are certain restrictions to the way the starch is treated (e.g., concerning hygiene) to classify the starch as GNV food starch.

The second quality of starch is called *'TAK food'*. TAK food starch is of less quality than GNV food starch and is mainly used in the dairy industry. The reason for the quality difference between TAK and GNV food starch is that for GNV food peracetic acid ('perazijnzuur' in Dutch) is used to clean the starch while for TAK food chlorine bleach ('chloorbleekloog' in Dutch) is used. TAK food starch is produced at the AMF in Ter Apelkanaal. The blue arrows in Figure 2, indicate the related flows.

Lastly, we have *'TAK food oude droger'* starch which is the lowest quality starch available and has non-food applications in amongst others paper, glue, and building materials. TAK food oude droger is also produced at the AMF in Ter Apelkanaal and cleaned using chlorine bleach. The distinction between TAK food and TAK food oude droger results from the fact that TAK food oude droger starch is dried using an old dryer that has a conveyor belt that transports the starch in the open air. Open-air transportation does not fulfill the requirements concerning hygiene to qualify the starch as TAK food starch.

Key in the transportation process is that starch of lower quality should not be mixed with starch of higher quality, since this implies that the higher quality starch is downgraded to the quality of the lower quality starch. To prevent this from happening, factories and silos are dedicated to a specific quality of starch.

Three states of starch
Next to different qualities of starch, starch can also have three different states. Once the potatoes are processed in one of the AMF's, the potatoes become *wet potato starch*. To extend the shelf life and the applications of the wet potato starch, the starch should be dried. Therefore, the second state of starch is *dried potato starch*. Lastly, dried potato starch that is stored for more than six weeks in a sealed silo becomes *matured potato starch*. These three starch states are important since some factories, for example, the Extruder and Dextak (see Figure 2), can only process matured starch and therefore should always be supplied from a silo.

Three periods in a year
The last factor that influences the transportation flows of starch is nature. Due to seasonal effects, we split our analysis into three periods. Each of these periods has its own transport demand. The first period is the *campaign*. In the campaign, potatoes are harvested and processed in the AMF's in Gasselternijveen and Ter Apelkanaal. Depending on the weather and the resulting potato harvest, this period starts around the first week of September and ends in the third week of February.

In Figure 2, the starch transported by the bulk trucks during the campaign is visualized. The bulk transport executed by the hired trucks starts directly after the AMF's in Gasselternijveen and Ter Apelkanaal. From the AMF in Gasselternijveen the obtained starch can go in three directions. First of all, the starch can be transported towards the starch packing/bulk sales factory which is located next to the AMF GNV. This transport is arranged using pipelines. Customers of Avebe pick up their bulk or packed starch orders at the starch packing factory themselves. Therefore, the hired bulk trucks are not involved in this first starch flow.

The second starch flow is from the AMF in Gasselternijveen to one of the four silos, summarized under the name 'Silo GNV', located next to the AMF GNV. This transport is again arranged by pipelines. From the silo GNV, the dried starch can be transported towards three different (outside) silos being 'Euro' located in Veendam, 'OKO' located in de Krim nearby Coevorden, or 'Hollandia' which is located in Nieuw-Buinen. All of the transport is arranged by the hired bulk trucks. When the dried starch becomes matured starch part of the matured starch stored in silo 'OKO' will be transported, again employing the hired bulk trucks, to the Dextak factory located in Ter Apelkanaal. The other starch stored in the silos will be transported during the intercampaign TAK or during the intercampaign.

The last starch flow originating from the AMF in Gasselternijveen is the pipeline towards 'Omo/Silo 13' (different names for the same silo) located next to the AMF in Gasselternijveen. The transportation in this flow is fully arranged by pipelines.

Looking at Figure 2 again, we can also distinguish five different flows that originate from the AMF in Ter Apelkanaal. These flows can be interpreted similarly. However, it is important to notice that from the AMF in Ter Apelkanaal we have TAK food, TAK food oude droger, and wet starch flows as indicated in the legend. The numbers on top of the arrows in Figure 2, provide the size of the transportation flow in kiloton based upon historical data between 1-8-2019 and 1-8-2020. Appendix A.1.1, provides the travel times in minutes.

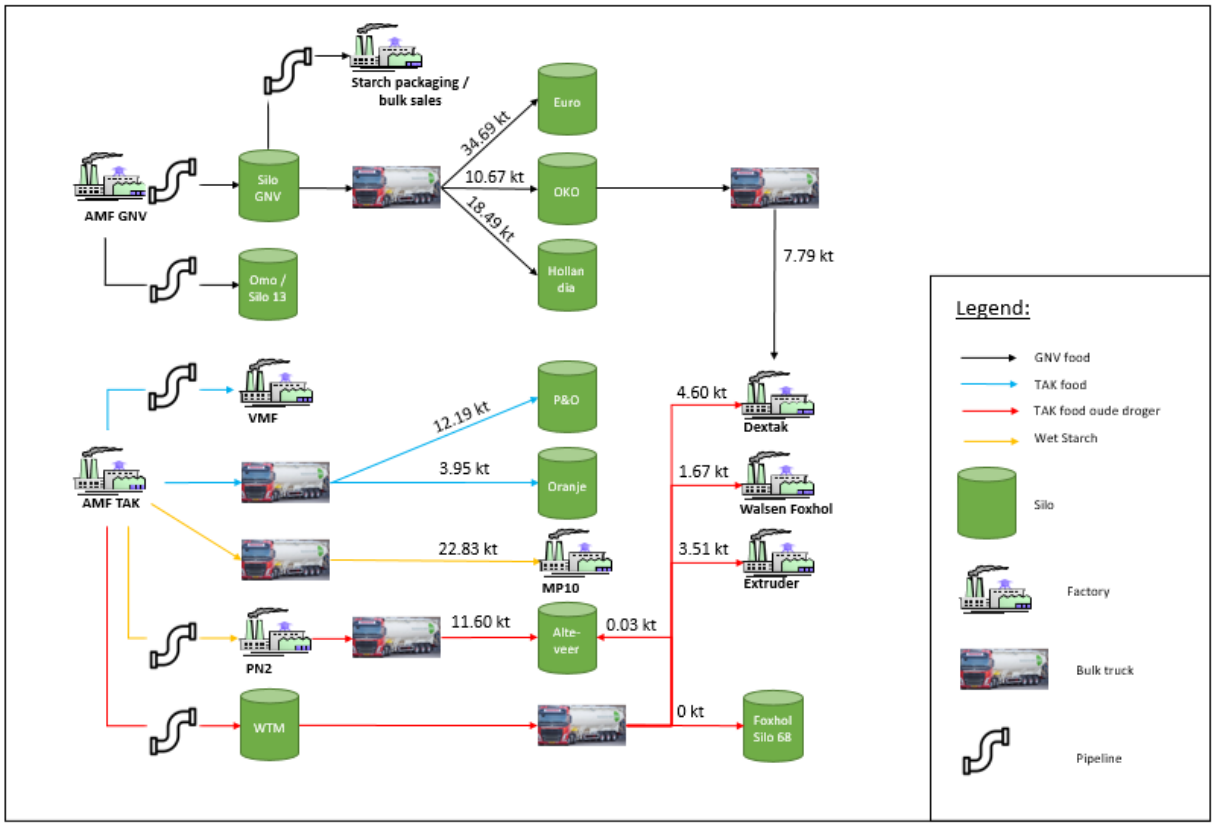

Figure 2: Starch transportation flows during the campaign, flow sizes are in kiloton

The intercampaign TAK

The second period is called the 'intercampaign TAK'. In this period the AMF of Gasselternijveen is still processing potatoes, while the AMF of Ter Apelkanaal is shut down. The intercampaign TAK starts directly after the campaign and ends around the second week of May, again depending on the weather conditions. Comparing the transportation flows during the campaign (Figure 2) and the intercampaign TAK (Figure 3) several differences can be observed.

The VMF is directly supplied from the silo GNV and silos Euro, OKO, Hollandia, P&O, and Oranje in the intercampaign TAK. The reason for this is that the AMF TAK is no longer processing potatoes since the volume of the harvested potatoes decreases and therefore can completely be handled by the AMF in Gasselternijveen. To keep the VMF running, the factory should therefore be supplied with starch stored in silos. The same principle holds for the factories Dextak, Extruder, Walsen Foxhol, and MP10, during the campaign these factories are supplied from the AMF in Ter Apelkanaal, but during the intercampaign TAK, these factories are kept running by supplying starch from the silos. The PN2 is only operational for starch during the campaign and therefore not present in Figure 3.

The numbers on top of the arrows in Figure 3, provide the size of the transportation flow in kiloton based upon historical data between 1-8-2019 and 1-8-2020. Appendix A.1.2, provides the travel times in minutes.

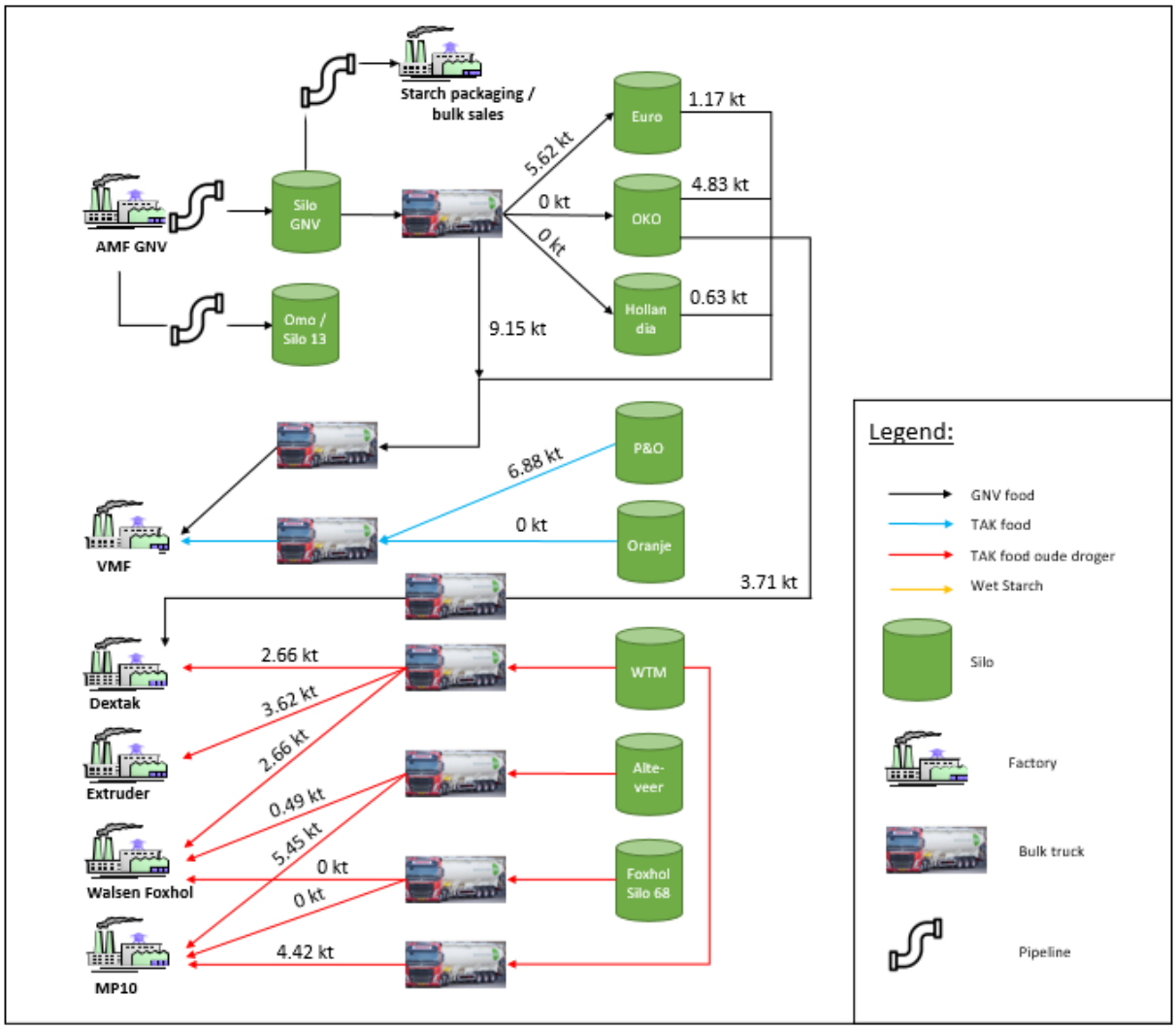

Figure 3: Starch transportation flows during the intercampaign TAK, flow sizes are in kiloton

The intercampaign
The third and last period we define is called the 'intercampaign'. Normally, the intercampaign starts directly after the intercampaign TAK and ends when the new potatoes are harvested, around the first week of September. During the intercampaign, both the AMF in Gasselternijveen and Ter Apelkanaal are out of use since no potatoes are harvested or processed in this period. The fact that both AMFs are out of use in this period, implies that all production lines must be supplied from silos which is shown in Figure 4.

The numbers on top of the arrows in Figure 4, provide the size of the transportation flow in kiloton based upon historical data between 1-8-2019 and 1-8-2020. Appendix A.1.3, provides the travel times in minutes.

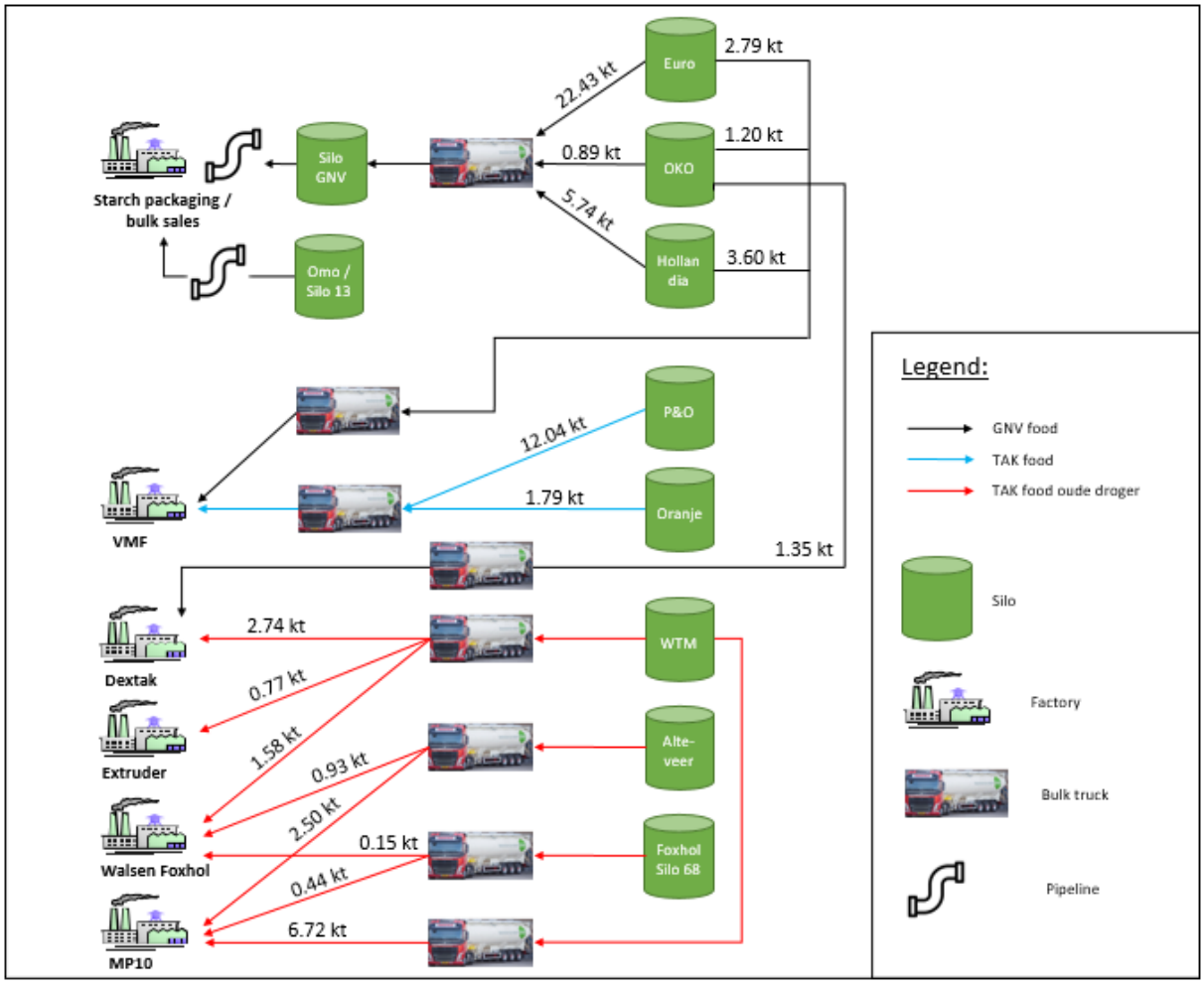

Figure 4: Starch transportation flows during the intercampaign, flow sizes are in kiloton

Now that we analyzed the starch flows during the three different periods of the year, the next sub-section will focus on the transportation flows of protein.

2.1.2 Transportation flows, volumes, and distances: Protein

In this sub-section, we analyze protein flows that are related to transport executed by the hired pool of bulk trucks. In the past, Avebe only extracted starch from the harvested potatoes at the AMF in Gasselternijveen and Ter Apelkanaal. When the starch was extracted, Avebe had some waste. This waste partly consisted of potato protein which was discharged in rivers. The protein in the rivers resulted in foam on the surface of the rivers. However, for a few years, the potato protein has an

application as well and therefore the protein starch became a valuable product instead of waste for Avebe. The potato protein has applications in amongst others the animal feed industry.

Three types of potato feed proteins are made by Avebe, which are Protastar, Protamylasse, and Protamyl. In Figure 5, we see that at the AMF GNV Protastar and Protamylasse are transported using pipelines to silos which are also located in Gasselternijveen. Looking at the Protastar flow we distinguish two options. The first option is to transport the Protastar from the silo in Gasselternijveen to a big bag installation, which is also located at Gasselternijveen, using pipelines. The big bags are then transported to a warehouse from where they are delivered to customers. All of this transport is executed by non-bulk trucks. However, Protastar from Gasselternijveen is also partly transported towards Ter Apelkanaal employing bulk trucks. In Ter Apelkanaal, the Protastar will then be packed in small bags which are sold to customers.

Looking at the Protamylasse flow, we observe that Protamylasse is made at both AMF's and stored in silos next to these AMF's using pipelines. When the Protamylasse silo at Ter Apelkanaal is filled for more than 70%, the Protamylasse is transported to the Protamylasse silo in Gasselternijveen. This 70% rule on the volume of the silo is set because of a fluctuating demand of customers of Avebe for Protamylasse. For this transport, a bulk truck is used.

Lastly, Protamyl is made at the AMF in Ter Apelkanaal and stored in a silo next to the AMF. From this silo onwards, the Protamyl can be packed in small bags and sold or transported in bulk using a bulk truck towards a customer of Avebe in Haulerwijk.

The numbers on top of the arrows in Figure 5, provide the size of the transportation flow in kiloton, which is partly based upon the forecast for 2021, and partly based upon historical data between 1-8-2019 and 1-8-2020. Appendix A.2 provides the related travel times in minutes.

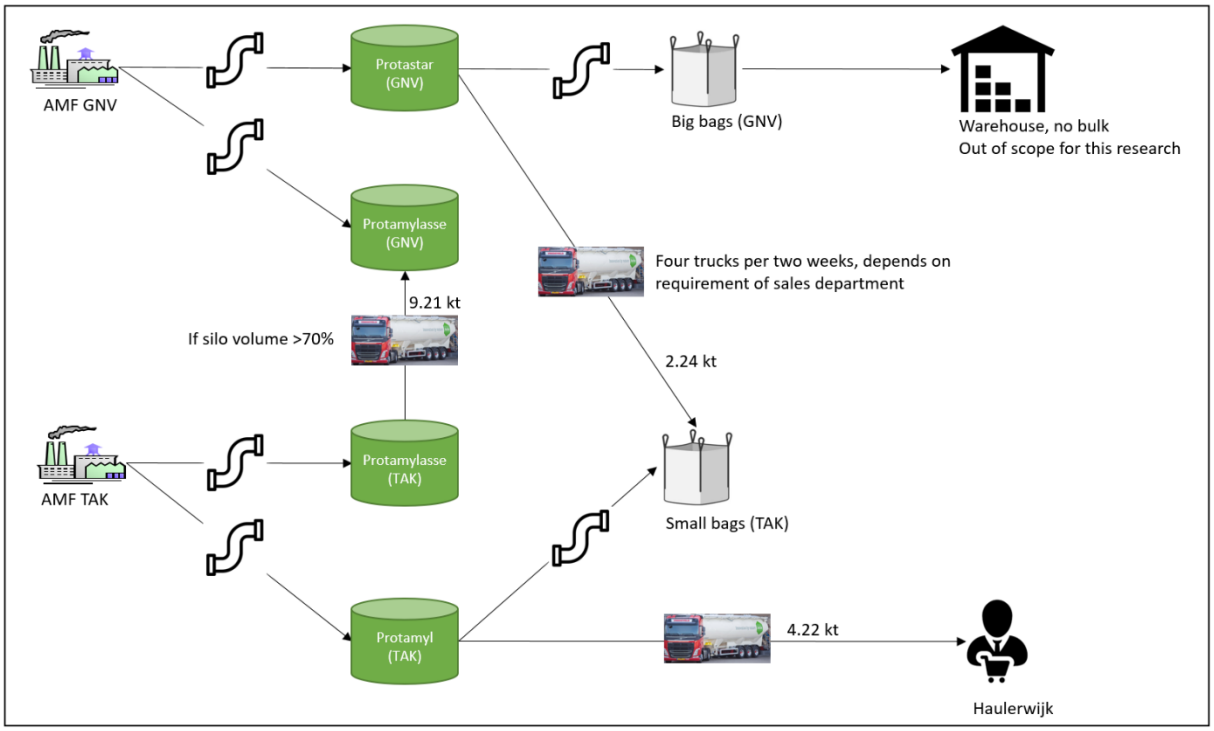

Figure 5: Protein transportation flows, flow sizes are in kiloton

2.1.3 Transportation flows, volumes, and distances: Derivatives

In this sub-section, we analyze the derivative flows. Figure 6, visualizes the derivative flows which can be separated into two flows. These two flows originate from the fact that the MP10 has several chemical reaction tubs that are used to make Oxies and Cation. However, the production of Oxies and Cation alternate. First Oxies are produced for five consecutive days, then Cation is produced for five consecutive days, and so on. When Oxies are produced at the MP10, Cation support production will take place at the PN2 meaning that Cation is made at the PN2. This corresponds to the top flow in Figure 6.

However, when Cation is made at the MP10 the PN2 is out of use which corresponds to the bottom flow in Figure 6, which is also present when the Cation support production takes place on the PN2. From silo Foxhol the Oxies are transported, using bulk trucks, toward hired silos 1 and hired silo 2 that Avebe hires. Hired silo 1 is located in Coevorden and hired silo 2 in Gieten. The same holds for the transportation of Cation from the TAK silo. The numbers on top of the arrows in Figure 6, provide the size of the transportation flow in kiloton which is based upon the forecast for 2021. Appendix A.3 provides the related travel times in minutes.

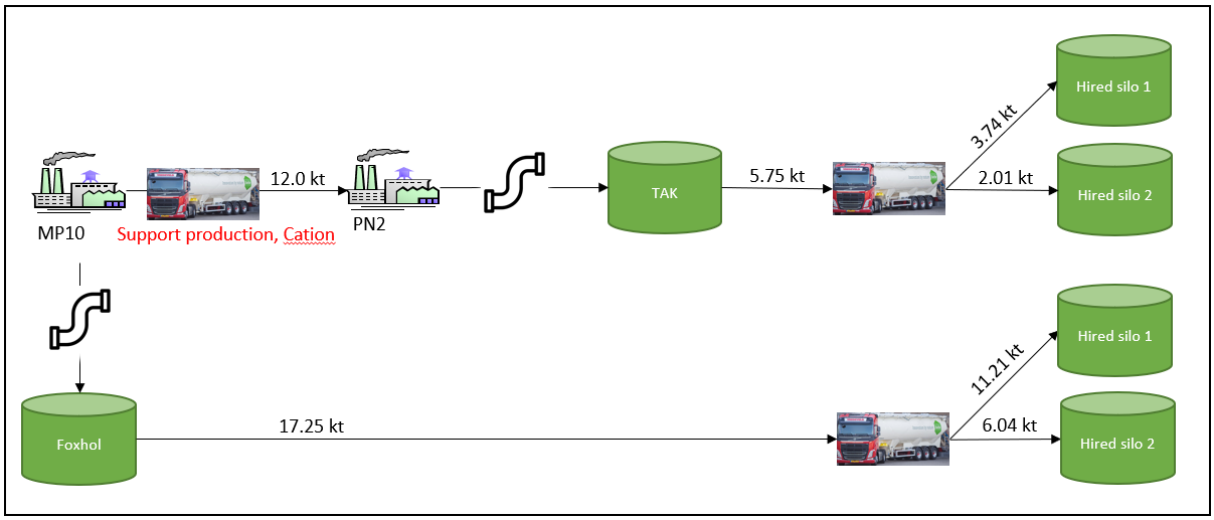

Figure 6: Derivatives transportation flows, flow sizes are in kiloton

2.1.4 Transportation flows, volumes, and distances: Dry flours

In this sub-section, we analyze the transportation flow related to dry fours Perfectamyl D8 and Perfectamyl D12. The difference between these two types of Perfectamyl is their humidity. The humidity of the Perfectamyl depends on the rotational speed of the dryer and the duration of drying at the AMF in Gasselternijveen. Perfectamyl D8 has a humidity of 8% while Perfectamyl D12 has a humidity of 12%. Figure 7, visualizes the transport related to the two types of Perfectamyl, which is identical and self-explanatory. The numbers on top of the arrows in Figure 7, provide the size of the transportation flow in kiloton which is based upon the forecast for 2021. Appendix A.4 provides the related travel times in minutes.

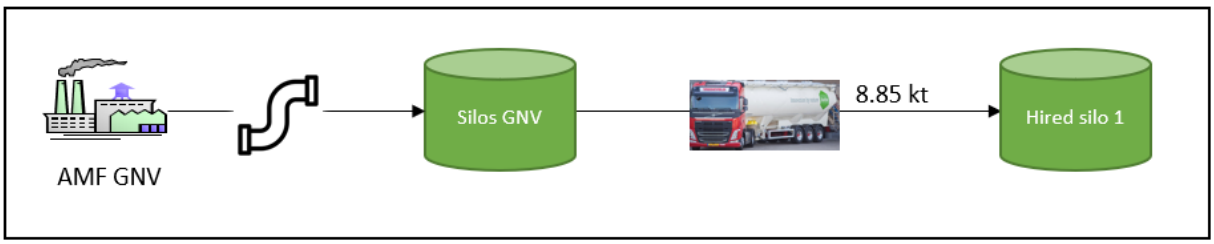

Figure 7: Dry flours transportation flows, flow sizes are in kiloton

2.1.5 Transportation flows, volumes, and distances: Waxy

In this sub-section, we analyze the transportation flows related to Waxy. Waxy is potato starch extracted from a genetically manipulated potato variety. Waxy potato starch is different from 'normal' potato starch in the sense that normal potato starch is composed of both amylose and amylopectin whereas Waxy potato starch only contains amylopectin. This results in stickier starch with other applications than 'normal' starch. Waxy starch is amongst others used in the textile industry to make sure that clothes wear less quickly.

Figure 8 visualizes the Waxy transportation flows. The transportation flows can be split into three different flows. First of all, the bulk truck transport flow from hired silo 3 in Veendam towards the four derivative lines. Secondly, Waxy is transported from hired silo 4 in Ter Apelkanaal to the train in Coevorden. Every Tuesday and Friday containers with Waxy can be transported to Customer 1 in Sweden. Being only able to transport the Waxy on Tuesday and Friday results in a fluctuating demand for transport according to the planner of this trajectory.

The third Waxy flow is the flow from hired silo 5 in Coevorden towards customers Customer 2 in Stampersgat and Customer 3 in Rotterdam. The transport of these flows can optionally be executed by a truck from the hired pool of bulk trucks. However, this is only done when one of the trucks in the hired pool is not utilized. Therefore, these two flows are classified as special transport flows. When it is possible to perform this transport by using a bulk truck from the hired pool it is favorable for Avebe since it saves the company the payment of a truck outside the hired pool of bulk trucks, and the bulk trucks in the pool are hired 24/7 anyway. The numbers on top of the arrows in Figure 8, provide the size of the transportation flow in kiloton which is based upon the forecast for 2021. Appendix A.5 provides the related travel times in minutes.

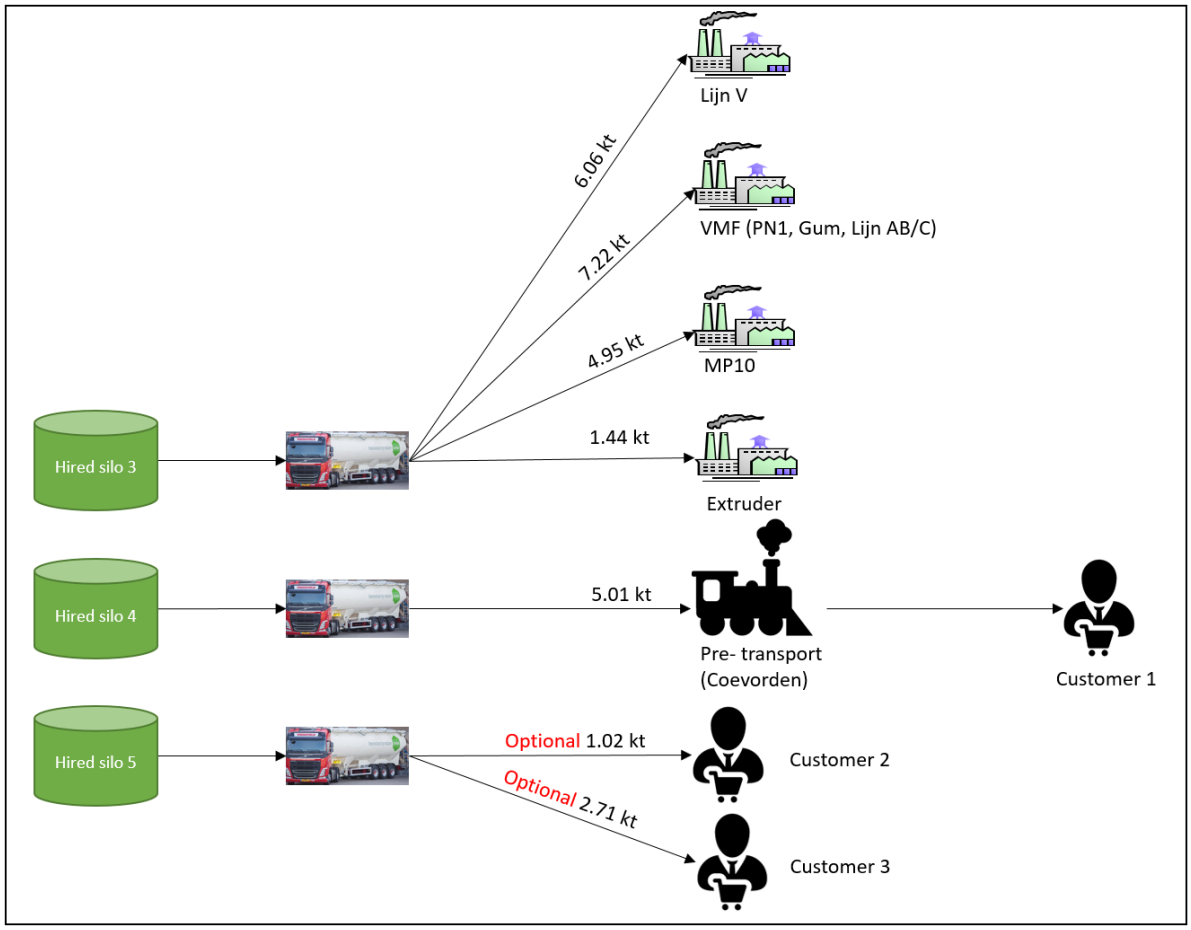

Figure 8: Waxy transportation flows, flow sizes are in kiloton

2.1.6 Transportation flows, volumes, and distances: Customer deliveries and pre-transport

In this sub-section, we analyze the transportation flows related to the customer deliveries and the pre-transport towards the train in Coevorden. Figure 9 visualizes these transportation flows. In this figure, flows of different materials are given. The numbers between brackets on top of the arrows are the material numbers. Similar to the Waxy flows discussed in Sub-section 2.1.5, we have some optional flows (special transport) related to customer deliveries as well. The optional flows are the starch flows from the AMF in Gasselternijveen to the factories of Customer 2 and Customer 3. For these flows again holds that they do not have to be performed by the pool of bulk trucks according to the new contract, but it is financially attractive to do so when possible.

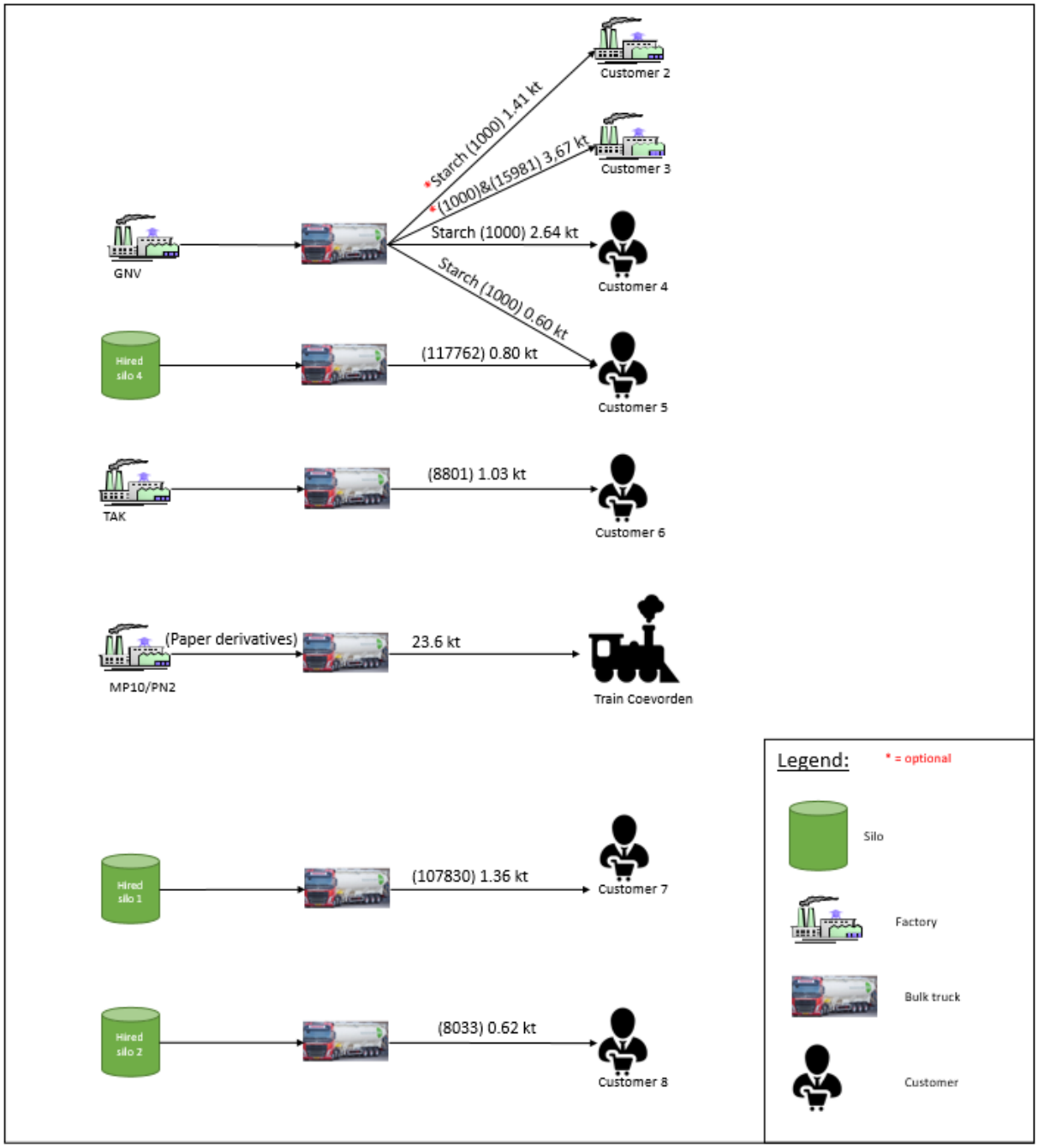

Figure 9: Customer deliveries and pre-transport transportation flows, flow sizes are in kiloton

Figure 9 also shows that we have again pre-transport of paper derivatives towards the train in Coevorden. As for the waxy flow, this train transport to Sweden only takes place on Monday and Friday which results in fluctuating demands for bulk trucks.

All other flows present in the figure are self-explanatory. Table 2 provides the locations of the customers present in Figure 9 and their demand expressed in kiloton.

Customer	**Location**	**Volume in kiloton**
Customer 4	Veendam	2.64 kt
Customer 5	Zwolle	1.40 kt
Customer 6	Meppel	1.03 kt
Customer 7	Dörpen (Germany)	1.36 kt
Customer 8	Eerbeek	0.62 kt
Customer 2	Stampersgat	2.43 kt
Customer 3	Rotterdam	6.38 kt
Pre-transport	Coevorden	28.61 kt

Table 2: Customer locations

The numbers on top of the arrows in Figure 9, provide the size of the transportation flow in kiloton. The transport volumes, of the customer deliveries and pre-transport, are based upon the forecast for 2021 related to these transportation flows. The volumes of the transportation flow to Customer 2 and Customer 3 are based upon historical data between 1-8-2019 and 1-8-2020. Appendix A.6 provides the related travel times in minutes.

2.2 Loading and unloading times

To properly schedule the bulk trucks, we need to know how long it takes before the truck can be scheduled for its next job in case the truck is assigned to a certain job. This time can be split into several time-consuming activities being loading, unloading, and the transport itself. Furthermore, the trucks should also be cleaned now and then. The frequency of cleaning is dependent on the type of material transported and on the frequency of changes in the material to be transported in the trailer. Besides, it can occur that a sample of the freight must be taken to check its quality or that the truck has to wait at the loading or unloading dock because of the dock being occupied or the silo is full or empty. Appendix A provides the transport times in minutes for the different transport flows discussed in Section 2.1. In this section, we analyze the loading and unloading times of the trucks.

During expert interviews with the line planners of Avebe, we encountered that the loading and unloading times vary among the silos dependent on the loading/unloading systems available at the silo and the product that is loaded or unloaded. Furthermore, the loading time is longer when a truck has to be loaded by emptying big bags compared to directly loading from the silo by means of screws or dump valves.

Table 3 provides the average and standard deviation of the loading and unloading times in minutes at the different silos used to load and unload starch. The loading and unloading times are determined using historical data of the period 1-8-2019 to 1-8-2020. This data is gathered in an application that bulk truck drivers use when they transport starch. The drivers upload every step of the transportation process. Examples of steps are, start loading, end loading, start driving, arriving at the unloading location, start unloading, and end unloading. Based on the time difference between start (un)loading and end (un)loading we determine the loading and unloading times.

Note that the drivers have to manually upload the steps in the application which sometimes results in misclicks in the application or steps that are forgotten meaning that the driver uploads the completion of several steps at once. This yields that according to the data several steps are completed in one minute. To filter out these administration-related mistakes in the data, we only considered loading and unloading times between five minutes and three hours based on expert advice. Appendix B.2 provides histograms showing the empirical distribution of the loading and unloading times at the starch silos present in Table 3.

For the transportation flows of protein, derivatives, dry flours, waxy and customer deliveries no truck driver application is used. This implies that we do not have data about the loading and unloading times in these transport processes. In order to derive realistic loading and unloading durations, expert interviews are conducted with the line planners of Avebe. The line planners were asked to provide the average loading and unloading times of bulk trucks at the production lines that they plan. Appendix B.3 presents these loading and unloading times.

Starch silo	**loading time (in min.)**		**Unloading time (in min.)**	
	Average	*Std. Dev.*	*Average*	*Std. Dev.*
GNV Silo 1	62.55	27.99	57.73	15.66
GNV Silo 2	60.66	26.25	64.62	27.84
GNV Silo 3	77.00	22.63	61.66	23.20
GNV Silo 4	62.59	23.11	60.27	22.07
Euro Veendam	36.31	19.87	81.22	18.84
OKO	52.85	17.98	61.99	15.59
Hollandia	61.59	18.42	68.53	19.69
P&O	30.45	17.18	80.96	18.70
Oranje	64.61	31.39	76.05	19.28
WTM	68.75	25.72	n/a	n/a
Alteveer	79.13	25.49	52.88	12.56
Foxhol/Silo 68	91.11	45.51	74.78	28.42

Table 3: Average and standard deviation of the loading and unloading times in minutes at the different silos used to load and unload starch

2.3 Storage capacity of silos

In this section, we provide the storage capacities of the silos involved in the transportation process described in Section 2.1. These silo capacities will become when building our model later on.

Table 36 in Appendix B.1 provides the storage capacities of the silos in tons (1 ton equals 1000 kilograms). The information present in the table is partly based upon data available within Avebe and partly based upon expert interviews.

2.4 The current bulk truck planning approach

In this section, we analyze the current bulk truck planning approach based upon expert interviews with the responsible planners from both Avebe and the transportation company. Furthermore, we incorporate the observations from the weekly meetings that the planners of both companies together have. The current planning approach provides us with insights into the complexity and restrictions present. Besides, analyzing the current planning approach helps to map the available potential. The current bulk transport planning process can be split into four consecutive phases which are repeated every week. Figure 10 provides a process flow of the current bulk truck planning approach consisting of four phases. Each of these four phases will be discussed below.

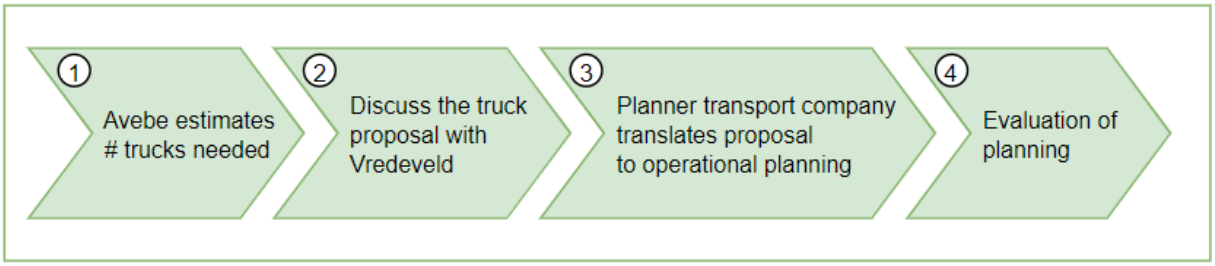

Figure 10: Process flow of the current bulk truck planning approach

Phase 1: Determine the number of trucks needed for each transportation flow by Avebe
In Phase 1, the planner of Avebe calculates the number of trucks needed for the coming week. To do so, he splits the total transportation process into the production lines. For each of the production lines, he receives the planned production volume in tons for the coming week from the responsible Sales and Operations Planner (S&OP). These production volumes for each production line are plain totals, meaning that no distinction is made between different materials that might be produced at the same production line while the number of tons that fit into a bulk truck is dependent on the material type. Then the planner clusters the production volumes into the transport clusters which are known to the transportation company. Table 4 provides an overview of the different transport clusters during the intercampaign TAK.

Name transport cluster	Clustered production lines	Production lines
P&O and Oranje	VMF	PN1, A, BC, V, GUM, MILP
Foxhol and Alteveer	MP10 and Walsen Foxhol	Wals L, Wals M, Wals N, MP10
WTM	Extruder, Dextak	Extruder, Dextak
GNV	GNV	GNV, Protamylasse, Protastar → TAK, Haulerwijk, Customer 4, Customer 5, Customer 6
Cation support production	Cation production MP10	Cation production MP10

Table 4: Relations between transport clusters, clustered production lines, and production lines

Now the planner of Avebe knows the number of tons that should be transported in each transport cluster. To translate this information into the number of bulk trucks needed the planner assumes that every bulk truck is operating 24 hours a day and 7 days per week. Besides, he assumes that one trip including (un)loading and driving time takes 4,5 hours implying that one bulk truck can do 37,3 trips per week. Lastly, he assumes that a bulk truck transports 29,5 tons per trip. Based on these assumptions the planner calculates the number of trucks needed for each transport cluster by dividing the number of tons to be transported for each transport cluster by the number of tons one truck can transport under the assumptions mentioned.

Furthermore, the planner will add a buffer to the number of trucks needed to account for the time that might get lost because of silo/factory breakdowns, cleaning of the trucks, and waiting time at occupied (un)loading docks. Lastly, in case that according to the calculations for a certain transport cluster 2,5 trucks are needed then three trucks are assigned, and the planner of Avebe describes what trips the third truck should make in case it becomes unutilized during the week. Often one of the optional trips discussed in Section 2.1 will be prescribed by the planner.

Phase 2: Discussing the truck proposal of Avebe with the transportation company
Phase 2 is the meeting with the planner of the transportation company to discuss the planning made by planner Avebe in Phase 1. The meeting starts with the Avebe planner proposing to assign the number of trucks determined in phase 1 to each of the transport clusters. Next to providing a table that summarizes the truck assignment, he provides a short explanation of how he came to the numbers. Besides, the planner of Avebe will give an update on the information that he received from the line planners of Avebe which might be useful to the planner of the transportation company.

After the proposal of the Avebe planner, the planner of the transportation company will share its view on the planning made by the Avebe planner. Typically, the planner of the transportation company believes that the planner of Avebe takes too much risk and proposes to add one extra truck. Arguments for this belief are often that they will have insufficient trucks when there is a malfunction of a silo or a factory, or when the quality of the starch turns out to be insufficient. When the starch quality is insufficient, the bad quality starch has to be transported towards silos where it will be mixed with better quality starch to obtain starch of sufficient quality. To arrange this, additional transportation capacity is needed.

Furthermore, the planner of the transport company will give an update on difficulties in the transport process of last week which might be a reason to adjust the proposal of the Avebe planner. After discussing all factors of influence, both planners will finally agree on truck distribution for the coming week.

Phase 3: Translating the plans toward operational activities
The planner of the transport company schedules the bulk trucks according to the result of phase 2 on a daily basis. This schedule, in practice, is more like a priority list for each of the trucks telling what transport has to be done in which shift and what stop work should be performed in case there is time left. Stop work is work that has to be done but does not yet have the priority.
According to the planner of the transport company, it frequently happens that production facilities of Avebe do not follow their planning which yields last-minute changes in the transport demands. Besides, silos or factories may have breakdowns, or the quality of the starch turns out to be insufficient which implies that the transportation plan radically changes. Furthermore, some line planners of Avebe want to have freight on call, meaning that they call the transport company when they want to have a freight instead of planning this. According to the planner of the transport company, all these features of the current process make it impossible to make a fixed day planning for each truck of the transport company.

Therefore, the planner of the transport company makes priority lists, instead of real schedules, for every truck on a daily basis which are as detailed as possible. However, in practice often priority lists are made for each transport cluster in Table 4 since the knowledge about the demand for transport is insufficient to make a planning on truck level. The transport company then assigns two coordination truck drivers who decide what should happen when unexpected things such as silo breakdowns or changes to the demand of production lines occur. These coordination truck drivers also contact the factories of Avebe when needed. Besides, the planner of the transport company contacts these coordination truck drivers at the start of their shifts to give updates on the priorities and particularities

of the previous shift. The disadvantage of this planning approach, using clustered priority lists and coordination truck drivers, is that the individual truck drivers feel less responsible for getting the work done compared to when they would have their individual tasks.

Phase 4: Planning evaluation
During next week's meeting with both the planners from Avebe and the transport company, the transport particularities that took place in the previous week are discussed after which this planning process starts again. In general, the planner of Avebe focuses on discussing the waiting times at the different locations that he observed in the data. The main point of discussion often is why it happens that several trucks were present at one loading/unloading location at a certain point in time, resulting in long waiting times. Frequently, the planner of the transport company explains this by a bad communication of the production operators of Avebe or another silo that cannot be delivered due to a breakdown or maintenance. We conclude that both improvements can be made in the planning decisions but also in the information delivered to the planner of the transport company. This often happens late which makes it hard to plan.

2.5 Reflection on transportation flows and planning approach

In Sub-section 2.5.1, we reflect on the transportation flows discussed in Section 2.1 and provide a priority list based on stakeholder interviews at Avebe. Furthermore, in Sub-section 2.5.2, we reflect on the planning approach described in Section 2.4.

2.5.1 Reflection on transportation flows

Reflecting on the transportation flows discussed in Section 2.1 we should notice that the transportation of all these different flows should be executed by the same hired pool of bulk trucks. One of the complexities of planning all these flows with one pool of bulk trucks is that each of these flows has its own material with its own characteristics such as loading, unloading time, density (and therefore maximum freight volume), demand/sales fluctuation, and chemical characteristics. The different chemical characteristics and hygiene requirements result in the need to clean the trailers of the bulk trucks every time a different product is transported.

Another complexity is that to convince both Avebe and the transport company about the planning solution that we will develop in this research, we should model all different flows that should be executed by the hired pool of bulk trucks. When we for example model only the starch flows, the companies might argue that the performance of our model related to the starch flows will negatively affect the performance of the other flows, which will be hard to disprove. Furthermore, the amount of additional special transport that can be undertaken is hard to determine when not the whole transportation process is considered.

However, due to the time constraint of this research and the complexity and size of the process, we asked the stakeholders of Avebe to make a priority list of the flows that we should consider. This resulted in the following prioritization, in order of decreasing priority:

1. Starch flows because these are responsible for about 85% of the total volume.
2. Waxy flows because this flow is the second largest in volume.
3. Protein, dry flours, derivatives, and customer delivery flows.
4. Pre-transport and cation support production, relatively easy to keep out of scope without affecting the conclusion on the performance of the planning approach.

2.5.2 Reflection on the current bulk truck planning

Reflecting on the current bulk truck planning approach we formulate the following critical remarks and insights.

The first remark concerning the current way of planning is related to Phase 1. The transport volumes and truck capacities are all based upon averages while in practice the material type highly influences the (un)loading time of the truck and the weight that fits into a bulk truck. These differences originate from the fact that different materials have different structures and densities. Furthermore, not every silo is identical. Loading might be twice as fast at one silo compared to another silo even when the product loaded is similar.

Taking one average for the total duration of loading, unloading, driving, and tons transported per trip is a manageable approach to make the planning however, when a more sensible approach is taken a more accurate planning can be obtained. Therefore, we aim to make the loading, unloading, driving, and tons transported per trip, transportation flow and material dependent.

The second insight obtained during an interview with the planner of Avebe is related to the transparency of the planning. The planner of Avebe told that he must rely on the fairness of the planner of the transport company concerning the transport of non-starch products. Only the starch transportation flows (see Sections 2.1.1, 2.1.2, and 2.1.3) are visible to Avebe using an application. In the application, Avebe can see which trucks are loaded/unloaded at a certain location, how long this took, and the weight of the freight. However, for all non-starch flows Avebe can only see the total volumes transported during the week and therefore not to what extent the bulk trucks were utilized to achieve this. In theory, Avebe can pay for bulk trucks of the transport company which might partly be used for transport orders of other clients of the transport company without Avebe noticing this.

Thirdly, during the weekly planning meetings with the planner of Avebe and the planner of the transport company, we noticed that the planner of the transport company now and then receives a transport order from another customer than Avebe during the week. When possible, he tries to fulfill this request with a truck from the pool of Avebe. Avebe will be financially compensated for this, but we do not know what the impact is on the planning of Avebe and how frequently this happens.
Lastly, we noticed that during the meetings, in which the number of bulk trucks that are hired by Avebe during the intercampaign TAK was determined, the transport company was focused on making Avebe's hired pool of bulk trucks as large as possible. The discussion was whether Avebe should have a pool of ten or eleven bulk trucks. Finally, they agreed to have eleven trucks in the pool and to evaluate after a certain time whether they can reduce this pool to ten trucks. However, in practice, we see that the trucks are spreading the work which makes it hard to investigate whether the transport could also be done by ten trucks.

In Chapter 3 we define quantitative performance indicators which we will use to assess the performance of the current bulk truck planning. These will provide additional insights on the performance of the current bulk truck planning next to the observations described in this section. The performance of the current bulk truck planning will then be used as a benchmark for the performance of the planning tool that we develop in Chapter 5.

2.6 Conclusion of Chapter 2

In this chapter, we encountered that the hired pool of bulk trucks performs transport orders from a large number of different transportation flows. The availability of the different transportation flows depends on the time of the year where we distinguished three different periods being the campaign, intercampaign TAK, and the intercampaign. Besides, we encountered that there are many different materials transported which cannot be combined in one truck. Therefore, we categorized the transportation flows based on their material types resulting in the categories starch, protein, derivatives, dry flours, waxy and customer delivers.

The different material types that are transported, the different states that starch can have, and the different loading and unloading systems at the silos and factories, result in deviations in the loading and unloading times of the trucks. In the model that we will build we use material and transportation flow-dependent averages based on historical data on the loading and unloading times when these are available, to gather the missing data we conduct expert interviews.

Analyzing how the pool of bulk trucks is currently planned we can conclude the following. The planning of the bulk trucks is done on a very high level and mainly based on the experience of the planner of the transport company. The planner of Avebe does make some calculations to come up with a proposal on how the trucks should be planned, however, these calculations are too high level and based on too many assumptions to convince the planner of the transport company that the proposal is feasible. Besides, the proposed planning of the planner of Avebe is not supported by any visualizations and no operational planning can be shown to support the proposal.

Therefore, we conclude that the model that we will build should be supported by an operational planning truck planning and visualizations of this truck planning. This will help to convince the planner of the transport company of the feasibility of the proposed number of trucks that are needed in the hired pool of bulk trucks. Besides, we aim to build the model for all different transportation flows to prevent the possibility of arguing that more truck capacity will be needed for the flows that are not considered in the model. Furthermore, we will discuss the assumptions that we make when building the model to ensure that we do not make assumptions that will put the validity of the model at risk.

3. Performance of the current bulk truck planning

In this chapter, we analyze the performance of the current bulk truck planning during the intercampaign TAK 2020 in order to answer research question 2 (see Section 1.6). To assess the performance of the current bulk truck planning we make use of performance indicators. "A Performance Indicator is a variable indicating the effectiveness and/or efficiency of a part or whole of the process or system against a given norm/target or plan" (Fortuin, 1988, p. 2). In Section 3.1, we make a list of possible performance indicators based upon expert interviews and a literature review. From this list, we select some performance indicators based upon requirements for good performance indicators defined by Fortuin (1988) and ourselves. Section 3.2 provides a detailed performance analysis of the current truck planning. Section 3.3 states the conclusion of Chapter 3.

3.1 Performance indicators

In this section, we determine the performance indicators that we use to measure the performance of the current bulk truck planning in Section 3.2 and to measure the performance of our proposed planning model in Chapter 6. To determine the performance indicators, Sub-section 3.1.1 provides insight into what good performance indicators are according to Avebe experts and Sub-section 3.1.2 according to experts of the transport company, based upon interviews. Sub-section 3.1.3 analyzes performance indicators used in the existing literature.

Sub-section 3.1.4 formulates a number of requirements that performance indicators should fulfill according to Fortuin (1988). In Sub-section 3.1.5, we select some performance indicators from the sub-sections 3.1.1, 3.1.2, and 3.1.3 that fulfill the requirements of Sub-section 3.1.4.

3.1.1 Performance indicators according to Avebe experts

To determine what good performance indicators for the bulk truck planning are, according to experts of Avebe, we interviewed an expert of Avebe. During this interview, we asked the expert: "What are good performance indicators to measure the quality of the bulk truck planning?". In response to this question, the expert formulated five performance indicators:

A1. *The average cost in hours per trip.* This performance indicator should be calculated by dividing the number of hours billed by the number of trips done. The lower the value of this performance indicator the better.
A2. *The number of special transport trips performed.* We define special transport to be transport that is normally performed by trucks outside the hired pool of bulk trucks but is done by trucks from the pool in case capacity permits. The higher the value of this performance indicator the better.
A3. *The total waiting time of bulk trucks*. We define waiting time to be the time that a truck is waiting at a loading or unloading dock before it can start loading or unloading. The lower the value of this performance indicator the better.
A4. *The number of factory breakdowns because of transport issues.* A factory breakdown can have several causes. This performance indicator should measure the number of factory breakdowns that are caused by insufficient supply toward the factory resulting in a factory breakdown or insufficient discharge of material resulting in a factory breakdown since the factory output cannot be stored. The lower the value of this performance indicator the better.
A5. *The number of bulk trucks used.* The lower the value of this performance indicator the better.

3.1.2 Performance indicators according to stakeholders of the transport company

To determine good performance indicators for the bulk truck planning we also interviewed an expert of the transport company. During this interview, we asked the expert: "What are good performance indicators to measure the quality of the bulk truck planning?". In response to this question, the expert formulated three performance indicators of which two performance indicators were also mentioned by the expert of Avebe, being the total waiting time of bulk trucks (A3) and the number of factory breakdowns because of transport issues (A4).

The third performance indicator mentioned by the expert of the transport company is the number of trailers cleaned (V1). Since different products are transported using the same trailers, the trailer should be cleaned before another product can be transported. Cleaning a trailer will take time since the trailer should be transported to the cleaning location in Ter Apelkanaal, the cleaning itself takes time, and the transport from the cleaning location to the loading location of the transport order takes time. In this time related to cleaning of the trailers, no material can be transported. Therefore, a planning in which trailers do not frequently change between materials and therefore are not often cleaned will be prioritized.

3.1.3 Performance indicators existing literature

In this sub-section, we analyze what performance indicators are used in the existing literature related to scheduling and assignment problems involving bulk transport. We exclude literature older than five years since we want to consider the newest insights in the field of bulk transport. Table 5, summarizes the performance indicator(s) used in each paper and provides comments concerning the context of the research.

Source	**Performance indicator(s)**	**Context**
(Creemers et al., 2021, p. 3)	- Customer waiting time - Server idle time - Server overtime	Assessment of the performance of appointment scheduling rules in a port for a wide variety of settings.
(Triska et al., 2020, p. 6)	- Average vessel turnaround time - Average waiting time to average service time ratio - Berth utilization rate - Cost per handled ton	Simulation study to perform a port capacity assessment and expansion planning.
(Tyurin & Kuvataev, 2020, p. 9)	- Tons per day - Average cost of work performed (cost/ton)	Dynamic programming with a two-level approach in the mining industry.
(Suliman et al., 2019, p. 7)	- Resource utilization	Measuring technical efficiency of dry bulk terminal performance using the frontier application of data envelopment analysis.
(Islam, 2018, p. 96)	- Number of empty truck trips	Simulation study to increase the seaport capacity by evaluating truck-sharing to decrease the number of empty truck trips.
(Cimpeanu et al., 2017, p. 121)	- Costs - Berth utilization rate - Queueing hours - Amount of unloaded material	Simulation study for the systematic study of extended port terminal operations at a refinery in Ireland.

Table 5: Performance indicators used in literature published between January 2017 and April 2021

Considering Table 5, we observe one trend concerning the performance indicators used in the studies and one trend concerning the context of the studies. Almost all studies in Table 5 have a performance indicator that directly or indirectly provides insight into the resource utilization rate except for Islam (2018). Islam (2018) only provides insight into the performance in terms of the number of empty truck trips. Creemers et. al. (2021) keep track of the server idle time which indirectly provides insight into the server utilization rate. Triska et al. (2020) and Cimpeanu et al. (2017) report the berth utilization rate. Tyurin & Kuvataev (2020) report the average cost of work performed which provides insight into utilization rate since the average cost of work performed increases when the resource utilization rate decreases. Suliman et al. (2019) directly report the resource utilization rate. Therefore, based on the recent literature on performance indicators related to scheduling and assignment problems involving bulk transport, we should directly or indirectly consider the utilization rate of our resources being the bulk trucks.

Considering the trend related to the context of the studies in Table 5, we observe that the majority of the existing literature related to bulk transport optimization studies use performance indicators related to port optimization. However, this does not imply that these studies do not use performance indicators that are suitable to measure the performance of our bulk truck transport planning. There are many process features, such as transportation time, loading time, unloading time, and waiting time because of occupied loading/unloading docks that are present in sea and road transport. Therefore, sea transport-related studies, are also input to our analysis of performance indicators used in the existing literature.

Using Table 5, we analyze the performance indicators one by one and translate the performance indicators to the context of our research. The numbered C's between brackets refer to the list of criteria at the end of this sub-section. Creemers et al. (2021) use the customer waiting time, server idle time, and server overtime as performance indicators. When we translate the customer waiting time to the context of our research we argue the factories to be the customers of the trucks. This yields the factory downtime because of transportation issues as a performance indicator (C1), which also was mentioned by the expert of both companies. The server idle time can then be seen as the time that the trucks are not utilized. Therefore, this performance indicator is translated into the truck utilization rate in our research (C2). Lastly, the server overtime does not apply to our research since the bulk trucks are hired 24 hours per day and seven days per week.

Triska et al. (2020) use the average vessel turnaround time, average waiting time (AWT) to average service time (AST) ratio, berth utilization rate, and the cost per handled ton as performance indicators. Translating these performance indicators into our research context we obtain the average silo/factory turnaround time (C3), the AWT/AST ratio (C4) where the AWT and AST equal the average time a truck is respectively waiting and served, the truck utilization rate (C2), and the costs in terms of hours or euros per ton material transported (C5).

Tyurin & Kuvataev (2020) use the tons mined per day and the average cost of work performed as performance indicators. In the context of our research, these performance indicators become the tons of material transported per day (C6) and again the average cost in terms of hours or euros per ton of material transported (C5). Suliman et al. (2019) apply the resource utilization rate as a performance indicator, which would yield to the truck utilization rate in our research (C2). Islam (2018) uses the number of empty truck trips as a performance indicator. However, Islam (2018) aims to increase the capacity of a seaport by sharing trucks and therefore the number of empty truck trips. Our research focuses on a fixed hired pool of bulk trucks which in principle are not used by other companies. Therefore, this performance indicator will be less interesting in our research.

Lastly, Cimpeanu et al. (2017) apply costs, berth occupancy, queueing hours, and unloaded material as performance indicators. The costs and the unloaded material performance indicators could be translated and merged into the costs in terms of hours or euros per ton of material transported in our research (C5). Furthermore, the berth occupancy and the queueing hours become the truck utilization rate (C2) and the truck waiting time (C7) in our research context.

Based upon the analysis of the performance indicators used in the literature, we make the following list of performance indicators translated to our research context:

C1. Factory-downtime because of transport issues
C2. Truck utilization rate/average time a truck is used
C3. Average silo/factory turnaround time
C4. AWT/AST ratio
C5. Costs (in euros or hours) per ton material transported
C6. Tons of material transported per day (average)
C7. Truck waiting time

3.1.4 Requirements of good performance indicators

According to Fortuin (1988), certain conditions should be fulfilled to obtain good performance indicators. Fortuin (1988) defines the following conditions:

1. The goal of the organization should be clear.
2. All stakeholders should accept the performance indicators as measures.
3. The performance indicators should yield insight into the state of affairs.
4. The performance indicators should be derived from quantities that can be influenced or controlled.
5. All stakeholders should agree that the performance indicators are relevant for measuring the process quality.

Furthermore, Fortuin (1988) emphasizes that it should be possible to monitor the performance indicators on a frequency that is agreed upon with the stakeholders (in our research for the intercampaign TAK which normally speaking 10 weeks). Besides, performance indicators should maintain their significance in the future. In Sub-section 3.1.5, we use these conditions and requirements, defined by Fortuin (1988), to select good performance indicators.

In the performance indicator selection process, we also add a practical requirement related to the feasibility of obtaining the value of a performance indicator. When the performance indicator cannot be measured for the current situation, for example, because of insufficient data availability, the performance indicator will be excluded because of the infeasibility to determine. Exceptions will be made when identifying the performance indicator for the model to be developed strongly increases the belief of the important shareholders (planners at Avebe and the transport company) in the model.

3.1.5 Selected performance indicators

This sub-section provides insight into the performance indicator selection procedure. The first column of Table 6 provides all performance indicators obtained in Sub-sections 3.1.1, 3.1.2, and 3.1.3. The second column states whether we select the performance indicator for this research. Column three of Table 6 provides the reason for the inclusion or exclusion of the performance indicator.

Performance indicator	**Selected?**	**Reason for inclusion/exclusion**
Average cost in hours per trip (turnaround time) → A1, C3.	No	Doing one trip of 30 tons would yield a worse score on this indicator than doing two trips of 15 tons in halftime each, while we prefer to do one trip of 30 tons.
Number of special transport trips performed → A2.	No	Only provides information when it is combined with insight into the non-special transport trips performed and the number of trucks hired.
Total waiting time of the bulk trucks → A3, C7.	Yes	Fulfills all requirements/conditions of Sub-section 3.1.4 and provides useful insights into how well the trucks are coordinated. An assumption has to be made for non-starch flows in assessing the current situation.
Factory downtime because of transport issues → A4.	Yes	Fulfills all requirements/conditions of Sub-section 3.1.4 and shows whether the trucks can handle the transport demand.
Number of factory breakdowns because of transport issues → C1.	No	Provides less information than the factory downtime because of transport issues.
The number of bulk trucks used → A5.	Yes	Fulfills all requirements/conditions of Sub-section 3.1.4 and provides context on how the bulk truck planning is obtained.
The number of trailers cleaned → V1.	Yes	Fulfills all requirements/conditions of Sub-section 3.1.4 except for the performance in the current situation. However, this performance indicator provides insight into what extend the trucks are assigned to one material or used for different materials. Besides, the importance of showing that we consider cleaning and how often we clean is of huge importance for the validity of the model according to the planner of the transport company. Therefore, we decide to include this performance indicator.
Truck utilization rate/average time a truck is used → C2.	No	The information needed to determine this performance indicator during the intercampaign TAK is not present within the company.
AWT/AST ratio → C4.	No	The information needed to determine this performance indicator is not present within the company.
Costs (in euros) per ton material transported → C5.	Yes	Fulfills all requirements/conditions of Sub-section 3.1.4 and provides useful insights on the quality of the bulk truck planning.
Tons of material transported per day (average) → C6.	No	Only interesting in combination with the number of trucks used and does not yield additional insights when we know the costs in terms of euros per ton material transported.

Table 6: Overview of considered and selected performance indicators based upon interviews and literature review

Considering Table 6, we decide to analyze the performance of the bulk truck planning on the following performance indicators:

1. Costs (in euros) per ton material transported.
2. Total waiting time (in minutes) of the bulk trucks.
3. Factory downtime because of transportation issues.
4. The number of trailers cleaned.
5. The number of trucks used.

The total waiting time (in minutes) of the bulk trucks will also be related to the tons of material transported. We decide to add this additional dimension because the total waiting time of the pool of bulk trucks does not provide much information if we do not know the volume transported by the trucks. When we do not add the volume transported, we are not able to prioritize a planning with 2 minutes waiting time per ton material transported over a planning with 5 minutes waiting time per ton material transported. Therefore, the performance indicator becomes the average waiting time (in minutes) of the bulk trucks per ton of material transported.

Furthermore, we should notice that the costs per ton material transported indirectly provides insight into the truck utilization rate. When the hired pool of bulk trucks has a high utilization rate, the cost per ton transported will be low since the transportation costs are fixed for the trucks in the hired pool of bulk trucks. Therefore, we follow the trend observed in Table 5 by indirectly considering the truck utilization rate.

3.2 Performance of the current bulk truck planning

In this section, we assess the performance of the current bulk truck planning. To assess the performance of the planning in the intercampaign TAK (20-2-2020 to 10-5-2020) of last year, we use the performance indicators selected in Subsection 3.1.5. All performance indicators are measured on a weekly basis.

In Sub-section 3.2.1 we determine the costs per ton of material transported. Sub-section 3.2.2 analyses the total waiting time of the bulk trucks in minutes. Sub-section 3.2.3 provides insight into the factory downtime because of transportation issues. In Sub-section 3.2.4 we provide the cleaning protocol for the trailers and insights into the frequency and location of the trailer cleaning. Sub-section 3.2.5 analyses the number of trucks used, and the corresponding number of hours billed. Lastly, Sub-section 3.2.6 provides a summarizing overview of the performance of the current bulk truck planning on each of the performance indicators.

3.2.1 Cost (in euros) per ton material transported

The first performance indicator of interest is the costs (in euros) per ton of material transported. The core task of a bulk truck is to transport material. For Avebe, the cost per ton of material transported therefore is an important financial indicator to assess the performance of the bulk trucks. We should interpret the performance indicator as follows, the lower the costs per ton material transported the better the performance of the planning.

To determine the performance of the current bulk truck planning, we first determine the total volume transported during the intercampaign TAK 2020. Table 7 provides an overview of the volumes transported in tons by the pool of bulk trucks between 20-2-2020 and 10-5-2020 on weekly basis.

In the calculation of the volumes related to customer deliveries, we assume that the transport towards customer 8, 7, 4, and 10% of pre-transport is performed by the bulk trucks. The other customer deliveries are assumed to be performed by trucks outside the pool and are therefore not included in Table 7. We had to make this assumption based on an expert interview at the transport company because the distinction between transport performed by the pool of hired bulk trucks and the commercial deliveries performed by the transport company was not made under the old contract which was active until January 2021.

Week number	Starch	Protein	Derivatives	Dry flours	Waxy	Customer deliveries	Total
8	3,521	0	70	300	440	18	4,348
9	7,102	0	142	475	1,030	97	8,847
10	6,403	62	374	867	1,350	56	9,112
11	6,700	0	92	389	880	120	8,182
12	7,315	0	906	788	307	154	9,470
13	6,133	0	171	312	516	73	7,206
14	6,166	0	24	423	442	110	7,165
15	7,599	0	458	243	613	119	9,030
16	7,292	0	253	0	287	142	7,975
17	6,288	0	186	214	385	120	7,193
18	7,184	0	164	57	274	108	7,787
19	7,108	49	367	0	394	125	8,043
Total	78,812	111	3,206	4,068	6,920	1,241	94,358

Table 7: Volume transportation flows in tons during intercampaign TAK 2020

To determine the costs per ton of material transported, we also need the costs of the bulk trucks which transported the volumes shown in Table 7. When we know the volume transported and the related costs, we use Equation 1 to determine the costs per ton of material transported which is the performance indicator of our interest.

Equation 1:

$$Costs\ per\ ton\ transported = \frac{Costs\ (in\ euros)}{Tons\ transported}$$

Table 8 provides the rental costs of the trucks, the tons transported, and the value of the performance indicator. The intercampaign TAK 2020 started on 20-2-2020 which is a Thursday, since we have the rental costs of the bulk trucks on weekly basis, we calculated the costs for week 8 by multiplying the total costs of week 8 by 4/7. Therefore, the costs and the tons transported in week 8 are low compared to the other weeks of the intercampaign. The costs shown in Table 8 are based upon the invoice of the intercampaign TAK 2020. We should notice that this was still in the period of the old contract implying that another cost structure was applicable than under the new contract which is applicable from 2021 onwards. Under the old contract, we had a low and a high hourly rate for dried starch, a rate for protein, and a rate for wet starch. While under the new contract there is an hourly rate for dried starch and all other materials which depends on whether it is done by a pool or a flex truck, an hourly rate for wet starch which is the same for pool and flex trucks, and an hourly rate for when a pool truck is not utilized. According to calculations performed by experts of Avebe, the total costs under the new contract will be comparable to the total costs under the old contract. Under the new contract, more commercial transport will be performed within the pool of bulk trucks which results in cost savings. However, under the new contract trucks should also be hired in quiet weeks implying that additional costs are obtained in these weeks.

Analyzing the results in Table 8, we observe large differences in the costs/ton of material transported over the weeks. Comparing the worst performance in week 8 (€10.10/ton) with the best performance in week 10 (€7.02/ton) we observe a difference of 3.08 euros per ton material transported. This equals an increase of 43.87% comparing the costs in week 10 to the costs in week 8.

Week number	Tons transported	Costs	Costs/ton
8	4,348	€ 43,896	€ 10.10
9	8,847	€ 71,390	€ 8.07
10	9,112	€ 64,003	€ 7.02
11	8,182	€ 69,550	€ 8.50
12	9,470	€ 69,750	€ 7.37
13	7,206	€ 71,237	€ 9.89
14	7,165	€ 66,193	€ 9.24
15	9,030	€ 70,459	€ 7.80
16	7,975	€ 70,979	€ 8.90
17	7,193	€ 70,925	€ 9.86
18	7,787	€ 65,981	€ 8.47
19	8,043	€ 70,342	€ 8.75
Total/Average	94,358	€ 804,705	€ 8.53

Table 8: Costs per ton transported during the intercampaign TAK 2020

Analyzing the relationship between the number of tons transported and the costs per ton transported on a weekly basis, we encounter a negative trend (see Figure 11). This implies that the costs per ton transported decrease with the number of tons transported. The negative trend can be explained by the fact that the transport company does not directly adjust the number of trucks that they used in case there is less demand for transport. This is logical considering that the transport company wants to have work for its truck drivers. This implies that the transport company tries to find work for the trucks which often do not have urgency e.g., preloading and cleaning of trailers, resulting in a relatively high cost per ton material transported in quite weeks. The related correlation coefficient, which measures the relationship between the costs per ton transported and the tons transported equals -0.86. Taylor (1990) states that a correlation coefficient smaller than -0.68 implies a strong or high negative correlation. However, the small number of data points ask for caution when interpreting the correlation coefficient. Unless this small number of data points we can still conclude that we observe a negative correlation between the costs per ton transported and the number of tons transported on weekly basis.

Figure 11: Negative relationship between tons transported and the costs per ton transported

However, this negative relationship is not constantly present in Table 8. Comparing, for example, week 10 with week 12 we observe that in week 12 more material is transported but also the costs per ton of material transported are higher than in week 10. In Table 12 of Sub-section 3.2.5, which identifies the number of pool and flex trucks used, we observe that in week 12 one pool truck less is used than in week 10. This implies that more transport has to be performed by flex trucks which are more expensive yielding a higher cost per ton of material transported. Based on this analysis, we conclude that having the right number of pool trucks is critical for the planning performance on this performance indicator. This decision is complicated by the fact that the demand for transport fluctuates while the number of trucks in the pool can only be changed by one between the campaign, intercampaign TAK, and the intercampaign according to the new contract.

Reasons for the fluctuations in the demand for transport are maintenance stops for factories, setup times of factories when changing between products, and small deviations in the production speeds at the factories. Besides, some factories have reaction tubs that are filled from the silo. Due to communication issues, the truck drivers do not always know when these reaction tubs will be filled. Therefore, the truck drivers tend to fill the silos way quicker than needed when a reaction tub is filled to prevent factory downtime because of an empty silo from happening. This behavior results in unneeded fluctuations in transport demand. Based on the average current performance of 8.53 euros per ton transported we aim to reduce the average costs per ton of material transported below 8 euros in this research.

3.2.2 The average waiting time (in minutes) of the bulk trucks per ton material transported

The second performance indicator of our interest is the average waiting time (in minutes) of the bulk trucks per ton of material transported. The waiting time of bulk trucks related to the starch transportation flows is based upon the data gathered in an application that the bulk truck drivers use when they transport starch. The drivers upload every step of the transportation process. Examples of steps are start loading, end loading, start driving, arriving at the unloading location, start waiting, start unloading, and end unloading. Truck drivers have to manually upload the steps in the application which sometimes results in misclicks in the application or steps that are forgotten meaning that the driver uploads the completion of several steps at once. This yields some outliers in the data that are unlikely to correspond to reality. To filter out these administration-related mistakes in the data, we rounded down waiting times longer than 12 hours (the duration of a shift) to 12 hours based on expert advice. For the protein, derivates, dry flours, waxy and customer delivery flows there is no application for the truck drivers in which they record the steps taken during their transportation trip. Based on expert interviews we conclude that the best indication of reality is obtained by assuming the ratio between tons transported and waiting time for non-starch flows to be similar to the ratio for the starch flows.

Table 9 provides an overview of the tons of starch transported and the related waiting time in minutes during the intercampaign TAK 2020 on a weekly basis. When we apply Equation 2, we obtain that the scaling factor for waiting time equals 210,765/78,812 ≈ 2.674.

Equation 2:

$$Scaling\ factor\ waiting\ time = \frac{Total\ starch\ transported\ in\ tons}{Total\ waiting\ time\ related\ to\ starch\ transport\ in\ min}$$

Week number	Tons transported	Waiting time (in min.)
8	3,521	9,100
9	7,102	18,463
10	6,403	17,594
11	6,700	18,905
12	7,315	19,606
13	6,133	18,788
14	6,166	18,651
15	7,599	18,670
16	7,292	18,388
17	6,288	14,474
18	7,184	15,923
19	7,108	22,203
Total	78,812	210,765

Table 9: Tons of starch transported and the related waiting time during the intercampaign TAK 2020 on a weekly basis

Based on the obtained waiting time scaling factor and the tons of materials transported for each material flow on a weekly basis in Table 7, we estimate the waiting time related to the non-starch flows by applying Equation 3.

Equation 3:

$$Estimated\ waiting\ time\ in\ minutes = Scaling\ factor\ waiting\ time * volume\ in\ tons$$

Table 10 provides an overview of the resulting waiting time in minutes related to the tons of material transported in each material flow.

	Starch		Protein		Derivatives		Dry flours		Waxy		Customer Deliveries	
Week number	Volume	Waiting	Volume	Est. waiting	Volume	Est. waiting	Volume	Est. waiting	Volume	Est. waiting	Volume	Est. waiting
8	3,521	9,100	0	0	70	186	300	802	440	1,178	18	47
9	7,102	18,463	0	0	142	379	475	1,270	1,030	2,756	97	260
10	6,403	17,594	62	165	374	1,001	867	2,318	1,350	3,611	56	149
11	6,700	18,905	0	0	92	246	389	1,041	880	2,354	120	322
12	7,315	19,606	0	0	906	2,423	788	2,106	307	822	154	412
13	6,133	18,788	0	0	171	457	312	835	516	1,380	73	196
14	6,166	18,651	0	0	24	64	423	1,131	442	1,182	110	293
15	7,599	18,670	0	0	458	1,224	243	649	613	1,639	119	317
16	7,292	18,388	0	0	253	678	0	0	287	769	142	380
17	6,288	14,474	0	0	186	496	214	574	385	1,029	120	321
18	7,184	15,923	0	0	164	437	57	153	274	734	108	288
19	7,108	22,203	49	131	367	983	0	0	394	1,054	125	333
Total	78,812	210,765	111	296	3,206	8,574	4,068	10,879	6,920	18,507	1,241	3,318

Table 10: Tons transported and the related waiting time in minutes during the intercampaign TAK 2020 on a weekly basis

Lastly, we determine the average waiting time in minutes of the bulk trucks per ton transported by dividing the total waiting time by the total number of tons transported in all transportation flows combined. Table 11 provides an overview of the performance indicator on a weekly basis.

Week number	Tons transported	Waiting time (in min.)	Minutes/ton
8	4,348	12,453	2.86
9	8,847	23,777	2.69
10	9,112	26,351	2.89
11	8,182	24,443	2.99
12	9,470	27,156	2.87
13	7,206	23,009	3.19
14	7,165	22,571	3.15
15	9,030	23,635	2.62
16	7,975	21,937	2.75
17	7,193	18,921	2.63
18	7,787	18,418	2.37
19	8,043	26,232	3.26
Total/Average	94,358	268,902	2.85

Table 11: The average waiting time in minutes per ton transported during the intercampaign TAK 2020 on a weekly basis

Figure 12 depicts the relationship between the waiting time in minutes per ton transported and the number of tons transported during the intercampaign TAK 2020. Analyzing the scatter plot, we do not observe that the waiting time in minutes per ton transported is positively or negatively correlated to the tons transported. The statement is confirmed by the scatterplot in Figure 13. Figure 13 provides a scatterplot depicting the relationship between the waiting times in minutes and the number of tons transported during the intercampaign TAK 2020. The points, in Figure 13, lie around the diagonal line from the origin to the top right corner of the scatter plot. Therefore, we conclude that the waiting time in minutes per ton transported does not show a clear dependency on the number of tons transported. This implies that there are sufficient loading and unloading docks, otherwise, the waiting time in minutes per ton transported would increase when the number of tons transported increases.

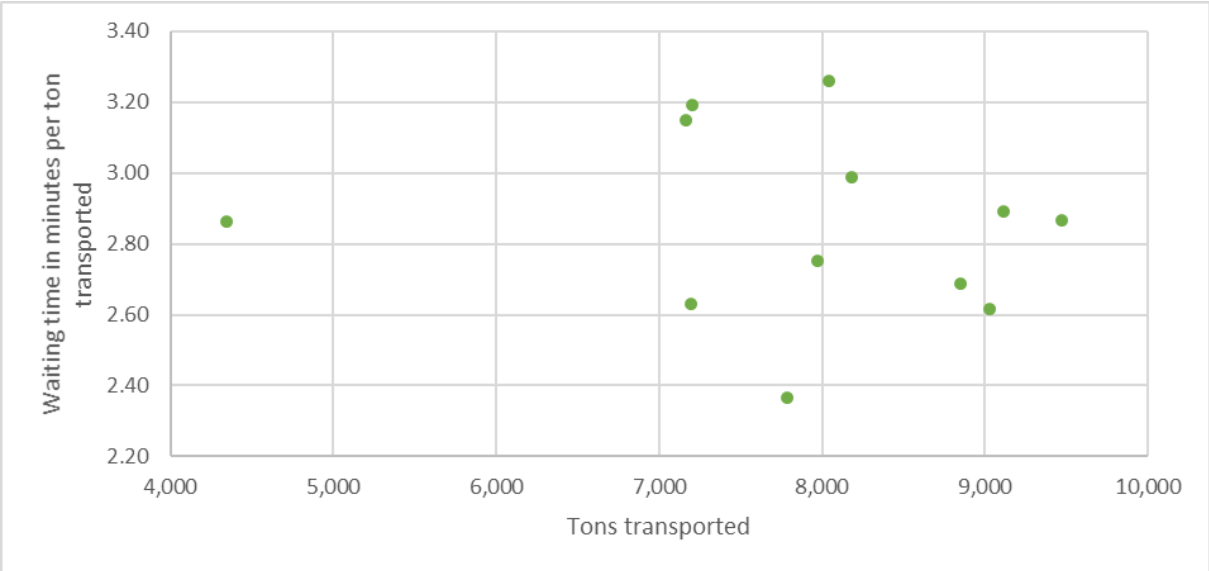

Figure 12: Relationship between the waiting time in minutes per ton transported and the tons transported during the intercampaign TAK 2020

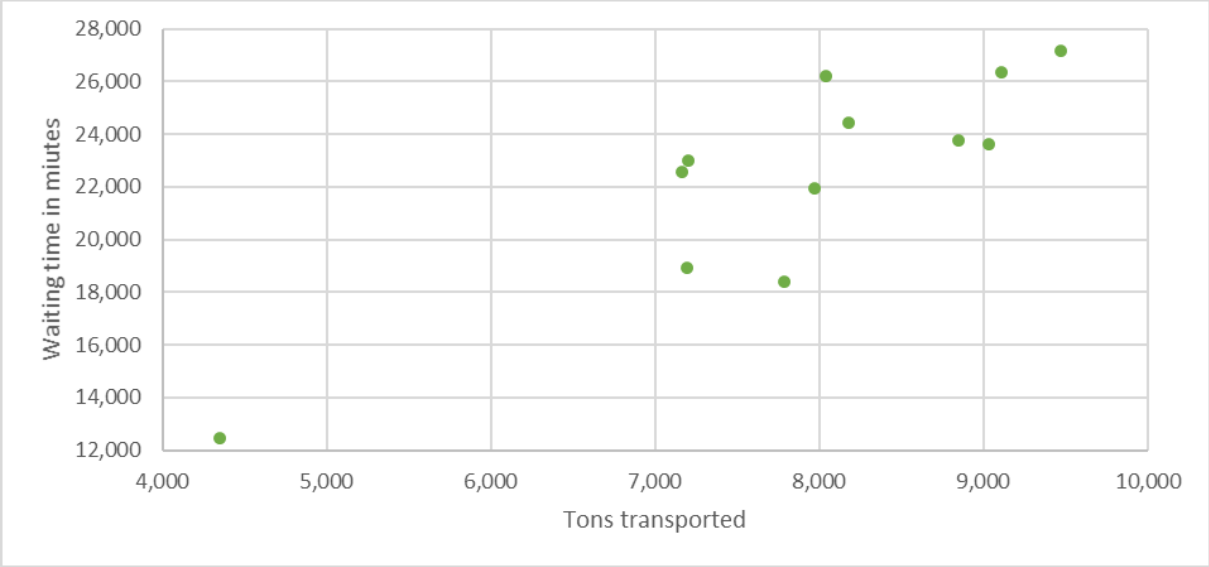

Figure 13: Relationship between the waiting time in minutes and the tons transported during the intercampaign TAK 2020

Analyzing the performance of the current planning during the intercampaign TAK 2020 based on the waiting time per ton material transported we conclude that there is a lot of space for improvement. Table 11 shows that the average waiting time per ton of material transported equals 2.85 minutes. Assuming that a truck transports 30 tons per freight, this implies that a truck on average waits 85.5 minutes per trip.

3.2.3 Factory-downtime because of transportation issues

According to experts of Avebe and the transport company no factory downtime, because of transportation issues, took place during the intercampaign TAK in 2020. Therefore, the factory downtime because of transportation issues between 20-2-2020 and 10-5-2020 was zero minutes. The zero minutes of downtime is a good performance on the factory-downtime because of transportation issues. However, we could also argue that this is a sign of truck overcapacity. Maybe we could still have zero minutes of factory downtime but use fewer trucks to achieve this. This would then also have a positive impact on the costs per ton of material transported and the truck waiting time per ton of material transported.

3.2.4 Number of trailers cleaned

The pool of bulk trucks transports different materials using the same trailers. To make sure that the different materials are not mixed, and the quality of the materials is retained, there is a cleaning protocol for the trailers.

Protocol trailer cleaning:

- During the intercampaign TAK, a trailer that is only used for one product type should be cleaned once every four weeks. Where GNV food, TAK food, and TAK oude droger are viewed as one product type.
- A trailer should always be cleaned when we switch between different product types. E.g., from Waxy to starch or from Waxy to Protamylasse.
- A trailer should be cleaned between customer deliveries of different product types.
- If a trailer is only used for Protamylasse, cleaning is only needed at the start and the end of the intercampaign TAK.
- When trailers are only used for the Cation support production, trailers do not need cleaning.

The cleaning of trailers takes place in Ter Apel, Zuidbroek, and Coevorden. The trailer cleaning in Ter Apel is owned by the transport company and around 95% of cleanings take place at this location. According to experts, cleaning one trailer takes 90 minutes.

During the investigation of the trailer cleaning frequency in the intercampaign TAK 2020, we encountered that the trailers that Avebe hires the transport company are not only used for the transport of Avebe materials. These trailers are also used for other customers of the transport company. This makes it impossible to get a clear overview of the trailer cleanings performed for Avebe during the intercampaign TAK in 2020. However, insight into the number of times that trailers are cleaned in proposed truck schedules is important to convince the planner of the transport company of the feasibility of the generated truck schedule. Therefore, we will consider this performance indicator when experimenting with our model in Chapter 6.

3.2.5 The number of trucks used

Instead of only providing an overview of the number of trucks used on a weekly basis during the intercampaign TAK 2020, we also relate the number of trucks used to the number of hours billed. We decide to add the number of hours billed since we encounter trucks that have an invoice for a few hours in one week. Based on the description of the contract before January 2021, we expected to see a fixed number of trucks that are used 24 hours per day and 7 days per week. Trucks that have an invoice for only a few hours will lead to a wrong interpretation of the number of trucks used when we do not also provide inside in how long these trucks are used.

In our analysis, we make a distinction between the number of flex trucks and pool trucks used. Flex trucks are more expensive than pool trucks. Besides, we distinguish between the number of flex truck hours invoiced and the number of pool truck hours invoiced. Table 12 summarizes the number of flex and pool trucks used on weekly basis during the intercampaign TAK. Furthermore, the number of flex and pool truck hours billed are provided.

Week number	# Flex trucks	# Pool trucks	Hours flex trucks	Hours pool trucks
8	8	12	313	1420
9	6	10	37	1670
10	3	9	27	1504
11	1	10	11	1659
12	3	10	27	1644
13	2	11	28	1676
14	-	10	-	1563
15	2	10	10	1651
16	-	10	-	1676
17	1	10	5	1669
18	-	10	-	1558
19	2	10	16	1639

Table 12: The number of trucks used, and related hours billed during the intercampaign TAK 2020 on a weekly basis

Analyzing the results of Table 12, we observe that sometimes flex trucks are used while the capacity of the pool trucks is not fully used. Looking at week 8 we used 12 pool trucks which should provide a capacity of 12*7*24 = 2016 hours. However, we observe that these pool trucks are only used for 1420 hours. Moreover, we used 8 flex trucks responsible for 313 flex truck hours. This implies that we used and paid for flex trucks while the cheaper bulk trucks were not fully utilized.

An explanation of this would be a high fluctuation in transport demand during the week which forces the planners to use the more expensive flex trucks. Discussing this result with the expert of Avebe we concluded that this might partly be the case but not in the size observed in Table 12. Therefore, we believe that the number of flex trucks used can be decreased which will have a positive impact on the costs per ton of material transported.

3.2.6 Overview of the current bulk truck planning performance

In this sub-section, we provide an overview of the current bulk truck planning performance. The numbers presented in this sub-section are based upon the results in Sub-section 3.2.1 to Sub-section 3.2.5.

Table 13 provides an overview of the current bulk truck planning performance, during the intercampaign TAK 2020, on the first four performance indicators discussed.

Performance indicator	Performance
1. Costs in euros per ton material transported	€8.53/ton
2. Average waiting time in minutes per ton material transported	2.85 min./ton
3. Factory downtime because of transportation issues	0 min.
4. Number of trailers cleaned	Not available

Table 13: Overview performance current planning during the intercampaign TAK 2020, performance indicators 1 to 4

Furthermore, Table 14 provides an overview of the current bulk truck planning performance, during the intercampaign TAK 2020, in terms of the number of trucks used and the related hours billed. The numbers presented are week averages.

Intercampaign TAK 2020	Average # flex trucks	Average # pool trucks	Average hours flex trucks	Average hours pool trucks
Week average	2.33	10.17	39.40	1610.75

Table 14: Average number of trucks used, and hours billed during the intercampaign TAK 2020 on a weekly basis

3.3 Conclusion of Chapter 3

Based on expert interviews with Avebe and the transport company, as well as literature, we selected the following five performance indicators, in line with the criteria of Fortuin (1988):

1) The costs in euros per ton material transported.
2) The average waiting time in minutes per ton material transported.
3) The factory downtime in minutes because of transportation issues.
4) The number of trailers cleaned.
5) The number of trucks used.

An assessment of the performance of the current bulk truck planning during the intercampaign TAK 2020 (20-2-2020 to 10-5-2020) based on the five performance indicators yielded the following numbers and insights. First of all, the average costs per ton of material transported are 8.53 euros. We observed large deviations of almost 44% in costs per ton material transported between the best and the worst week which we can explain by the deviations in the demand for transport and the difference in price between pool and flex trucks. Therefore, we conclude that having the right number of trucks in the pool is of key importance. With this research, we aim to reduce the cost per ton of material transported to 8 euros.

Secondly, the average waiting time per ton of material transported is 2.85 minutes. This implies that a bulk truck on average waits more than 85 minutes per trip which is very long. The long waiting times of bulk trucks are an indication of the overcapacity of the bulk trucks or unbalanced planning.
Furthermore, we observed no clear relationship between that the waiting time in minutes per ton transported and the number of tons transported. This indicates that there are sufficient loading and unloading docks, otherwise, we would observe that the waiting time in minutes per ton transported increases when the number of tons transported increases.

Thirdly, the current bulk truck planning resulted in zero minutes of factory downtime because of transportation issues. This is a good performance, which we want to maintain. However, it can also be seen as a sign of truck overcapacity. Maybe we can still have (almost) zero minutes of factory downtime because of transportation issues while using fewer trucks. This might then result in less truck waiting time and a lower price per ton of material transported.

During the analysis of the number of trailers cleaned in the intercampaign TAK 2020, we encountered that it was not possible to determine the number of trailers cleaned, since the trailers used by Avebe are also used for other customers of the transport company. Lastly, Avebe used 2.33 flex trucks and 10.17 pool trucks on average. Furthermore, the average weekly hours billed were 39.40 per flex truck and 1610.75 per pool truck. The balance between the average weekly use of pool and flex trucks looks fine. However, when we investigated this balance in the separate weeks we concluded, together with the expert of Avebe, that the number of flex trucks used can be decreased. This will have a positive impact on the costs per ton of material transported.

In conclusion, based on the assessment of the current bulk truck planning on the five performance indicators, we observe that there is a significant improvement potential which can be revealed by a data-driven model that schedules the bulk trucks. In Chapter 4, we conduct literature research to determine the type of model that we should build in order to utilize the observed improvement potential.

4. Literature

In this chapter, we conduct extensive literature research in order to answer research question 3 (see Section 1.6). This literature research is split into the following sections.

- Section 4.1 provides a hierarchical placement of our planning problem.
- Section 4.2 broadly classifies our research problem.
- Section 4.3 provides a detailed classification of our research problem.
- Section 4.4 analyses different modeling approaches observed in the literature related to our research problem.
- Section 4.5 analyses different constructive heuristics used in the literature related to our research problem.
- Section 4.6 analyses different improvement heuristics and their neighborhood operators used in the literature related to our research problem.
- Section 4.7 provides a conclusion concerning Chapter 4.

Due to the time constraints of this research, we leave the implementation of the improvement heuristic for further research. However, in Section 4.6, we do analyze different types of improvement heuristics and their neighborhood operators applied in the literature. Based on this analysis we will also provide some recommendations for when an improvement heuristic is implemented in the future.

4.1 Hierarchical placement of the planning problem

In this section, we hierarchically place our planning problem. The literature on planning and control problems is often placed in a hierarchical framework. Many of these frameworks are based upon, or extended versions of, the framework proposed by Anthony (1965). Antony (1965) build a framework that consists of three levels of control being strategical, tactical, and operational. This framework is later on extended by Hans et al. (2012). They propose to make a distinction between online operational planning and offline operational planning.

Hans et al. (2012) explain the framework in the context of healthcare planning and control. They define four managerial areas being medical planning, resource capacity planning, materials planning, and financial planning. Additionally, Hulshof et al. (2012) provide a detailed explanation of the implementation of this taxonomy in six managerial areas being the ambulatory care services, emergency care services, surgical care services, inpatient care services, home care services, and residential care services.

Both Hans et al. (2012) and Hulshof et al. (2012) implement the hierarchical framework in the context of healthcare. We apply the framework, and the related definitions of the hierarchical levels involved in Hans et al. (2012), to our research context. This implies that we will provide examples in the transportation planning context. The different hierarchical planning levels are discussed in a decreasing length of time considered.

Hierarchical planning levels
Defining the organization's mission, and translating this mission into the design, dimensioning, and development of processes is called *strategical planning*. The mission of Avebe is to achieve an optimal performance price for its members (the potato farmers). Relating this mission to the transportation process in this research, questions like; "Are we going to arrange the transport of our material ourselves or are we going to outsource this?", "If we are going to arrange the transport ourselves, how many people should we employ?", "Which types of trucks do we need?" and "Are we going to insure against disasters?". Strategical planning is done in the long term and involves decisions that typically have a long-term impact. If we decide to arrange the transport ourselves, implying that we buy trucks, it will be a huge investment which cannot easily be reversed.

Tactical planning relates to the organization of the operations of processes. On a tactical level, questions like what, where, how, when, and who following from the decisions taken on a strategical level should be answered. We should for example decide how many trucks we should have in the dedicated pool of bulk trucks during the campaign or intercampaign TAK, or when maintenance should be performed on the trucks, silos, and factories. Tactical plannings often have a time horizon of a few months.

Offline operational planning relates to short-term decision-making. The time horizon of the planning differs from days to a few weeks. Questions answered on the offline operational level are: "Which transportation order should be performed by which truck?", "When are we going to do a certain order", "When should which truck driver work?", and "When should we clean the trailers?". In operational planning we have to deal with dimensioning decisions made on a tactical level, this results in limited flexibility.

Online operational planning has little to do with planning since decisions have to be made instantly when something unexpected occurs. When we have a factory breakdown or a technical failure of a truck, the trucks should instantly be rescheduled to make sure that customers are still delivered in time. The ad hoc decisions that should be made are the focus of online operational planning.

Conclusion on the hierarchical placement of our planning problem
In our research, we try to answer the following question: *"How many trucks should Avebe have in the hired pool of bulk trucks, for normal and special transport, during the intercampaign TAK, in order to reduce the total transportation cost without significantly increasing the factory downtime because of transportation issues."* To answer this research question, we should plan the trucks. The time windows in which transportation orders should be fulfilled, the number of trucks available, the capacity of the trucks, and the capacity of storage locations are inputs for planning that we will make. Furthermore, our planning will not account for factory breakdowns or illness of truck drives.

Therefore, based on the hierarchical classification discussed, we conclude that we are going to plan on an *offline operation level*. However, the ultimate research question that we are trying to answer by making this offline operational planning is on the *tactical leve*l. Namely, how many trucks should we have in the dedicated pool of bulk trucks for normal and special transport, during the intercampaign TAK, in order to reduce the total transportation cost without significantly increasing the factory downtime because of transportation issues.

4.2 Classification of problem

Thoroughly examining the existing literature related to transport planning or resource to job assignment on an offline operational planning level, we observe three types of problem classes being the Transportation Problem, the Machine Scheduling Problem (MSP), and the Vehicle Routing Problem (VRP).

The *transportation problem* is often used when a group of customers (demand nodes) demanding a homogeneous good should be supplied by a number of factories (supply nodes) producing that homogeneous good. The goal is to optimally assign the factories to the customers while considering their supply and demand capacity. Furthermore, the costs related to a certain assignment of a factory to a customer are often expressed in the travel time or distance. We expect the following difficulties when we approach our problem as a transportation problem. First of all, our problem contains different product flows while the transportation problem assumes one type of product. Secondly, the transportation problem aims to match supply nodes to demand nodes. However, the transportation problem does not generate a schedule for the trucks that need to perform this transport. This implies that the transportation problem does not fulfill the goal of our research. Therefore, we do not classify our problem as a transportation problem.

The *Machine Scheduling Problem (MPS)* can generally be defined as the assignment of restricted resources to a set of tasks to be performed (Abedinnia et al., 2017). The MSP aims to find a sequence of jobs to be processed on machines in a way that optimizes an objective (or a set of objectives) without violating any of the constraints (Graves, 1981). This could be translated to the context of our research problem where the resources are the trucks and the jobs to be processed the transportation orders. However, in our research, we also want to account for the storage capacity at different loading and unloading locations. Furthermore, the literature on MSP related to transportation planning is limited.

Unlike the MSP the literature on the *Vehicle Routing Problem (VRP)* related to transportation planning is extensive. VRP is a generalized version of the Travelling Salesman Problem (TSP). In the TSP we aim to find the shortest route visiting all cities exactly once given that we know the distances between the cities. On the other hand, VRP seeks to find a set of vehicle routes such that each route begins and ends at the depot, each customer is included on exactly one route, the total demand of each route does not exceed the vehicle capacity, and the total costs associated with each route is minimized (Rader, 2010, p. 127).

There are many variants of Vehicle routing problems present in the literature. Lahyani et al. (2015) provide a taxonomy of Rich Vehicle Routing Problems (RVRPs). In the literature, a VRP becomes an RVRP when the problem simultaneously includes several types of challenging and complicating features, or when real-world complexities are considered (Lahyani et al., 2015), (Derigs & Döhmer, 2008). We refer to the Lahyani et al. (2015) for their proposed new definition of RVRP, summarized they propose to consider the number of strategic, tactical, and operational aspects applied in the VRP in order to decide whether the VRP at hand should be classified as RVRP or as VRP.

Based on the good fit between the problem contexts observed in studies using VRP and our problem context, and the many different variants of VRP available, we conclude to approach our problem as a *Vehicle Routing Problem*. To determine how we should classify our research according to the RVRP taxonomy of Lahyani et al. (2015), we first state our problem characteristics in Section 4.3.

4.3 Detailed classification of problem

In this section, we first provide an overview of the important problem characteristics that should be considered to provide a detailed classification of our research problem. Based on these problem characteristics we classify our problem using the RVRP taxonomy of Lahyani et al. (2015). We will following step by step the features related to scenario characteristics (classification related to input data, number of depots, operation type, load splitting constraints, planning period, and multiple uses of vehicles) and problem physical characteristics (classification related to vehicles, time-related constraints, incompatibility constraints, specific constraints, and the objective function) described by Lahyani et al. (2015). Lastly, we provide insight into a gap in the existing literature on VRP that makes this research even more interesting.

To classify our problem according to the taxonomy of Lahyani et al. (2015) we should have a clear overview of the problem features to consider. Problem features that should be accounted for are:

- The trailer cleanings. Section 3.2.4 provides the policy for trailer cleaning that the models should be able to account for.
- The capacity of the storage locations. It should not be possible to have 10 freights to the same factory within a few hours since the storage capacity at this factory will be insufficient.
- The time windows. We have to consider delivery time windows for factories that require a spread supply of material in order to be able to produce without factory downtime due to supply issues.
- The variations in the time needed to fulfill a transport order. This variability in order fulfillment time is caused by variability in loading/unloading time, waiting time, the location of the truck, and the possible need for trailer cleaning.
- The capacity of the trucks. For example, a freight to Lijn V always equals 16.5 tons while a freight to Customer 4 equals 30 tons.

Based on the problem features mentioned, we will give a detailed classification of our research problem in two steps. First, we discuss the classification related to scenario characteristics. Then we provide a classification related to problem physical characteristics.

Classification related to scenario characteristics

The first scenario characteristic is the *input data*. According to the taxonomy, four types of input data can be distinguished being deterministic, stochastic, static, and dynamic routing. In our research, we aim to provide a schedule for the trucks during the intercampaign TAK. This truck schedule is made once before the intercampaign TAK and cannot be updated. This is in line with the static routing type of input data. Therefore, we decide to classify our VRP to be a *static VRP*.

The next scenario characteristic is the *number of depots*. Lahyani et al. (2015) define two possibilities related to the number of depots, being single depot and multiple depot problems. As the name suggests, in a single depot VRP there is only one central depot at which the vehicles start and end their routes while in multiple depot VRP there are multiple depots at which a vehicle can start and end a tour. However, in our problem, a loading location can be an unloading location at the same time and trucks do not have a fixed starting point and ending point after each transportation order. Therefore, our problem *cannot be classified based on the number of depots*. We will further elaborate on this when discussing the gap in the literature on VRP at the end of this section.

The *operation type* is the next scenario characteristic to consider. The taxonomy defines four operation types being 'pickup or delivery', 'pickup and delivery', 'backhauls', and 'dial-a-ride'. In our problem materials are transported between pickup and delivery locations where a pickup location can also be a delivery location. Furthermore, each transportation order has a predetermined pickup location and delivery location. Therefore, we classify our problem as a *paired pickup and delivery* problem. For the distinction between paired and unpaired pickup and delivery problems, we refer to the research of Parragh et al. (2008).

In our research problem a truck always delivers its freight to one demand point, trucks are not allowed to serve more demand points in one trip. Therefore, we classify that *load splitting is not allowed*. Furthermore, the *planning period* considered in our research is the intercampaign TAK. No decision has to be taken on in which planning period certain orders should be performed since we will only consider one planning period being the intercampaign TAK. This implies that *we do not have a periodic vehicle routing problem (PVRP)*. The last scenario characteristic-related classification is based upon whether vehicles may perform *several tasks during one planning period*. Our trucks perform many transportation jobs during a planning period (the intercampaign TAK). Therefore, we classify our problem as a *VRP with multiple trips*.

Classification related to problem physical characteristics

Now that we analyzed our problem related to its scenario characteristics defined by Lahyani et al. (2015), we will further classify our problem based on problem physical characteristics. The first problem physical characteristic relates to the *vehicles*. The trucks considered in our research problem are all identical implying that we can classify our fleet of vehicles to be a *homogeneous fleet containing a fixed number of vehicles*. The decision for a fixed number of vehicles relates to the fact that the alternative is an unlimited number of vehicles, which is not realistic in real-life cases. Besides, the trucks considered in this research are bulk trucks. Bulk trucks have a cylindrical trailer that does not have compartments. The size of this *cylindrical single compartment trailer* is expressed in tons and therefore material dependent. Furthermore, the *loading policy* of a bulk truck is not relevant since the truck transports one material type which is loaded and unloaded at once. The loading policy is only interesting if for example pallets containing different products are loaded and unloaded at different locations. Lastly, the *regulations* related to driver working hours are not considered in this research. Drivers work in shifts of 12 hours and are relieved by a new truck driver at the location of the truck. Therefore, we do not take this into the scope of our research.

The second problem physical characteristic considers *time-related constraints*. In our research, we deal with time windows in which transportation orders should be fulfilled. These time windows are defined by a start time (the earliest time at which the transportation order can start) and an end time (the latest point in time at which the order should be completed). Three types of time windows are distinguished in the literature, namely hard, soft, and semi-soft time windows. In case of hard time windows, the vehicle is allowed to arrive earlier but has to wait until the defined starting time. However, the vehicle may not arrive late. When soft time windows are applied, early and late arrival are penalized (Lahyani et al., 2015). Semi-soft time windows do not allow early arrival but do allow late arrival Karami et al. (2020). In our research, *hard time windows* will be applied. Furthermore, each order will get one time window. Therefore, we classify our problem as a VRP with Time Windows (VRPTW).

Analyzing the *incompatibility constraints* provided by Lahyani et al. (2015), we conclude that no incompatibility constraints are present in our research problem. However, some of the specific constraints described in the taxonomy are present in our research. The first one is the constraint related to *open routes*. In our research problem trucks do not have to finish their routes at a depot since truck drivers are changed at the location of the truck at the end of a shift. Problems in which a tour does not have to end at a depot are called Open Vehicle Routing Problems (OVRP). The second

special constraint is related to the number of vehicles that are simultaneously present on a site. In our research, we want to keep the number of vehicles that are simultaneously present on a location low to prevent queuing at loading or unloading locations. Furthermore, as described in Sub-section 3.2.4, we should consider the protocol for trailer cleaning. Lastly, the objective of our research is to develop a model/dashboard that provides insight into the number of bulk trucks to be assigned to normal and special transport, during the intercampaign TAK, in order to reduce the total transportation cost without significantly increasing the factory downtime because of transportation issues. Since we want to simultaneously minimize the transportation costs and the factory downtime due to transportation issues, we classify our research problem to be *multi-objective*.

Conclusion on classification

Table 15, provides an overview of the classification of our research problem based upon how we will translate practice into a model in Chapter 5. Following the step-by-step classification provided, we classify our research problem as a multi-objective Static Open Vehicle Routing Problem with pickup and delivery, where load splitting is not allowed, and vehicles can perform multiple trips. Furthermore, we have a fixed number of non-compartmentalized homogeneous vehicles with heterogeneous freights where transportation orders have hard time windows, and both waiting times and cleaning are considered.

Scenario Characteristics	Classification of our research
1. Input data	Static
2. Number of depots	Not applicable
3. Operation type	Pickup and delivery
4. Load splitting constraints	Splitting not allowed
5. Planning period	Single period
6. Multiple use of vehicles	Multi-trip
Problem physical characteristics	**Classification of our research**
1. Vehicles	
Type	Homogeneous
Number	Fixed
Structure	Not compartmentalized
Loading policy	No policy
2. Time constraints	Hard time windows
3. Time window structure	Single time window
4. Incompatibility constraints	Not applicable
5. Special constraints	Open routes, number of vehicles simulataneously present at one location, cleaning protocol
6. Objective function	Multiple objectives

Table 15: Summarizing table of the problem classification

The gap in the literature on VRP

Looking at the specific VRP classification, our research deviates from the standard Vehicle Routing Problem in which vehicles start and end their routes at a central depot. In our research, freights only consist of one material that has to be fully loaded at one location and fully unloaded at another location. Furthermore, each truck is hired 24 hours a day and seven days per week, and truck drivers work in shifts of 12 hours. Shift changes occur at the location of a truck. The new truck driver goes to the truck by car, and the old truck driver takes the same car to go home. We encountered one class of VRP called Open VRP (OVRP) which allows trucks to not end their tour at a depot, however, OVRP still assumes the truck to start its tour at a central depot.

In conclusion, to the best of the authors' knowledge, this research considers a new variant of VRP. To solve this new variant, we will get our inspiration from the modeling approaches applied to existing VRP problems.

4.4 Modeling approach

In this section, we analyze the modeling approaches used in the existing literature on VRPPDTW and PDPTW.

Conducting literature research on a multi-objective static open vehicle routing problem with pickup and delivery, where load splitting is not allowed, and vehicles can perform multiple trips and have a fixed number of non-compartmentalized homogeneous vehicles with heterogeneous freights where transportation orders have hard time windows and both waiting times and cleaning are considered, results in no exact matches. Therefore, we have to broaden our scope by focusing on the vehicle routing problem with pickup and delivery and time windows (VRPPDTW or PDPTW) since these are the most critical features of our problem. The VRPPDTW is a problem in which a fleet of homogenous vehicles must meet all customer requests and in addition, each customer can specify the pickup or delivery location (Carabetti et al., 2010). Furthermore, the time window is often specified by the earliest possible time of delivery or pickup and the latest possible time of pickup or delivery.

A literature research in Scopus on VRPPDTW and PDPTW yielded 192 documents. Limiting these results to publications done in 2019, 2020, and 2021 we remain with 28 documents that represent the current state-of-the-art literature on VRPPDTW and PDPTW. Assessing these 28 documents on the models applied to solve the VRPPDTW we observed that only 2 studies apply exact methods, and 23 studies used some kind of heuristic, the remaining 3 studies did not solve a VRPPDTW. Therefore, we conclude that the majority of VRPPDTW studies are solved by applying heuristics. This observation is in line with the observation made by Lahyani et al. (2015). Lahyani et al. (2015) noticed that only two papers included in their analysis propose exact algorithms while 39 papers use approximation methods like heuristics and/or meta-heuristics.

The decision to apply heuristics instead of exact algorithms is supported by the fact that VRPPDTW is an NP-hard integer optimization problem (Cinar et al., 2016), (Karami et al., 2020). This implies that it is difficult to find an optimal solution for large problem instances within reasonable time since the only known method for finding a global optimal solution is to enumerate all possible solutions (Keçeci et al., 2021), (Rader, 2010). The time and space needed to solve such an exact model grow exponentially with the number of variables in the problem (Rader, 2010).

In the 23 state-of-the-art papers, that apply heuristics to solve the VRPPDTW, we frequently observe the use of two-step scheduling heuristics (Cai et. al, 2020), (Karami et. al, 2020). In the two-step scheduling heuristic, a feasible solution is generated in the first step, and the obtained feasible solution is improved in the second step (Karami et. al, 2020). The construction of a feasible solution is performed by employing a constructive heuristic, while the improvement is made by the implementation of an improvement heuristic.

Based on the frequently observed two-step modeling approach we review the state of affairs related to constructive heuristics for VRPPDTW in Section 4.5. Section 4.6 focuses on the state of affairs of improvement heuristics applied to the VRPPDTW.

4.5 Constructive heuristic (first step)

In this section, we identify which constructive heuristics applied in the literature on VRPPDTW apply to our research problem. To do so, we first discuss different types of constructive heuristics. Sub-section 4.5.1 provides an overview of the constructive heuristics applied in literature on VRPPDTW and their applicability to our research problem. Sub-section 4.5.2 provides a conclusion on which constructive heuristic we select for our research problem.

Constructive heuristics are divided into sequential and parallel route-building heuristics. Sequential methods expand one route at a time, whereas parallel methods consider more than one route simultaneously (Cordeau et al., 2007). In our research context, sequential route building implies that we determine the whole schedule of truck 1 before starting with the schedule of truck 2. A parallel approach would be to assign jobs to our trucks simultaneously implying that orders can be assigned to truck 2, while the schedule of truck 1 is not completely filled yet.

4.5.1 State of affairs related to constructive heuristics for VRPPDTW

Conducting a literature research in Scopus on 'VRPPDTW' or 'PDPTW' and 'constructive' or 'construction' we find 36 documents. Papers published before 2000, and papers that do not clearly describe the implementation or use of one or more constructive heuristics in the VRPPDTW context are excluded. After this exclusion, we remain with 13 documents. Table 16, provides an overview of the constructive heuristics applied in these 13 documents. We will assess the applicability of these constructive heuristics and not all other types of constructive heuristics that exist since the heuristics in Table 16 are applied to studies considering VRPPDTW. Therefore, we expect these heuristics to be interesting in our research as well.

Constructive heuristic	**Source**
Clarke & Wright (C&W) algorithm	(Cinar et al., 2016), (Geiger, 2010)
Partitioned insertion heuristic (hybrid heuristic combining the standard insertion heuristic and sweep heuristic)	(Lau & Liang, 2001)
Cheapest insertion	(Carotenuto et al., 2014), (Chbichib et al. 2011), (Holborn et al., 2012), (Kalina et al., 2012), (Kammarti et al., 2005), (Campbell & Savelsbergh, 2004), (Karami et al., 2020), (Rachmawati & Wilyanto, 2020), (Sartori et al., 2018), (Carabetti et al., 2010)

Table 16: Constructive heuristics applied in literature on VRPPDTW

The first constructive heuristics applied by Cinar et al. (2016) and Geiger (2010) is the Clarke & Wright saving algorithm (C&W). The C&W saving algorithm is one of the most widely used classical heuristics in VRP (Osman, 1993). The algorithm is known for its ease of implementation and good solutions that can be obtained while having a short computation time (Cinar et al., 2016). However, the C&W saving algorithm does not apply to our problem since the algorithm is based upon the saving obtained from visiting two demand points combined in one trip instead of two separate trips. In our research context, it is not allowed to split and/or combine freights. This implies that we cannot calculate the savings, and therefore the algorithm cannot be implemented.

The second constructive heuristic encountered in our literature study is the partitioned insertion heuristic implemented by Lau & Liang (2001). The partitioned insertion heuristic is a combination of the standard insertion heuristic (or cheapest insertion heuristic) and the sweep heuristic. The standard insertion heuristic works as follows. We have a set of vehicles that are to be assigned to jobs. Then we assign the job (or group of jobs) to the vehicle which results in the smallest increase in costs (costs in terms of the objective). We iterate these steps until all jobs are assigned to a vehicle. A disadvantage of this standard insertion heuristics is that jobs close to the depot are combined in one truck, and jobs far away from the depot are combined resulting in an imbalance between trucks. Therefore, Lau & Liang (2001) propose a combination of the standard insertion heuristic and the sweep heuristic.

The standard sweep heuristic assumes a central depot and assigns angles to the jobs. This can be done clockwise or counterclockwise. Then the jobs are assigned to the truck by adding jobs with an increasing angle to the truck until the truck is full. This process is iterated until all jobs are assigned to a truck. To take advantage of both the insertion heuristic and the sweep heuristic, Lau & Liang (2001) apply the partitioned insertion heuristic. This heuristic starts with a set of empty vehicles and jobs to be assigned. The jobs to be assigned are sorted on increasing angles like in the sweep heuristic. Then the list with jobs to be assigned is divided into as many sub-lists as we have vehicles. Out of these sub lists, a random sub list is chosen, and a truck is assigned to this sub list. Then the route of this vehicle is built by the insertion heuristic. These steps are iterated until all jobs are assigned to a vehicle and all vehicle routes are built. The vehicle schedules and routes are created one by one in the partitioned insertion heuristic. Therefore, the partitioned insertion heuristic is a sequential construction heuristic.

Looking at our research problem, we do not have a central depot from which the trucks start their routes. Therefore, we will not have the disadvantage of an imbalance between trucks when applying the standard insertion heuristic. This implies that we can obtain good initial solutions by the application of the standard insertion heuristic. The partitioned insertion heuristic of Lau et al. (2001) would therefore only be more complicated to implement while we do not expect it to provide better results than the standard insertion heuristic.

Another constructive heuristic that is frequently applied to VRP and TSP in the literature is Cheapest Insertion. Table 16 shows that the majority of the selected literature applies the cheapest insertion constructive heuristic in a pickup and delivery problem with time windows (DPDTW). The heuristic works by calculating the increase in the objective function when sub-tours are created at different existing tours (Campbell & Savelsbergh, 2004). The objective often is to minimize the transportation distance or time (Cinar et al., 2016). Then the sub-tour (or task) is added at the point where the increase in transportation time is minimal (Rader, 2010). The Cheapest Insertion heuristic is known for being fast, the possibility to add complicated constraints, providing suitable solutions, and simple implementation (Rachmawati & Wilyanto, 2020).

To apply the cheapest insertion heuristic to our research, we should not create sub-tours, since our trucks are only allowed to perform one pickup and one delivery in each tour. However, we can apply the reasoning behind the cheapest insertion heuristic on the pool of bulk truck level. This implies that we add a transportation order to the truck that can fulfill the order in e.g., the least amount of time. To determine the time needed, we should account for the location of the truck after finishing its current order, the time at which the truck becomes available, the material previously transported in the truck to determine whether the truck should first be cleaned when the order is assigned to the truck (which comes with additional cleaning and traveling time), and the traveling time towards the pickup location of the order to be assigned to a truck. Then, according to the cheapest insertion heuristic, we add the order to the truck which has the minimum total time required to fulfill this order. Looping over the different orders to be performed, our modified cheapest insertion heuristic will build the schedule of the trucks. The schedules of the trucks are simultaneously built, therefore implementing our modified cheapest insertion heuristic in the way described is classified as parallel route building.

4.5.2 Conclusion on constructive heuristics

In the existing literature on VRPPDTW we encountered three types of constructive heuristics, which are the C&W savings algorithm, the partitioned insertion heuristic, and the cheapest insertion heuristic. Analyzing these three constructive heuristics we concluded that the C&W savings algorithm does not apply to our research problem and that the partitioned insertion heuristic is more complex to implement compared to the standard insertion heuristic (or cheapest insertion heuristic) while we do not expect it to provide better initial solutions in our research context. Lastly, we analyzed the cheapest insertion heuristic which is most often applied in the literature. Furthermore, we provided an idea on how the cheapest insertion heuristic can be applied to our research problem which looks promising. Therefore, we conclude the modified cheapest insertion heuristic to be our constructive heuristic.

4.6 Improvement heuristic (second step)

In this section, we focus on improvement heuristics present in the current state-of-the-art literature related to VRPPDTW. To do so we first define what an improvement heuristic is and provide a classification of the three different types of improvement heuristics. Sub-section 4.6.1 provides an overview of the improvement heuristics used in the current state-of-the-art literature on VRPPDTW. Sub-section 4.6.2 provides our recommendation related to the type of improvement heuristic and the neighborhood operators that we advise to apply when an improvement heuristic is implemented in future research.

Improvement heuristics aim to improve a feasible solution obtained by a constructive heuristic. In the literature on VRP problems, three classes of improvement heuristics are distinguished being traditional descent methods, meta-heuristics, and hyper-heuristics.

Traditional descent methods are the oldest class of improvement heuristics and in general, provide the least good solutions. These methods are characterized by the fact that the order in which new solutions are generated is only dependent on the information gathered during the execution of the heuristic (Osman, 1993). Local search methods stop when no improvement of the objective function is observed. The advantages of local search methods are their short computation time and simple implementation (Laporte et al., 2000). However, a clear disadvantage is the high probability of quickly getting trapped in a local optimum, yielding poor solutions (Osman, 1993).

To solve the issue of getting stuck in local optima when applying traditional descent methods, meta-heuristics are developed. *Meta-heuristics* perform a more thorough search of the solution space and are therefore less likely to end up in a local optimum (Cordeau et al., 2007). A higher level of search thoroughness is often obtained by allowing some moves that worse the objective function value (Van Breedam, 2001), (Cordeau et al, 2007). In meta-heuristics, the procedure used to generate a new solution out of a current one is embedded in a heuristic that determines the search strategy (Van Breedam, 2001), (Taner et al., 2012). The disadvantage of applying meta-heuristics is that the stop criterion is defined by the computation time, this implies that the longer the model is allowed to run, the higher the chance of finding a global optimum (Van Breedam, 2001).

The third and newest class of improvement heuristic are *hyper-heuristics*. Burke et al. (2010), define hyper-heuristics as follows: “A hyper-heuristic is an automated methodology for selecting or generating heuristics to solve hard computational search problems”. A distinction is made between constructive hyper-heuristics, which do not start with an initial feasible solution, and local search hyper-heuristics which start from an initial feasible solution and iteratively select, from a set of neighborhood structures, appropriate heuristics to navigate the search in a promising direction (Burke

et al., 2010). In general, hyper-heuristics provide the best solutions. However, hyper-heuristics are the most difficult improvement heuristics in terms of implementation.

Now that we discussed the three different classes of improvement heuristics, we analyze the current state of affairs literature using this classification in Sub-section 4.6.1.

4.6.1 State of affairs related to improvement heuristics for VRPPDTW

In this sub-section, we analyze the improvement heuristics used in the existing literature related to VRPPDTW (or PDPTW). To find this existing literature, we perform literature research in Scopes on VRPPDTW (or PDPTW) and traditional decent, meta-, and hyper-heuristics. The analysis of these sources is split into three parts based upon the classification of improvement heuristics in traditional descent methods, meta-heuristics, and hyper-heuristics.

Traditional descent methods

Table 17 provides an overview of the source, found in our literature research, that applies a type of traditional decent method. Savran et al. (2015) apply an extended Heuristic Bubble Algorithm (HBA) to solve a PDPTW. The HBA is an extended HBA because a merge, join, result elimination, split, and swap operator are used instead of only using the merge and join operator in the standard HBA. The performance of the algorithm is tested on five case studies. However, no conclusions are given on how good or bad the extended HBA is compared to other methods.

Type of traditional descent method	Neighborhood operator(s)	Source
Heuristic Bubble Algorithm (HBA) for PDPTW	Merge, join, result elimination, split, and swap	(Savran et al., 2015)

Table 17: Traditional decent methods used in the literature on VRPPDTW

Meta-heuristics

Table 18 provides an overview of the sources, found in our literature research, that apply a type of meta-heuristic. The first type of meta-heuristic we discuss is the Ant Colony Optimization (ACO) algorithm. Tchoupo et al. (2017), Badaloni et al. (2008), and Carabetti et al. (2010) all apply the ACO algorithm. Tchoupo et al. (2017) and Carabetti et al. (2010) apply the ACO algorithm as a constructive heuristic and not as an improvement heuristic. Therefore, these studies do not match our interest in improvement heuristics. However, based on the abstract, Badaloni et al. (2008) seems to apply the ACO algorithm as an improvement heuristic yielding solutions comparable to the best algorithms in the state of art. Unfortunately, we could not get access to the full paper which makes it hard to assess the applicability of the ACO algorithm to our research problem.

Sombuntham & Kachitvichyanukul (2010) apply a Particle Swarm Optimization (PSO) algorithm to a multi-depot VRPPDTW. In the improvement step, the move neighborhood operator is applied. The authors notice that their solution approach works well for problems in which customer locations are clustered, but that the general performance of their method needs further research. Derigs & Döhmer (2008) apply an indirect local search method with greedy decoding (GIST) to solve a VRPPDTW. The idea of indirect local search methods is to remove a part, or all of the constraints related to the feasibility of neighborhood solutions, which makes it possible to generate neighborhood solutions by employing a large variety of meta-heuristics. Then the generated neighborhood solutions are decoded resulting in only feasible neighborhood solutions. While direct local search methods immediately check the feasibility of all neighborhood solutions during the generation of these neighborhood solutions. Derigs & Döhmer (2008) show that their indirect local search method with greedy decoding provides a solution quality that is comparable to the method proposed by Li & Lim (2003) and the method of Pankrat (2005) on VRPPDTW problems. However, the method of Derigs & Döhmer (2008) requires less computation time.

Type of meta-heuristic	Neighborhood operator(s)	Source(s)
Ant colony optimization algorithm for PDPTW or VRPPDTW (constructive).	Not applicable, only constructive heuristic.	(Tchoupo et al., 2017), (Badaloni et al., 2008), (Carabetti et al., 2010)
Particle swarm optimization algorithm for a multi-depot VRPPDTW (population-based).	Move operator	(Sombuntham & Kachitvichyanukul, 2010)
Indirect local search with greedy decoding (GIST) for VRPPDTW.	Random swap	(Derigs & Döhmer, 2008)
First improvement local search for VRPPDTW.	Relocation movement and exchange movements of pickup and delivery pairs.	(Carabetti et al., 2010)
Tabu Search (TS) for PDPTW.	?	(Jia et al., 2004)
Hybrid intelligent method for PDPTW (combination of Cluster Algorithm (CA), Genetic Algorithm (GA), and Tabu Search (TS).	Move between routes operators.	(Li et al., 2007)
Simulated Annealing (SA) and LNS for PDPTW.	Pair relocation operator in SA and random customer selection with branch and bound algorithm in LNS.	(Bent & Hentenryck, 2006)
Genetic Algorithm (GA), Simulated Annealing (SA), and a hill-climbing algorithm for single-vehicle PDPTW.	In the SA algorithm, a swap and two types of move operators are applied.	(Hosny & Mumford, 2010)

Table 18: Meta-heuristics used in the literature on VRPPDTW

Carabetti et al. (2010), create an initial feasible solution by applying the Ant Colony Optimization (ACO) algorithm for VRPPDTW after which they employ the first improvement local search method to optimize the obtained feasible solutions. In the first improvement local search method, Carabetti et al. (2010) use two neighborhood operators being relocation movement and exchange movement of pickup and delivery pairs. Furthermore, three refinement strategies are used being Pickup and Delivery Small Route Killer (PD-SRK), Pickup and Delivery Down Hill First Improvement (PD-DHFI), and Pickup and Delivery Exchange (PD-Ex). The obtained solutions by Carabetti et al. (2010) are close to the best-known results on well-known problem instances. However, the computation time to achieve this performance is not reported.

Another meta-heuristic applied to the PDPTW is Tabu Search (Li et al., 2007), (Jia et al., 2004). Li et al. (2007) first construct a feasible solution using a Cluster Algorithm (CA) and a Genetic Algorithm (GA). After which the obtained feasible solutions are improved using Tabu Search (TS) employing a between routes move operator. The proposed hybrid intelligent method proves to be especially interesting for larger problem instances because of the relatively slow increase in computation time. Jia et al. (2004) apply an insertion heuristic to create feasible solutions, followed by a Tabu Search improvement heuristic which they claim to be an effective and quick algorithm to solve PDPTW. Unfortunately, we cannot get access to their full article which makes it impossible to analyze their method and resulting solution quality.

Bent & Hentenryck (2006) use Simulated Annealing (SA) to minimize the number of vehicle routes and Large Neighborhood Search (LNS) to minimize the traveling costs. The SA procedure employs a pair relocation operator and the LNS algorithm uses a random customer selection followed by a branch and bound algorithm. The idea of applying both SA and LNS together looks promising in terms of solution quality. However, no comparison is made on the performance in terms of computation times related to other methods.

Lastly, Hosny & Mumford (2010) compare the performance of a Genetic Algorithm (GA), Simulated Annealing (SA) algorithm, and a hill-climbing algorithm for the single-vehicle PDPTW. The 3-stage SA algorithm outperforms the random swap SA algorithm and all variants of the GA and hill-climbing algorithms evaluated in the research. In the proposed 3-stage SA algorithm every stage uses a different neighborhood operator. The first stage uses a random swap operator which only takes place if the job with the shortest deadline is served first. In the second stage, a neighborhood move operator is used which depends on the earliest time at which a job is allowed to start while in the third stage a neighborhood move operator depending on the center of the time window is applied.

Hyper-heuristics

Table 19 provides an overview of the sources found in our literature research, that apply a type of hyper-heuristic. The study of Bent & Hentenryck (2006) is already discussed at the meta-heuristics. Therefore, we only discuss Lu & Huang (2020) and Barodziej et al. (2010) here.

Lu & Huang (2020) apply Distance-based Adaptive Large Neighborhood Search (DALNS) to solve a PDPTW. Lu & Huang (2020) aim to reduce the CO_2 emission related to transport by increasing the influence of the distance between customers on the destroy and repair heuristic used in the ALNS algorithm. To determine whether a destroy or repair heuristic will take place a SA procedure is used. In the DALNS algorithm, the destroy operators used are random removal, worst removal, Shaw removal, and distance-based removal. The adaptive regret-k algorithm is used as repair operator. The authors conclude that their model is especially good in terms of CO_2 emission when customers are located in clusters close to each other, and less than full truckloads are transported.

Barodziej et al. (2010) apply parallel LNS to solve a VRPPDTW. To do so the authors use pb.net which is based on the Microsoft .NET Framework runtime environment and its programming libraries. Limited information on the selected destroy and repair operators is given which makes it difficult to understand the problem-solving method applied.

Type of hyper-heuristic	**Operator(s)**	**Source**
Distance-based ALNS (DALNS) combined with SA for PDPTW.	Destroy operators are random removal, worst removal, Shaw removal, and distance-based removal. The repair operator is an adaptive regret-k algorithm.	(Lu & Huang, 2020)
Simulated Annealing and LNS for PDPTW.	The branch and bound algorithm is used in the LNS.	(Bent & Hentenryck, 2006)
Parallel LNS for VRPPDTW.	Different destroy and repair heuristics are applied, which specifically is not mentioned.	(Bartodziej et al., 2010)

Table 19: Hyper-heuristics present in the literature on VRPPDTW

4.6.2 Recommendation on improvement heuristics

Summarizing Sub-section 4.6.1, we conclude that there is not just one way in which a VRPPDTW can be solved. In the literature, we encountered that VRPPDTW is solved using different variants of traditional descent methods, meta-heuristics, and hyper-heuristics. Therefore, we conclude that our research problem can also be solved using many different approaches. However, these different approaches will not result in the same solution quality, computation time, and implementation difficulty.

We exclude the traditional descent methods based on the fact that these methods get stuck in local optima yielding poor solutions compared to research in which meta-heuristics or hyper-heuristics are implemented. Comparing meta-heuristics and hyper-heuristics applied to VRPPDTW we observe that more frequently meta-heuristics are applied. Our literature research resulted in 3 studies that applied hyper-heuristics and 10 studies using meta-heuristics. Out of these 10 studies, in which meta-heuristics are applied, especially Hosny & Mumford (2010) convinced us that Simulated Annealing has a high potential to provide a good solution to our research problem. Hosny & Mumord (2010) show that their SA algorithm outperforms the GA and hill-climbing algorithm. Besides, the implementation of a Simulated Annealing meta-heuristic into our research problem seems to be feasible. This statement is supported by the fact that 3 out of the 13 studies applying hyper-heuristics or meta-heuristics use Simulated Annealing in some way (Bent & Hentenryck, 2006), (Hosny & Mumford, 2010) and (Lu & Huang, 2020).

Analyzing the neighborhood operators used in the meta-heuristics (see Table 18), we conclude that all meta-heuristics use a move, a swap, or a combination of move and swap neighborhood operators. Hosny & Mumford (2010) show that their 3-stage SA algorithm in which a combination of one swap and two move neighborhood operators is applied outperforms the SA algorithm with a simple random move neighborhood operator. Therefore, we recommend applying a combination of move and swap operators when an improvement heuristic is implemented in future research.

4.7 Conclusion of Chapter 4

Based on literature research on offline operational transport planning and the taxonomy of Lahyani et al. (2015), we classify our research problem to be a multi-objective static open vehicle routing problem with pickup and delivery, where load splitting is not allowed, and vehicles can perform multiple trips. Furthermore, we have a fixed number of non-compartmentalized homogeneous vehicles with heterogeneous freights where transportation orders have hard time windows, and both waiting times and cleaning are considered. However, we encountered that there is one interesting difference between the standard VRP and our research problem, being that our research does not assume that a vehicle's route starts and ends at a depot. This implies that according to the best of the authors' knowledge, we are studying a new variant of VRP in this research.

In order to solve this new VRP variant we will, based on a thorough assessment of the state-of-the-art literature related to constructive heuristics to VRPPDTW or PDPTW, apply a modified cheapest insertion constructive heuristic. Due to the time constraints of this research, the implementation of an improvement heuristic will be left for future research. However, based on an analysis of the improvement heuristic applied in the literature related to VRPPDTW we recommend implementing the simulated annealing improvement meta-heuristic with a combination of move and swap neighborhood operators.

Chapter 5 will provide insight into how we build our truck planning tool in the Delphi Software.

5. Model design and validation

In this chapter, we explain how we constructed the Avebe Planning Tool in Delphi and the logic behind the tool in order to answer research question 4 (see Section 1.6). Section 5.1 discusses the input data used to build the Avebe Planning Tool and our data gathering approach. Section 5.2 provides insight into the modeling assumptions made while building the Avebe Planning Tool. In Section 5.3, we give a step-by-step explanation of the logic behind the Avebe Planning Tool and the important calculations performed during the planning process. Section 5.4 states the model verification and model validation techniques that we applied to ensure that the Avebe Planning Tool corresponds to the model on paper, and the real transportation process. Section 5.5 provides insight into what the Avebe Planning Tool looks like, how it can be used, and what output it generates. Lastly, Section 5.6 contains the conclusion of Chapter 5.

5.1 Input data Avebe Planning Tool

In this section, we provide insight into the input data that we use for the bulk truck planning. As argued in Chapter 4, we build a tool to solve vehicle routing problems with pickup and delivery, and time windows (VRPPDTW). Therefore, the tool should deal with transportation orders which have a loading location (pickup) and an unloading location (delivery). Furthermore, the transportation orders should be performed after a certain point in time (start of the time window) and before a later point in time (end of the time window).

The number of transportation orders and their time window depend on several things. First of all, the weather. The weather influences the number of potatoes harvested and the moment that potatoes are supplied from the fields. More potatoes harvested means more production and therefore a higher demand for transportation. Secondly, the customer demand influences the production flows. Depending on the demand of different customers, different products can be made out of the potatoes which influences the demand for the different transport orders. Lastly, the capacity of the silos and the production speed at the factories influence the demand for transportation orders. To ensure that factories do not have downtime because of an empty input supply silo, or an overflow of the output silo, transport is demanded.

Due to uncertainties and dependencies in demand for transportation, it is hard to determine which transport orders should take place during the whole intercampaign TAK which is generally speaking about 70 days. According to the transport planner of the transport company, he should be happy when his one-day ahead planning corresponds for 10 percent to the real transport on the next day. To avoid making about 3000 transportation orders with time windows, loading, unloading locations, and material types by hand, which might not be representative for the real transportation demand, we decide to simultaneously simulate and plan the transportation process during the intercampaign TAK in Delphi. To simulate and plan the transportation process, we apply the push and pull supply chain logic.

Push and pull flows

In a *push flow*, the factory pushes the output into its output silo and a bulk truck should make sure that the output silo never reaches its silo capacity. When the silo capacity is reached the factory cannot push the output into the silo anymore, implying that the factory must be shut down which we want to avoid. Figure 14, visualizes a push flow.

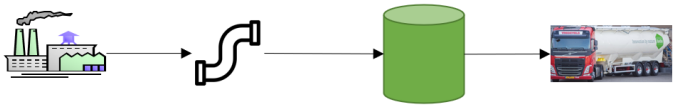

Figure 14: Visualization of a push flow

In a *pull flow*, the factory pulls the material out of the input silo and a bulk truck should make sure that the input silo is never empty. When the input silo is empty, the factory does not have material to process, implying that the factory must be shut down which we want to avoid. Figure 15, visualizes a pull flow.

Figure 15: Visualization of a pull flow

Flow input

Based on Figure 3, Figure 5, Figure 6, Figure 7, Figure 8, Figure 9, showing the different transportation flows, and based on expert interviews, we select 39 transportation flows that we consider in the Avebe Planning Tool. Parts of the flows present in the figures are not present during the intercampaign TAK. Therefore, we exclude these flows. Furthermore, we combine some flows like the waxy flow from the Houtuni to lijn V, PN1, Gum, lijn AB, and lijn C, which are combined to TAK (VMF) since these factories have the same loading and unloading locations. For each of these 39 transport flows, we determine the input data needed to simulate and plan the transport. Table 42 of Appendix C.1 provides the flows and the information related to the flows. The data in Table 42, is also the first input file of the Avebe Planning Tool (the file is called 'FlowInput').

In Table 42, the columns FlowID, FlowAvailability, LoadingPoint, UnloadingPoint, Material, NormalSpecial, PushPull, LeadingSilo, SiloCapacity, TruckVolume, ProductionSpeed, InitialVolume, StartVolume, EndVolume, LoadingTime, and UnloadingTime are present. Most of the data will be self-explanatory, therefore we discuss only the non-self-explaining columns. First of all, the FlowAvailability of a flow can be TRUE or FALSE. At the beginning of the planning horizon, all flows will be available (TRUE), implying that we are allowed to generate an order for every flow. However, towards the end of the planning horizon, flows become unavailable since their time window will be behind the end of the planning horizon (day 70). This means that the FlowAvailability will be set to FALSE and no more orders of this flow will be done. Secondly, the column NormalSpecial indicates whether the flow is a flow that must be performed by a truck from the hired pool of bulk trucks (normal) or that we want to do the flow by a truck inside the pool of hired bulk trucks (special) because of financial advantages, but according to the contract between Avebe and the transport company, these do not have to be performed by the hired pool of bulk trucks.

The column PushPull indicates whether the flow is a push or a pull flow. When the transport is needed because the factory or customer beyond the unloading point needs product, we classify the flow to be a pull flow. When transport is needed to prevent an overflow of the loading silo, we classify the flow to be a push flow. The column LeadingSilo provides the name of the silo that generates the demand for transport of that flow. When the flow is a push flow, the leading silo equals the loading point while for a pull flow the leading silo is the unloading point. The SiloCapacity, TruckVolume, InitialVolume, StartVolume, and EndVolume are all given in tons and the loading and unloading times are in minutes. The silo capacity is the maximum volume that fits into the leading silo of that flow. The Truck volume is the volume that equals one freight of the flow. The production speed of the flow relates to the production speed in tons per hour of the factory in front of the leading silo when the leading silo is a push silo and to the factory behind the leading silo when the leading silo is a pull silo.

Furthermore, the initial volume is the volume in the leading silo at time zero of our planning. The start volume is the minimum volume needed to perform a transport order of the flow. For a push order, the start volume corresponds to the volume of 1 freight of the flow, while for a pull order the start volume corresponds to the volume equal to the silo capacity of the leading silo minus 1 freight. For the push flows with the leading silo 'GNV silo 1+2' we make an exception since the 'GNV silo 1+2' is also the loading point for the pull flows with FlowID's 4, 5, 6, and 7. The push flows from 'GNV silo 1+2' should only be done to ensure that we will not have a silo overflow, but it might not happen that flow 4, 5, 6, or 7 cannot be done because of the push flows from 'GNV silo 1+2'. Therefore, we set the start volume for these push flows equal to 100 tons.

The end volume is equal to the silo capacity in case of a push flow because the silo capacity is the maximum volume allowed in the silo. The latest point in time at which a freight must be loaded at this push leading silo is when the volume in the silo equals the maximum volume. The end volume of the leading silo of a pull flow equals zero. The latest point in time at which a freight must be unloaded at the pull leading silo is when the silo is empty. Lastly, the loading time and unloading time is the time in minutes needed to load a truck of the flow at the loading location respectively unloaded a truck of the flow at the unloading location.

Leading silos

Next to the input data related to the different transportation flows we also made the 'LeadingSilos' input data for the Avebe Planning Tool. Table 43 in Appendix C.1 provides an overview of the leading silos of the 39 flows that we discussed. For every leading silo, the table provides the production speed in tons per hour. The production speed is obtained by adding the production speeds of the different flows with the same leading silo. Again, an exception is made for 'GNV silo 1+2' since this silo is the loading point for both push and pull flows. This implies that the factory prior to the 'GNV silo 1+2' must also produce for these pull flows. Therefore, also the production speed of the pull flows loading at 'GNV silo 1+2' is added. Furthermore, Table 43 shows whether the leading silo is a push or a pull silo, the initial volume of the silo, and the silo capacity. The goal of the 'LeadingSilos' table is to keep track of the silo inventory levels during the planning period. These silo inventory levels are an important input to the generation of transportation orders during the planning period. How exactly, will be discussed in Section 5.3.

Availability of loading and unloading docks at silo locations

When planning the transport of the materials by the trucks, it is also important to consider the capacity of the silos in terms of the number of loading and unloading docks. Table 44 in Appendix C.1 provides an overview of the number of loading docks, the number of unloading docks, and the total number of docks at all unique loading and unloading points of the flow input table (Table 42). Furthermore, the time that the loading and unloading docks are available is initialized at either 0 or 100800. The availability = 0 when the loading or unloading dock is available at time 0. The availability = 100800 for loading and unloading locations 2 and 3, when the silo location only has 1 dock which can be used for loading and unloading but not for loading and unloading at the same time. 100800 corresponds to the end of our planning horizon in minutes (70 days * 24 hours * 60 minutes = 100800 minutes).

Most of the silos do have 1 dock which can both be used for loading and unloading but it is not possible to load and unload simultaneously. However, there are three exceptions being the 'GNV silo 1+2', 'OKO', and 'hired silo 1'. At the GVN silo 1+2, there are two docks that can both be used for loading and unloading. This implies that it is possible to have 2 trucks loading and 0 trucks unloading, or 1 truck loading and 1 truck unloading, or 0 trucks loading and 2 trucks unloading.

At silo OKO, we have 2 docks of which one dock is dedicated to loading and one to unloading. This implies that it is possible to simultaneously load and unload from the OKO silo. However, it is not possible to load with two trucks at the same time or to unload with two trucks at the same time. Lastly at 'hired silo 1', we have 3 docks that can be used for loading and unloading. Therefore, it is possible to have 3 trucks loading and 0 trucks unloading, or 2 trucks loading and 1 truck unloading, or 1 truck loading and two trucks unloading, or 0 trucks loading and 3 trucks unloading.

Travel times
The last input data to make the transport planning are the travel times. To determine the travel time from each possible location of the truck to each possible next location of the truck we made a distance matrix with all unique loading and unloading locations in both the horizontal and vertical direction. This resulted in 1936 transportation times which are determined by filling in the from- and to addresses in Google Maps, and picking the first suggested route and corresponding transport duration. Because of the size of the distance matrix, we refer to the Delphi input file 'DistanceMatrix' instead of showing the distance matrix explicitly in this report.

Now that we discussed all the input data used to plan the bulk transport, we discuss the assumptions that we make to build the Avebe Planning Tool in Section 5.2.

5.2 Modelling assumptions

In this section, we mention the assumptions that we make while building the Avebe Planning Tool. Besides, we indicate how these assumptions deviate from reality which makes it possible to estimate the impact of these assumptions. First, the assumptions related to the trucks are discussed, then the assumptions related to the silos and factories, and lastly the assumptions related to the orders.

Trucks
One truck uses one trailer
In the Avebe Planning Tool, we assume that each truck uses one trailer. However, in reality, one truck can use multiple trailers. In the current transportation planning, a pool of 10 bulk trucks can use 30 different trailers. The reason for assuming that one truck uses one trailer is that the trailers of the transport company are also used for customers other than Avebe. Since it is not feasible within this research to account for the planning of the trailers used by other companies than Avebe, we assume that one truck has one trailer. This also implies that it is not possible to load a trailer and put it aside until the material is needed (a kind of buffering in trailers done in the current planning). Therefore, this assumption results in a bit less storage capacity and more frequent cleaning of trailers since the trailer should be cleaned every time a truck transports a different product. On the other hand, in our planning, Avebe will not be dependent on the trailers used by other companies anymore. Furthermore, the cleaning costs become more transparent since we know what materials are transported in the trailer and when cleaning is needed.

Availability of trucks
In the Avebe Planning Tool, we assume that the trucks will not have traffic accidents and that the truck drivers will not become ill. In reality, accidents can occur, and drivers can become ill. However, these events occur very infrequently. Furthermore, when a truck driver is ill or a truck is damaged, the transport company has backup drivers and backup trucks. Therefore, the impact of this assumption will be very low.

Volume per freight
For each freight, we assume a fixed volume based on the loading location, unloading location, and the material transported (see Table 42 in Appendix C.1). In reality, these truck volumes are often fixed as well. However, for some of the flows, the volumes fluctuate a bit to manage the volumes in the silos. For these flows, we, together with an expert of Avebe, assumed a truck volume based on historical data. There were no flows with truck volume fluctuations larger than 2 tons. Therefore, the impact of this assumption will be very low.

Start and cleaning location of the trucks
In the Avebe Planning Tool, we assume that all trucks start clean at the Baptistenkade 40, Gasselternijveen. This address is the address of the Avebe site in Gasselternijveen. Setting the start locations of the bulk trucks equal to Baptistenkade 40 will only impact the travel time to the first order of the trucks. Therefore, the impact of this assumption on the performance of the bulk truck planning will be marginal. Furthermore, we assume that all trailer cleanings are performed in Ter Apelkanaal. In reality, 95% of the cleaning takes place in Ter Apelkanaal and 5% in Zuidbroek and Coevorden. The impact of this assumption will be relatively low since the travel time also depends on the location of the truck to be cleaned.

No changes of drivers
In our Avebe Planning Tool, we assume that changing the truck driver does not impact the transportation schedule. The truck drivers work in shifts of 12 hours and the driver changes take place at the location of the truck. The new truck driver goes to the truck by car, and the old truck driver takes the same car to go home. Therefore, we expect the impact of this assumption on the truck planning to be very low.

Silos
Availability, capacity, and initial volume of silos
In our Avebe Planning Tool, we assume that the silos are 24 hours a day and 7 days per week accessible. This assumption corresponds to reality for the largest part of the silos. However, some customer silos have a limitation on their opening hours. Table 45 of Appendix C.2 provides an overview of the opening hours of all silos. In order to consider this restriction on the opening times without making this an input to the Avebe Planning Tool, we assume that the customers have a relatively small silo capacity of 40 tons. This ensures that the tool will generate relatively short time windows in which the customer orders should be fulfilled which corresponds to reality. Furthermore, we tackle the issue that we do not know the capacity of the customer silos while this value is needed to let the push and pull system, discussed in Section 5.1, work. The impact of this assumption is hard to estimate since we do not know what the capacity of the customer silos is.

Loading and unloading times
In the Avebe Planning Tool, we assume location- and material-specific fixed loading and unloading times. The loading and unloading times for the starch flows (material 1000) are set equal to the average times in the historical data, for the other flows the times are based upon expert interviews. In reality, there will be fluctuations in the loading and unloading times. The fluctuations in loading and unloading times can be explained by the presence of craters in the silo. When craters are present in the silos, the loading times will increase. However, the size of the impact of craters in the silos on the loading speed of trucks is not known. Based on expert interviews, we expect the impact of our assumption to be low.

Initial volume
In our Avebe Planning Tool, we have to initialize the volumes in the leading silos. To make sure that the tool directly produces useful output, without the need for long warm-up periods, we decided to set the initial volume of a pull flow equal to the start volume of that push flow. This implies that the pull flows are directly available at time zero of the planning period. For the push flows, we make the initial volume equal to the start volume minus 1 hour of production of the factory related to the leading silo. This implies that the push flows become available 1 hour after the start of the planning horizon. This assumption can impact the first few days of the planning. However, we expect the impact on the complete bulk truck planning during the intercampaign TAK to be marginal.

Factories
Production speed factories
In our Avebe Planning Tool, we assume that the factories do not have any breakdowns and produce 24 hours a day 7 days per week at a constant speed. The reason for this assumption is that the key focus of Avebe is to keep the factories running. Therefore, an expert of Avebe emphasized the importance that no factory downtime may occur due to supply issues. This implies that we have to build the system such that it can handle the maximum demand in terms of transport, which corresponds to the situation in which all factories produce without breakdowns or maintenance stops. The production speeds are provided by an expert of Avebe and are based on historical data and sales forecasts for the intercampaign TAK 2021. The impact of this assumption is that more transport is done related to push flows than needed in reality. When a factory is down for maintenance, we do not have to transport the material to prevent overflows of silos. Therefore, this assumption will lead to a planning in which more transport capacity is needed than will be needed in reality.

Orders
Special transport orders
In our Avebe Planning Tool, we assume that all special transport orders should be performed by the hired pool of bulk trucks while in reality, these orders do not have to be performed by the pool of bulk trucks. However, unless we need an additional truck in the hired pool of bulk trucks to do the special transport orders it will be financially attractive to perform the special transport orders within the pool of hired bulk trucks. The reason for this is that a truck in the pool of hired bulk trucks costs Avebe 42.35 euros per hour, while a commercial truck, which has to do the special transport orders otherwise, will cost €100.77 per hour. We should notice that we must hire a pool truck 24/7, which corresponds to 24*7*10 = 1680 hours, during the intercampaign TAK. This implies that one truck in the hired pool of bulk trucks costs €42.35*1680 = €71,148. Therefore, it is financially attractive to have an additional truck in the pool of hired bulk trucks when the truck is used for more than €71,148/€100.77 = 706 hours. This implies that the utilization of the truck should be higher than 706/1680 = 42%. Since the special transport orders can be divided over the entire pool of bulk trucks and the break-even point between doing the orders within the pool or not lies at a relatively low truck utilization rate of 42%, we decided to perform the special transport orders with the hired pool of bulk trucks. In reality, Avebe will try to do as much as special transport orders within the hired pool of bulk trucks as well, for the same financial reasons. Therefore, the impact of this assumption will be low.

Now that we discussed both the input data of the Avebe Planning Tool and the assumption made to simulated and plan the transportation process, we will provide insight into the logic behind the Avebe Planning Tool in Section 5.3.

5.3 Model building

In this section, we explain the logic behind the Avebe Planning Tool. To do so, we make use of the flow diagram given in Figure 17. Figure 17 provides an overview of all steps taken to simulate and plan the transportation flows discussed in Section 5.1. The green dotted lines are placed around the procedures and functions present in the code of the Avebe Planning Tool. The name of the procedures in the code is provided in red and can be found in the corners of the dotted line boxes. The procedure 'PlanOrderOnTruck' is the main planning procedure, therefore the dotted box covers the complete flow diagram. Furthermore, we explain the important calculations done by the Avebe Planning Tool.

Figure 16 provides a process flow containing the seven steps in which we discuss the Avebe Planning Tool. The numbers in the process flow correspond to the numbers of the bold headers in this section.

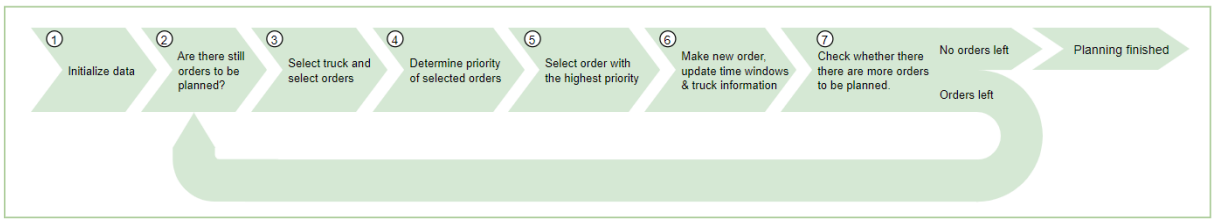

Figure 16: Process flow providing an overview of the structure in Section 5.3

1. Initialize data

The first step of the Avebe Planning Tool is to initialize the input data. In this step, we make sure that there is one order of each flow present in the order array, that the number of trucks present in the truck array equals the number of trucks set on the controls tab of the tool, and that these trucks are all available and clean at time zero. Furthermore, the silo array is initialized, meaning that the silo array equals the 'LeadingSilos' input data provided in Table 43. Besides, the current volume of the silo is set equal to the initial volume and all other variables needed during the planning process are set equal to zero. The procedure in which this initialization takes place in the code is called 'InitializeData'.

2. Are there still orders to be planned?

The second step is to check whether the number of orders in the order array is still larger than zero. When during the iterative process of generating orders and assigning these orders to the trucks the start time window of the order becomes larger than minute 100800 (the latest minute of our planning horizon), the flow related to this order becomes unavailable and there will no longer be an order of this flow available in the order array. Therefore, the number of orders in the order array will decrease. When all flows become unavailable, the order array becomes empty meaning that we are finished planning the orders during our planning horizon of 70 days.

3. Select truck and select orders

When there are still orders available in the order array, the next step is to determine which truck is available first. The truck that is first available is the truck that we are going to schedule the next order on. Therefore, we apply parallel route building as motivated in Section 4.5. The function built, in the Avebe Planning Tool, to find the truck that is first available is called 'SelectTruck'. Once we selected the truck that we are going to schedule, we determine which orders in the order array will be selected and placed in the 'SelectedOrders' array. The 'SelectedOrders' array is a list of orders from which we will, later on, select the order to be assigned to the truck using our priority rule (see Equation 4). This order selection step makes it possible to balance between the weight added to the 'Earliest Due Data' (EDD) and the 'Travel, Waiting, and Cleaning' (TWC) time in the priority rule. The priority rule will be explained after we explained the different selection methods that we tested. For all selection methods, we tested with 8 trucks and different weights added to the EDD and the TWC time. The selection of

the orders from the 'OrderArray' for the 'SelectedOrders' array takes place in the Avebe Planning Tool procedure called 'PriorityArray'. Below we will provide the results of experiments that we performed without an order selection method and with three different order selection methods.

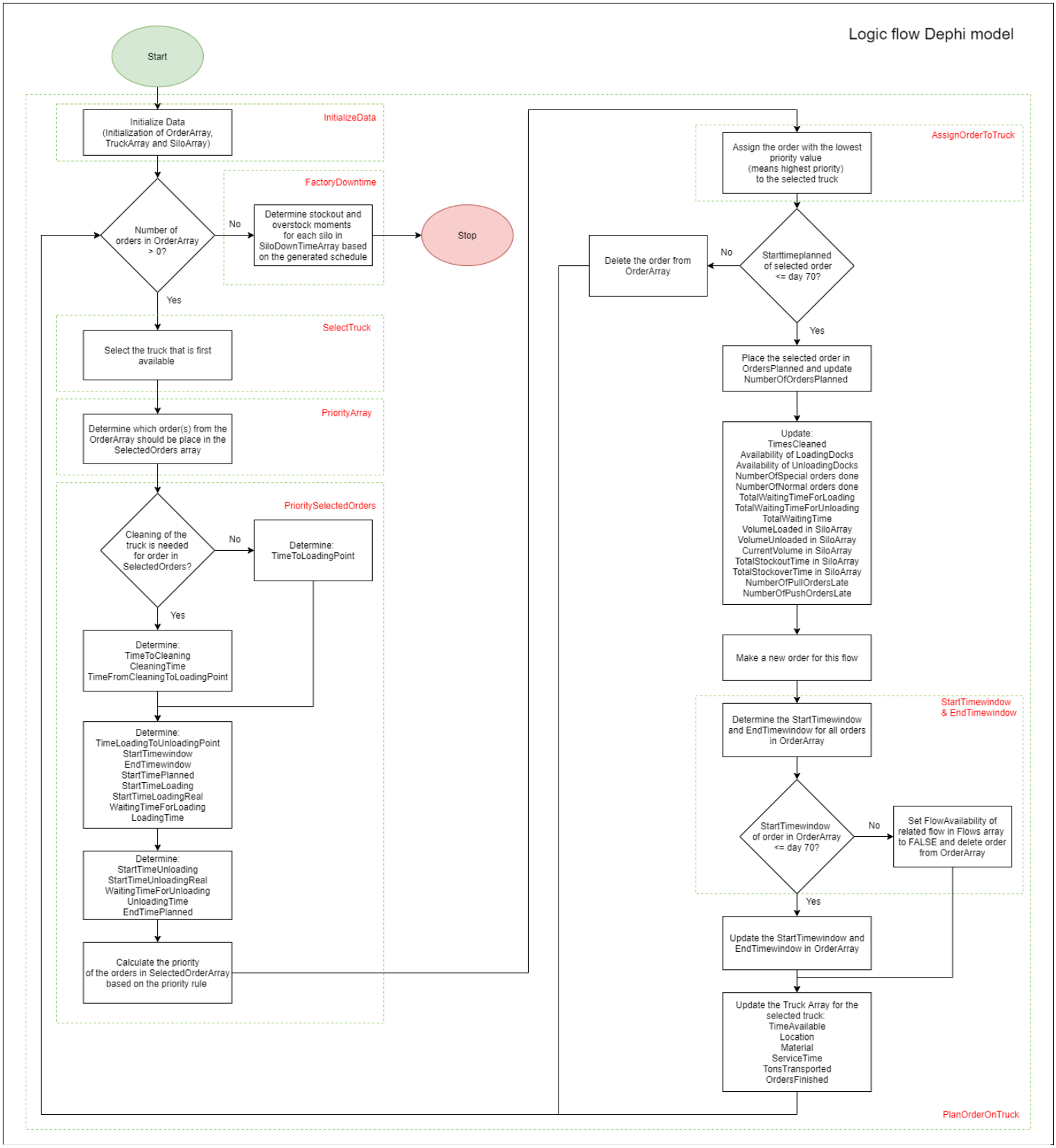

Figure 17: Logic flow of the Avebe Planning Tool

No order selection method before applying the priority rule
During the tool building phase, we started without a selection method to place orders from the 'OrderArray' into the 'SelectedOrders' array. This implies that we directly apply the priority rule (see Equation 4) to all orders in the 'OrderArray'. Table 20, provides the experiment results. Analyzing these results, we observe that the waiting time per ton material transported and the number of times that we clean, nicely decrease when more weight is given to the TWC time which is in line with what we would expect. When we give more weight to the TWC time, orders for which the travel time is short, and for which the waiting time at the (un)loading dock is short, and for which we do not have to clean the truck, are prioritized. Besides, the number of late orders and therefore the factory downtime also decreases when more weight is given to the TWC time which is explained by the fact that orders can be done faster when the loading location is closer to the truck, the truck does not have to wait at the loading and unloading location and the truck does not have to be cleaned. We should notice, that when no weight is given to the EDD, the deadline of the orders is no longer considered implying that we always perform the order which has the lowest TWC time. This implies that a lot of orders are never done, which explains the low number of tons transported and the high factory downtime in the last experiment.

Furthermore, we observe that the weights, given to the EDD and the TWC time, strongly influence the performance of the Avebe Planning Tool. Therefore, the weight added to the EDD and TWC should be determined very carefully and has a huge impact on the solution quality when no selection method is used before applying the priority rule. This relatively small range of weights for the EDD and TWC time, resulting in low factory downtimes, can be explained by the fact that the EDD can become very large for the orders compared to the TWC time. This implies that the impact of the TWC time on the order to select for the truck becomes negligible, resulting in a lot of cleaning and long waiting times at the (un)loading docks when insufficient weight is given to the TWC times. Furthermore, frequently cleaning and long waiting times at the (un)loading docks will result in many orders that are done late causing factory downtime.

Selection Method	# Trucks	W_EDD	W_TWC	Costs/ton	Waiting/ton	Factory-downtime	# Cleaned	# Trucks	# Special	# Normal	Tons trans.	Waiting loading	Waiting unloading	Total waiting	Pull late	Push late
No	8	1.0	0.0	6.42	0.277	34183	1576	8	136	2959	88657	22059	2510	24569	2143	754
No	8	0.9	0.1	6.442	0.281	37490	1582	8	136	2949	88361	22544	2242	24786	2124	748
No	8	0.8	0.2	6.419	0.281	35883	1554	8	136	2960	88676	22845	2090	24935	2114	737
No	8	0.7	0.3	6.394	0.264	32472	1545	8	136	2972	89011	21705	1814	23520	2157	752
No	8	0.6	0.4	6.379	0.247	34678	1541	8	136	2980	89233	20117	1903	22020	2111	734
No	8	0.5	0.5	6.233	0.177	10939	1482	8	136	3059	91317	14466	1687	16153	1903	646
No	8	0.4	0.6	6.167	0.109	2486	1448	8	136	3105	92297	8643	1462	10105	1338	487
No	8	0.3	0.7	6.144	0.08	174	1252	8	136	3136	92638	6643	811	7454	20	9
No	8	0.2	0.8	6.143	0.04	0	914	8	136	3137	92659	2753	918	3671	0	0
No	8	0.1	0.9	6.139	0.026	25	614	8	137	3137	92711	1520	877	2397	6	19
No	8	0.0	1.0	34.028	0.003	460292	0	8	4	565	16727	43	2	45	30	145

Table 20: Performance of the Avebe Planning Tool without selection method

To make the decision for the weight to be added to the EDD and the TWC time less critical, we decide to apply an order selection method to selected orders from the 'OrderArray' for the 'SelectedOrders' array. After which we will only apply the priority rule to the orders in the 'SelectedOrders' array. Below we will show the experiment results related to three different order selection methods that we tested. We should notice that the implementation of a selection method before applying the priority rule reduces the impact of the priority rule on the order that will be assigned to the truck. Therefore, also the weights added to EDD, TWC time and the corresponding performance of the planning based on the performance indicators will become harder to explain.

First order selection method before applying the priority rule
The first order selection method consists of the following three situations:

1. All orders that are available, *and* for which the material of the order equals the material in the selected truck.
2. All orders that are available, *or* for which the order material is the same as the material in the selected truck.
3. All orders from 'OrderArray' are placed in the 'SelectedOrders' array.

In this order selection method, we start by checking which orders in the 'OrderArray' correspond to situation 1. When there are orders that correspond to situation 1, we place these orders in the 'SelectedOrders' array and we skip situations 2 and 3. However, when there are no orders in 'OrderArray' that corresponds to situation 1, we check whether there are orders in the 'OrderArray' that corresponds to situation 2. Again, we place the orders corresponding to situation 2 into the 'SelectedOrders' array. When no orders correspond to situation 2, we place all orders from the 'OrderArray' into the 'SelectedOrders' array.

Table 21 provides the experiment results related to the first selection method. Analyzing the number of orders that are done late and the resulting factory downtime of the different experiments, we observe that the weights assigned to the EDD and the TWC time are way less critical than in the experiments without the selection method. Furthermore, we observe that the trucks are cleaned less frequently which is in line with what we would expect based on situations 1 and 2 of the first selection method. However, analyzing the generated truck schedule on order level we encountered that we select orders which are not yet close to their deadline, but which are already available and have the same material as the material in the selected truck. This implies that orders which have a very tight deadline and that have another material than the material in the truck selected, are done way too late. This results in factory downtime, which we want to avoid. To solve this issue, we experiment with a second order selection method. In this selection method, we focus less on cleaning and more on reducing the number of orders that are done late.

Selection Method	# Trucks	W_EDD	W_TWC	Costs/ton	Waiting/ton	Factory-downtime	# Cleaned	# Trucks	# Special	# Normal	Tons trans.	Waiting loading	Waiting unloading	Total waiting	Pull late	Push late
1	8	1.0	0.0	6.131	0.157	449	649	8	142	3137	92844	13405	1197	14602	26	9
1	8	0.9	0.1	6.129	0.148	221	659	8	142	3138	92870	12742	1041	13783	32	9
1	8	0.8	0.2	6.13	0.164	442	665	8	142	3137	92848	13975	1216	15192	29	11
1	8	0.7	0.3	6.132	0.132	207	660	8	141	3137	92824	11240	977	12218	28	3
1	8	0.6	0.4	6.133	0.138	344	646	8	142	3134	92803	11886	930	12816	27	5
1	8	0.5	0.5	6.127	0.172	1573	638	8	142	3136	92891	15083	887	15971	40	17
1	8	0.4	0.6	6.131	0.142	388	623	8	142	3135	92844	12004	1157	13160	40	23
1	8	0.3	0.7	6.126	0.129	416	596	8	142	3139	92911	10262	1690	11952	30	6
1	8	0.2	0.8	6.137	0.111	2483	556	8	142	3132	92743	7764	2557	10322	40	18
1	8	0.1	0.9	6.137	0.21	10844	488	8	142	3126	92744	17745	1704	19449	79	47
1	8	0.0	1.0	7.62	0.668	394073	11	8	97	2485	74694	47586	2304	49890	429	72

Table 21: Performance of the Avebe Planning Tool with selection method 1

Second order selection method before applying the priority rule

1. All orders that are available within two hours from the time that the selected truck is available.
2. All orders from 'OrderArray' are placed in the 'SelectedOrders' array.

The second order selection method starts by checking whether there are orders available within two hours from the time that the selected truck is available and place these orders in the selected orders array. When none of the orders in the order array is available within two hours of the time that the truck becomes available, we place all orders in the selected orders array. The time that a truck is available is equal to the time that the truck finished its previous order. By implementing this logic, we accept the possibility that an order is assigned to the truck for which the truck should wait two hours. We do this to avoid that orders, having very short time windows and therefore a high urgency, are not selected because they are not yet available. While these orders might already be late when the next truck becomes available.

Table 22 provides the experiment results related to the second order selection method. Analyzing the performance indicators, we observe that the results of this selection method are comparable to the results that we obtained without a selection method (see Table 20). The performance of the planning is again strongly dependent on the weights added to the EDD and the TWC time. Also, the trucks are again frequently cleaned. The results are in line with what we could expect, since the only difference between planning without selection method and with selection method 2, is that orders which are not available within two hours are not considered in selection method 2. However, the probability of selecting the orders which are not yet available is also relatively small when the priority rule is directly applied.

Selection Method	# Trucks	W_EDD	W_TWC	Costs/ton	Waiting/ton	Factory-downtime	# Cleaned	# Trucks	# Special	# Normal	Tons trans.	Waiting loading	Waiting unloading	Total waiting	Pull late	Push late
2	8	1.0	0.0	6.44	0.284	36700	1587	8	136	2951	88377	22930	2181	25111	2091	735
2	8	0.9	0.1	6.43	0.271	36173	1584	8	136	2957	88523	22323	1673	23995	1992	701
2	8	0.8	0.2	6.405	0.265	31510	1568	8	136	2969	88867	21642	1917	23559	2022	705
2	8	0.7	0.3	6.398	0.247	33406	1577	8	136	2972	88965	19882	2055	21937	2013	702
2	8	0.6	0.4	6.317	0.211	21162	1533	8	136	3012	90101	16997	2050	19047	2037	695
2	8	0.5	0.5	6.291	0.193	22427	1535	8	136	3025	90479	15824	1621	17445	2021	688
2	8	0.4	0.6	6.201	0.163	6034	1458	8	136	3084	91793	13044	1951	14995	1480	504
2	8	0.3	0.7	6.141	0.139	85	1391	8	136	3138	92689	11928	988	12916	1	1
2	8	0.2	0.8	6.134	0.105	60	1380	8	142	3136	92795	8576	1130	9706	0	0
2	8	0.1	0.9	6.136	0.1	7	1284	8	142	3135	92766	7382	1929	9311	0	0
2	8	0.0	1.0	6.265	0.284	38955	930	8	142	3032	90846	18490	7319	25809	146	49

Table 22: Performance of the Avebe Planning Tool with selection method 2

Analyzing the generated truck schedule on order level we observe the following disadvantage of the second selection method. When we have multiple orders, which have their deadline far in the future but are already available within two hours, we want to select the order for which we have the smallest traveling, waiting, and cleaning time. However, it is hard to account for this using the priority rule when the EDD becomes much larger than the TWC time (see Equation 4). To reduce the number of times cleaned and to balance the priority rule, we design a third selection method.

Third order selection method before applying the priority rule

1. All orders that 1) should be finished within 10 hours from the time that the selected truck is available and 2) the time that the order becomes available is within 2 hours from the time that the selected truck is available.
2. All orders that 1) are available within two hours from the time that the selected truck is available and 2) for which the material of the order equals the material in the selected truck.
3. All orders from 'OrderArray' are placed in the 'SelectedOrders' array.

The third selection method starts by checking whether there are orders in the 'OrderArray' that should be loaded/unloaded (loaded for a push order and unloaded for a pull order) within 10 hours and can be loaded/unloaded within two hours from the time that the selected truck is available. These orders are placed in the 'SelectedOrders' array. The 10 hours are based upon an analysis of the longest time possibly needed to complete an order. When no orders in 'OrderArray' correspond to situation 1, we check whether there are orders available within two hours from the time that the selected truck is available and for which no truck cleaning is needed. When there are orders in the 'OrderArray' that correspond to this second situation, we place these orders in the 'SelectedOrders' array. However, when none of the orders in the 'OrderArray' correspond to situation 2, all orders in the 'OrderArray' are placed in the 'SelectedOrders' array.

Table 23 provides the experiment results related to the third selection method. Analyzing the number of orders done late and the resulting factory downtime we observe that applying the third selection method will give a good performance of the truck schedule for almost all weights added to the EDD and the TWC time. Only, when no weight is given to the EDD the factory downtime will be high which can be explained by the fact that we do not consider the deadline of the order when we select the order, out of the 'SelectedOrders' array, to be assigned to the truck. The fact that good truck schedules are generated for a wide range of weights added to the EDD and the TWC time, implies that when selection method 3 is applied, selection method 3 has more impact on the truck schedule than the priority rule. However, the experiment in which no weight is given to the EDD shows that the priority rule still does have some impact on the truck schedule.

Note that the fact that the priority rule has less influence on the order selection process, complicates the explanation of the performance of the bulk truck planning based on the weights added to the EDD and the TWC time as compared to without a selection method. However, we can still observe a decreasing trend in the waiting time per ton/transported and the number of trucks cleaned when more weight is given to TWC time (when we exclude the experiment with no weight for EDD, which has a bad performance for the above-mentioned reason).

Selection Method	# Trucks	W_EDD	W_TWC	Costs/ton	Waiting/ton	Factory-downtime	# Cleaned	# Trucks	# Special	# Normal	Tons trans.	Waiting loading	Waiting unloading	Total waiting	Pull late	Push late
3	8	1	0	6.132	0.145	81	844	8	142	3137	92821	12436	1000	13437	0	0
3	8	0.9	0.1	6.13	0.128	127	838	8	142	3138	92854	10896	978	11875	0	0
3	8	0.8	0.2	6.134	0.154	120	841	8	142	3136	92792	13212	1066	14279	0	0
3	8	0.7	0.3	6.132	0.146	55	834	8	142	3137	92821	12455	1116	13571	0	0
3	8	0.6	0.4	6.13	0.128	59	829	8	142	3138	92850	10910	1016	11926	0	0
3	8	0.5	0.5	6.132	0.155	131	843	8	142	3137	92821	13341	1071	14412	0	0
3	8	0.4	0.6	6.13	0.134	102	804	8	142	3138	92850	11456	995	12451	0	0
3	8	0.3	0.7	6.13	0.139	126	769	8	142	3138	92850	11842	1092	12934	0	0
3	8	0.2	0.8	6.132	0.103	33	705	8	142	3137	92821	6751	2853	9605	0	0
3	8	0.1	0.9	6.134	0.11	61	581	8	142	3136	92795	7195	3032	10228	0	0
3	8	0	1	6.232	0.175	36496	955	8	137	3067	91340	11215	4726	15941	246	123

Table 23: Performance of the Avebe Planning Tool with selection method 3

Conclusion order selection methods before applying the priority rule

Table 24 provides an overview of the advantages and disadvantages of the order selection methods discussed. The robustness of the quality of the bulk truck planning is of key importance to ensure that deviations in the input data compared to reality do not result in going from a good to a poor truck planning. Based on this criterion, we decide to apply the third selection method in our Avebe Planning Tool.

Order selection method	Advantages	Disadvantages
No order selection method & Second order selection method	The impact of changing the weights of the EDD and TWC time is easy to interpret. Besides, a good truck planning is obtained when the weights added to EDD and TWC time are correctly chosen.	The weights given to the EDD and the TWC time are very critical for the quality of the resulting bulk truck planning. Besides, it is hard to account for TWC time when orders have a deadline far in the future.
First order selection method	The frequency of trailer cleaning and the dependency of the quality of the bulk truck planning on the weights given to EDD and TWC time are relatively low compared to the situation without order selection method.	Orders which are not yet close to their deadline but have the same material as the selected truck are scheduled. This results in orders with a tight deadline done late which causes a relatively high factory downtime.
Third order selection method	A good truck planning is obtained for almost all weights added to EDD and TWC time resulting in a robust planning tool.	The resulting truck planning is largely dependent on the order selection method which makes it harder to interpret the impact of the weight given to EDD and TWC time in the priority rule.

Table 24: Advantages and disadvantages of the different order selection methods

4. Priority of selected orders

Once we filled the selected order array using order selection method 3, we will determine the priority of the orders available in the selected order array. This is done in by procedure 'PrioritySelectedOrders' in the code of the Avebe Planning Tool. The priority of the orders is calculated using Equation 4. The weight given to the earliest due date (W_{EDD}) and the weight given to the travel, waiting, and cleaning time (W_{TWC}) are both equal to the number filled in on the controls tab of the Avebe Planning Tool. We select the order with the lowest priority value according to Equation 4, since this will be the order with the highest priority.

Equation 4:

$$Priority = (W_{EDD} * EDD) + (W_{TWC} * \big(C * (TTC + CT + TFCTL + WTFL + WTFU)\big) + ((1 - C) * (TTL + WTFL + WTFU))$$

Where:

- *W_{EDD} = Weight Earliest Due Date*
- *EDD (= Earliest Due Date) = End Time Window – Time Truck Available*
- *W_{TWC} = Weight Travel Waiting Cleaning*
- *C = Cleaning*
- *TTC = Time To Cleaning*
- *CT = Cleaning Time*
- *TFCTL = Time From Cleaning To Loading point*
- *WTFL = Waiting Time For Loading*
- *WTFU = Waiting Time For Unloading*
- *TTL = Time To Loading point*

The priority rule consists of two parts. The first part considers the due date of the orders. To make sure that orders are not done late, we want to perform the orders that have a short deadline first. However, we also want to consider the location of the truck that we are scheduling, the possible waiting time at the loading and unloading docks when the truck is assigned an order, and whether we should first clean the truck in case the truck is assigned to an order. When the travel, waiting, and cleaning times are relatively large when the order is assigned to the truck, we do not want to assign that order to our truck. The reason for this is that we hope that one of the next trucks that becomes available might have to travel less, wait less, or does not have to clean. This truck will then be able to perform the order much quicker which results in a better truck schedule.

Below we will explain how the different input parameters of the priority rule are determined. This will be done in the following structure:

1. We discuss how we determine whether truck cleaning is needed and what times are considered when truck cleaning is or is not needed. See: “1. Cleaning of the truck needed?”.
2. We explain how the current volume, start time window, and end time window is determined for orders from push flows. See: “2. Current volume, start time window, end time window for orders from push flows.”.
3. We explain how the current volume, start time window, and end time window is determined for orders from pull flows. See: “3. Current volume, start time window, end time window for orders from pull flows.”.
4. We explain the difference in meaning between the start & end time window in the ‘OrderArray’ and the ‘SelectedOrders’ array. Besides, we determine the start & end time window in the ‘SelectedOrders’ array. See: “4. Time windows in OrderArray versus time windows in SelectedOrder array.”.
5. We explain how the time that the selected truck starts working on the order and the time that the truck arrives at the loading point of the order are determined. See: “5. Start time planned and time truck arrives at loading location of the order.”.
6. We explain how the time that the truck starts loading at the loading location of the order and the time the truck has to wait before it can start loading are determined. See: “6. Start time loading, waiting time for loading, and loading time.”.
7. Lastly, we explain how we determine the time of arrival at the unloading location, time the truck starts unloading, waiting time for unloading, unloading time, and time that the truck finishes the order. See: “7. Time of arrival at unloading location, time truck starts unloading, waiting time for unloading, unloading time, and time that the truck finishes the order.”.

1. Cleaning of the truck needed?

To be able to calculate the priority of orders in the selected orders array, the first step is to determine whether cleaning of the truck is needed to perform the order. Cleaning is needed when the latest material transported by the selected truck is unequal to the material that should be transported in the order present in the selected orders array. When this is the case 'C' is set equal to 1, otherwise 'C' is set equal to 0 in Equation 4. The next step, when cleaning is needed, is to determine the travel time from the current location of the truck to the cleaning location (TTC), the time it takes to clean the truck (CT), and the travel time from the cleaning location to the loading location of the order (TFCTL).

Next, we determine, for both the situation that cleaning is needed and the situation that cleaning is not needed, the following times. The travel time from the loading location to the unloading location of the order, the start of the time window of the order, the end of the time window of the order, the start time planned (is the time that the truck starts working on the order when the selected truck is assigned to the order), the time the truck arrives at the loading location (called 'StartTimeLoading' in the Avebe Planning Tool), the time the truck starts loading at the loading location (called 'StartTimeLoadingReal' in the Avebe Planning Tool), the time that the truck has to wait before it can start loading at the loading location, and the time it takes to load the truck.

The travel time from the current location to the cleaning location, from the cleaning location to the loading point, and from the loading point to the unloading point are determined using the distance matrix (see Section 5.1). Furthermore, the cleaning time is equal to the cleaning time set at the controls tab of the Avebe Planning Tool (standard equal to 90 minutes based on expert interviews). To determine the start time window and the end time window of the order we use different formulas for orders from push flows compared to orders from pull flows. We explain these formulas under the italic headers 2 and 3.

2. Current volume, start time window, end time window for orders from push flows

To determine the start time window of an order from a push flow, we should first determine the current volume in the leading silo of the flow. To determine this current volume, we apply Equation 5. The initial volume is the volume in the leading silo at time zero and the volume loaded and volume unloaded are updated based on the truck volumes loaded and unloaded at the leading silo. Besides, the time truck available equals the time that the truck finished its previous order and the stock over time is the duration that the factory prior to the leading silo had to stop production because of a completely filled output silo. Furthermore, since the production speed in the flow input data is given in hours (see Table 42) we should divide the production speed by 60. Therefore, the fractional in Equation 5 determines the total production of the factory prior to the leading silo. When the calculated current volume is higher than the capacity of the leading silo, we set the current volume of the leading silo equal to the capacity of the leading silo since it is not possible to have a current volume that is higher than the capacity of the leading silo.

Equation 5:

$$Current\ volume = Initial\ volume - volume\ loaded + volume\ unloaded + \left((Time\ truck\ available\ -\ stockovertime) * \left(\frac{Production\ speed}{60}\right)\right)$$

Now that we know the current volume of the leading silo, we determine the start time window of the order using Equation 6. The start volume is obtained from the flow input data (see Table 42). When the calculated start time window is smaller than 0, we set the start time window equal to 0. This makes sure that the order will not have a time window that lies before the start of the planning horizon (day 0). Furthermore, when the start time window is larger than or equal to 100800 (the latest minute of the planning horizon), we set the start time window of the order equal to 100800. Besides, we set the

flow availability of the corresponding flow equal to FALSE to ensure that no new orders from this flow will be generated.

Equation 6:

$$Start\ time\ window = Time\ truck\ available\ + \left(\frac{(Start\ volume - Current\ volume\ silo)}{(Production\ Speed/60)}\right)$$

Based on the found start time window we can now also determine the end of the time window using Equation 7. The end volume is obtained from the flow input data (see Table 42).

Equation 7:

$$End\ time\ window = Start\ time\ window + \left(\frac{(End\ volume - Current\ volume\ silo)}{(Production\ Speed/60)}\right)$$

3. Current volume, start time window, end time window for orders from pull flows

The equations to determine the current volume of the leading silo of a pull flow look very similar to the equation to determine the current volume of the leading silo of a push flow, the difference is that in a push flow the factory fills the leading silo while in a pull flow the factory empties the leading silo. Therefore, we determine the current volume of the leading silo of an order from a pull flow by using Equation 8. In case the calculated current volume is smaller than 0 we set the current volume equal to 0 since it is not possible to have a current volume in the silo.

Equation 8:

$$Current\ volume = Initial\ volume - volume\ loaded + volume\ unloaded - \left((Time\ truck\ available\ -\ stockouttime) * \left(\frac{Production\ speed}{60}\right)\right)$$

The calculation of the start time window and the end time window of an order of a pull flow also slightly differs from the calculation for orders of a push flow. Instead of doing the start volume minus the current volume in the calculation for the start time window, we do the current volume minus the start volume for orders from a pull flow. Therefore, we determine the start time window of an order from a pull flow using Equation 9. The reason for this is that the earliest point in time at which a pull order can be performed is when there is sufficient storage capacity available in the leading silo to store the volume of 1 freight of the flow related to the order. Like we did with the start time window of a push order, we set the start time window of the order equal to 0 when the start time window calculated is smaller than 0. Furthermore, we set the start time window equal 100800 when the calculated start time window is larger than or equal to 100800. Besides, we set the flow availability of the corresponding flow equal to FALSE when the start time window is larger than or equal to 100800 to ensure that no new orders from this flow will be generated.

Equation 9:

$$Start\ time\ window = Time\ truck\ available\ + \left(\frac{(Current\ volume\ silo - Start\ volume)}{(Production\ Speed/60)}\right)$$

Following the same reasoning as applied in Equation 9, the end time window of an order of a pull flow can be calculated using Equation 10.

Equation 10:

$$End\ time\ window = Start\ time\ window + \left(\frac{(Current\ volume\ silo - End\ volume)}{(Production\ Speed/60)}\right)$$

4. Time windows in OrderArray versus time windows in SelectedOrder array

Important to mention, is the difference between the start & end time window in the 'OrderArray' and the 'SelectedOrders' array. In the 'OrderArray', the start & end time windows are determined as described by Equation 5 till Equation 10. This start time window should be interpreted as the first point in time that a push order may be loaded at the loading location and that a pull order may be unloaded at the unloading location. Besides, the end time window in 'OrderArray' is the latest point in time that a push order may be loaded at the loading location and that a pull order may be unloaded at the unloading location.

However, when we selected the orders from the 'OrderArray' we recalculate the start time window and the end time window such that the start time window becomes the first point in time at which the selected truck may start working on the order and the end time window becomes the last point in time before which the selected truck must start working on the order to prevent silo over/under stocks. The start time window and the end time window are again calculated differently for push orders compared to pull orders.

Push

The start time window of a push order is determined using Equation 11. In case the start time window becomes smaller than zero, we set the start time window equal to zero. The end time window of a push order is determined using Equation 12. In Equation 11 and Equation 12, the time to the cleaning location (TTC) and the time from the cleaning location to the loading location (TFCTL) are dependent on the truck that we selected. Furthermore, we should notice that the time related to cleaning and the time needed to go to the loading location of the order can be subtracted from the start time window and end time window as calculated in Equation 6 and Equation 7 because these tasks must be completed before the truck can start loading.

Equation 11:

$$Start\ time\ window\ (SelectedOrders) = STW - \big(C * (TTC + CT + TFCTL)\big) - ((1 - C) * TTL)$$

Equation 12:

$$End\ time\ window\ (SelectedOrders) = ETW - \big(C * (TTC + CT + TFCTL)\big) - ((1 - C) * TTL)$$

Where:

- *STW = Start Time Window according to Equation 6*
- *ETW = End Time Window according to Equation 7*
- *C = Cleaning*
- *TTC = Time To Cleaning*
- *CT = Cleaning Time*
- *TFCTL = Time From Cleaning To Loading point*
- *TTL = Time To Loading point*

Pull

The start time window of a pull order is determined by using Equation 13. In case the start time window becomes smaller than zero, we set the start time window equal to zero. The end time window of a push order is determined using Equation 14. In Equation 13 and Equation 14, the time to the cleaning location (TTC) and the time from the cleaning location to the loading location (TFCTL) are dependent on the truck that we selected. Furthermore, we should notice that the time related to cleaning, the time needed to go to the loading location of the order, the loading time (LT), and the time needed to go from the loading point to the unloading point (TFLTU) can be subtracted from the start time window and end time window as calculated in Equation 9 and Equation 10 because these tasks must be fulfilled before the truck can start with unloading.

Equation 13:

$$Start\ time\ window\ (SelectedOrders) = STW - \big(C * (TTC + CT + TFCTL + LT + TFLTU)\big) - ((1 - C) * (TTL + LT + TFLTU))$$

Equation 14:

$$End\ time\ window\ (SelectedOrders) = ETW - \big(C * (TTC + CT + TFCTL + LT + TFLTU)\big) - ((1 - C) * (TTL + LT + TFLTU))$$

Where:

- *STW = Start Time Window according to Equation 9*
- *ETW = End Time Window according to Equation 10*
- *C = Cleaning*
- *TTC = Time To Cleaning*
- *CT = Cleaning Time*
- *TFCTL = Time From Cleaning To Loading point*
- *LT = Loading Time*
- *TFLTU = Time From Loading To Unloading point*
- *TTL = Time To Loading point*

5. Start time planned and time truck arrives at loading location of the order

To determine the start time planned, which is the time the selected truck starts working on the order, and the time that the truck arrives at the loading point of the order (called 'StartTimeLoading' in the Avebe Planning Tool), we should distinguish two situations. In the first situation, the time that the truck selected becomes available is later than the start time window of the order. In this case, the start time planned of the order equals the time at which the selected truck becomes available and the time that the truck arrives at the loading point of the order can be calculated using Equation 15.

Equation 15:

$$Arrival\ time\ at\ loading\ point\ order = TTA + \big(C * (TTC + CT + TFCTL)\big) + ((1 - C) * TTL)$$

Where:

- *TTA = Time Truck Available*
- *C = Cleaning*
- *TTC = Time To Cleaning*
- *CT = Cleaning Time*
- *TFCTL = Time From Cleaning To Loading point*
- *TTL = Time To Loading point*

However, when the time that the selected truck becomes available is earlier than the start time window of the order, the start time planned equals the start time window of the order. Therefore, the time that the truck arrives at the loading point of the order can be calculated using Equation 16.

Equation 16:

$$Arrival\ time\ at\ loading\ point\ order = STW + \big(C * (TTC + CT + TFCTL)\big) + ((1 - C) * TTL)$$

Where:

- *STW = Start Time Window of the order*
- *C = Cleaning*
- *TTC = Time To Cleaning*
- *CT = Cleaning Time*
- *TFCTL = Time From Cleaning To Loading point*
- *TTL = Time To Loading point*

6. Start time loading, waiting time for loading, and loading time

To determine the time that the truck starts loading at the loading point of the order and the time the truck has to wait before it can start loading, we again define two situations. In the first situation, there is a loading dock available at the time the truck arrives at the loading location of the order. In this case, the start time loading of the truck (called the 'StartTimeLoadingReal' in the Avebe Planning Tool) equals the arrival time of the truck at the loading point. In this situation, the waiting time for loading equals 0.

However, when there is no loading dock available when the truck arrives at the loading location of the order the start time loading of the truck is the time that the first loading dock becomes available. Therefore, the waiting time for loading equals the time that the first loading dock becomes available minus the time that the truck arrived at the loading location. The loading time of the truck is dependent on the flow of the order and can be found in the flow input data (see Table 42).

7. Time of arrival at unloading location, time truck starts unloading, waiting time for unloading, unloading time, and time that the truck finishes the order.

Using the results found so far and applying a similar logic as we applied to determine the 'StartTimeLoading', 'StartTimeLoadingReal', 'WaitingTimeForLoading', 'UnloadingTime' we can also determine the 'StartTimeUnloading', 'StartTimeUnloadingReal', 'WaitingTimeForUnloading' and the 'UnloadingTime'. Once we calculated all these values, we can determine the time at which the truck finishes the order (called the 'EndTimePlanned' in the Avebe Planning Tool) using Equation 17.

Equation 17:

$$Time\ order\ finished = STP + \big(C * (TTC + CT + TFCTL + WTFL + LT + TFLTU + WTFU + UT)\big) + ((1 - C) * (TTL + WTFL + LT + TFLTU + WTFU + UT))$$

Where:

- *STP = Start Time Planned*
- *C = Cleaning*
- *TTC = Time To Cleaning*
- *CT = Cleaning Time*
- *TFCTL = Time From Cleaning To Loading point*
- *WTFL = Waiting Time For Loading*
- *LT = Loading Time*
- *TFLTU = Time From Loading To Unloading point*
- *WTFU = Waiting Time For Unloading*
- *UT = Unloading Time*
- *TTL = Time To Loading point*

Based on all information gathered, we now calculate the priority value of all orders that are present in the selected order array using Equation 4.

5. Select order with the highest priority

The next step is to select the order with the lowest priority value (which is the order with the highest priority). This selection takes place in the procedure 'AssignOrderToTruck' in the Avebe Planning Tool. When we select the order, we check whether the time that the selected truck starts working on the order lies still within our planning horizon (so ultimately on day 70). When the time that the truck starts working on the order is later than day 70, we delete the selected order from the order array and continue by checking whether the number of orders in the order array is still larger than zero (see the bolded header '2. Are there still orders to be planned?'). However, when the time that the truck starts working on the order lies still within the planning horizon, we place the selected order in the orders planned array and we update the number of orders planned. Furthermore, we update the total number of times a truck is cleaned, the availability of the loading and unloading docks, the number of

normal and special transport orders done, the total waiting time for loading and unloading (and combined), the volumes loaded and unloaded at the leading silos, the current volume of the leading silos, total stockout and overstock time at the leading silos, and the number of push and pull orders that are late.

To determine the number of orders that are late, we make a distinction between orders from push and pull flows. A push order is classified late when the time that the truck starts loading at the loading location (called the 'StartTimeLoadingReal' in the Avebe Planning Tool) is later than the end of the time window of the order (called the 'EndTimewindow' in the Avebe Planning Tool). However, a pull order is classified late when the time that the truck starts unloading at the unloading location (called the 'StartTimeUnloadingReal' in the Avebe Planning Tool) is later than the end of the time window of the order (called the 'EndTimewindow' in the Avebe Planning Tool).

6. Make a new order for the flow scheduled, update time windows of all orders, and update the truck information

After scheduling the selected order on the selected truck, we generate a new order for the flow of the order that we just scheduled. Besides, we update the start time window and the end time window for all orders in the order array based upon the new information related to the order that we scheduled, and the amount of time passed. When the updated start time window of the order is later than the end of our planning horizon (70 days), we set the flow availability of the flow related to this order to FALSE and delete this order from the order array. However, when the start time window of the order lies still within the planning horizon, we update the start time window in the order array.

Since we now also know, which order is assigned to the truck selected, we can update the truck array. This implies that we update the time that the truck becomes available (is equal to the time the truck finished the scheduled order), the location of the truck (is the unloading point of the order scheduled), the material in the truck (is the material of the order scheduled), the total tons transported by the truck, and the number of orders finished by the truck.

7. Check whether there are still orders to be planned

The last step of the planning routine is to check whether the number of orders in the order array is still larger than zero. When the number of orders in the order array is larger than zero, the planning procedure continues from the header bolded '2. Are there still orders to be planned?'. However, when the number of orders in the order array equals zero, the planning is complete. The last step is to determine when and how long we have stockout and overstock moments at the leading silos. In the Avebe Planning Tool, we determine the stockout and overstock moments in a procedure called 'FactoryDowntime'. Figure 55 in Appendix C.3 provides a flow diagram to visualize the logic in this procedure.

During the planning procedure we update the volumes loaded, volumes unloaded, and the current volume of the leading silos directly when the selected order is assigned to the selected truck. However, in reality, the volume loaded should be updated when the truck starts loading and the volume unloaded when the truck starts unloading. Therefore, there will be a slight delay between the point in time that the volume loaded, volume unloaded, and the current volume of the leading silos is updated, and the time that these are updated in reality. In the procedure 'FactoryDowntime' we update the volume loaded, volume unloaded, and the current volume of the leading silos as in reality based on the completely generated truck schedule. Therefore, we determine what the factory downtime is when we implement the generated truck schedule in reality. This gives an indication of the quality of the Avebe Planning Tool.

On the dashboard at the performance indicator 'factory-downtime in minutes', we only consider the overstock duration of push silos and the stockout duration of pull silos. However, in the output file called 'SiloDownTime', we show overstock and stockout durations for both the push and the pull orders. A stockout at a push silo can occur according to the output file. This happens when there is an overstock at the push silo which is not observed during the planning procedure, but which is observed in the 'FactoryDowntime' procedure. This implies that the factory prior to the push silo has downtime according to the 'FactoryDowntime' procedure, but this factory downtime is not considered during the planning procedure. Therefore, the current volume with which we plan is higher than the current volume according to the 'FactoryDowntime' procedure. The higher volume, with which we plan, makes that the trucks load earlier at the push silo which results in stockouts at the push silo according to the 'FactoryDowntime' procedure.

When we make sure that we unload the volume equal to the volume that would have been produced during the overstock duration at the push silo and we load this volume at the time that we observe the overstock at the push silo, we will no longer have the stockouts at the push silos. The same logic holds for the pull silos. Therefore, it is important to look at the overstock duration at push silos and the stockout duration at the pull silos. When we solve these, the stockouts at the push silos and the stock overs at the pull silos will also disappear.

Now that we discussed the planning logic behind the Avebe Planning Tool, we focus on the verification and validation of the Avebe Planning Tool in Section 5.4.

5.4 Verification and validation of the Avebe Planning Tool

In this section, we start by checking whether the conceptual model discussed in Section 5.3 is correctly implemented which is called model verification (Law, 2015). Once we finished the model verification, we check whether the Avebe Planning Tool accurately represents reality considering our research objective. This is called model validation (Fishman & Kiviat, 1968).

Verification
To verify whether the conceptual model discussed in Section 5.3 is correctly implemented in the Avebe Planning Tool, which we build in Delphi, we did five things. First of all, we build the tool in small steps while making use of separate functions and procedures. This made it possible to verify these separate functions and procedures before building a new function or procedure. In this way, we avoided the struggle of debugging a whole tool at once which is way more complex. Secondly, we walked through the complete code with a colleague IEM master student to check whether the student agrees upon the logic and the way this is implemented. This validation technique is called a structured walk-through of the program (Law, 2015). Thirdly, we ran the tool for a variety of input parameter settings to check whether the output of the tool was reasonable. Fourthly, we debugged the code implemented using the 'watches window' in the Delphi software. This made it possible to check whether the variable values calculated by the tool correspond to our calculations on paper. Lastly, we analyzed the Avebe Planning Tool output. We did this by checking the planning generated using the Gantt chart that visualizes the planning that we make. This makes it possible to see whether the generated planning is in line with the code implemented.

Validation
To check whether the Avebe Planning Tool is an accurate representation of the system, considering the objective of this study, we performed several checks and validity enhancing measures which we describe below.

First of all, we carefully gathered the input data of the tool based on representative historical data when possible, and on expert interviews with a variety of experts when insufficient data was available. During these interviews, we first clearly explained the reason for asking for the data and the units in which the data is required. This will help to make sure that we gather the data which we think that we are gathering. In case the expert might have the interest to provide incorrect data, we always checked the data provided with an expert that does not have this interest, to prevent having biased input data.

Next to gathering historical data and gathering data by means of expert interviews, we also had a guided tour around the Avebe site in Gasselternijveen. This tour helped to get a feeling for the size of the factories and silos. Besides, we observed the loading and unloading docks, the truck weighing stations, and the packing process. Visiting the Avebe site helps to prevent making model decisions that are not possible in reality without knowing that it is not possible in reality. Therefore, observing the process next to gathering historical data and data by means of expert interviews helped to enhance the validity of the Avebe Planning Tool.

Secondly, we had meetings with the experts of Avebe and the transport company on a daily to weekly basis to provide updates on the progress made and the important decisions taken in the tool building process. This helps to make sure that no decisions are taken that bring the validity of the Avebe Planning Tool in danger. While gathering data and building the tool we also maintained a document in which we wrote down all assumptions that we made. These assumptions were also discussed with the expert of Avebe.

Thirdly, we examined the validity of components of the Avebe Planning Tool and the output of the overall tool. To do so, we checked whether the number of tons transported in the Avebe Planning Tool and the number of tons transported during the intercampaign TAK of 2020 are in line with our expectations. The number of tons transported during the intercampaign TAK 2020 which was from 20-2-2020 till 10-5-2020 was 94,358 tons. When we run Avebe Planning Tool for 70 days, we transport around 92,827 tons (based on the experiment's average number of tons transported in Table 23 excluding the last experiment). It is important to notice that the intercampaign TAK 2020 was relatively long namely 80 days therefore we would expect the volume transported to be higher than in the Avebe Planning Tool. However, on the other side, the tool assumes that all factories produce 168 hours per week, which in reality will not happen due to factory maintenance and factory breakdowns that can happen. The fact that the tool does assume 168 hours of production per week at the factories implies that we expect the tons transported to be higher.

When we correct for the difference in length between the planning horizons, we expect Avebe Planning Tool to transport (94,358/80)*70 = 82,526 tons. However, according to the tool, we do transport 92,827 tons. These 92,827 tons are based on 168 hours of production in the factories. However, the expected weighted average production hours considering the maintenance and factory breakdowns due to non-transport-related issues equals 147.26 hours. When we consider 147.26 hours of production instead of the 168 hours which we did consider, as explained in Section 5.2, the tool output would have been (147.28/168)*92,827 = 81,378 tons. This implies that the tons transported according to the Avebe Planning Tool are 100% - (81,378/82,526)*100% = 1.39% higher than expected based on historical data. Therefore, we can conclude that the Avebe Planning Tool produces a realistic output for the real process.

The last way in which we validated Avebe Planning Tool is by means of expert opinion. The output files containing the complete truck schedule and the stockout and overstock moments for the complete planning horizon are shown to the expert. Furthermore, the performance on the performance indicators defined in Chapter 3 are discussed and the Gantt chart on the dashboard is checked for its validity. The working of the Avebe Planning Tool, the dashboard, and the generated output files are discussed in Section 5.5.

5.5 Using the Avebe Planning Tool

In this section, we show what the Avebe Planning Tool looks like and how the Avebe Planning Tool can be used. Besides, we provide insight in the dashboard that visualizes the generated truck planning and shows the performance on the defined performance indicators. Furthermore, the output files show the generated truck schedule and the silo downtime moments due to transport issues.

To create the transport schedule, we first set the input value on the controls tab of the Avebe Planning Tool which is shown in Figure 18. On the controls tab we can fill in the number of trucks available for the planning, the time it takes to clean a truck, and the weights given to the 'earliest due date' (EDD), and the 'travel, waiting, cleaning -time' (TWC). The weight given to the EDD and the TWC time should add to one. For the interpretation of these weights, we refer to the explanation of the priority rule in Section 5.3.

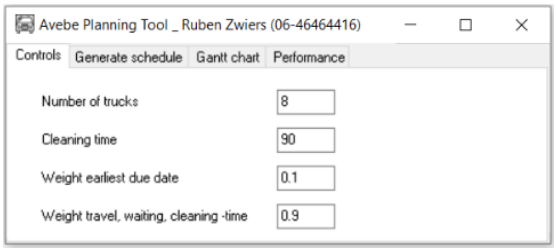

Figure 18: The controls tab of the Avebe Planning Tool

Once we filled in the controls tab, we go to the 'Generate Schedule' tab. First, we should read in the flows, silos, (un)loading docks, and distance matrix. The data in these input files is discussed in Section 5.1. Once all input data is in the tool, we press the 'Generate schedule' button and the truck schedule is made. The messages box shows the orderID of the order that the tool is currently scheduling, and when the planning is finished, also the total runtime in seconds is given.

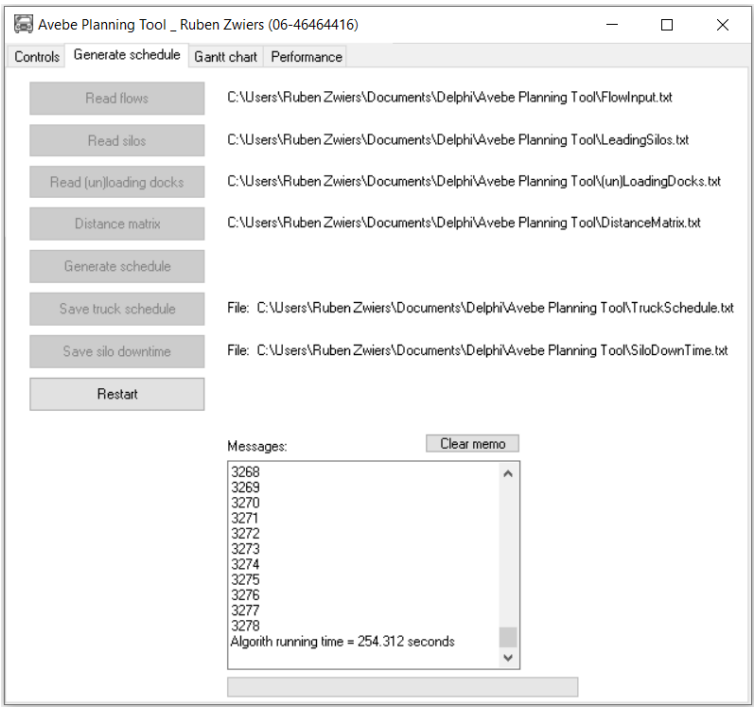

Figure 19: Generate schedule tab of the Avebe Planning Tool

When the truck schedule is made, we can press the 'Save truck schedule' and the 'Save silo downtime' buttons to save the truck schedule in the output file called 'TruckSchedule' and to save the stockout and overstock moments in the output file called 'SiloDowntime'. Table 46 and Table 47 in Appendix C.4, respectively show the silo downtime output file and the truck schedule output file.

Next to observing the generated truck schedule in the output file, the truck schedule is also visualized in a Gantt chart on the 'Gantt chart' tab of the application. Figure 20 shows what the Gantt chart looks like. On the top left of the dashboard, there is a dropdown bar with which we can select the day of the planning that we are interested in. Then the dashboard shows the Gantt chart for the day selected. Each column of the Gantt chart corresponds to one truck, the number of the truck (TruckID) is given on top of each column. Within the columns, the orders done by the trucks are shown. The green boxes correspond to the normal transport orders and the blue boxes correspond to the special transport orders. The numbers shown on the boxes correspond to the orderID of the order. Besides, the bottom of the Gantt chart corresponds to minute zero of the day, while the top of the Gantt chart corresponds to the end of the day. When the latest order on a truck for a day starts on the day selected but is finished on the next day, the part of the order that is done on the next day is drawn smaller in the box of the order.

Furthermore, when we move our mouse over an order, additional information related to this order is presented. In Figure 20, we did this for the order with orderID 120. Lastly, when we move our mouse over the truck schedule, the minute of the day at which we have our mouse is given on top of the column of the truck that our mouse is in. In Figure 20, we did this for truck 8 and our mouse was at minute 1262 of the day as can be seen on top of the column of truck 8.

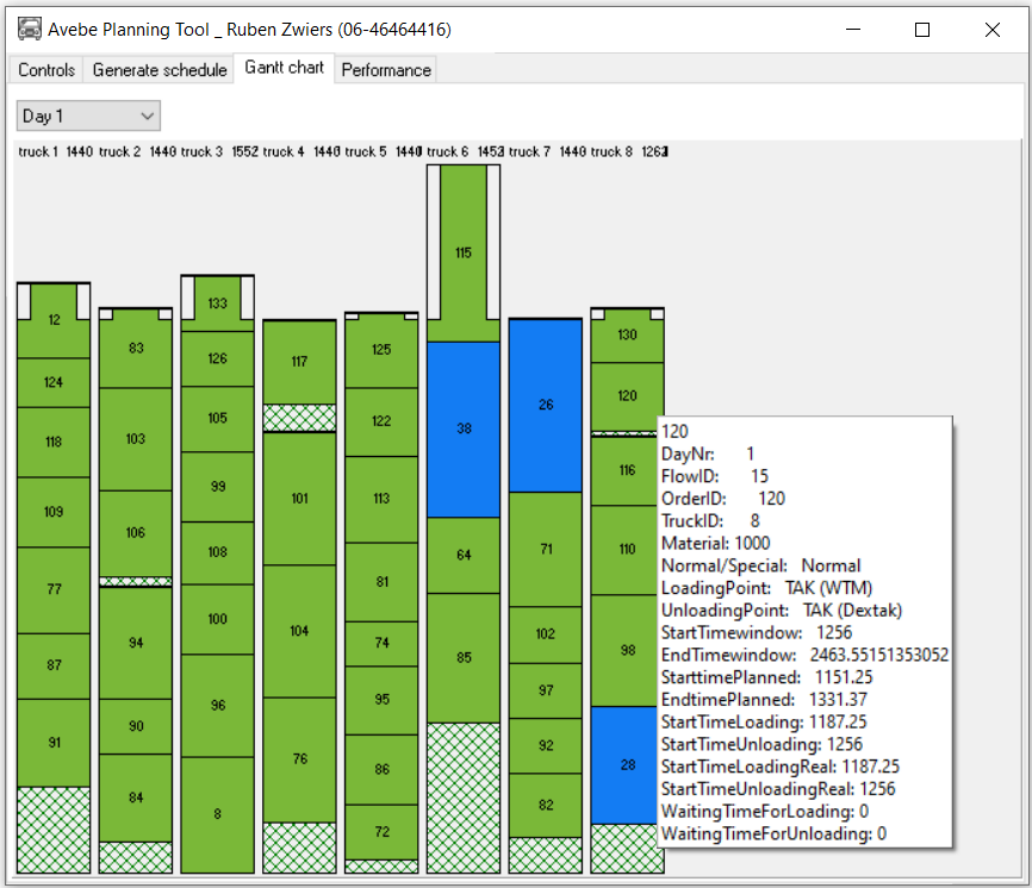

Figure 20: Gantt chart of truck schedule in the Avebe Planning Tool

Next to looking at the generated truck schedule, we can also get insight into the performance of the generated truck schedule. Figure 21 shows the performance tab of the Avebe Planning Tool. First, we see the performance of the generated truck schedule on the defined performance indicators in Chapter 3. Then we see some additional performance indicators which were useful when building the Avebe Planning Tool and that might also be interesting for Avebe. The performance indicators will be used to evaluate the experiments which we perform in Chapter 6.

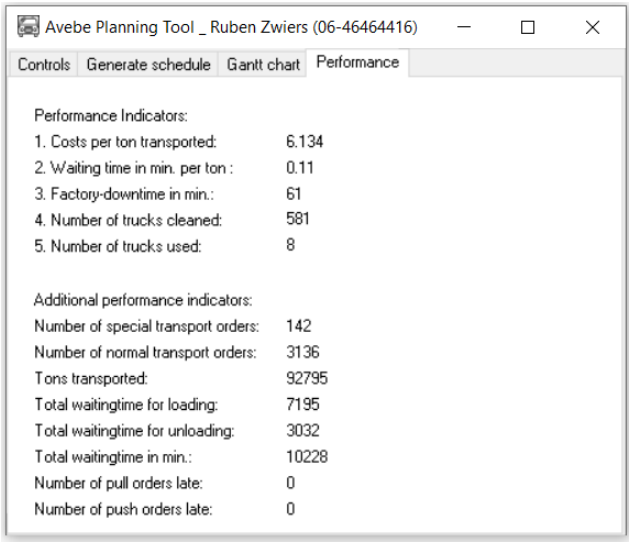

Figure 21: Performance of the generated truck schedule in Avebe Planning Tool

5.6 Conclusion of Chapter 5

Based on the data available to model the transportation process during the intercampaign TAK, the level of uncertainty involved in making a transport planning for the whole intercampaign TAK, and the dependency of the demand for transport on factors as the weather and the demand of customers, we decided to simultaneously simulate the demand for transport and plan the trucks to fulfill this demand. In order to do so, we made an overview of the unique transport flows and classified each of these flows to be a push or a pull flow. All data needed to model the transportation process and schedule the trucks is based upon data available within Avebe and the transport company when possible, when the data was not available, we performed expert interviews.

Figure 22 provides an overview of the 7 modeling steps taken in the Avebe Planning Tool to generate a truck planning. Two key activities in generating the truck planning are the order selection process performed by the order selection method and the priority rule which will be applied to the orders selected by the order selection method.

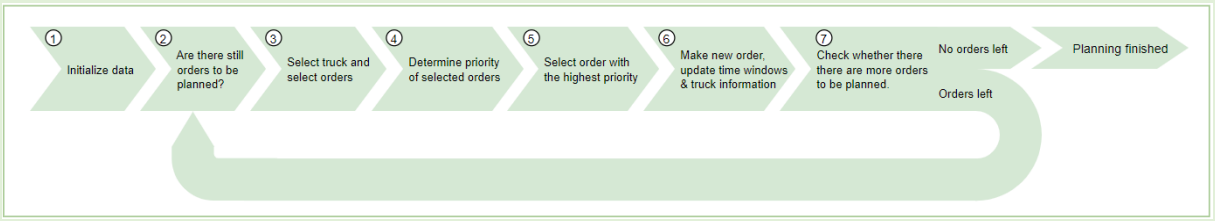

Figure 22: Modeling steps taken in the Avebe Planning Tool

Based on experiments without order selection method and with three different kinds of order selection methods, we decided to apply the following order selection method consisting of three statements:

1. All orders that 1) should be finished within 10 hours from the time that the selected truck is available and 2) the time that the order becomes available is within 2 hours from the time that the selected truck is available.
2. All orders that 1) are available within two hours from the time that the selected truck is available and 2) for which the material of the order equals the material in the selected truck.
3. All orders from 'OrderArray' are placed in the 'SelectedOrders' array.

When there are orders available in the order array that fulfill the requirements of the first statement, then these orders are placed into the selected order array. When no orders in the order array fulfill the first statement, we check whether there are orders in the order array that fulfill the second statement. When this is the case, these orders are placed in the selected order array. If none of the orders in the order array correspond to the first and the second statement, all orders in the order array are placed in the selected orders array. The reason for choosing this order selection method is that this order selection method provided the highest quality bulk truck planning in terms of robustness for deviations in the input data.

For the orders in the selected orders array, we determine the priority value using the equation below. The order with the lowest priority value is the order with the highest priority and will therefore be scheduled on the selected truck.

$$Priority = (W_{EDD} * EDD) + (W_{TWC} * \big(C * (TTC + CT + TFCTL + WTFL + WTFU)\big) + ((1 - C) * (TTL + WTFL + WTFU))$$

Where:

- W_{EDD} = *Weight Earliest Due Date*
- *EDD (= Earliest Due Date) = End Time Window – Time Truck Available*
- W_{TWC} = *Weight Travel Waiting Cleaning*
- *C = Cleaning*
- *TTC = Time To Cleaning*
- *CT = Cleaning Time*
- *TFCTL = Time From Cleaning To Loading point*
- *WTFL = Waiting Time For Loading*
- *WTFU = Waiting Time For Unloading*
- *TTL = Time To Loading point*

After providing insight into the logic behind the Avebe Planning Tool we applied different model verification and model validation techniques described by Law (2015). We could show that the model the conceptual paper model is correctly implemented in the Avebe Planning Tool and that the transport volumes resulting from the Avebe Planning Tool are representative for the real transport process. Lastly, we showed what the resulting Avebe Planning Tool looks like and how the tool can be used.

In the next chapter, we will perform experiments with the EDD and TWC time weights in the priority rule and with the number of trucks in the pool. Besides, we will perform a sensitivity analysis on the input parameter which can have a different value in reality impacting the truck planning generated by the Avebe Planning Tool.

6. Experiment design and results

In this chapter, we perform experiments with different parameter settings of the Avebe Planning Tool., The output of these experiments will provide insights into the number of trucks that Avebe should hire during the intercampaign TAK and how these trucks should be assigned to normal and special transport in order to reduce transportation costs without increasing the factory downtime above the predefined bound. Therefore, this chapter will provide an answer to research question 5 (see Section 1.6).

Section 6.1 provides an overview of the experiments that we perform and the assessment of the experiment results. In Section 6.2 we state the experiment results. Based on the experiment results, we perform a sensitivity analysis on the most important input parameters of the Avebe Planning Tool in Section 6.3. Lastly, Section 6.4 provides a conclusion of Chapter 6.

6.1 Experiment setup and assessment criteria

In this section, we first discuss the experiments that we perform with the Avebe Planning Tool and argue why we decide to perform these experiments. Once we determined the experiments that we will perform, we explain how the experiment results will be assessed.

Experiment setup
To determine how Avebe should assign its bulk trucks to normal and special transport, we should schedule the hired pool of bulk trucks. In order to schedule these bulk trucks, we need to know the number of bulk trucks available. Therefore, we first determine the number of trucks that Avebe should hire. However, the number of bulk trucks to be hired according to our Avebe Planning Tool depends on the weights we give to the EDD and the TWC time in our priority rule (see Equation 4). When the weights, given to the EDD and the TWC time, are changed, the priority of the orders will change, resulting in a different truck schedule.

To find the best truck schedule, we will therefore experiment with the number of trucks and the weights given to the EDD and the TWC time. We experiment with 7 and 8 trucks. Furthermore, the weights will be changed by 0.1 from experiment to experiment and the sum of the EDD and TWC time weights always equals 1. Table 25 provides an overview of the resulting experiments which we perform.

Assessment criteria
When we performed the experiments shown in Table 25, we should be able to compare the different experiment results and decide which experiment provides the best solution. To compare the different experiment results, we determine the performance of the experiments on the following performance indicators which correspond to the performance indicators defined in Chapter 3.

Performance indicators:
1. The costs in euros per ton material transported (cost per ton).
2. The average waiting time in minutes per ton material transported (waiting time per ton).
3. The total factory downtime in minutes because of transportation issues (factory downtime).
4. The number of trailers cleaned (trailers cleaned).
5. The number of trucks used (trucks used).

Besides, we keep track of some additional performance indicators to get some additional insight into the generated transportation schedule.

Additional performance indicators:

6. The total number of special transport orders done.
7. The total number of normal transport orders done.
8. The total amount of tons transported.
9. The total waiting time for loading in minutes.
10. The total waiting time for unloading in minutes.
11. The total waiting time in minutes.
12. The number of pull orders that are done late.
13. The number of push orders that are done late.

Based on expert interviews at Avebe, we assess the performance of an experiment in two steps. The first step is to exclude the experiments which have a factory downtime larger than 600 minutes. The expert of Avebe said that a total factory downtime of more than 600 minutes, because of transport issues, during the intercampaign TAK is unacceptable. Once we limited the experiment results to the experiments which have less than 600 minutes of factory downtime, the best experiment according to the expert of Avebe is the experiment that has the lowest cost per ton material transported. Therefore, the performance assessment of the experiments resulting from the expert interview only considers the costs per ton and the factory downtime.

Analyzing the five performance indicators defined, we can agree upon the method to assess the experiments resulting from the expert interview for the following reasons. First of all, looking at the average waiting time in minutes per ton material transported, we can argue this performance indicator to be indirectly covered by the costs per ton. Imagine, when the average waiting time in minutes per ton material transported increases, the number of trucks needed to fulfill the transport demand increases, resulting in an increase of the costs per ton material transported. Therefore, it is sufficient to assess an experiment result on the costs per ton.

Secondly, looking at the total number of trailers cleaned, we argue this performance indicator to be indirectly covered by the cost per ton. Cleaning of the trailers takes time, the trucks must drive from its current location to the cleaning location, the trailer must be cleaned, and the truck must drive from the cleaning location to the loading location. Therefore, more cleaning implies less time for the truck to transport material, and therefore we will need more trucks to perform the same number of transportation orders. Hiring more trucks will be more expensive resulting in a higher cost per ton of material transported. Therefore, it is sufficient to assess an experiment result on the costs per ton of material transported.

Lastly, the number of trucks used directly relates to the costs per ton of material transported. When more trucks are used to transport the same amount of material, the costs per ton transported increase. Therefore, also no separate assessment of the number of trucks used is needed when we already assess the experiment on the costs per ton material transported.

Based on this analysis, we decide to apply the assessment method resulting from the expert interview at Avebe. This implies that we will first exclude the experiments with a total factory-downtime during the intercampaign TAK which is larger than 600 minutes. After which, we select the experiment with the lowest cost per ton transported to be the best experiment. However, we still show the performance of the experiment on the other performance indicators that we defined since these will help to analyze the causes of the performance that we observe.

Experiment number	Number of trucks	Weight EDD	Weight TWC
1	7	1	0
2	7	0.9	0.1
3	7	0.8	0.2
4	7	0.7	0.3
5	7	0.6	0.4
6	7	0.5	0.5
7	7	0.4	0.6
8	7	0.3	0.7
9	7	0.2	0.8
10	7	0.1	0.9
11	7	0	1
12	8	1	0
13	8	0.9	0.1
14	8	0.8	0.2
15	8	0.7	0.3
16	8	0.6	0.4
17	8	0.5	0.5
18	8	0.4	0.6
19	8	0.3	0.7
20	8	0.2	0.8
21	8	0.1	0.9
22	8	0	1

Table 25: Experiments

Now that we discussed the experiments that we are going to run and the way that we are going to assess the results from these experiments, we provide the experiment results in Section 6.2.

6.2 Experiment results

In this section, we provide the experiment results related to the experiments defined in Table 25. Besides, we analyze the obtained results using the two-step method which we described in Section 6.1. The weight to be assigned to the EDD and the weight to be assigned to the TWC time corresponding to the best experiment will be used in the sensitivity analysis in Section 6.3.

Table 26 provides the performance of the experiments formulated in Table 25. Analyzing the obtained experiment results based on the total factory downtime in minutes, we observe that 12 out of the 22 experiments have a total factory downtime of less than 600 minutes during the intercampaign TAK. In Table 26 we highlighted the cells corresponding to these experiments green, while the experiments with a factory downtime above 600 minutes are highlighted red.

Note that when the number of truck cleanings increases, the factory downtime also increases. The same holds for the average waiting time per ton transported. These effects can be explained. When the trucks are often cleaned and/or have to wait long before they can start loading or unloading, and/or have to travel long before arriving at the loading location of the order (corresponding to the situation in which the weight added to TWC is relatively low), the orders will take much more time compared to the situation in which no cleaning is needed, the waiting time at the loading and unloading docks is short, and the truck is already close to the loading location of the order

(corresponding to the situation in which the weight added to TWC is relatively high). When more time is needed to perform the same order (due to longer travel, waiting, and cleaning times), more trucks will be needed to perform all orders. When the truck capacity is insufficient, orders will be done late resulting in fewer tons transported and more factory downtime. This effect can best be observed when looking at the experiments with 7 trucks. The number of tons transported increases as the weight added to the TWC time increases. Based on the performance of the experiments with 8 trucks, we conclude that with 8 trucks the inefficient way of planning in terms of travel, waiting and cleaning times can be handled. Therefore, this pattern is not as clearly visible looking at the experiments with 8 trucks.

Furthermore, looking at experiments 17 up un till 21, we observe the effect of adding more weight to the TWC time on the number of times the trucks are cleaned. The number of times the trucks are cleaned nicely decreases when more weight is added to the TWC time. This effect is not visible when we look at experiments 12 up un till 16. Therefore, we conclude that TWC time will have the expected impact on the truck schedule when at least 0.5 weight is added to the TWC time. Lastly, we notice that giving no weight to the EDD results in a high factory downtime. This can be explained by the fact that we do not consider the deadline of the order when we select the order out of the 'SelectedOrders' array.

Exp. Nr.	# Trucks	W_EDD	W_TWC	Costs/ton	Waiting/ton	Factory-downtime	# Cleaned	# Trucks	# Special	# Normal	Tons trans.	Waiting loading	Waiting unloading	Total waiting	Pull late	Push late
1	7	1.0	0.0	6.420	0.306	142564	1409	7	136	2570	77572	21816	1941	23757	1867	791
2	7	0.9	0.1	6.401	0.316	147703	1389	7	136	2576	77801	21949	2614	24563	1873	791
3	7	0.8	0.2	6.409	0.313	154278	1392	7	136	2572	77714	22098	2244	24341	1869	791
4	7	0.7	0.3	6.412	0.311	156042	1391	7	136	2571	77669	22250	1876	24126	1868	791
5	7	0.6	0.4	6.358	0.293	144415	1366	7	136	2593	78329	20918	1999	22917	1890	791
6	7	0.5	0.5	6.250	0.256	133382	1331	7	136	2641	79689	18688	1707	20395	1938	789
7	7	0.4	0.6	6.167	0.231	130474	1283	7	136	2677	80753	17097	1517	18614	1970	788
8	7	0.3	0.7	5.943	0.180	107446	1196	7	136	2783	83797	13816	1254	15069	2071	785
9	7	0.2	0.8	5.370	0.099	65	701	7	138	3138	92752	8203	970	9173	8	2
10	7	0.1	0.9	5.362	0.085	42	657	7	142	3139	92880	6998	905	7903	2	5
11	7	0.0	1.0	5.457	0.064	43070	957	7	135	3059	91264	3804	2064	5868	360	189
12	8	1.0	0.0	6.132	0.145	81	844	8	142	3137	92821	12436	1000	13437	0	0
13	8	0.9	0.1	6.130	0.128	127	838	8	142	3138	92854	10896	978	11875	0	0
14	8	0.8	0.2	6.134	0.154	120	841	8	142	3136	92792	13212	1066	14279	0	0
15	8	0.7	0.3	6.132	0.146	55	834	8	142	3137	92821	12455	1116	13571	0	0
16	8	0.6	0.4	6.130	0.128	59	829	8	142	3138	92850	10910	1016	11926	0	0
17	8	0.5	0.5	6.132	0.155	131	843	8	142	3137	92821	13341	1071	14412	0	0
18	8	0.4	0.6	6.130	0.134	102	804	8	142	3138	92850	11456	995	12451	0	0
19	8	0.3	0.7	6.130	0.139	126	769	8	142	3138	92850	11842	1092	12934	0	0
20	8	0.2	0.8	6.132	0.103	33	705	8	142	3137	92821	6751	2853	9605	0	0
21	8	0.1	0.9	6.134	0.110	61	581	8	142	3136	92795	7195	3032	10228	0	0
22	8	0.0	1.0	6.232	0.175	36496	955	8	137	3067	91340	11215	4726	15941	246	123

Table 26: Experiment results step 1

Following our assessment procedure, the next step is to determine which experiment results in the lowest cost per ton material transported. Table 27 provides an overview of the experiments that passed step 1. Furthermore, we added color scales to the performance indicators. Considering the costs per ton of material transported, we conclude that experiment 10 has the lowest cost per ton of material transported. The cost per ton material transported in experiment 10 equals €5.36. Therefore, experiment 10 corresponds to the best number of trucks, in combination with the weights added to the EDD and the TWC time. This implies that Avebe should use 7 trucks, the weight added to the EDD should equal 0.1, and the weight added to the TWC time should be 0.9 when the reality corresponds exactly to the input data described in Section 5.1.

However, in reality, this will never be the case. Therefore, we need to determine the robustness of this advice based upon sensitivity analyses on the input parameters that involve uncertainty which can influence the performance of the Avebe Planning Tool. Section 6.3 provides these sensitivity analyses.

Exp. Nr.	# Trucks	W_EDD	W_TWC	Costs/ton	Waiting/ton	Factory-downtime	# Cleaned	# Trucks	# Special	# Normal	Tons trans.	Waiting loading	Waiting unloading	Total waiting	Pull late	Push late
9	7	0.2	0.8	5.370	0.099	65	701	7	138	3138	92752	8203	970	9173	8	2
10	7	0.1	0.9	5.362	0.085	42	657	7	142	3139	92880	6998	905	7903	2	5
12	8	1.0	0.0	6.132	0.145	81	844	8	142	3137	92821	12436	1000	13437	0	0
13	8	0.9	0.1	6.130	0.128	127	838	8	142	3138	92854	10896	978	11875	0	0
14	8	0.8	0.2	6.134	0.154	120	841	8	142	3136	92792	13212	1066	14279	0	0
15	8	0.7	0.3	6.132	0.146	55	834	8	142	3137	92821	12455	1116	13571	0	0
16	8	0.6	0.4	6.130	0.128	59	829	8	142	3138	92850	10910	1016	11926	0	0
17	8	0.5	0.5	6.132	0.155	131	843	8	142	3137	92821	13341	1071	14412	0	0
18	8	0.4	0.6	6.130	0.134	102	804	8	142	3138	92850	11456	995	12451	0	0
19	8	0.3	0.7	6.130	0.139	126	769	8	142	3138	92850	11842	1092	12934	0	0
20	8	0.2	0.8	6.132	0.103	33	705	8	142	3137	92821	6751	2853	9605	0	0
21	8	0.1	0.9	6.134	0.110	61	581	8	142	3136	92795	7195	3032	10228	0	0

Table 27: Experiment results step 2

6.3 Sensitivity analyses

In this Section, we determine the input parameters for the sensitivity analysis based upon the certainty of the input parameters and the impact the parameter has on the resulting bulk truck planning. Once we determined the input parameters on which we will perform a sensitivity analysis, we provide the experiment setup, experiment results and our interpretation of the experiment results, and some additional insight that can be obtained.

Selection of input parameters for sensitivity analysis

To make sure that the Avebe Planning Tool still provides a good bulk truck planning when the input data, in reality, deviates from the input data discussed in Section 5.1, we should perform a sensitivity analysis on the uncertain input data parameters for which a deviation from the expected parameter value will have a high impact on the resulting bulk truck planning. Table 28 provides an overview of the input parameters of the Avebe Planning Tool. For each of these input parameters, the table states how sure we are of the expected parameter value and how large the impact of a deviation from the expected parameter value will be. For the interpretation of the input parameters, we refer to Section 5.1.

Input parameter	Certainty of value	Expected impact of deviation from the parameter value
Capacity silos	High	Moderate
Capacity of truck	High	Moderate
Travel time	High	Moderate
Cleaning time	High	Moderate
Initial volume silos	Moderate	Low
Start volume silos	High	Moderate
End volume silos	High	Moderate
Loading and unloading times trucks	Moderate	Moderate
Production speeds of factories	Moderate	High
Number of trucks	-	High

Table 28: Certainty and value deviation impact of the Avebe Planning Tool input parameters

The lower the certainty of the expected input parameter value and the higher the impact of a deviation from the expected parameter value, the higher the interest to perform a sensitivity analysis on the input parameter value. The capacity of the silos, the capacity of the trucks, travel time, cleaning time, start volume, and end volume are known with high certainty. Therefore, these parameters will not be interesting to conduct a sensitivity analysis on. However, the certainty of the initial volume, the loading and unloading times of the trucks, and the production speeds of the factories are moderate.

The initial volume in the silo at the start of the intercampaign TAK is dependent on the campaign and therefore not know with certainty. However, a different initial silo volume will only influence the truck planning for the first few days of the intercampaign TAK and therefore have a low impact on the complete truck planning. To determine the expected loading and unloading times of the trucks, we used the average loading and unloading times of the trucks available for each loading and unloading location. However, for some locations no or limited data related to loading and unloading times was available. Therefore, we had to base the expected loading and unloading times at these locations on expert interviews yielding a moderate certainty of the accuracy of resulting loading and unloading times. Depending on the transport order, the loading and unloading times will represent a larger or smaller part of the order completion time. Therefore, we assess that the impact of changes in the loading and unloading times on the resulting truck planning will be moderate.

The production speeds obtained in Section 5.1 are based upon the sales forecasts for the special transport trips. According to the expert of Avebe, the production speeds for the transportation flows discussed in Section 5.1 can be in the range from 10% below to 10% above the expected production speeds. These deviations can have a high impact on volumes of different materials to be transported, the number of trailer cleanings, the travel times, the waiting times, the amount of transport needed, and therefore on the bulk truck planning.

Lastly, at the start of the intercampaign TAK Avebe should decide how many trucks they want to have in the hired pool of bulk trucks. Because of the parallel planning of the bulk truck in the Avebe Planning Tool, the number of bulk trucks in the pool will strongly influence the resulting bulk truck planning. Besides, the number of bulk trucks in the hired pool of bulk trucks has a large impact on the performance in terms of cost per ton transported (see conclusion Sub-section 3.2.1).

Concluding, we decide to perform a sensitivity analysis on the production speed of factories in combination with the number of bulk trucks since deviations in the values of these two parameters will have a high impact on the resulting bulk truck planning. Due to the time constraints of this research, we will leave a sensitivity analysis on the impact of deviations in the loading and unloading times of the trucks on the resulting bulk truck planning for future research.

Experiment setup

To assess the impact of deviations in the production speeds, we generate 10 new input data sets, consisting of new 'FlowInput' data and new 'LeadingSilos' input data. In these new input data sets, deviations in the production speeds are obtained by a uniform distribution around the production speeds determined in Section 5.1. The lower bound of the uniformly distributed production speed will be equal to 90% of the production speed and the upper bound of the uniformly distributed production speeds will be equal to 110% of the production speeds determined in Section 5.1.

For each of the 10 input data sets, we will generate a truck planning using 7 trucks and giving 0.1 weight to the EDD and 0.9 weight to the TWC time. In this way, we can assess whether the planning with 7 trucks resulting from Section 6.2 will be robust to changes in the production speeds.

Experiment results and interpretation

Table 29 provides an overview of the performance of the truck planning for the different data sets. Besides, the performance of experiment 10 from Section 6.2 is provided again.

Input dataset Nr.	# Trucks	W_EDD	W_TWC	Costs/ton	Waiting/ton	Factory-downtime	# Cleaned	# Trucks	# Special	# Normal	Tons trans.	Waiting loading	Waiting unloading	Total waiting	Pull late	Push late
1	7	0.1	0.9	5.446	0.08	17	639	7	143	3088	91449	6445	859	7304	1	2
2	7	0.1	0.9	5.322	0.058	2524	919	7	133	3150	93576	3475	1943	5417	467	260
3	7	0.1	0.9	5.481	0.097	0	620	7	135	3069	90870	6603	2230	8833	0	2
4	7	0.1	0.9	5.401	0.079	44	723	7	136	3125	92212	6516	765	7281	16	17
5	7	0.1	0.9	5.346	0.086	52	707	7	142	3151	93164	6757	1268	8026	16	14
6	7	0.1	0.9	5.331	0.044	1595	933	7	135	3152	93421	3288	383	4126	364	241
7	7	0.1	0.9	5.375	0.086	740	833	7	136	3131	92656	6076	1888	7964	174	99
8	7	0.1	0.9	5.384	0.071	763	899	7	140	3114	92505	5358	1226	6584	165	98
9	7	0.1	0.9	5.424	0.09	65	639	7	145	3101	91813	6816	1444	8260	0	1
10	7	0.1	0.9	5.341	0.051	1575	895	7	133	3137	93241	3545	1210	4755	371	223
Exp. 10 (Section 6.2)	7	0.1	0.9	5.362	0.085	42	657	7	142	3139	92880	6998	905	7903	2	5

Table 29: Sensitivity analysis on production speeds with 7 trucks

Table 30, compares the performance related to the different input data sets with the performance obtained using the original input data set from Section 6.2. Besides, the last column of Table 30 states the leading silos at which a stockout or overstock moment occurs. Stockout moments occurred at the TAK VMF (1000), PN2 (Cation), and TAK VMF (waxy) silo. Overstock moments took place at the MP10 (derivaten) silo and GNV silo 5 (D12) silo. All these leading silos are interesting to analyze since these are the bottleneck silos for the planning. Next to these silos, we are interested in the leading silos that relate to a factory with a high production speed since a small percentual difference to the production speeds of these factories will have a relatively high impact on the planning. We decide to classify a production speed to be high when the production speed exceeds 5 tons per hour. Therefore, we also more closely analyze the GNV silo 1+2 and MP10 (1000) silos. Lastly, we marked the rows related to input data sets resulting in a factory downtime larger than 600 minutes red, and the rows related to input data sets resulting in a factory downtime lower than 600 minutes green in Table 30.

Input dataset Nr.	#Orders	#Orders %	Factory-Downtime	Tot. prod. speed	GNV silo 1+2	MP10 (1000)	TAK VMF (1000)	PN2 (Cation)	TAK VMF (waxy)	MP10 (derivaten)	GNV silo 5 (D12)	location(s) stockout(s)/overstock(s)
1	-50	-1.52%	17	-1.45%	-7.62%	-4.94%	-0.99%	-2.64%	-0.04%	-3.53%	-4.37%	TAK VMF (1000)
2	2	0.06%	2524	1.25%	-2.31%	1.05%	6.29%	5.35%	4.88%	0.61%	-9.41%	TAK VMF (1000), PN2 (Cation), TAK VMF (waxy)
3	-77	-2.35%	0	-2.13%	-4.18%	2.30%	0.72%	-4.61%	-8.11%	-5.17%	7.56%	n/a
4	-20	-0.61%	44	-0.51%	1.25%	0.68%	-5.72%	-2.72%	6.71%	1.47%	-3.03%	TAK VMF (1000)
5	12	0.37%	52	0.30%	1.93%	2.50%	-1.12%	-7.66%	6.01%	-1.57%	-3.19%	TAK VMF (1000)
6	6	0.18%	1595	0.97%	5.37%	2.17%	-4.52%	-0.66%	7.53%	4.24%	-4.54%	TAK VMF (1000), PN2 (Cation), TAK VMF (waxy), MP10 (derivaten)
7	-14	-0.43%	740	0.19%	-0.72%	-2.03%	-0.55%	-0.25%	-1.09%	5.49%	-4.54%	TAK VMF (1000), PN2 (Cation), TAK VMF (waxy), MP10 (derivaten)
8	-27	-0.82%	763	-0.01%	3.47%	3.23%	0.41%	-5.11%	-4.25%	-5.27%	6.89%	TAK VMF (1000), PN2 (Cation), TAK VMF (waxy)
9	-35	-1.07%	65	-1.09%	-1.88%	-1.91%	1.32%	-3.13%	3.32%	-2.44%	7.56%	TAK VMF (1000)
10	-11	-0.34%	1575	0.81%	6.72%	-1.05%	2.69%	-1.40%	-4.64%	-2.79%	-8.74%	TAK VMF (1000), PN2 (Cation), TAK VMF (waxy), GNV silo 5 (D12)
Abs. Original	3281		42	56.067	8.022	9.864	12.089	1.214	2.564	5.046	0.595	TAK VMF (1000)

Table 30: Detailed analysis on output data related to the production speed sensitivity analysis

Analyzing the truck schedules for which the factory downtime is larger than 600 minutes, we notice several things. For almost all the input data sets resulting in a factory downtime larger than 600 minutes, the total production speed of the factories increased. Figure 23 depicts this relationship between the percentual difference in the total production speed and the factory downtime in minutes. Only for input data set 8 a decrease of 0.01% is observed. This implies that with 7 trucks an increase in total transport demand can directly result in transportation issues causing factory downtime.

Looking at input data 5, which is the only input data set in which the total production speed increases and the factory downtime is still below 600 minutes, we observe that only factory downtime occurs at the TAK VMF (1000) silo while the production speed at the TAK VMF (1000) silo decreases with 1.12%. For all the generated truck schedules, except for data set 3, the TAK VMF (1000) silo has one (or multiple) stockout(s). Therefore, the storage capacity of the TAK VMF (1000) silo is the bottleneck for the input data sets in which a relatively large number of tons should be transported during the intercampaign TAK. This effect is reinforced when the production speed of the factory behind the TAK VMF (1000) silo is relatively high (see data set 2 and 10).

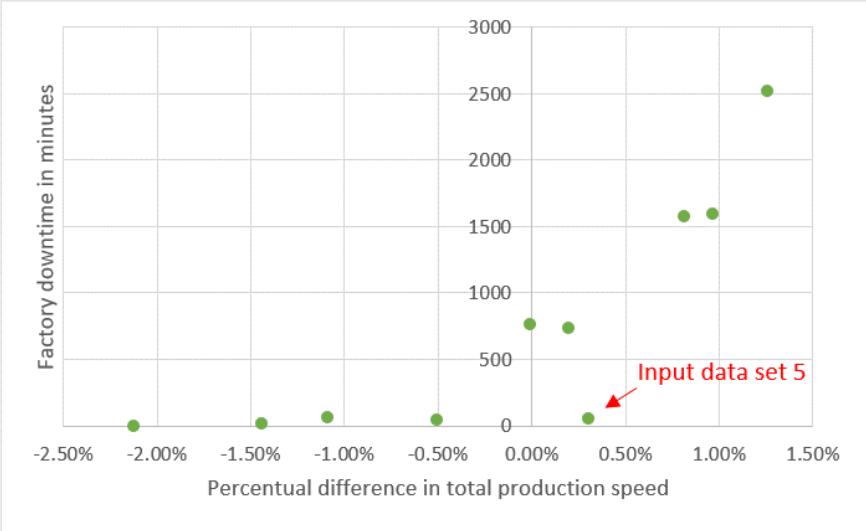

Figure 23: Relationship between the percentual difference in the total production speed and the factory downtime in minutes

It is not surprising that the stockouts occur at the TAK VMF (1000) silo. The factory related to the TAK VMF (1000) silo is with 12.089 tons/hour the factory with the highest production speed, while the silo capacity of the TAK VMF (1000) silo is only 95 tons (both numbers are based upon the input data explained in Section 5.1, see Table 43). This results in small time windows for the transport orders related to the TAK VMF (1000) silo. The smaller the time windows of the orders, the less flexible the planning of the order and therefore the higher chance that we cannot perform the order within the time window.

During our research, we also repeatedly heard the complaint from the transportation company that the communication of important transport-related data should be improved to be able to improve the truck planning. This complaint in combination with the 5 out of 10 satisfactory performances in the sensitivity analysis, and the fact that often some optimality gets lost in practice, made us conclude that the robustness of the bulk truck planning is insufficient with 7 trucks.

Therefore, we decide to perform additional experiments for the same 10 input data sets but now with 8 instead of 7 trucks. Besides, we keep the weights given to the EDD and the TWC time constant. Table 31 provides the results of these experiments. Also, the average performance of the generated truck planning based upon the 10 different input data sets is provided.

Input dataset Nr.	# Trucks	W_EDD	W_TWC	Costs/ton	Waiting/ton	Factory-downtime	# Cleaned	# Trucks	# Special	# Normal	Tons trans.	Waiting loading	Waiting unloading	Total waiting	Pull late	Push late	Stockout location
1	8	0.1	0.9	6.227	0.139	74	577	8	143	3087	91412	9574	3090	12664	0	0	TAK VMF (1000)
2	8	0.1	0.9	6.055	0.117	37	604	8	138	3184	94000	7348	3670	11018	0	0	TAK VMF (1000)
3	8	0.1	0.9	6.26	0.15	42	582	8	136	3070	90917	9136	4489	13624	0	1	TAK VMF (1000)
4	8	0.1	0.9	6.166	0.127	5	577	8	140	3126	92314	9499	2256	11755	0	1	TAK VMF (1000)
5	8	0.1	0.9	6.113	0.115	41	586	8	143	3150	93117	7636	3091	10727	0	0	TAK VMF (1000)
6	8	0.1	0.9	6.074	0.117	5	580	8	142	3174	93709	9029	1972	11002	0	0	TAK VMF (1000)
7	8	0.1	0.9	6.119	0.132	46	606	8	142	3145	93013	9167	3155	12322	0	0	TAK VMF (1000)
8	8	0.1	0.9	6.135	0.127	86	569	8	144	3128	92770	8910	2858	11767	0	0	TAK VMF (1000)
9	8	0.1	0.9	6.207	0.118	73	575	8	145	3097	91695	7415	3427	10842	0	2	TAK VMF (1000)
10	8	0.1	0.9	6.081	0.117	52	591	8	141	3160	93602	7885	3082	10966	0	1	TAK VMF (1000)
Average	**8**	**0.1**	**0.9**	**6.144**	**0.126**	**46**	**585**	**8**	**141**	**3132**	**92655**	**8560**	**3109**	**11669**	**0**	**0.5**	

Table 31: Sensitivity analysis on production speeds with 8 trucks

Analyzing the results in Table 31, we observe that for all input data sets the factory downtime dropped below 600 minutes and the input data sets result in a good performance on the other performance indicators. Therefore, we can conclude that for all input data sets a satisfying planning is generated by the Avebe Planning Tool. This implies that the Avebe Planning Tool is robust and provides a good truck planning when we use 8 trucks and the weight added to the EDD and TWC time are respectively 0.1 and 0.9.

Additional insights

Three more interesting insights can be obtained based on these experiments. First of all, all factory downtimes observed are caused by a stockout at the TAK VMF (1000) silo. This confirms the comment that we made earlier being, that the TAK VMF (1000) silo is the bottleneck silo.

The second interesting insight is obtained when we compare the total number of tons transported with 7 and with 8 trucks for the different input data sets. Table 32 summarizes this comparison. The yellow rows correspond to the input data sets that had a factory downtime larger than 600 minutes when we used 7 trucks. We observe that the total number of tons transported with 8 trucks increased for all input data sets for which we had a factory downtime larger than 600 minutes with 7 trucks. This is in line with our conclusion that for these input data sets the transportation capacity available with 7 trucks is insufficient.

Input dataset Nr.	Tons trans. 7 trucks	Tons trans. 8 trucks	Tons 8 trucks - tons 7 trucks
1	91449	91412	-37
2	93576	94000	424
3	90870	90917	47
4	92212	92314	102
5	93164	93117	-47
6	93421	93709	288
7	92656	93013	357
8	92505	92770	265
9	91813	91695	-118
10	93241	93602	361
Average	**92491**	**92655**	**164**

Table 32: Difference in tons transported with 7 and with 8 trucks

The last insight is obtained by analyzing the percentage of that the trucks are utilized, where the time that a truck is utilized is the time from which the truck starts working on an order to the time that the truck finishes that order. Besides, we determined for what percentage of the time that the truck is utilized, the truck is working on normal respectively special transport. Based on this number we could determine how many trucks are needed to perform the normal transport orders and how many are needed to perform the special transport orders. Table 33 shows that on average a truck utilization of 84.78% is obtained on the ten different input data sets when we used 8 bulk trucks. Comparing the obtained 84.78% truck utilization with the current 65% truck utilization rate during the campaign of the bulk trucks, according to the research of Kuperus (2020, p. 22), a significant improvement is made. Experts of Avebe expect the current truck utilization rate during the intercampaign TAK to be comparable to the current truck utilization rate during the campaign. Furthermore, Table 33 shows that on average 7.43 trucks are used to perform the normal transport orders and 0.57 trucks to perform the special transport orders.

Input dataset Nr.	Total time normal	Total time special	Total time	Truck utilization	% of time normal	% of time special	Trucks normal	Trucks special
1	629958	49029	678987	84.20%	92.78%	7.22%	7.42	0.58
2	648620	46814	695434	86.24%	93.27%	6.73%	7.46	0.54
3	614594	46531	661125	81.98%	92.96%	7.04%	7.44	0.56
4	634133	47965	682099	84.59%	92.97%	7.03%	7.44	0.56
5	631178	49026	680204	84.35%	92.79%	7.21%	7.42	0.58
6	643840	49427	693267	85.97%	92.87%	7.13%	7.43	0.57
7	644077	49058	693135	85.95%	92.92%	7.08%	7.43	0.57
8	639148	48648	687796	85.29%	92.93%	7.07%	7.43	0.57
9	618384	49808	668192	82.86%	92.55%	7.45%	7.40	0.60
10	648046	48186	696232	86.34%	93.08%	6.92%	7.45	0.55
Average	**635198**	**48449**	**683647**	**84.78%**	**92.91%**	**7.09%**	**7.43**	**0.57**

Table 33: Truck utilization and truck capacity assigned to normal and special transport

6.4 Conclusion of Chapter 6

Considering the Avebe Planning Tool with the input data discussed in Chapter 5, we conclude based on experiments with the number of trucks, the weight of the EDD, and the weight of the TWC time that the transport demand during the intercampaign TAK can be handled with 7 trucks. This yields a factory downtime of 42 minutes caused by a stockout of the TAK VMF (1000) silo. Besides, the costs per ton transported equal €5.36. However, reality will never exactly equal the expected input data. Therefore, we performed a sensitivity analysis on the production speeds and the number of trucks used. These input parameters are selected based on the high impact that deviations in the parameter values will have on the bulk truck planning. Based on expert interviews, we generated uniformly distributed production speeds between 10% above and 10% below the production speeds in the input data discussed in Chapter 5.

In this sensitivity analysis, we observed that we could not fulfill the performance threshold of fewer than 600 minutes of factory downtime in 5 out of 10 generated input data sets when using 7 trucks. During our research, we also repeatedly heard the complaint from the transportation company that the communication of important transport-related data should be improved to be able to improve the truck planning. This complaint in combination with the 5 out of 10 satisfactory performances in the sensitivity analysis, and the fact that often some optimality gets lost in practice, made that we tested whether a planning with 8 trucks is robust. In a transport planning with 8 trucks, Avebe Planning Tool generates a transport planning with less than 600 minutes of factory downtime for all ten input data sets. Therefore, we conclude the transport planning with 8 trucks to be robust. With 8 trucks, the costs per ton material transported equal €6.14 and the factory downtime 46 minutes. Besides, the utilization rate of these 8 trucks equals 84.78% while 7.43 trucks should be assigned to normal transport and 0.57 trucks to special transport.

Lastly, we observed that all factory stockouts with 8 trucks took place at the TAK VMF (1000) silo. Therefore, the TAK VMF (1000) silo is the bottleneck of the bulk truck planning. We advise Avebe to investigate the possibilities to increase the storage capacity of this silo.

In Chapter 7, we will use the insight that we need 8 trucks to generate a robust transport planning and the experimental output data obtained in this chapter to answer our research question; *"How many trucks should Avebe have in the hired pool of bulk trucks for normal and special transport, during the intercampaign TAK, in order to reduce the total transportation cost without significantly increasing the factory downtime because of transportation issues."*

7. Conclusion and recommendation

In this chapter, we provide the conclusion and recommendations of this research in order to answer research question 6 (see Section 1.6). Section 7.1 contains both the practical conclusions for Avebe as well as the theoretical conclusions that can be drawn based on this research. Section 7.2 provides a recommendation to Avebe and our advice containing the steps that Avebe should take to employ the observed improvement potential related to the bulk truck planning. Section 7.3 discusses the limitations of our research and the directions for future research.

7.1 Conclusion

In this section, we first answer the central research question using the insights that we obtain from the experiments and sensitivity analysis performed in Chapter 6. Then we will provide insight into the contribution of this research to the current state of knowledge related to the Vehicle Routing Problem with Pickup and Delivery, and Time Windows (VRPPDTW). Lastly, we will share our vision on the generalizability of the problem-solving approach underlying the 'Avebe Planning Tool' that we developed.

Based on our context analysis in Chapter 1, we formulated the following research question:

"How many trucks should Avebe have in the hired pool of bulk trucks, for normal and special transport, during the intercampaign TAK, in order to reduce the total transportation cost without significantly increasing the factory downtime because of transportation issues."

To answer this research question, we developed the Avebe Planning Tool which is based upon a modified cheapest insertion heuristic. In our modified cheapest insertion heuristic, the cheapest insertion is determined using a selection method followed by a priority rule. The selection method and priority rule together consider the deadline of the order, the travel time, waiting time at the (un)loading docks, and the cleaning time.

Practical conclusions

Based on the experiments performed with the Avebe Planning Tool we conclude that if the input data, related to the production speeds of the defined production flows, is as expected based on expert interviews, historical data, and forecasts, the transport planning can be performed by 7 trucks. Then a weight of 0.1 should be given to the 'Earliest Due Date' and 0.9 to the 'Travel, Waiting, and Cleaning time'. Table 34 provides an overview of the performance of the intercampaign TAK 2020 and the 'Avebe Planning Tool'.

Performance indicator	Intercampaign TAK 2020	Avebe Planning Tool
1. Costs/ton transported	€8.53	€5.36
2. Waiting time in minutes per ton transported	2.85	0.085
3. Factory downtime because of transportation issues	0 min.	42 min.
4. Number of trailers cleaned	Not available	657
5. Number of trucks used	10 pool and 2 flex	7 pool 0 flex

Table 34: Performance 'Avebe Planning Tool' with expected input data using 7 trucks

However, in reality, the production speeds related to the different transportation flows will never be exactly equal to the production speeds that we expect. Therefore, we performed sensitivity analyses on the input parameters that involve the highest uncertainty and for which a change in parameter value has the highest impact on the transport planning. These input parameters are the production speeds and the number of trucks used. Based on the experience of the expert, we concluded that the deviation in the production speeds can best be approached by a uniform distribution around the expected production speeds where the lower bound equals 90% and the upper bound 110% of the expected production speeds. In this way, we generated 10 different input data sets for the Avebe Planning Tool. Planning the bulk trucks with these 10 input data sets, we observe that only five out of 10 input data sets result in a truck planning for which the total factory downtime is below the predefined 600 minutes when we use 7 trucks. Therefore, the robustness of the transport planning is insufficient when we have 7 trucks in the hired pool of bulk trucks.

Additional experiments on the same generated input data sets, but with 8 trucks and 0.1 weight added to the 'Earliest Due Date' and 0.9 weight added to the 'Travel, Waiting, and Cleaning time' resulted in 10 out of 10 input data sets that yield a truck planning in which the total factory downtime is smaller than 600 minutes. Therefore, we recommend that Avebe should have 8 trucks in the hired pool of bulk trucks. Table 35 provides the average performance of the Avebe Planning Tool on the generated input data sets and the performance of the intercampaign TAK 2020 planning.

Performance indicator	**Performance current planning approach**	**Average performance of developed 'Avebe Planning Tool'**	**Difference**
1. Costs/ton transported	€8.53	€6.14	-28.02%
2. Waiting time in minutes per ton transported	2.85	0.126	-95.58%
3. Factory downtime because of transportation issues	0 min.	46 min.	+46 min.
4. Number of trailers cleaned	Not available	585	Not Available
5. Number of trucks used	10 pool and 2 flex trucks	8 pool and 0 flex trucks	-2 pool and -2 flex trucks

Table 35: Comparison average performance 'Avebe Planning Tool' with the performance of the current planning approach

Comparing the performance of the intercampaign TAK 2020 with the performance of the Avebe Planning Tool, we observe that the cost per ton transported is reduced from €8.53/ton to €6.14/ton transported which corresponds to a reduction of more than 28%. Besides, the bulk trucks only have to wait 0.126 minutes per ton transported in the planning generated by the Avebe Planning Tool, while the trucks had to wait 2.85 minutes per ton transported during the intercampaign TAK 2020. This corresponds to a reduction in waiting time for loading and unloading of more than 95%. The expected factory downtime because of transport issues when employing the Avebe Planning Tool equals 46 minutes for the whole intercampaign TAK, while according to expert interviews no transport-related factory downtime took place during the intercampaign TAK 2020. This is a small increase in factory downtime however, the factory downtime is still far below the maximum acceptable factory downtime of 600 minutes.

Furthermore, according to the Avebe Planning Tool, we will clean 585 times during the intercampaign TAK. Since the generated truck schedule of Avebe Planning Tool contains 3132 normal transport orders and 141 special transport orders, cleaning 585 times corresponds to an average of 5.59 orders that will be performed before a trailer is cleaned. Lastly, during the intercampaign TAK 2020 on average 10 pool trucks and 2 flex trucks were used while the Avebe Planning Tool uses 8 pool trucks for the whole

intercampaign TAK. The 8 trucks have a utilization rate of 84.78%. From these 8 trucks, 7.43 trucks will be needed to perform the normal transport orders and 0.57 trucks will be needed to perform the special transport orders. However, we should notice that the Avebe Planning Tool treats the special transport orders as if they are normal transport orders implying that the priority of normal and special transport orders is determined similarly. Besides, the Avebe Planning Tool does not dedicate one truck to the special transport orders. Instead, all trucks are used for both special and normal transport orders.

All in all, our research showed that there is a huge improvement potential related to the bulk truck transport. The expected reduction in costs per ton transported when we plan the bulk trucks as in the Avebe Planning Tool equals €8.53 - €6.14 = €2.39 per ton transported. Multiplying this reduction in costs by the tons transported according to the Avebe Planning Tool yields a potential saving of 92655*€2.39 = €221,445 during the intercampaign TAK. The total transportation costs during the intercampaign TAK 2020 equaled €804,705 (excluding the costs for trailer rent, fuel, and cleaning which we do not consider in the current situation as well as in the Avebe Planning Tool). This implies that we expect a yearly cost reduction of 27.52% on the total transportation costs during the intercampaign TAK.

Discussing this improvement potential with the expert of Avebe, the expert confirmed that he believes that a similar cost reduction can be obtained during the other weeks of the year. This implies that the yearly potential cost reduction equals (€221,455/10)*52 = €1,151,566. Noted should be that in order to release this improvement potential, Avebe should invest time and money to develop the application, maintain the application, and train its employees on how to use the application.

Theoretical conclusions

The planning problem that we solve with the Avebe Planning Tool, is classified as a multi-objective static open vehicle routing problem with pickup and delivery, where load splitting is not allowed, and vehicles can perform multiple trips. Furthermore, we have a fixed number of non-compartmentalized homogeneous vehicles with heterogeneous freights where transportation orders have hard time windows, and both waiting times and cleaning are considered. Contrary to the current standard in the literature on VRP, we do not have a central depot where the vehicles start and end their routes.

To solve this new variant of the VRPPDTW problem we build the Avebe Planning Tool in which we simultaneously generated and plan transport orders. In order to generate the transport orders, we apply push and pull reasoning to 39 transportation flows which are either classified as a push or a pull flow. For each of these flows, we generate new transportation orders, after assigning the flow-specific order to a truck, as long as the time window of the order is still within our planning horizon (the intercampaign TAK). To assign the orders to the bulk trucks we employed our modified cheapest insertion heuristic. In the modified cheapest insertion heuristic, the cheapest insertion is determined using a selection method followed by a priority rule. The selection method and priority rule together consider the deadline of the order, the travel time, waiting time at the (un)loading docks, and the cleaning time.

Based on the performance of planning generated by the Avebe Planning Tool compared to the performance of the current transport planning of Avebe, we conclude that our method to solve the VRPPDTW without a central depot is good. However, how good is hard to tell since we only compared the performance of our planning tool with the performance of the current transport planning approach of Avebe.

Considering the generalizability of the modeling approach, we believe that the logic behind Avebe Planning Tool can be implemented in all transport processes in which buffers (e.g., silos) are present and there is a demand (e.g., factory or customer) that should be fulfilled by non-compartmentalized homogeneous vehicles. We should notice that the accuracy of the Avebe Planning Tool increases as the demand for transport increases and therefore the number of trucks needed increases. Important parameters in the Avebe Planning Tool such as the current volumes of the silos and the time windows of the orders are updated when a truck becomes available. The larger the number of transport orders to be done, the more trucks we need to perform the transport, and the shorter the time between trucks that become available. This implies that the parameters are more frequently updated and therefore the knowledge in the planning procedure will be closer to reality. Therefore, the logic behind the Avebe Planning Tool can best be used in large transportation processes in which multiple trucks are used.

7.2 Recommendation

In this section, we provide our recommendation to Avebe based on the results obtained in this research. The recommendations aim to accompany Avebe in the steps that should be taken to employ the potential cost savings demonstrated in this research. Lastly, we provide a recommendation based on an additional insight obtained during this research which is not directly related to the goal of this research.

To perform the bulk truck planning with the proposed 8 trucks and to employ the potential cost savings of €221,445 during the intercampaign TAK we advise Avebe to combine the logic behind the Avebe Planning Tool, with the already existing application called the 'ISF app'. In the ISF app, the truck drivers upload all tasks that they performed, e.g., loading, driving, and waiting. Currently, this app only works for the starch transportation, however, when the app can also handle the transport of derivatives, protein, dry flours, waxy, and customer deliveries, an online bulk truck planning can be generated based on the data available in the ISF app. Next to the truck drivers, also the operators should have access to the ISF app. Then the operators can make sure that the production speeds of the factories in the ISF app correspond to the production speeds in reality. Besides, factory downtimes or maintenance stops of the factories can then be put in the ISF app by the operators.

This approach would resolve several undesirable properties of the current planning process. First of all, the lack of data transparency and overview. Currently, the planner of the transport company is continuously calling the truck drivers, to tell them what they should do next, and to update them on changes in the transport planning. When the truck schedule is automatically generated based upon the input data provided by the truck drivers and the operators, the schedule of the truck driver will automatically be updated and the next order to be done will be visible in the app. This will prevent the loss of information from happening when it is orally transferred by the Avebe planner to the truck drivers. Besides, planning the trucks using the app will save the planner of Avebe a lot of work. Furthermore, the information will directly be available to all truck drivers and operators so there will be less delay in knowledge.

Next to the cost-saving, time-saving, and information transparency enhancing benefits of online generating the bulk truck planning in the ISF app, there will also be advantages in terms of administration afford. Currently, all transport hours and trailer cleanings are registered by hand in an Excel file by the transport planner of the transport company. Based on these Excel files, the invoice for Avebe is made and discussed in a weekly meeting. When the tasks performed by all truck drivers are updated in the ISF app and the completed transport orders and cleanings are stored in the ISF app,

also the invoices can be automatically generated by this ISF app. This will strongly increase the transparency of the invoices but also decrease the amount of effort needed to make these invoices.

Once, Avebe managed to integrate the Avebe Planning Tool with the ISF app for the intercampaign TAK, we advise Avebe to add the campaign and the intercampaign to the application. The logic behind the Avebe Planning Tool can directly be applied to the other periods of the year. Only the input data of the tool will be different in the other periods since other transportation flows will be present and other factories will be operational. Chapter 2 provides information on the transportation flows present in the campaign and the intercampaign. Besides, the size of the different flows and the transportation times can be found in Chapter 2. Therefore, the largest part of the input data needed to make the application applicable during the whole year is already provided in this research.

Therefore, we conclude that when the application works for the intercampaign TAK, it will be relatively easy to extend its applicability to the whole year. This would make it possible to employ a potential cost savings of 1,151,566 euros per year. However, we should notice that Avebe should invest time and money to develop the application, maintain the application, and train its employees on how to use the application.

Lastly, we advise Avebe to research the cost of increasing the storage capacity of the TAK VMF (1000) silo. Our research showed that this silo location is the bottleneck silo. We expect that increasing the capacity of this silo to result in a decrease in the number of trucks needed. The reason for this is that the time windows of the orders related to this silo will become larger and therefore the truck planning more flexible.

7.3 Discussion and future research

In this section, we discuss the practical and theoretical limitations of this research which we translate into interesting directions for future research. The limitations are divided into limitations related to loading and unloading, the trucks, the factories, the costs, and the methodology.

<u>Loading and unloading</u>

Opening hours of silos

The Avebe Planning Tool assumes that the silos can be used 24/7, however in reality some of the silos have restrictions on their opening hours. Table 45 in Appendix C.2 provides an overview of the opening hours of the silos. We expect the impact of these opening hours on the truck capacity needed according to the Avebe planning took to be very small for the reasons given in Section 5.2. However, additional research on the impact of these opening hours could be conducted to validate this expectation with data.

Deviations in loading and unloading times

The Avebe Planning Tool assumes that the loading and unloading times at the silo locations depend on the location and the material to be loaded or unloaded. These loading and unloading times are based upon historical data when available and otherwise on expert interviews. Besides, all loading times and unloading times are checked by the expert of Avebe since the data is gathered using an app in which truck drivers manually have to fill in the loading and unloading times. In Appendix B.2, we provide histograms of the loading and unloading times of bulk trucks at starch silos. Loading and unloading times longer than three hours and shorter than 5 minutes are excluded since we consider these to be outliers. Analyzing these histograms, we observe that for some locations very limited data is present and that for some locations the loading and unloading times deviate.

Discussing this observation with the expert of Avebe, we identified several reasons for the deviation in loading and unloading times. First of all, the loading and unloading times are based upon the period between 1-8-2019 and 1-8-2020 since this is the most recent complete season of data. However, the truck drivers who upload the loading and unloading times manually were not yet used to working with the application. This might have resulted in very long times because the truck driver forgot to upload the loading/unloading time or very short times because of misclicks or performing several forgotten steps at one point in time. Secondly, deviations in loading and unloading times can be explained by the presence of craters in the silo. When craters are present in the silos, the loading times will increase. However, the size of the impact of craters in the silos on the loading speed of trucks is not known. Based on the poor data quality of the loading and unloading times at the starch silos, and the absence of loading and unloading data at all non-starch silos, we advise Avebe to perform research on the loading and unloading times such that the assumption made based on expert interviews can be validated by properly gathered data. Currently, the installation of GPS trackers on the trucks is investigated. This would make it possible to derive the loading and unloading times based on GPS data which could help the research in this direction.

Order in which trucks are treated at (un)loading docks

In the Avebe Planning Tool, it can happen that a truck is waiting at a(n) (un)loading dock when the dock is free. This happens when a truck, that is scheduled later arrives earlier at the (un)loading dock. The truck that was scheduled earlier but did not yet arrive will make the dock unavailable while in reality, the dock is available. The probability that this happens is very small for two reasons. First of all, we update the current volume, volume loaded, volume unloaded directly when a truck is assigned to an order. The new order that we generate for this flow will be based upon the updated current volume, volume loaded, and volume unloaded and therefore it will be unlikely that the same order will be performed, within a few hours, again. Secondly, the start time windows and end time windows, of all orders that still have to be planned, will also be updated based on the new current volume, volume loaded, and volume unloaded. This makes the probability that a truck, that is scheduled later, arrives earlier at the silo location is very small. However, theoretically, it is possible. Solving this shortcoming of the Avebe Planning Tool will slightly improve the truck planning because no truck waiting takes place when this is not needed. Therefore, additional research could be performed to find a method of updating the availability of the loading/unloading docks in which it cannot happen that a truck is waiting for a loading/unloading dock while the dock will be available in reality.

<u>Trucks</u>

Flex trucks

In the truck planning generated by the Avebe Planning Tool, we observe fluctuations in the transport demand over the days. Therefore, we advise Avebe to investigate whether it is possible to have one truck less in the fixed pool of hired bulk trucks and to hire a flex truck when transport demand is high. As discussed earlier, the trade-off between a pool truck and a flex truck lies at 132 hours of use per week. This implies that a flex truck becomes more expensive than a pool truck when the flex truck is used for more than 132 hours per week. This breakeven point seems to be very high, implying that it is worthwhile to investigate this potential cost reduction approach. However, when this direction is chosen, we should observe how 'flex' these flex trucks are in reality. Currently, the transport company does not reserve trucks in case that Avebe would like to use a flex truck. Therefore, we do not expect the flex truck to be immediately available when needed which is contradictory to what is stated in the contract.

The Avebe Planning Tool assumes that all normal and special transport orders should be performed by the pool of hired bulk trucks. This assumption is made since the tradeoff between using a pool truck instead of a commercial truck to perform special transport lies at a utilization rate of 42% of the commercial truck (see Section 5.2). However, an interesting alternative approach towards special and normal transport orders would be to perform as much as possible transport orders with the hired pool

of bulk trucks. In case the pool of bulk trucks cannot handle all the transport orders, a flex truck should be hired instead of a commercial truck. A flex truck will cost Avebe 53.96 euros per hour while an average commercial truck costs Avebe €100.77 per hour. As mentioned above, an additional truck should be added to the pool when this truck will be used for more than 132 hours per week, otherwise, a flex truck should be used.

One truck is one trailer
In the Avebe Planning Tool, we assume that each truck uses one trailer. However, in reality, one truck can use multiple trailers. Having one trailer for each truck in the future will have several advantages for Avebe. First of all, Avebe will not be dependent on the trailers used by other companies anymore. Secondly, the cleaning costs become more transparent since we know what materials are transported in the trailer and when cleaning is needed. However, a disadvantage of having one trailer for each truck will be that it is not possible to load a trailer and put it aside until the material is needed (a kind of buffering in trailers done in the current planning). Additional research could be done to decide whether Avebe should go for the 'one truck is one trailer' approach, or that Avebe should still hire multiple trailers of each truck. When multiple trailers are hired for each truck, the Avebe Planning Tool should be adjusted to be able to account for this.

<u>Factories</u>
Factory downtime calculation
According to the output file called 'SiloDownTime', we can have a stockout at a push silo and a stock over at a pull silo which seems not logical. This happens when there is an overstock at the push silo which is not observed during the planning procedure, but which is observed in the 'FactoryDowntime' procedure. This implies that the factory prior to the push silo has downtime according to the 'FactoryDowntime' procedure, but this factory downtime is not considered during the planning procedure. Therefore, the current volume with which we plan is higher than the current volume according to the 'FactoryDowntime' procedure. The higher volume, with which we plan, makes that the trucks load earlier at the push silo which resulting in stockouts at the push silo according to the 'FactoryDowntime' procedure. Research could be conducted to develop a method to overcome the discrepancy between the current volume during the planning procedure and during the 'FactoryDowntime' procedure to ensure that the stockout moments at pull silos and stock over moments at push silos are always observed during the planning procedure.

No maintenance stops
The Avebe Planning Tool assumes that all factories produce 24 hours a day 7 days per week, while in reality there will be some factory downtime because of maintenance activities at the factories. When a factory is down for maintenance, we do not have to transport the material to prevent overflows of the push silos from happening. Besides, no material has to be delivered to the pull silos when the factories are down. Therefore, this assumption will lead to a planning in which more transport capacity is needed than will be needed in reality. Within Avebe a distinction is made between two types of maintenance stops, the periodical stops (called 'PPO') and the large stops (called the 'maintenance' or 'energy' stops). The PPOs take place once every six weeks and have a duration of eight hours, while the maintenance stops occur once per year and have a duration of five to seven days. Further research should be conducted to tell how large the impact of stops will be on the transport capacity needed.

<u>Costs</u>
In this research, we did not consider the costs of fuel, trailer cleaning, and the rental costs of the tailers. Considering the trailer rent we note that, based on the fact that the Avebe Planning Tool assumes that one truck uses one trailer, the rental costs for the trailers will be about one-third of the costs for trailer rent paid in the current situation. In the current situation roughly speaking each truck uses three trailers. However, the one truck uses one trailer approach will also lead to more trailer cleanings and therefore higher costs for trailer cleaning. Lastly, it is hard to estimate the impact of planning with the

Avebe Planning Tool on fuel costs. On one hand, we expect that the transport kilometers will drop because the Avebe Planning Tool does not allow buffering in trailers. But on the other hand, the Avebe Planning Tool does not consider fixed routes for the trucks which might have a positive or a negative impact on the transport kilometers. Therefore, future research should be conducted to assess the impact of the fuel costs, trailer cleaning costs, and trailer rental costs on the observed potential costs saving.

Methodology

Implementation of Simulated Annealing improvement meta-heuristic

Due to the time constraints of this research, we did not manage to implement the Simulated Annealing improvement meta-heuristic. In the Avebe Planning Tool, we implemented our modified cheapest insertion heuristic to assign the transport orders to the trucks. In Section 7.1 we conclude that this modified cheapest insertion heuristic yields very good results compared to the current planning approach at Avebe. However, we expect that even better truck schedules can be obtained by implementing a Simulated Annealing improvement meta-heuristic, which is described as the second step in Chapter 4 of this research. The expectation that the truck schedule can be improved by the implementation of a Simulated Annealing improvement heuristic, is based upon the presence of gaps in the truck schedules. The presence of these gaps might be prevented or reduced by implementing a Simulated Annealing algorithm which might make it possible to further reduce the number of trucks needed. On the other hand, the gaps in the truck planning also ensure the robustness of truck planning.

Based on a thorough assessment of the state-of-the-art literature related to Simulated Annealing algorithms in Sub-section 4.6.1, we advise applying a combination of move and swap neighborhood operators when further research is conducted on the implementation of the Simulated Annealing algorithm.

Other selection methods/priority rules

To develop the Avebe Planning Tool, we considered three different methods to select the orders on which our priority rule will be applied, yielding the order to be selected to the truck. The selection method that we applied in combination with our priority rule proved to provide good results compared to the current planning approach of Avebe (see the comparison in Section 7.1). Besides, we showed that the applied order selection method combined with the priority rule results in good truck planning for almost all weight given to the EDD and TWC time which makes our modified cheapest insertion heuristic robust and easy to use. However, only applying the priority rule without the selection method might yield better results when the input data is known with more certainty.

Additional research on other selection methods and priority rules might yield even better truck schedules. An interesting direction could be to develop a priority rule which prioritizes normal transport orders over special transport orders because the special transport orders, in general, take more time and do not have to be performed by the pool of bulk trucks according to the contract. When more order selection methods and priority rules are assessed, additional insights into the quality of the order selection method and priority rule applied in this research can be obtained.

Number of input data sets

In the sensitivity analyses performed in our research, we generated 10 input data set based on which we assessed the robustness of the bulk truck planning and explained the performance of the Avebe Planning Tool. However, when the Avebe Planning Tool is tested on more input data sets, the presence of coincidence will be filtered out. Besides additional insights on possible dependencies or boundaries of the truck planning tool might be obtained. Therefore, testing the Avebe Planning Tool on more input data sets could be an interesting direction for future research.

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Appendices

Appendices are excluded for confidentiality reasons.